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Whether and How Much: Nonlinear Thresholds in Discrete Emotional Responses to Workplace Events

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Abstract

Appraisal theories imply that emotions may arise only once events exceed a threshold relative to a personal frame of reference, whereas dynamical accounts propose that emotional systems can become bistable. We tested whether discrete emotions respond to event valence and strength proportionally, through thresholds, or discontinuously, and whether people differ in these responses. In a diary study, 100 employees reported 1,479 work events and rated six discrete emotions. Two-part generalized additive models revealed nonlinear relations, mostly in intensity: anger intensified for events worse than usual, happiness for events better than usual, and disgust and, less robustly, fear for events stronger than usual, whereas sadness and surprise responded linearly. Cusp catastrophe models showed no evidence of the bistability proposed by the Bifurcation Model of Affect Structure. People differed in asymmetry, but not detectably in bifurcation, parameters. Emotional responses to everyday events are thus better described by emotion-specific thresholds relative to each person's typical experience than by proportional or catastrophic change.

Introduction

How does the appraisal of an event translate into emotion? Appraisal theories hold that emotions arise from evaluations of events against a person's goals and concerns (Lazarus, 1991; Scherer, 2000), but they differ in what they imply about the form of this translation. Most empirical tests implicitly assume proportionality, typically by applying linear models (e.g., the more negative an important event is appraised to be, the more intense the resulting negative emotion). Yet several classic accounts suggest otherwise. Ortony, Clore, and Collins (1988) proposed that an emotion is experienced only when its potential exceeds a threshold, with intensity reflecting the excess over that threshold. Frijda's (1988) law of comparative feeling holds that emotional intensity depends not on an event's absolute features but on its discrepancy from a frame of reference. And dynamical accounts propose that, beyond critical values, emotional systems may become bistable and shift abruptly between qualitatively different states (Li et al., 2010). Whether emotions respond proportionally, through thresholds relative to a reference point, or discontinuously is therefore a central, and largely untested, question for emotion theory.

Workplaces offer a particularly suitable context to examine this question. Work events are frequent and highly relevant to people's goals. Moreover, Affective Events Theory (AET; Weiss & Cropanzano, 1996) proposes that work events are proximal causes of discrete emotions. Two features of these events are central. The first is valence, the appraisal of an event as conducive or obstructive to one's goals, which determines whether positive or negative emotions are likely to arise. The second is strength, defined by Event Systems Theory (EST; Morgeson et al., 2015) in terms of novelty, disruption, and criticality, facets that correspond closely to the early appraisal checks of novelty and goal relevance (Scherer, 2000). Valence thus governs the direction of the response, and strength how much an event matters. Yet empirical tests of AET and related frameworks have typically modeled event-emotion relations as linear (e.g., Junça-Silva & Ferreira, 2025; Navarro, Rueff-Lopes, & Otero, 2026), leaving their functional form unexamined.

The accounts above imply three distinct forms for these relations. The proportional account predicts that emotional intensity increases linearly with event valence and strength. The threshold account predicts that an emotion arises only once an event departs sufficiently from the person's frame of reference and intensifies beyond that point; because negative and positive information engage partly separable evaluative systems (Cacioppo et al., 1997), these thresholds should also be asymmetric, with negative emotions responding to events worse than usual and positive emotions to events better than usual. The discontinuous account makes a stronger claim. The Bifurcation Model of Affect Structure (BMAS; Li et al., 2010) proposes that when the perceived intensity of an affective event exceeds a critical value, the emotional system bifurcates, so that similar events may elicit either a weak or a strong response, with abrupt transitions between them. Event strength would then act as a bifurcation factor, destabilizing emotion rather than merely intensifying it, whereas valence would shift the response toward one state or the other. Cusp

catastrophe models provide a statistical operationalization of this idea in which bistability can be tested directly (Cobb, 1978; Grasman et al., 2009). Despite their different implications, these three forms have rarely been tested against each other with naturally occurring events.

