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Affect-Dynamic Signatures of Psychosis Risk Across Multiple Time Scales and Contexts

Lilian Y. Li[1,2], Jason Schiffman[1], and Elizabeth A. Martin[1]
[1]Department of Psychological Science, University of California, Irvine, and [2]Department of Psychiatry and Behavioral Sciences, Northwestern University

Abstract
There is a critical need for identifying time-sensitive and cost-effective markers of psychosis risk early in the illness course. One solution may lie in affect dynamics, or the fluctuations of affect across time, which have been demonstrated to predict transitions in psychopathology. Across three studies, the current research is the first to comprehensively investigate affect dynamics in relation to subthreshold positive symptoms (perceptual aberration and magical ideation) and negative symptoms (social anhedonia) of the psychosis spectrum. Across multiple time scales and contexts, we modeled affect dynamics from inexpensive laboratory paradigms and social-media text. Findings provided strong evidence for positive symptoms linked to heightened magnitude and frequency of affective fluctuations in response to emotional materials. Alternatively, negative symptoms showed modest association with heightened persistence of baseline states. These affect-dynamic signatures of psychosis risk provide insight on the distinct developmental pathways to psychosis and could facilitate current risk-detection approaches.

Keywords
psychosis, risk detection, affect dynamics, sentiment analysis, networks, open data

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Psychotic disorders, such as schizophrenia, affect approximately 0.4% of the population (Moreno-Küstner et al., 2018) yet are a leading contributor to disability and economic burden worldwide (GBD 2019 Diseases and Injuries Collaborators, 2020). A much larger segment of the population—estimates range from 7% to 12% (Linscott & van Os, 2013; Meehl, 1990; Nuevo et al., 2012)—experiences subthreshold psychosis, including maladaptive personality traits and psychotic-like experiences that can be categorized primarily into positive symptoms (e.g., perceptual disturbance and magical thinking) and negative symptoms (i.e., diminution in experiences, e.g., social anhedonia; Kotov et al., 2020; Kwapil & Barrantes-Vidal, 2015). Mounting research suggests that these subthreshold psychotic experiences are not qualitatively distinct from full-blown psychosis. Instead, psychosis is better conceptualized as a severity spectrum that ranges from individual differences to clinical disorders (Kotov et al., 2020; Kwapil & Barrantes-Vidal, 2015; Linscott & van Os, 2013; van Os et al., 2000).

Individuals with subthreshold experiences of psychosis, such as people with elevated psychosis-related personality traits (also known as schizotypy) and people meeting the criteria for clinical high-risk status, have an elevated risk for more severe forms of psychosis and nonpsychotic psychopathology (Chapman et al., 1994; Fusar-Poli et al., 2013; Kaymaz et al., 2012; Kelleher et al., 2014; Kwapil, 1998; Lenzenweger, 2021). Although the majority of people with subthreshold psychosis do not develop a clinically significant psychotic disorder,

Corresponding Author:
Elizabeth A. Martin, Department of Psychological Science, University of California, Irvine
Email: emartin8@uci.edu

individuals along the psychosis severity spectrum share risk factors across biopsychosocial domains (Kwapil & Barrantes-Vidal, 2015; Linscott & van Os, 2013). In addition, subthreshold psychosis can be distressing and has been associated with worse physical health, poor daily functioning, and suicidality (DeVylder & Hilimire, 2015; Kelleher et al., 2014; Nuevo et al., 2012; Phillips & Seidman, 2008). Given the phenotypic and risk-factor overlap with clinical psychosis and the inherent associated impairment and distress, research on people with subthreshold psychosis informs the psychosis spectrum and may provide insight into risk factors for illness progression.

Affective abnormalities emerge as a key indicator of risk given their central role in the presentation, etiology, and maintenance of psychopathology in general (Kring & Mote, 2016) and psychotic disorders in particular (Horan et al., 2008; Li, Dent, et al., 2021; Myin-Germeys & van Os, 2007). There is a burgeoning body of research showing that beyond mean levels of affect, affect dynamics, or the fluctuations of affect across time, can provide a mechanistic understanding of the risk and resilience for psychopathology (Bringmann et al., 2016; Houben et al., 2015; Trull et al., 2015; Wichers et al., 2015). In particular, recent theorizing about the dynamics of complex systems such as affect has proposed a set of indices that typically precede the critical transition from normality to abnormality (Scheffer et al., 2009, 2012; for a brief overview, see Table 1). In the affect system, the dynamic-systems theory posits that a few densely connected positive affect (PA) and negative affect (NA) states can make an individual less able to adapt to various internal and external demands (e.g., a vicious cycle of sadness, guilt, and unhappiness). Over time, these emotional states may become more persistent and unstable until only a slight perturbation (e.g., an unpleasant work meeting) may be enough to precipitate a synchronized shift from typical functioning to a pathological state. Indeed, these theoretically important affect-dynamic indices have been linked to a wide range of psychopathological conditions (Houben et al., 2015), most notably, predicting future transitions in symptom severity (Van De Leemput et al., 2014; Wichers et al., 2020; Wichers & Groot, 2016). Thus, examining affect dynamics in relation to the spectrum of positive and negative psychosis symptoms may uncover novel affective signatures useful for the prediction of psychosis risk.

Despite ample historical accounts linking psychosis to altered affect dynamics (e.g., affective lability and ambivalence; Bleuler, 1911/1950; Meehl, 1990), few studies to date have empirically tested affect-dynamic indices as they relate to the psychosis spectrum. Previous studies have relied on the experience-sampling method (ESM) to assess naturally occurring affect. Findings have converged to indicate that positive symptoms are tied to elevated NA variability overall and from one moment to the next (i.e., instability) and, to a lesser extent, elevated instability in PA (Kwapil et al., 2012; Myin-Germeys et al., 2000; Nittel et al., 2018, 2019; Oorschot et al., 2013; Westermann et al., 2017). Variability and instability in either PA or NA do not appear to characterize negative symptoms; the majority of studies have failed to find any significant associations (Kwapil et al., 2012; Oorschot et al., 2013; Westermann et al., 2017). Instead, one study found that negative symptoms were related to a stronger pull of affect to baseline (i.e., affective set point) that was characterized by low PA and high NA, which suggests elevated inertia of baseline states and elevated regulatory tendencies to baseline following emotional events (Westermann et al., 2017). Likewise, another study showed that negative symptoms were associated with a lower likelihood of maintaining or increasing PA and a greater likelihood of maintaining or increasing NA (Strauss et al., 2020). Overall, evidence points to positive and negative symptoms conveying the opposite patterns of affect dynamics; the former is related to an increased magnitude and frequency of change, whereas the latter is related to an increased resistance to change from baseline.

Nevertheless, because previous studies have typically focused only on variability or instability in NA, it is relatively unclear how other affect-dynamic indices (e.g., emodiversity, density, and synchrony) relate to symptoms of the psychosis spectrum. Preliminary evidence indicates that these less studied affect-dynamic indices are related to the psychosis spectrum. For example, Strauss and colleagues (2020) found greater density of connections between PA and NA, particularly an inhibition of NA on PA, for individuals with schizophrenia than control subjects. Kimhy and colleagues (2014) showed that compared with control subjects, individuals with schizophrenia had lower differentiation in discrete emotional states generally (e.g., all states are labeled as "good" or "bad" rather than "happy," "sad," "angry," etc.) but not for negatively valenced discrete states specifically, which possibly points to a reduced overall, but not negative, emodiversity. However, little is known regarding whether emodiversity, density, and synchrony could differentially relate to positive and negative symptoms of the psychosis spectrum as do other affective dynamic indices. At the same time, a comprehensive examination of affect dynamics is needed in light of findings showing that a combination of different indices enhanced the predictive sensitivity and specificity for depressive-symptom transition (Van De Leemput et al., 2014; Wichers et al., 2020; Wichers & Groot, 2016).