These accounts also bear on individual differences. Emotion theories have long recognized that emotions are personal (i.e., the same event can elicit different emotions in different people; Frijda, 1988; Lazarus, 1991), and that individuals differ systematically in emotional reactivity (Davidson, 1998). Empirical practice, however, typically estimates event-emotion relations across people and reads them as describing how each person responds, treating individual differences as variations in the strength of a common relation rather than in its form. Such inferences are warranted only for ergodic processes, in which variation within persons mirrors variation between persons (Molenaar, 2004; Molenaar & Campbell, 2009), a condition that emotional processes are unlikely to meet; indeed, the number and nature of recurring affective patterns vary considerably across individuals (Fisher et al., 2018). If each person's frame of reference is shaped by their own history of experiences, thresholds should be located relative to each person's typical events, and the BMAS similarly notes that the perceived intensity of events varies with personality and experience (Li et al., 2010). Within a cusp framework, two kinds of individual differences can be distinguished: in asymmetry, reflecting a person's habitual tendency toward a weaker or stronger emotional response, and in bifurcation, reflecting their susceptibility to abrupt shifts between states (Butner et al., 2014).

The present study examines these questions in diary study in which employees from different occupational sectors reported their daily work events and the discrete emotions they elicited. We pursue three aims. First, we test which of the three forms best describes how each of six discrete emotions responds to event valence and strength, distinguishing whether an emotion arises from how intense it becomes once present, because a threshold should govern the former and the excess over it the latter (Ortony et al., 1988). Second, we test the central claim of the discontinuous account, that event strength acts as a bifurcation factor. Third, we test whether people differ in the asymmetry and bifurcation parameters that govern their responses. In doing so, the study tests whether appraisal-based thresholds are located relative to each person's typical experience, provides a test of bistability with naturally occurring events, and examines whether individual differences lie in the form, and not only the intensity, of event-emotion relations.

Theoretical Framework

Appraisal, Thresholds, and Reference Points

AET (Weiss & Cropanzano, 1996) posits that discrete emotions at work arise from the appraisal of workplace events. Two appraisals are central to the present study: goal congruence, which gives an event its valence, and goal relevance, which determines how much the event matters (Lazarus, 1991). EST (Morgeson et al., 2015) adds that events differ in strength, defined by their novelty, disruption, and criticality. Criticality, the degree to which an event is important to the person or the organization, overlaps conceptually with goal relevance, and it is in this sense that we operationalize it. Appraisal theories also make explicit claims about how appraisals become emotions. In the model proposed by Ortony et al. (1988), an appraised event generates an emotion potential, but an emotion is experienced only when this potential exceeds a threshold, and its intensity corresponds to the amount by which the potential exceeds it. This formulation separates two questions that linear models conflate: whether an emotion arises and how intense it becomes once present. A threshold governs the first, and the excess over the threshold governs the second. The relation between appraisals and emotion should therefore be flat below the threshold and increasing above it, and the two parts of the response need not depend on appraisals in the same way.

Where should such thresholds lie? Frijda's (1988) law of comparative feeling holds that emotional intensity depends on the discrepancy between an event and a frame of reference, typically the conditions to which the person has become accustomed. If so, thresholds should be located not at fixed values of valence or strength but relative to what is typical for each person: an event slightly worse than usual may leave emotion untouched, whereas one clearly worse than usual may elicit it. EST makes a convergent claim for strength, holding that only sufficiently strong events affect individual responses (Morgeson et al., 2015). Appraisal theorists have further argued that the appraisal process is itself nonlinear, so that the same appraisal may yield different responses depending on the person's prior state (Scherer, 2000). This possibility, a dependence on prior state, or hysteresis, goes beyond thresholds and is the signature of the discontinuous account developed below.

Classic research on the asymmetry between positive and negative events suggests that thresholds need not be the same for all emotions. Negative events elicit stronger and more rapid responses than positive events of comparable magnitude (Baumeister et al., 2001; Taylor, 1991). The evaluative space model formalizes this asymmetry as distinct activation functions for the positive and negative motivational systems: the positive system is more active at low levels of input (positivity offset), whereas the negative system responds more steeply as input increases (negativity bias; Cacioppo et al., 1997). If positive and negative emotions follow different activation functions, their relation with event valence cannot be linear across the full range of events. Combined with a person-specific frame of reference, this implies that negative emotions should respond mainly to events worse than usual and positive emotions mainly to events better than usual, so that the form of the event-emotion relation should be emotion-specific rather than common to all emotions.

From Thresholds to Bistability: The Bifurcation Model of Affect Structure

Nonlinear dynamics (Guastello et al., 2009) provides a vocabulary for distinguishing thresholds from genuinely discontinuous change. In a dynamical system, a state variable (here, the intensity of a discrete emotion) depends on control parameters that shape the landscape of possible states. Catastrophe theory distinguishes two roles that control parameters can play (Zeeman, 1976). An asymmetry factor biases the system toward one state or another, whereas a bifurcation factor determines whether the system responds smoothly or becomes bistable, with two states available for the same input. In a bistable region, the state the system occupies depends on its previous state, which produces hysteresis and abrupt jumps when the system is pushed beyond the edge of one of its states. Zeeman's (1976) classic illustration was itself emotional: aggression in dogs, modeled with rage and fear as control factors.

The BMAS (Li et al., 2010) applies this logic to affect in organizations. Drawing on complexity theory and on May's (1976) bifurcation model, it proposes that the affective system can occupy qualitatively different regimes: equilibrium, in which affect is diffuse and dimensional; a state near equilibrium, in which the system bifurcates and discrete emotions emerge; and, at the extreme, chaos. Movement between these regimes is governed by the perceived intensity of the affective event, not by the intensity of the emotion itself (Li et al., 2010). Low-intensity events leave the system in equilibrium, whereas events of sufficient intensity push it past a critical point at which discrete emotions appear.

The BMAS and the threshold account therefore agree that discrete emotions emerge only beyond a critical level of event intensity. They differ in what happens at that point. In the threshold account, emotion changes smoothly, if steeply, once the threshold is crossed, and each appraisal corresponds to a single expected response. In the BMAS, the system bifurcates: beyond the critical point, similar appraisals may yield either a weak or a strong emotional response, and the system may shift abruptly between them. Bistability, rather than the onset of emotion, is thus the claim that distinguishes the discontinuous account.

Because the BMAS is formulated as a discrete-time bifurcation model, it does not by itself specify a statistical test. To evaluate its central claim with diary data, we translate it into Cobb's (1978) stochastic cusp catastrophe model, an established framework for estimating catastrophe models (Grasman et al., 2009). In this translation, event strength, the closest counterpart of the BMAS's perceived event intensity, acts as the bifurcation factor, and event valence acts as the asymmetry factor, pushing each emotion toward higher or lower intensity depending on whether it is positive or negative. This mapping is our operationalization rather than part of the BMAS itself, but it preserves its core prediction: as events become stronger, the emotional system should move from a regime of smooth change to one in which two emotional states are available for the same appraisal. Evidence from affect dynamics suggests that such features are plausible: in daily-life data, nonlinearity in affect persisted after accounting for the valence of the events people experienced (Vanhasbroeck et al., 2024), and catastrophe models have been applied to work behavior and organizational outcomes (Butner et al., 2014; Guastello, 2002). To our knowledge, however, they have not been used to model discrete emotional responses to workplace events, which is where the BMAS locates its central prediction.

Nonergodicity and Person-Specific Emotional Dynamics

Appraisal theories imply that people differ in how they experience the same events (Lazarus, 1991; Moors et al., 2013). Subjectivity alone, however, implies only that people differ; it does not imply that the process linking events to emotions differs across people. The latter is what ergodicity concerns. A process is ergodic (Molenaar, 2004; Molenaar & Campbell, 2009) when it is homogeneous (i.e., the same model holds for every individual) and stationary (i.e., its properties do not change over time). When these conditions fail, between-person associations may differ in size, and even in direction, from the same within-person associations they are assumed to represent (Hamaker, 2012). Psychological processes, including affect, appear to be a case in point: across six intensive longitudinal samples measuring mood, affect, and physiological variables, the variance around expected values was two to four times larger within individuals than between individuals (Fisher et al., 2018).

The accounts reviewed above suggest that individual differences can arise at two levels. The first concerns the location of thresholds. If each person evaluates events against their own frame of reference (Frijda, 1988), the same event may fall below one person's threshold and above another's even when both follow the same process. Expressing valence and strength relative to each person's typical events captures this source of heterogeneity: if a common relation then describes the data, people share the same dynamic relative to their own baseline. The second level concerns the parameters of the process itself, to which the BMAS points directly. Because the control parameter of the affective system is the perceived intensity of events, and perception depends on prior experience, the point at which the system bifurcates need not be the same for everyone (Li et al., 2010). In the cusp framework, people can differ here in two distinct ways. They can differ in asymmetry, that is, in the emotional state toward which they tend for a given appraisal, as when one person reacts with more anger than another to comparable events. This reflects differences in emotional level but remains compatible with a shared dynamic. Alternatively, they can differ in bifurcation, that is, in the event strength at which smooth change gives way to bistability. This would mean that people differ not only in how much they feel but in where their thresholds for abrupt emotional change lie. The second form implies qualitatively different dynamics across individuals and is therefore the stronger form of nonergodicity, one that neither AET nor EST, as typically tested, can accommodate.