Table 1. The Definition and Operationalization of Affect Dynamic Indices

Affect dynamics	Theoretical relevance	Statistical operationalization	Substantive interpretation
Emodiversity	Low diversity and high connectivity density are structural indicators of resistance to change, which reflects a system that is vulnerable for critical transitions (vs. gradual adaptations; Scheffer et al., 2012).	Shannon's entropy (Quoidbach et al., 2014) Shannon's entropy for person j $j = -\sum_{i=1}^{s} p_{ij} \times \ln(p_{ij})$, in which s is the total number of emotions experienced and P_{ij} is the proportion of the ith emotion in all instances of s	Lower emodiversity indicates lower variety and relative abundance of the emotional repertoire.
Density	Low diversity and high connectivity density are structural indicators of resistance to change, which reflects a system that is vulnerable for critical transitions (vs. gradual adaptations; Scheffer et al., 2012).	The mean of all absolute within-persons centered autoregressive and cross-regressive slopes in a multilevel vector autoregressive model, in which an emotion (i.e., positive or negative) at time_i is predicted from its past state at time_{i-1} and the past state of the other emotion (i.e., negative or positive; Bringmann et al., 2016)	Greater density indicates greater temporal interdependency and thus resistance to change of the emotional network.
Inertia	High inertia, variability, and synchrony are features of a system that is slow to recover from minor perturbations (i.e., critical slowing down) when at the vicinity of a critical transition (Scheffer et al., 2009, 2012).	The within-persons centered autoregressive slope in a multilevel model, in which an emotion at time_i is predicted from its past state at time_{i-1} (Kuppens et al., 2010)	Greater autocorrelation indicates greater temporal interdependency and thus resistance to change of the emotion.
Variability (overall)	High inertia, variability, and synchrony are features of a system that is slow to recover from minor perturbations (i.e., critical slowing down) when at the vicinity of a critical transition (Scheffer et al., 2009, 2012).	The standard deviation of a person's emotion across time (Eid & Diener, 1999)	Greater standard deviation indicates greater overall amplitude or range of emotional changes.
Instability (moment-to-moment variability)	High inertia, variability, and synchrony are features of a system that is slow to recover from minor perturbations (i.e., critical slowing down) when at the vicinity of a critical transition (Scheffer et al., 2009, 2012).	SSD and AC (Jahng et al., 2008) For both indices of instability, successive differences between time_i and time_{i-1} are first calculated. SSDs are calculated as the squared SDs. The AC at time_i is defined by whether the associated SD exceeds a meaningful cutoff (c), with $\text{AC}_i = 1$, if successive differences between time_i and $\text{time}_{i-1} \geq c$ and $\text{AC}_i = 0$ otherwise. A recommended AC cutoff is the 90th percentile of all instances of successive differences (Jahng et al., 2008).	Greater SSD indicates greater amplitude and frequency of emotional changes, whereas greater AC indicates greater acute increase in emotions.
Synchrony	High inertia, variability, and synchrony are features of a system that is slow to recover from minor perturbations (i.e., critical slowing down) when at the vicinity of a critical transition (Scheffer et al., 2009, 2012).	The correlation between within-persons centered positive and negative emotions (Dejonckheere et al., 2018)	Given that positive and negative emotions are typically negatively correlated (Russell & Carroll, 1999), a more negative correlation thus indicates greater synchrony or greater inhibition of opposite-valenced emotions.

Note: SD = successive difference; SSD = square successive difference; AC = acute change.

The extant literature is not only sparse but also suffers from a critical limitation. Past studies have not controlled for mean levels of affect, which have considerable influence on affect dynamics (Dejonckheere et al., 2019). For example, greater mean score usually leads to greater variability (Dejonckheere et al., 2019; Ebner-Priemer et al., 2009). Because high NA is a core feature of the psychosis spectrum (Horan et al., 2008), it is possible that the observed elevated NA variability could be a by-product of elevated mean-level NA. Thus, to clarify whether altered affect dynamics are a specific feature of the psychosis spectrum, it is important to partial out the influence of mean-level affect.

The following three studies comprehensively examined affect-dynamic indices in relation to psychosis-spectrum symptoms over and above mean levels of affect. To attempt to replicate and expand prior ESM findings, in Study 1, we modeled affect dynamics from naturally occurring linguistic expressions on a social-media platform (i.e., Twitter). In Study 2 and Study 3, we further probed the effects of time scales and contexts because the dynamical phenomena at varying time scales and contexts are likely governed by different processes and could show differential relations with psychopathology (Ebner-Priemer & Sawitzki, 2007; Hollenstein, 2015; Hollenstein et al., 2013; Koval et al., 2013; Lapate & Heller, 2020). Specifically, in Study 2, we anchored affect dynamics to a wide range of internal contexts, including a baseline state and subjectively meaningful pleasant and unpleasant events. In Study 3, we applied a finer temporal resolution and stricter control of external contexts by investigating moment-to-moment affective experiences in response to a standardized emotional film clip. All three studies separately examined subthreshold positive and negative symptoms of the psychosis spectrum as measured, respectively, by perceptual aberration and magical ideation (Chapman et al., 1978; Eckblad & Chapman, 1983) and social anhedonia (Eckblad et al., 1982). These psychosis-related personality traits have been shown to predict future psychosis-spectrum development in nonclinical samples (Chapman et al., 1994; Kwapil, 1998; Lenzenweger, 2021), which were used in current studies to elucidate risk for more severe spectrum pathology. Overall, the current research represents an essential step toward uncovering the affect-dynamic signatures of psychosis risk.

Study 1

The objective of Study 1 was to test the association between psychosis-spectrum symptoms and naturally occurring affect dynamics in spontaneous language expressions on Twitter. For many people, especially young adults, social media has become a part of the daily routine (DataReportal.com, 2020). Of particular relevance is the social-media language usage, which has been abundantly demonstrated to reveal psychological states of the user. For example, the extent to which social-media posts express positive or negative feelings, or text sentiments, provides a sensitive reflection of the user's emotional states (Fan et al., 2019; Jones et al., 2016; Liu et al., 2017) and has concurrent and predictive validity in tracking mental-health and physical-health conditions (De Choudhury et al., 2013; Eichstaedt et al., 2015, 2018; Reece et al., 2017). This, together with the time-sensitive and low-cost features, makes social-media language a rich resource for identifying affect-dynamic risk markers of psychosis.

In Study 1, we downloaded posts (i.e., tweets) from participants' Twitter timelines and used text sentiment of the tweet as a proxy for their affective experience in that moment. Given previous ESM findings, we expected that positive symptoms would be associated with greater sentiment variability and instability, particularly for NA, whereas social anhedonia would be associated with greater sentiment inertia. We also explored the association of positive symptoms and social anhedonia with three other dynamic indices because of their theoretical relevance (i.e., emodiversity, density, and synchrony).

Method

Participants. Participants were undergraduate students who, as part of a larger online study, provided a valid Twitter username and completed scales for psychosis-spectrum symptoms. They received course extra credit for completing the study, which was administered via Qualtrics (https://www.qualtrics.com/). This study was approved by the University of California, Irvine, institutional review board.

There were 1,291 participants who completed the online study, after we removed 167 people with extremely careless or invalid responses and 932 people who reported having never used Twitter. Participants were then asked to provide their Twitter usernames; 1,162 (90.01%) were excluded because (a) they declined to provide their usernames (1,093 excluded), (b) they had a private or suspended account (50 excluded), or (c) they had insufficient tweets (i.e., < 10; 19 excluded). The final sample size consisted of 129 participants (for participant characteristics for Studies 1–3, see Table 2). Compared with the excluded participants, included participants had greater positive symptoms, $t(1,289) = 2.04$, $p = .042$, $d = 0.19$, and lower social anhedonia, $t(1,289) = -2.02$, $p = .044$, $d = 0.19$. Nevertheless, differences in psychosis-spectrum symptoms, although statistically significant, were small in magnitude.

Table 2. Participant Demographic Characteristics and Psychosis-Spectrum Symptoms

Variable	Study 1	Study 2	Study 3
N	129	154	154
Female	108 (83.72)	114 (74.02)	130 (84.42)
Age (years)			
M	20.27	21.32	20.92
SD	3.08	4.24	4.42
Race			
African American	6 (4.65)	4 (2.60)	2 (1.30)
Asian	45 (34.88)	66 (42.86)	63 (40.91)
European American	25 (19.38)	25 (16.23)	32 (20.78)
Latinx	37 (28.68)	47 (30.52)	38 (24.68)
Other	16 (12.40)	12 (7.79)	19 (12.34)
Country of origin: United States	107 (82.94)	121 (78.57)	110 (71.43)
Psychosis-spectrum symptoms			
Perceptual aberration			
M	1.13	1.09	1.71
SD	1.90	2.16	2.78
Range	0–10	0–13	0–11
Magical ideation			
M	3.18	2.69	3.76
SD	2.65	2.81	3.41
Range	0–11	0–13	0–13
Social anhedonia			
M	2.37	2.28	3.28
SD	2.35	2.41	3.35
Range	0–12	0–10	0–12

Note: Values are *n*s with percentages in parentheses unless otherwise noted.

Power analysis indicated that the current sample size had 80% power to detect a small-to-medium effect of $r = .24$ at an α level of .05. This is sufficient to test the primary hypotheses of the current study given previous ESM findings using nonclinical samples (e.g., $r = .24$ for the association between positive symptoms and NA variability; Kwapil et al., 2012). In addition, meta-analytic effect sizes ranged from $r = .24$ to $r = .36$ for the association of various psychopathological symptoms with NA variability and instability (Houben et al., 2015).

Materials.

Psychosis-spectrum symptoms. Psychosis-spectrum symptoms were assessed with the short versions of the Wisconsin Schizotypy Scales (Winterstein et al., 2011). The 15-item Short Perceptual Aberration Scale ($\alpha = .76$) and the 15-item Short Magical Ideation Scale ($\alpha = .72$) measure perceptual distortions and unusual beliefs, respectively (e.g., "Parts of my body occasionally seem dead or unreal"; "I have occasionally had the silly feeling that a TV or radio broadcaster knew I was listening to him"). As in previous research (e.g., Kerns et al., 2008), a single positive-symptom score was calculated by summing the standardized scores of perceptual aberration and magical ideation. The 15-item Short Revised Social Anhedonia Scale ($\alpha = .72$) measures lack of relationships and lack of pleasure from relationships (e.g., "Having close friends is not as important as many people say"). Scores on the Wisconsin Schizotypy Scales have shown high correspondence with clinician-rated psychosis-spectrum symptoms (i.e., the Structured Interview for Prodromal Syndromes; Cicero et al., 2014) and are predictive of future development of psychosis-spectrum disorders (Chapman et al., 1994; Kwapil, 1998; Lenzenweger, 2021). The short, rather than full, versions of these scales were chosen because of their superior psychometric properties (Cicero et al., 2019; Li, Cicero, et al., 2021).