Research Question and Hypotheses

Building on these premises, the central research question of the present study is whether the relationship between workplace events and discrete emotions follows a linear, smoothly nonlinear, or discontinuous form, and whether this

form differs across discrete emotions and across individuals. We examine six discrete emotions (anger, disgust, happiness, sadness, surprise, and fear) for two reasons. First, they are the emotions most widely considered basic (Ekman, 1992), each associated with distinct appraisals and action tendencies, which makes emotion-specific forms plausible. Second, a small set favors parsimony, keeping diary reports brief and the number of models tractable (Fisher & To, 2012). We test three hypotheses, one for each of the accounts reviewed above.

Following the threshold account (Frijda, 1988; Ortony et al., 1988), we expect the relations of event appraisals with both the occurrence and the intensity of emotions to depart from linearity.

Hypothesis 1

(Nonlinearity): The relationships of event valence and event strength with the occurrence and intensity of discrete emotions will be nonlinear, with forms that differ across emotions. Operationally, generalized additive models will fit better than linear models (ΔAIC and likelihood-ratio tests).

Extending the BMAS logic (Li et al., 2010) into a cusp catastrophe framework, we hypothesize that event strength makes emotional responses bistable.

Hypothesis 2

(Bifurcation): Discrete emotions will follow a cusp catastrophe in which event valence acts as the asymmetry factor and event strength as the bifurcation factor, such that stronger events increase bistability. Operationally, cusp models will outperform both linear and logistic alternatives (AIC and BIC), event strength will have a positive bifurcation coefficient, and a non-trivial share of observations (≥ 10%) will fall within the bifurcation set, a necessary condition for bistability.

Finally, because the perceived intensity of events is subjective and depends on prior experience (Li et al., 2010), we expect people to differ in the parameters that govern their responses, beyond differences in their frames of reference.

Hypothesis 3

(Nonergodicity): Participants will differ in the control parameters of their emotional responses, (H3a) in the asymmetry factor and (H3b) in the bifurcation factor. Operationally, cusp models with person-specific asymmetry and bifurcation intercepts will predict new observations from the same participants better than models with parameters common to all participants (within-person cross-validation).

In addition, the threshold and asymmetry accounts suggest two more specific expectations, which we examine in an exploratory way. First, if thresholds are set by each person's frame of reference, changes in emotion should occur near or beyond the values of valence and strength that are typical for that person. Second, if positive and negative emotions follow different activation functions (Cacioppo et al., 1997), negative emotions should respond mainly to events worse than usual, and positive emotions mainly to events better than usual. Neither the hypotheses nor these expectations were preregistered.

Method

Participants

A total of 102 employees began the study, recruited through snowball sampling from public and private organizations across different sectors, including education, healthcare, manufacturing, and services. These data are part of a larger

diary data set used in a previous publication (Authors, 2026) with other research questions. We excluded two participants who provided fewer than four daily records, as too few observations would not allow event appraisals to be centered on each person's typical values. The final sample comprised 100 participants. Participants' mean age was 39.58 years (*SD* = 13.82), and 60% were women. On average, participants reported working 39.91 hours per week (*SD* = 13.67). The most frequent occupational groups (ISCO-08; International Labour Organization, 2012) were technicians and associate professionals (19%), professionals (18%), managers (13%), clerical support workers (7%), and service and sales workers (7%).

Inclusion criteria required participants to hold a full- or part-time job and to commit to completing the diary daily over 10–15 consecutive working days. Participants provided a total of 1,479 daily records, an average of 14.79 per participant (*SD* = 8.17). Participation was voluntary and uncompensated; instead, participants could receive personalized feedback on their emotional patterns and workplace well-being based on their diary data. Before the study began, participants gave informed consent and received detailed instructions on the daily reporting procedure. All procedures were approved by the Institutional Review Board of the University of ANONYMIZED (reference ANONYMIZED).

Design and Procedure

The Day Reconstruction Method (DRM; Kahneman et al., 2004) was used to collect data on participants' affective events and emotional experiences. Participants were asked to complete one daily questionnaire over 10–15 consecutive workdays, at the beginning of each workday, selecting a salient event from the previous working day. Those who wished could continue beyond this period, and some did, so the number of records varied across participants (*M* = 14.79, *SD* = 8.17). Participants received a daily email with a link to the diary, which they completed on their own devices. Each entry required them to recall and describe a work-related event and to rate its characteristics and the discrete emotions it evoked.