Twitter data processing. Using Twitter's application programming interface, tweets (up to the most recent 3,200) were downloaded on November 1, 2020. On average, participants contributed 644.59 tweets (SD = 670.85, range = 11–2,713) across 210.24 weeks (SD = 113.14, range = 8.71–516.71). There was a large variation in the frequency of posting tweets; the average time interval between successive tweets ranged from 2.21 h to 24.24 weeks (M = 1.42 weeks, SD = 2.91 weeks).

After basic preprocessing (Silge & Robinson, 2017; for details, see the Supplemental Material available online), sentiment analysis was conducted using the Valence Aware Dictionary and sEntiment Reasoner (VADER; Hutto & Gilbert, 2014). VADER uses dictionary- and rule-based model to extract sentiment polarity and intensity and is especially sensitive to social-media text. It has been shown to outperform other established automatic sentiment analytic tools (e.g., linguistic inquiry and word count) and even individual human raters (Hutto & Gilbert, 2014). For each tweet, an overall-sentiment valence score was estimated by summing the valence score of each word in the VADER dictionary, adjusted by rules such as negations (e.g., "not" and "wasn't") and degree modifiers (e.g., "very" and "kind of") and normalized to be between −1 (most negative) and 1 (most positive). The proportion of text that was positive or negative was also estimated, referred to hereafter as *positive sentiment* and *negative sentiment*, respectively. Note that positive and negative sentiments represent only the categorization of individual words into positive and negative classes and that unlike overall sentiment, they do not take into account sentiment strength and rule-based adjustments (e.g., negations, degree modifiers). Finally, the frequency of unique sentiment-expressing words (i.e., those that matched words in the VADER dictionary) was tallied for each participant. All processing steps were carried out in Python using custom scripts (available online at https://osf.io/bu2rs/).

Affect-dynamic indices. Affect-dynamic indices were computed using the methods described in Table 1. All indices were computed separately for overall sentiment, positive sentiment only, and negative sentiment only, except for density and synchrony, which were computed according to the relations between positive and negative sentiments. Because of the unequal time intervals between successive tweets, adjustments were made for time-reliant indices (i.e., instability, inertia, and density). For instability measures, adjusted successive differences (ASDs) were computed by dividing successive differences by $[(\text{time}_i - \text{time}_{i-1}) / Mdn(\text{time}_i - \text{time}_{i-1})]^{\lambda}$, in which $Mdn(\text{time}_i - \text{time}_{i-1})$ is the median time interval for all is (Jahng et al., 2008). A value of λ was chosen so that the expected absolute ASDs across time intervals, obtained via lowess, were as constant as possible. The ASDs were used for the subsequent calculation of square successive difference (SSD) and acute change (AC). For inertia, time since first tweet was added as a covariate in a multilevel model that simultaneously estimated the moderating role of positive symptoms and social anhedonia in individual differences in the sentiment's autocorrelation (detailed below). Likewise for density, time since first tweet was added as a covariate in the multilevel vector autoregressive models, which provided estimates for the population or average sentiment network across participants and participant-specific slopes for the calculation of density scores (Bringmann et al., 2016).

Data analytic strategy. All analyses were performed using the R software environment (Version 4.0.3; R Core Team, 2020). Separate linear regressions were fitted to examine the effect of positive symptoms and social anhedonia on mean-level sentiment and all affect-dynamic indices except for instability and inertia. Instability indices were examined using generalized multilevel models with positive symptoms and social anhedonia as predictors and random intercepts of participants. Specifically, SSD was modeled by a gamma error distribution and log link, whereas AC was modeled by a binomial error distribution with one trial and logit link (Jahng et al., 2008). Inertia was fitted by a multilevel model to examine whether positive symptoms and social anhedonia moderate the autoregressive slope of sentiment at time_i predicted from its past state at time_{i-1}, accompanied by random intercepts of participants and random slopes of sentiment at time_{i-1} (Kuppens et al., 2010). To test a specific relation with psychosis-spectrum symptoms, we included demographic variables (i.e., gender, age, and race/ethnicity) as covariates in all models. In models involving dynamic indices, mean-level sentiment was also added as a covariate.

Results

Population-sentiment network. Figure 1a shows the population-sentiment network. Similar to affect ratings collected using ESM (e.g., Bringmann et al., 2016), the sentiments expressed on Twitter exhibited excitatory self-loops and an inhibitory edge from positive sentiment to negative sentiment but not vice versa. Thus, the expression of positive sentiment at one tweet was linked to greater expression of positive sentiment and lower expression of negative sentiment at the next tweet. In contrast, the expression of negative sentiment at one tweet was linked to greater expression of negative sentiment at the next tweet but did not significantly influence the subsequent expression of positive sentiment.

Affect dynamics and psychosis-spectrum symptoms. As shown in Table 3, greater positive-symptom scores were associated with elevated variability and instability (both SSD and AC) in overall sentiment. In contrast,

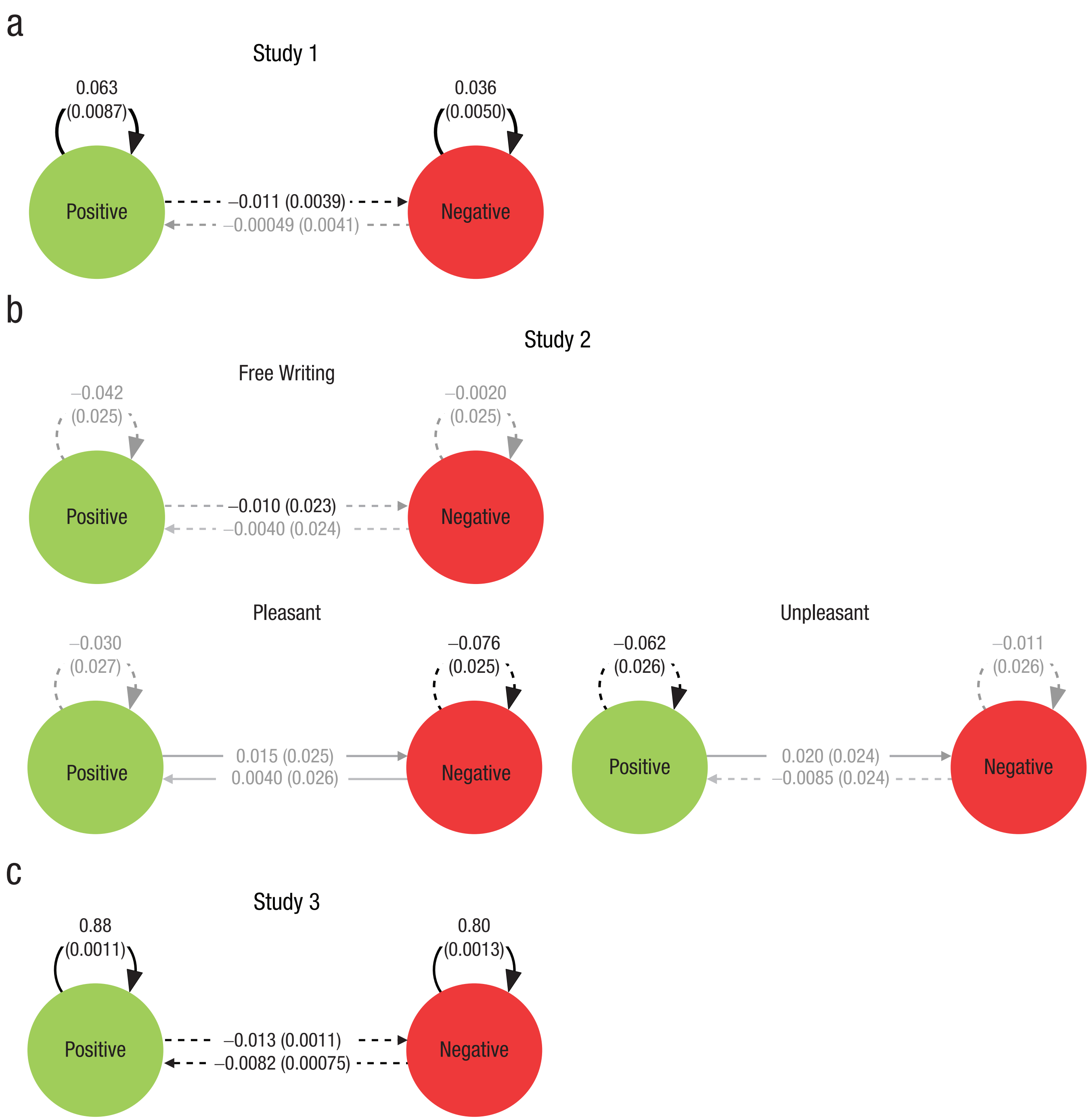

Fig. 1. Population-sentiment/affect networks for (a) Study 1 Twitter data, (b) Study 2 writing data, and (c) Study 3 film clip data. Values are standardized coefficients (β) with standard errors in parentheses. Solid edges correspond to excitatory relations. and dashed edges correspond to inhibitory relations. Significant relations (p < .05) are shown in black, and nonsignificant relations are shown in gray.

greater social-anhedonia scores were associated with marginally reduced variability and instability (AC) in overall sentiment and elevated inertia in overall sentiment, positive sentiment, and, marginally, negative sentiment. Thus, people who are high in positive symptoms exhibit greater overall and moment-to-moment fluctuations in sentiment valence. People who are high in social anhedonia exhibit the opposite pattern and show a greater resistance to change, primarily for positive sentiment, coupled with a trend for reduced sentiment-valence fluctuations.

Table 3. Association of Positive Symptoms and Social Anhedonia With Twitter-Affect Dynamics

	Positive symptoms				Social anhedonia				Mean sentiment			
Outcome	Estimate	Test statistic	*df*	*p*	Estimate	Test statistic	*df*	*p*	Estimate	Test statistic	*df*	*p*
Mean sentiment												
Overall	0.014 (0.094)	0.15	119	.88	0.049 (0.096)	0.51	119	.61		—		
Positive	0.039 (0.093)	0.42	119	.67	–0.024 (0.095)	–0.26	119	.80		—		
Negative	0.041 (0.092)	0.44	119	.66	–0.076 (0.094)	–0.80	119	.42		—		
Variability												
Overall	**0.24 (0.087)**	**2.80**	**117**	**.0059**	***–0.16 (0.089)***	***–1.80***	***117***	***.074***	0.090 (0.085)	1.06	117	.29
Positive	–0.038 (0.066)	–0.58	118	.56	–0.091 (0.068)	–1.34	118	.18	**0.68 (0.066)**	**10.44**	**118**	**< .001**
Negative	–0.071 (0.046)	–1.54	118	.13	–0.0045 (0.047)	–0.096	118	.92	**0.86 (0.046)**	**18.69**	**118**	**< .001**
Instability (SSD)												
Overall	**0.020 (0.0062)**	**3.25**		**.0012**	–0.0091 (0.0064)	–1.42		.15	–0.0064 (0.0050)	–1.26		.21
Positive	–0.0011 (0.0020)	–0.54		.59	–0.0034 (0.0021)	–1.64		.10	**0.010 (0.0016)**	**6.29**		**< .001**
Negative	–0.0013 (0.0011)	–1.11		.27	–0.00035 (0.0012)	–0.29		.77	**0.017 (0.0011)**	**15.38**		**< .001**
Instability (AC)												
Overall	**0.10 (0.029)**	**3.57**		**< .001**	***–0.058 (0.031)***	***–1.90***		***.057***	–0.0081 (0.026)	–0.32		.75
Positive	0.000073 (0.031)	0.0023		1.00	–0.033 (0.033)	–1.00		.32	**0.17 (0.026)**	**6.67**		**< .001**
Negative	–0.017 (0.021)	–0.81		.42	–0.018 (0.023)	–0.76		.45	**0.37 (0.024)**	**15.67**		**< .001**
Inertia												
Overall	–0.0081 (0.0075)	–1.08	98.70	.28	**0.015 (0.0077)**	**2.01**	**109.66**	**.047**	**0.24 (0.0035)**	**70.20**	**112.93**	**< .001**
Positive	0.0012 (0.0078)	0.15	98.06	.88	**0.017 (0.0078)**	**2.21**	**104.26**	**.029**	**0.24 (0.0056)**	**43.49**	**141.54**	**< .001**
Negative	–0.0067 (0.0046)	–1.44	54.42	.15	***0.0099 (0.0052)***	***1.90***	***96.69***	***.060***	**0.16 (0.0065)**	**24.45**	**131.82**	**< .001**
Emodiversity												
Overall	0.072 (0.091)	0.79	118	.43	0.014 (0.094)	0.15	118	.88	**–0.30 (0.089)**	**–3.43**	**118**	**< .001**
Positive	0.078 (0.094)	0.83	118	.41	0.00060 (0.096)	0.0062	118	1.00	–0.15 (0.093)	–1.64	118	.10
Negative	0.060 (0.090)	0.66	118	.51	0.028 (0.093)	0.31	118	.76	**0.35 (0.090)**	**3.89**	**118**	**< .001**
Density	–0.0022 (0.058)	–0.037	117	.97	0.090 (0.060)	1.51	117	.13	**Pos: 0.71 (0.060)**	**11.71**	**117**	**< .001**
									Neg: –0.25 (0.061)	**–4.07**	**117**	**< .001**
Synchrony	–0.026 (0.078)	–0.33	117	.74	0.026 (0.080)	0.32	117	.75	**Pos: –0.52 (0.081)**	**–6.44**	**117**	**< .001**
									Neg: –0.39 (0.082)	**–4.81**	**117**	**< .001**

Note: Estimates are βs for psychosis-spectrum symptoms except for (a) square successive difference (SSD), for which the estimates are log of SSD, and (b) acute change (AC), for which the estimates are the log odds of AC. Values in parentheses are standard errors. Inertia refers to the interaction between psychosis-spectrum symptoms and lagged sentiment. Test statistic refers to the t statistic, except for SSD and AC, for which it refers to the z statistic. Significant and trend-level significant results are indicated by boldface type and boldface italic type, respectively. Pos = positive sentiment, Neg = negative sentiment.

Discussion

This is the first study to examine affect dynamics in relation to the psychosis spectrum using natural language expressions on Twitter. Building on work by previous ESM studies, the present findings provide evidence that positive and negative symptoms of the psychosis spectrum are characterized, respectively, by more and less changeable affect in daily life. Findings also demonstrate that the dynamics of affect can be captured by Twitter data and that they behave in a similar fashion as data collected using established naturalistic methods. Together, social-media data have proved feasible in providing a time-sensitive and cost-effective assessment of affect-dynamic markers of psychosis risk and may be a useful supplement to existing screening and monitoring approaches.

Consistent with our hypotheses, positive symptoms were associated with elevated variability and instability in overall-sentiment valence, whereas social anhedonia was associated with elevated inertia that was driven by the positive sentiment and a trend for reduced valence variability and instability. This suggests that in terms of longer time-scale mood fluctuations in daily life across various contexts, positive symptoms of the psychosis spectrum are related to a larger amplitude and frequency of valence fluctuations, whereas negative symptoms are related to a greater resistance to change in PA. However, note that there are two sources of noise inherent in the Twitter data. In the time domain, there is a large variation in the interval between successive tweets and thus necessitates adjustment for the calculation of time-reliant indices. In addition, people share their thoughts and feelings via tweets for a variety of reasons, from reacting to emotional events to simply describing their daily routine. This mixture of contexts may attenuate the association between affect dynamics and psychosis-spectrum symptoms that might be apparent only under emotional provocations (Lapate & Heller, 2020; Myin-Germeys & van Os, 2007). At the same time, there may be individual differences in the tendency to post tweets under one type of situations compared with another, which potentially muddies the interpretation of the current results. For example, the elevated inertia associated with social anhedonia could be driven by the possibility that people who are high in social anhedonia tend to post about less emotional contents under relatively neutral, baseline states rather than a resistance to change per se. Disentangling the effects of time scales and contexts is therefore crucial in parsing the noise in people's affective time series (Dejonckheere et al., 2019; Lapate & Heller, 2020). This was what we sought to do in Study 2.

Study 2

The objective of Study 2 was to examine the relations between psychosis-spectrum symptoms and momentary affect dynamics under baseline, pleasant, and unpleasant contexts. These contexts were experimentally induced in the lab. Participants were asked to provide an unprompted response about their current thoughts (i.e., baseline state) and the most pleasant and unpleasant events in their lives. We used sentence-level sentiment as a proxy for their affective experience in that moment and modeled affect dynamics across sentences within each context. In addition, participants were preselected to represent a wide range of positive and negative psychosis-spectrum symptoms. Because psychosis risk has been linked to heightened affective reactivity (Myin-Germeys & van Os, 2007), we expected that positive symptoms' elevated variability and instability and that social anhedonia's elevated inertia would be particularly pronounced under emotionally charged contexts compared with the baseline state. As in Study 1, we also conducted exploratory analyses for the association of positive symptoms and social anhedonia with other affect-dynamic indices.

Method

Participants. To ensure adequate variation in psychosis-spectrum symptoms, we recruited participants from a large pool of undergraduates according to their scores on psychosis-related personality characteristics. Specifically, facets within the Psychoticism and Detachment domains of the Personality Inventory for DSM-5 (Krueger et al., 2012) were used as selection criteria (Grazioplene et al., 2016), and people who scored low (i.e., all facet scores ≤ 1) and high (i.e., at least one facet score ≥ 2) were invited to the lab. There were 1,787 participants who completed the online screening survey, after we removed 699 people with careless or invalid responses and 863 people who declined to be contacted for future research studies. Eight hundred ninety-one participants fulfilled the selection criteria, of whom 154 (17.28%) participated and completed the laboratory session (for participant characteristics, see Table 2). Included participants had greater positive symptoms of small magnitude than eligible participants who did not participate in the laboratory session, $t(889) = 2.68$, $p = .0075$, $d = 0.24$, but did not significantly differ in social anhedonia, $t(889) = 0.35$, $p = .72$, $d = 0.031$. Power analysis indicated that the current sample size had 80% power to detect a small-to-medium effect of $r = .22$ at an α level of .05, which is sufficient to test the primary hypotheses of the current study.

Materials and procedure. During the laboratory session, participants rated their baseline affect, followed by a free-writing task and two autobiographical memory-recall tasks (i.e., pleasant and unpleasant). Participants rated their current affect again immediately following each writing task. Subsequent to affect ratings after the autobiographical memory-recall tasks, participants performed a simple cognitive task (i.e., 80-trial Stroop color-word task) to minimize the emotion carryover. After completion of both the online screening battery and the laboratory session, participants received course extra credit as compensation. Online questionnaires were administered via Qualtrics, and the in-lab tasks were administered via MediaLab (Empirisoft Corporation, New York, NY). This study was approved by the University of California, Irvine, institutional review board.

Psychosis-spectrum symptoms. Same as in Study 1, psychosis-spectrum symptoms were assessed with the short versions of the Wisconsin Schizotypy Scales (Winterstein et al., 2011; all αs > .72).

Writing tasks. For the free-writing task, participants were instructed to write "whatever comes to mind" (e.g., Fung et al., 2017). The autobiographical memory-recall tasks were adapted from expressive writing paradigms (e.g., Burton & King, 2004) that instructed participants to write about the most pleasant/unpleasant event they have experienced in their lives. The order of the pleasant and unpleasant conditions was counterbalanced across participants. For all three writing tasks, participants typed their response in a text box that was programmed to be visible for only 6 min. However, participants were told that they had 10 min to encourage them to write for the entire time period.

Text entries were segmented into sentences after basic preprocessing (Silge & Robinson, 2017; for details, see the Supplemental Material). On average, participants contributed 13.29 sentences (*SD* = 6.91, range = 1–39) for the free-writing condition, 12.15 sentences (*SD* = 5.40, range = 2–31) for the pleasant condition, and 12.99 sentences (*SD* = 5.96, range = 2–32) for the unpleasant condition. Then, sentence-level sentiments (i.e., overall-sentiment valence and proportions of positive and negative sentiments) were estimated using VADER, and the frequency of unique sentiment-expressing words was tallied. The calculation of affect-dynamic indices were carried out in the same way as in Study 1 except that (a) no adjustment of time was made and (b) for participants who expressed only one sentiment valence (e.g., expressed only positive sentiment in the pleasant condition), their emodiversity for the nonexpressed valence (e.g., negative sentiment) and synchrony were set to zero.

Current affect. Current affect was assessed at baseline and immediately after each writing task (i.e., four times). Participants were given 16 positively and negatively valenced words with both high arousal levels and low arousal levels (e.g., "serene," "elated," "sad," "anger"). The words have been frequently used in previous research to assess self-reported affect (e.g., Martin et al., 2011). Participants were instructed to rate their feelings at the moment using a 5-point scale (1 = *not at all*, 5 = *very strongly*). Ratings within each valence category were averaged to yield a composite score for PA (all αs > .82) and NA (all αs > .85).

Data analytic strategy. All analyses were performed using the R software environment (R Core Team, 2020). First, as a manipulation check, separate multilevel models were fitted to examine the effect of writing condition on (a) affect ratings (PA and NA) and (b) sentiment expressions (overall, positive, and negative sentiment). Next, separate multilevel models were fitted to examine the effect of positive symptoms and social anhedonia and their interactions with writing condition on mean-level sentiment and all affect-dynamic indices except for instability and inertia. Instability indices were examined using generalized multilevel models; SSD was modeled by a gamma error distribution and log link, and AC was modeled by a binomial error distribution with one trial and logit link (Jahng et al., 2008). Inertia was fitted by a multilevel model to examine whether positive symptoms and social anhedonia moderate the autoregressive slope of sentiment at time_i predicted from its past state at time_{i-1} and their interactions with writing condition. All models included demographic variables (i.e., gender, age, and race/ethnicity) as covariates and random intercepts of participants. Inertia models additionally included random slopes of sentiment at time_{i-1}. In models involving dynamic indices, mean-level sentiment was also added as a covariate.

Results

Manipulation check. Overall, the writing tasks were successful in eliciting the desired emotion and sentiment expression. With respect to current affect, relative to baseline, free writing did not significantly change PA (p = .27) or NA (p = .19). The pleasant condition increased PA (p = .04) and decreased NA (p < .001), whereas the unpleasant condition decreased PA (p < .001) and increased NA (p < .001). With respect to sentiment expressions, relative to the free-writing condition, the pleasant condition showed increased overall-sentiment valence, increased positive sentiment, and decreased negative sentiment (all ps < .001). On the other hand, the unpleasant condition showed decreased overall-sentiment valence, decreased positive sentiment, and increased negative sentiment (all ps < .001).

Population-sentiment network. Figure 1b shows the population sentiment network for each writing condition. Overall, the sentiment expressed at one sentence was generally unrelated to the sentiment expressed at the next sentence. There is one notable exception: An inhibitory self-loop was observed for the nontarget emotion in the induction conditions. That is, for the pleasant condition, the expression of negative sentiment at one sentence was linked to lower subsequent expression of negative sentiment; for the unpleasant condition, the expression of positive sentiment at one sentence was linked to lower subsequent expression of positive sentiment. Closer examination of the text entries showed that participants tend to adopt a narrative form that consisted of multiple points of inflections for the induction conditions (e.g., an event was particularly pleasant/unpleasant during a bad/good day; for illustrative examples, see Table S1 in the Supplemental Material). On the other hand, freely expressed thoughts did not convey predictable patterns of sentiments.

Affect dynamics and psychosis-spectrum symptoms. Estimates for free-writing, pleasant, and unpleasant conditions are separately shown in Table 4 (for the full multilevel model results, see Table S2 in the Supplemental Material). For the free-writing condition, greater positive-symptom scores were associated with (a) more positive autocorrelation in negative sentiment and, marginally, positive sentiment; (b) elevated negative sentiment emodiversity; and (c) marginally elevated synchrony between positive and negative sentiments. On the other hand, greater social-anhedonia scores were associated with reduced overall-sentiment instability (SSD and marginally for AC). Note that the interpretation of positive symptoms' association with autocorrelation requires additional consideration. For the free-writing condition, positive sentiment's autocorrelation at mean-level psychosis-spectrum symptoms was $\beta = -0.046$, $SE = 0.021$, $p = .034$. The more positive autocorrelation associated with positive symptoms therefore represents weaker negative temporal dependency or inertia (e.g., autocorrelation at 1 *SD* below the mean of positive symptoms: $\beta = -0.089$, $SE = 0.032$, $p = .0055$; autocorrelation at 1 *SD* above the mean of positive symptoms: $\beta = -0.0024$, $SE = 0.032$, $p = .94$). On the other hand, negative sentiment's autocorrelation at mean-level psychosis-spectrum symptoms was $\beta = -0.0032$, $SE = 0.024$, $p = .89$. The more positive autocorrelation associated with positive symptoms therefore represents stronger positive inertia (e.g., autocorrelation at 1 *SD* below the mean of positive symptoms: $\beta = -0.066$, $SE = 0.037$, $p = .072$; autocorrelation at 1 *SD* above the mean of positive symptoms: $\beta = 0.058$, $SE = 0.034$, $p = .090$). Thus, at baseline, people who were high in positive symptoms expressed diverse negative sentiments that lingered and inhibited positive sentiments, whereas people who were high in social anhedonia expressed reduced sentiment-valence fluctuations across time.

The pattern observed for the free-writing condition is in stark contrast to people observed under emotionally charged contexts. For the pleasant condition, greater positive-symptom scores were associated with (a) reduced overall sentiment; (b) elevated variability in negative sentiment, and, marginally, overall sentiment; (c) more positive overall-sentiment autocorrelation; and (d) reduced density. For the unpleasant condition, greater positive-symptom scores were associated with elevated overall sentiment and elevated variability and instability (SSD) in negative sentiment. In contrast, significant associations with social anhedonia were observed for the pleasant condition but not the unpleasant condition, in which greater social-anhedonia scores were marginally associated more negative overall-sentiment autocorrelation. Again, the interpretation of psychosis-spectrum symptoms' association with autocorrelation requires considering the autocorrelation at mean level, which was $\beta = -0.037$, $SE = 0.022$, $p = .085$, for the pleasant condition. Therefore, the more positive autocorrelation associated with positive symptoms represents weaker negative inertia (e.g., autocorrelation at 1 *SD* below the mean of positive symptoms: $\beta = -0.087$, $SE = 0.031$, $p = .0046$; autocorrelation at 1 *SD* above the mean of positive symptoms: $\beta = 0.011$, $SE = 0.030$, $p = .72$). Alternatively, the more negative autocorrelation associated with social anhedonia represents stronger negative inertia (e.g., autocorrelation at 1 *SD* below the mean of social anhedonia: $\beta = -0.00070$, $SE = 0.031$, $p = .98$; autocorrelation at 1 *SD* above the mean of social anhedonia: $\beta = -0.074$, $SE = 0.030$, $p = .015$). Thus, people who were high in positive symptoms exhibited dramatic and ambivalent fluctuations when induced to feel and express both positive and negative emotions, whereas people who were high in social anhedonia tended to exhibit a temporally dependent and alternating pattern of opposing sentiment valence when induced to feel and express positive emotions.

Discussion

Study 2 extended Study 1 by taking into account the effect of emotional contexts on momentary affect dynamics. Consistent with our hypotheses, we found that positive symptoms' more changeable sentiments, demonstrated by elevated variability and instability and reduced inertia and network density, are tied primarily to emotionally charged contexts. This is consistent with a large body of literature that has shown that positive symptoms of the psychosis spectrum are linked to increased affective reactivity (Myin-Germeys & van Os,

Table 4. Association of Positive Symptoms and Social Anhedonia With Affect Dynamics Under Free-Writing, Pleasant, and Unpleasant Conditions

	Free writing		Pleasant		Unpleasant	
Outcome	Positive symptoms	Social anhedonia	Positive symptoms	Social anhedonia	Positive symptoms	Social anhedonia
Mean sentiment						
Overall	–0.019 (0.059)	–0.020 (0.058)	**–0.13* (0.059)**	–0.061 (0.058)	**0.16** (0.059)**	–0.064 (0.058)
Positive	0.0089 (0.069)	–0.023 (0.068)	–0.096 (0.070)	–0.043 (0.068)	0.11 (0.070)	–0.027 (0.068)
Negative	0.068 (0.065)	–0.033 (0.064)	0.095 (0.066)	0.040 (0.064)	–0.080 (0.066)	0.039 (0.064)
Variability						
Overall	0.091 (0.083)	–0.094 (0.082)	***0.15† (0.084)***	–0.0058 (0.082)	0.064 (0.084)	–0.015 (0.082)
Positive	0.056 (0.063)	0.053 (0.063)	0.080 (0.064)	0.065 (0.063)	0.071 (0.064)	–0.094 (0.063)
Negative	0.054 (0.054)	–0.057 (0.054)	**0.14** (0.055)**	0.0024 (0.053)	**0.16** (0.055)**	–0.027 (0.053)
Instability (SSD)						
Overall	0.0066 (0.0090)	**–0.018* (0.0083)**	0.0031 (0.0092)	0.0092 (0.0085)	0.0028 (0.0087)	0.00044 (0.0083)
Positive	–0.0016 (0.0019)	0.0023 (0.0017)	–0.00052 (0.0020)	0.0029 (0.0018)	–0.000068 (0.0018)	–0.0012 (0.0017)
Negative	–0.00096 (0.0013)	–0.00019 (0.0012)	0.00051 (0.0013)	–0.00059 (0.0012)	**0.0025* (0.0012)**	–0.0010 (0.0011)
Instability (AC)						
Overall	0.12 (0.080)	***–0.15† (0.084)***	–0.060 (0.094)	0.053 (0.077)	–0.025 (0.078)	0.051 (0.069)
Positive	–0.045 (0.086)	0.040 (0.070)	0.047 (0.078)	0.053 (0.074)	0.099 (0.083)	–0.15 (0.11)
Negative	0.063 (0.085)	–0.037 (0.084)	0.14 (0.089)	0.12 (0.094)	0.074 (0.066)	0.073 (0.064)
Inertia						
Overall	0.020 (0.023)	0.024 (0.022)	**0.049* (0.021)**	***–0.037† (0.022)***	0.0089 (0.018)	–0.0048 (0.019)
Positive	***0.043† (0.024)***	–0.0084 (0.021)	0.033 (0.023)	–0.032 (0.022)	0.0067 (0.025)	–0.038 (0.030)
Negative	**0.062* (0.026)**	–0.020 (0.026)	–0.018 (0.030)	–0.016 (0.033)	0.026 (0.018)	0.011 (0.018)
Emodiversity						
Overall	0.089 (0.084)	0.026 (0.082)	–0.037 (0.085)	0.029 (0.082)	0.023 (0.085)	0.094 (0.082)
Positive	–0.017 (0.065)	0.066 (0.064)	–0.033 (0.065)	0.016 (0.064)	0.069 (0.065)	0.057 (0.064)
Negative	**0.14* (0.060)**	0.0079 (0.059)	0.010 (0.061)	0.035 (0.059)	0.030 (0.061)	0.050 (0.059)
Density	0.023 (0.048)	0.0015 (0.048)	**–0.17*** (0.048)**	0.013 (0.047)	0.013 (0.048)	0.0088 (0.047)
Synchrony	***–0.13† (0.079)***	0.032 (0.078)	–0.021 (0.080)	–0.046 (0.078)	–0.059 (0.080)	0.041 (0.078)

Note: Values are βs for psychosis-spectrum symptoms except for (a) square successive difference (SSD), for which the values are log of SSD, and (b) acute change (AC), for which the values are the log odds of AC. Values in parentheses are standard errors. Inertia refers to the interaction between psychosis-spectrum symptoms and lagged sentiment. Significant and trend-level significant results are indicated by boldface type and boldface italic type, respectively.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

2007). Surprisingly, positive symptoms' baseline sentiment expressions are characterized by the reverse pattern, which shows diverse negative sentiments that are persistent over time. This suggests that people who are high in positive symptoms spontaneously engage in prolonged processing of negative information, which is in line with prior self-report findings of increased trait attention to negative emotions (Li et al., 2019; Martin et al., 2011). Overall, the present findings provide strong evidence for more changeable affect in response to emotional provocations as a risk signature for positive symptoms of the psychosis spectrum.

At the same time, there were only relatively modest associations for social anhedonia across all contexts. It appears that social anhedonia's less changeable sentiments, demonstrated by reduced instability, are tied primarily to the baseline state. Under the pleasant context, social anhedonia's sentiment expressions are characterized by temporally dependent alternations of opposing valence. Considering that, on average, participants used points of inflections to provide contrasts in their stories, this finding indicates that people who are high in social anhedonia use more unpleasant contrasts in their narratives of the pleasant event in a rigid, self-predictable fashion. Therefore, people who are high in social anhedonia do experience PA in response to pleasant materials, but in short bursts that cannot be maintained for extended periods because of the opposing valence effect. This is consistent with prior work that linked social anhedonia to deficits in sustained processing of pleasant stimuli in the lab (Martin et al., 2020) and failures to sustain PA coupled with exaggerated diminishing influence of NA on PA in daily life (Strauss et al., 2020; Westermann et al., 2017). Nevertheless, findings for negative symptoms are relatively weak and thus await further replication studies.

Although automatic sentiment analytic tools such as VADER have been extensively validated (Fan et al., 2019; Hutto & Gilbert, 2014), there are nuances to people's subjective feelings that cannot be captured by text. Mainly, sentiment analysis takes people's linguistic expressions "at face value," yet the same words can be used to communicate very different feelings. For example, one of our participants wrote "this girl quickly became a friend with my best friend!," which seemingly conveyed positive feelings and indeed received a highly positive overall-sentiment valence score (0.8977). However, this participant was most likely expressing a negative feeling (e.g., anger and annoyance) because her best friend was pried away from her. Findings therefore need to be validated against self-reports, the sine qua non assessment of subjective feelings (Quigley et al., 2014). Furthermore, although the same writing prompts were used across participants, they nonetheless generated responses that vary greatly in content. It could be argued that the characteristics of the event, rather than people's emotional reaction to the event, drive the observed findings (or lack thereof). To address these remaining questions, in Study 3, we assessed momentary self-reports of affective experiences in response to a standardized emotional stimulus.

Study 3

The objective of Study 3 was to examine momentary affect dynamics in the psychosis spectrum during a standardized emotional film clip that contained a fixed sequence of pleasant and unpleasant scenes. We used a novel paradigm that continuously assessed affective experiences over the duration of the film clip. In addition, participants were preselected to represent a wide range of positive and negative symptoms of the psychosis spectrum. We expected that the results obtained in Study 2 under emotional contexts would be replicated in Study 3; that is, positive symptoms would be associated with elevated variability and instability. Because of the observed modest relations between affect-dynamic indices and social anhedonia under emotional contexts, we did not have specific hypothesis for social anhedonia. The association of positive symptoms and social anhedonia with other affect-dynamic indices were also explored.

Method

Participants. Participants were recruited from a large pool of undergraduates according to their scores on the short versions of the Wisconsin Schizotypy Scales (Winterstein et al., 2011; all αs > .83). Specifically, people who scored low (i.e., < 0.5 *SD* above the mean) and high (i.e., > 1.5 *SD* above the mean) on the three scales were invited to complete a continuous affect assessment task either in the lab or online.[1] After completion, participants received course extra credit and monetary compensation. All measures were administered via Qualtrics. This study was approved by the University of California, Irvine, institutional review board.

There were 2,022 participants who completed the online screening survey, after we removed 922 people with careless or invalid responses and 1,049 people who declined to be contacted for future research studies. One thousand sixty-two participants fulfilled the selection criteria, of whom 167 (15.72%) participated in the continuous affect assessment task. A further 13 participants (7.78%) were excluded because (a) they failed to watch the film clip to its entirety (eight) and

(b) they had more than 50% missing data (five). The final sample size consisted of 154 participants (for participant characteristics, see Table 2). Included participants had greater social anhedonia of small magnitude than eligible participants who did not participate or complete the task, $t(195.26) = 2.56$, $p = .011$, $d = 0.24$, but did not significantly differ in positive symptoms, $t(191.40) = 1.56$, $p = .12$, $d = 0.15$. Power analysis indicated that the current sample size had 80% power to detect a small-to-medium effect of $r = .22$ at an α level of .05, which is sufficient to test the primary hypotheses of the current study.

Materials. Participants watched a 12-min film clip from the tragicomic movie *Life Is Beautiful* (Benigni, 1997), depicting a father's humorous attempts to shield his son from the horrors of a Nazi concentration camp. To provide a coherent story, the film clip included emotionally evocative excerpts from the beginning, middle, and end of the movie that have been shown to elicit positive and negative emotions (Cohen et al., 2016; Schaefer et al., 2010; available on request).

Affective experiences were assessed using the evaluative space grid (Larsen et al., 2009). This 5 × 5 grid was composed of PA ratings on the *x*-axis ("How POSITIVE do you feel?") and NA ratings on the *y*-axis ("How NEGATIVE do you feel?"). Both ratings were made on a 5-point scale (0 = *not at all*, 4 = *extremely*). Participants were instructed to use the mouse cursor to continuously indicate their affective experiences in that moment. The cursor appeared outside of the grid at the beginning of the film clip, after which participants were instructed to use the mouse to move the cursor throughout the grid as fast or slow as they wished. The cell location of the cursor was recorded every 100 ms. Immediately after the film clip, participants were asked if they were experiencing any emotions right now and, if they indicated yes, to list all emotions in a text box.

Affect ratings were down-sampled to every 1 s offline for the current analysis. Out of the 723 possible assessments (12.05 min × 60 s/min × 1 assessment/s), participants contributed 702.98, on average ($SD = 57.47$, range = 433–723). Affect-dynamic indices were calculated using the same methods described in Study 1 according to affect ratings and open-ended responses, except that no adjustment of time was made. In addition, a more stringent cutoff was used for AC. Because the majority of affect ratings did not change from one moment to the next (PA = 93.54%; NA = 93.03%), the cutoff for acute increase was set as any positive change in affect ratings (i.e., PA = top 3.68%; NA = top 3.60%). Finally, emodiversity was set to zero for participants who did not provide any sentiment-expressing words, and synchrony was set to zero for one participant who did not show any variability in PA.

Data analytic strategy. All analyses were performed using the R software environment (R Core Team, 2020). Separate linear regressions were fitted to examine the effect of positive symptoms and social anhedonia on mean-level affect and all affect-dynamic indices except for instability and inertia. Instability indices were examined using generalized multilevel models with positive symptoms and social anhedonia as predictors and random intercepts of participants. Specifically, SSD was modeled by a multilevel zero-inflated gamma model because excessive zeros represent no change in affect from one moment to the next (Min & Agresti, 2002; Zuur & Ieno, 2016). This model considered separately (a) the likelihood of obtaining nonzero (vs. zero) SSDs, which was modeled by a binomial error distribution with one trial and logit link, and (b) the magnitude of nonzero SSDs, which was modeled by a gamma error distribution and log link. AC was modeled by a binomial error distribution with one trial and logit link (Jahng et al., 2008). Inertia was fitted by a multilevel model to examine whether positive symptoms and social anhedonia moderate the autoregressive slope of sentiment at time$_i$ predicted from its past state at time$_{i-1}$, accompanied by random intercepts of participants and random slopes of sentiment at time$_{i-1}$ (Kuppens et al., 2010). To test a specific relation with psychosis-spectrum symptoms, all models included demographic variables (i.e., gender, age, and race/ethnicity) as covariates. In models involving dynamic indices, mean-level sentiment was also added as a covariate.

Results

Population-affect network. Average affect ratings showed that the film clip was successful in inducing PA and NA that were largely alternating over the entire duration (see Fig. S1 in the Supplemental Material). Correspondingly, the population-affect network (Fig. 1c) showed strong excitatory self-loops and weaker inhibitory edges between PA and NA.

Affect dynamics and psychosis-spectrum symptoms. As shown in Table 5, greater positive-symptom scores were associated with (a) elevated PA; (b) elevated instability (SSD–binomial models and AC), characterized by greater likelihood of changes and large increases in PA and NA; (c) reduced inertia in PA and, marginally, NA; and (d) elevated emodiversity in negative sentiment and, marginally, overall sentiment. On the other hand, greater social-anhedonia scores were associated with (a) reduced PA; (b) reduced NA instability (SSD–gamma model),

Table 5. Association of Positive Symptoms and Social Anhedonia With Film-Clip-Affect Dynamics

	Positive symptoms				Social anhedonia				Mean affect			
Outcome	Estimate	Test statistic	*df*	*p*	Estimate	Test statistic	*df*	*p*	Estimate	Test statistic	*df*	*p*
Mean affect												
Positive	**0.29 (0.077)**	**3.74**	**145**	**< .001**	**−0.17 (0.076)**	**−2.26**	**145**	**.025**		—		
Negative	0.10 (0.081)	1.25	145	.21	−0.026 (0.080)	−0.33	145	.74		—		
Variability												
Positive	0.11 (0.076)	1.50	144	.14	−0.079 (0.073)	−1.09	144	.28	**0.41 (0.078)**	**5.31**	**144**	**< .001**
Negative	0.12 (0.081)	1.47	144	.14	−0.11 (0.080)	−1.36	144	.18	**0.27 (0.083)**	**3.23**	**144**	**.0015**
Instability (SSD)												
Positive–binomial	**0.15 (0.055)**	**2.65**		**.0079**	−0.033 (0.054)	−0.61		.54	**0.12 (0.058)**	**2.04**		**.041**
Positive–gamma	0.010 (0.032)	0.31		.76	−0.036 (0.032)	−1.12		.26	**0.15 (0.031)**	**4.94**		**< .001**
Negative–binomial	**0.17 (0.053)**	**3.14**		**.0017**	−0.056 (0.053)	−1.05		.29	0.011 (0.055)	0.20		.84
Negative–gamma	0.037 (0.034)	1.07		.28	**−0.073 (0.035)**	**−2.08**		**.037**	0.039 (0.033)	1.18		.24
Instability (AC)												
Positive	**0.13 (0.050)**	**2.56**		**.010**	−0.039 (0.049)	−0.80		.42	***0.090 (0.053)***	***1.69***		***.092***
Negative	**0.14 (0.048)**	**2.90**		**.0037**	−0.049 (0.049)	−1.00		.32	0.043 (0.051)	0.85		.39
Inertia												
Positive	**−0.0017 (0.00077)**	**−2.21**	**105.80**	**.029**	0.0011 (0.00081)	1.38	121.16	.17	**0.45 (0.00051)**	**879.33**	**107,671.86**	**< .001**
Negative	***−0.0015 (0.00090)***	***−1.69***	**125.00**	***.092***	0.0014 (0.00094)	1.48	138.71	.14	**0.57 (0.00048)**	**1193.22**	**107,763.41**	**< .001**
Emodiversity												
Overall	***0.14 (0.085)***	***1.67***	***143***	***.096***	***−0.14 (0.081)***	***−1.75***	***143***	***.081***	***PA: 0.15 (0.088)***	***1.70***	***143***	***.091***
									NA: 0.089 (0.084)	1.06	143	.29
Positive	0.044 (0.087)	0.51	144	.61	−0.11 (0.084)	−1.30	144	.20	***0.16 (0.090)***	***1.80***	***144***	***.074***
Negative	**0.22 (0.081)**	**2.68**	**144**	**.0081**	−0.066 (0.080)	−0.82	144	.41	0.12 (0.082)	1.48	144	.14
Density	−0.096 (0.086)	−1.12	142	.26	0.067 (0.082)	0.82	142	.42	**PA: −0.26 (0.088)**	**−2.98**	**142**	**.0034**
									NA: 0.093 (0.084)	1.11	142	.27
Synchrony	−0.026 (0.086)	−0.30	143	.76	0.059 (0.082)	0.72	143	.47	***PA: −0.16 (0.088)***	***−1.82***	**143**	***.071***
									NA: −0.30 (0.084)	**−3.52**	**143**	**< .001**

Note: Estimates are βs for psychosis-spectrum symptoms except for (a) square successive difference (SSD), for which the estimates are log of SSD, and (b) acute change (AC), for which the estimates are the log odds of nonzero (vs. zero) SSD for binominal models and the log of nonzero SSD for gamma models. Values in parentheses are standard errors. Inertia refers to the interaction between psychosis-spectrum symptoms and lagged sentiment. Test statistic refers to the *t* statistic, except for SSD and AC, for which it refers to the *z* statistic. Significant and trend-level significant results are indicated by boldface type and boldface italic type, respectively. PA = positive affect; NA = negative affect.

characterized by lower magnitude of NA changes; and (c) marginally reduced overall emodiversity. Thus, mirroring Study 2 findings under emotionally charged contexts, we found that people who were high in positive symptoms exhibited dramatic and ambivalent fluctuations in their affective experiences during the film clip. People who were high in social anhedonia stably focused on the unpleasant aspect of the film clip and, similar to Study 2 under the unpleasant context, did not show strong patterns of affect dynamics.

Discussion

Study 3 provided the strictest test of the momentary affect dynamics in the psychosis spectrum by tapping into self-reports of affective experiences in response to a standardized emotional stimulus. Largely replicating the findings of Study 2 under emotionally charged contexts, Study 3 showed that positive symptoms were associated with elevated instability and NA emodiversity and reduced PA inertia, whereas social anhedonia was related to reduced NA instability. Extending Study 2, Study 3 had the added experimental control of external inputs and directly assessed people's subjective feelings. Thus, positive symptoms' more changeable affect in response to emotional provocations is likely due to endogenous processes that are specific to the pathophysiology of positive symptoms. On the other hand, social anhedonia is characterized by a small reduction in the magnitude of NA fluctuations but otherwise displays unremarkable disturbances in affect dynamics when reacting to emotional materials.

General Discussion

There is a long tradition of research identifying risk markers in the service of the goal of anticipating and preventing transitions toward psychotic disorders. Nevertheless, current approaches have proved to be less than satisfactory (Fusar-Poli et al., 2019). This insufficiency has recently been brought to the forefront with the $99-million initiative calling to "further define early stages of risk and predict the likelihood of progression to psychosis and other outcomes" (National Institutes of Health, 2020). Given the substantial theoretical and empirical support for affect dynamics in anticipating transitions in psychopathology, the current research provided an initial inquiry into identifying affect-dynamic signatures of psychosis risk. Across three studies, we comprehensively examined affect-dynamic indices as they relate to positive and negative symptoms of the psychosis spectrum under varying time scales and contexts both in daily life and in laboratory settings. Collectively, findings provided (a) strong support for heightened magnitude and frequency of affective fluctuations following emotional provocations as a hallmark for positive symptoms and (b) modest support for greater persistence of baseline states as a hallmark for negative symptoms. Furthermore, these findings are observed over and above mean-level affect, even in nonclinical samples, which underscores the utility of affect dynamics in capturing and perhaps predicting risk for psychosis.

Heightened affective fluctuations: strong risk signature for positive symptoms

Extending previous ESM findings into the digital space of social media, we showed that positive symptoms were associated with elevated affect variability and instability in daily life. Subsequent studies further showed that elevated variability and instability in both PA and NA were tied to emotional contexts rather than baseline contexts. These findings add to the growing knowledge of the affect-reactive profile of positive symptoms, substantiating the affective pathway to psychosis (Myin-Germeys & van Os, 2007). A large body of literature has shown that people with high positive symptoms display marked response to emotional materials (Cohen & Minor, 2010; Li, Dent, et al., 2021; Myin-Germeys & van Os, 2007). Observed not only at the group level, the increased affective reactivity has been associated with greater concurrent and future experience of positive symptoms within a person (Kasanova et al., 2020; Klippel et al., 2017; Kramer et al., 2014; Krkovic et al., 2020; Simor et al., 2019). We provided additional insights on the role of altered affect-reactive dynamics in the developmental trajectory of psychosis. Specifically, elevated variability and instability may progressively build up to trigger the onset of clinically significant psychosis. To leverage affect dynamics into building individualized prediction models, future research on within-subjects affect time series is needed, such as testing whether windows of rising fluctuations predict exacerbation in positive symptoms down the line.

People who are high in positive symptoms showed a paradoxical increase of nontarget emotions (i.e., lower sentiment valence for the pleasant condition, higher sentiment valence for the unpleasant condition, and greater PA and a trend toward greater NA for the mixed-valence film clip). This experience of contradictory emotions at close temporal proximity supports the notion of "schizotypal ambivalence," a construct that has been assigned considerable theoretical importance but has yet received much empirical attention (Bleuler, 1911/1950; Kwapil et al., 2002; Meehl, 1990). Specifically, ambivalence has been suggested to reflect two distinct processes, either (a) simultaneous coactivation of contradictory emotions or (b) rapid change of emotions over time (Raulin & Brenner, 1993). It is currently unclear which process gives rise to ambivalence, which contributes to the difficulty and inconsistency in operationalizing this construct in research (Docherty et al., 2014; Kwapil et al., 2002; MacAulay et al., 2014; Trémeau et al., 2009). Our findings of altered affect intensity, in conjunction with elevated fluctuations in both PA and NA, imply that ambivalence is likely the result of high frequency changes, rather than simultaneous coactivation, for people with high positive symptoms. Thus, the present findings fill an important gap in elucidating the nature of schizotypal ambivalence.

Persistent baseline states: modest risk signature for negative symptoms

In contrast to positive symptoms' profound alterations in affect dynamics, social anhedonia showed only relatively weak associations and displayed a pattern of reduced variability, instability, and elevated inertia primarily at baseline. Under pleasant and mixed-valence contexts, social anhedonia additionally showed elevated negative inertia and reduced NA instability, respectively. This general lack of significant associations is consistent with the handful of studies that examined negative symptoms in relation to affect dynamics in daily life (Kwapil et al., 2012; Oorschot et al., 2013; Westermann et al., 2017). Although we urge caution in interpreting trend-level findings, results seem to indicate that negative symptoms are associated with more persistent affect at baseline, which perhaps results in difficulties to disengage from NA and sustain PA when reacting to pleasant and mixed-valence materials. These findings correspond well with previous studies that showed negative symptoms in individuals with schizophrenia were associated with a stronger pull of affect to low-PA/high-NA baseline states (Strauss et al., 2020; Westermann et al., 2017). Overall, our findings, and that of others, suggest that people with high negative symptoms could generate only short-lived positive feelings, perhaps not powerful enough to serve the function of altering to and preparing for potential opportunities in the environment (Ellsworth & Scherer, 2003). Thus, a persistent baseline state may underlie motivational and social deficits associated with negative symptoms and thus may be a useful target for improving functional outcomes.

Future directions

Several important questions remain for future research. Chiefly, we focused on the broad categories of PA and NA and did not examine the myriad of discrete emotions subsumed under these categories. Although examining broad PA and NA dynamics is the commonly adopted approach for past studies, it nonetheless limits understanding the dynamics within each valence. For example, there is reason to believe that certain discrete emotions (e.g., anxiety and fear) might be a central node in eliciting positive symptoms (Krkovic et al., 2020). Therefore, mapping the multivariate space of discrete emotions, within and between broad categories of PA and NA, will be a necessary next step in providing a fine-grained understanding of affect-dynamic signatures of psychosis risk. Furthermore, we focused on nonclinical individuals because the interaction between affective and psychotic symptoms is hypothesized to be particularly relevant for the early stage of psychopathology (van Os, 2013). It remains unclear the extent to which current findings generalize to clinical samples. Although it has been suggested that the same dynamical pattern underlies both the development and maintenance of psychosis (Ciompi, 2015), future research is clearly warranted.

Conclusions

The current research provides initial evidence that positive and negative psychosis-spectrum pathology are signified by distinct alterations in affect dynamics. Findings highlight the importance of distinguishing time scales and contexts in the study of affect dynamics. Broadening the scope of literature, we further demonstrated the feasibility of using various inexpensive laboratory paradigms and preexisting social-media text in capturing affect dynamics. This is significant given the high demand for training and outreach infrastructure of the prevailing clinical high-risk approach to risk detection. Because of its validity and cost-effectiveness, affect dynamics are poised to be an efficient way to answer the multimillion-dollar question of early risk detection and possibly subsequent prediction and prevention.

Transparency

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L. Y. Li designed the study, performed data analysis and interpretation, and drafted the manuscript under the supervision of E. A. Martin. E. A. Martin and J. Schiffman provided critical comments on the manuscript. All of the authors approved the final manuscript for submission.
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The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

Open Practices

All data have been made publicly available via OSF and can be accessed at https://osf.io/f8325. This article has received the badge for Open Data. More information about the Open Practices badges can be found at https://www.psychologicalscience.org/publications/badges.

ORCID iDs

Lilian Y. Li https://orcid.org/0000-0001-7507-3632

Elizabeth A. Martin https://orcid.org/0000-0001-8893-1667

Supplemental Material

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Note

1. The majority of participants (80.52%) completed the task in the lab. Task format was not significantly related to any outcome measures, except for a marginal difference in SSD (PA–binominal model: $B = -0.24$, $SE = 0.13$, $p = .068$; NA–gamma model: $B = -0.16$, $SE = 0.090$, $p = .072$). Participants who completed the task online had a lower likelihood of nonzero (vs. zero) SSDs in PA and lower magnitude of nonzero SSDs in NA than participants who completed the task in the lab.

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