This daily diary design captures both within-person fluctuations and between-person differences in emotional responses (Bolger & Laurenceau, 2013; Wang et al., 2017). Because emotional processes are likely nonergodic (see Theoretical Framework), modeling the dynamics linking events to discrete emotions, including potential nonlinear shifts, requires observing each person across multiple events.

Instrument and Measures

The daily diary was designed to assess affective events and their corresponding discrete emotional responses in the workplace. It was composed of a short sequence of open- and closed-ended questions, adapted from previous research grounded in Affective Events Theory (Weiss & Cropanzano, 1996) and Event Systems Theory (Morgeson et al., 2015). We also followed the Day Reconstruction Method (Kahneman et al., 2004). The diary items and response scales were as follows:

1. 1. *Event*: "Try to remember an important event that happened at work yesterday. Describe it below providing details: what happened, who participated, how the sequence of events unfolded, etc."
2. 2. *Emotional responses*: "How did this event make you feel, and to what degree?":

I felt angry (from 0 "None" to 10 "A lot")

I felt disgusted (from 0 "None" to 10 "A lot")

I felt happy (from 0 “None” to 10 “A lot”)

I felt sad (from 0 “None” to 10 “A lot”)

I felt surprised (from 0 “None” to 10 “A lot”)

I felt afraid (from 0 “None” to 10 “A lot”).

1. 3. *Relevance*: “How relevant do you consider this event?” (from 0 “None” to 10 “A lot”).
2. 4. *Event valence*: “How do you generally evaluate this event?” (from 0 “Very negative” to 10 “Very positive”).
3. 5. *Novelty*: “How novel did you find this event?” (from 0 “Not very novel” to 10 “Very novel”).
4. 6. *Disruption*: “Was the event disruptive (did it involve an interruption, a change, in the previous activity)?” (from 0 “Little” to 10 “A lot”).

Each discrete emotion was measured with a single item, a common practice in intensive longitudinal designs, where brief measures reduce participant burden and allow repeated assessment (Fisher & To, 2012; Gabriel et al., 2019). Because the reliability of single items cannot be estimated from internal consistency, we examined their validity through the structure of their within-person associations. As expected, negative emotions were positively intercorrelated, happiness was negatively related to anger and sadness, and the valenced emotions were associated with event valence in the theoretically expected directions (see Results and Table 2). Event valence was likewise measured with a single bipolar item.

Following EST, an event strength composite was calculated as the mean of its three facets: novelty, disruption, and criticality (Morgeson et al., 2015). Criticality was measured with the relevance item, consistent with its conceptual overlap with goal relevance (see Theoretical Framework). Higher scores indicated stronger events. Although EST conceptualizes event strength formatively, we explored its empirical cohesion within a reflective multilevel confirmatory factor framework (Geldhof et al., 2014): reliability was ω = .62 (95% CI [.59, .66]) within-persons and ω = .80 (95% CI [.72, .88]) between-persons. The moderate within-person value is consistent with EST’s view of strength as a formative combination of distinct features that need not co-occur in every episode: a routine task can be highly disruptive, and a novel interaction can be smooth. We therefore treat the composite as an index of event strength rather than as a measure of a single latent attribute, and we return to its limitations in the Discussion. Event strength was moderately related to surprise within persons (r = .41, p < .01) and only weakly related to event valence (r = .17, p < .01), indicating that strength and valence captured distinct features of events.

Data Analysis

The data consisted of daily records nested within participants. All analyses were conducted in R (R Core Team, 2023) using, as main packages, psych (Revelle, 2023), lme4 (Bates et al., 2015), performance (Lüdecke et al., 2021), lavaan (Rosseel, 2012), correlation (Makowski et al., 2020), mgcv (Wood, 2017), and cusp (Grasman et al., 2009). All the analysis scripts and data set are available at https://osf.io/sudc3/overview?view_only=074554031a674ee5beb9afc4591b5819.

We computed descriptive statistics for all study variables and intraclass correlation coefficients (ICCs) from intercept-only mixed models to quantify the proportion of variance due to between-person differences. Associations among event characteristics (valence and strength) and discrete emotions were estimated with Spearman correlations at two levels: within-person correlations, estimated as repeated-measures correlations from mixed-effects models (Bakdash & Marusich, 2017), and between-person correlations computed on participant means; p values were Holm-adjusted.

In all models, event valence and event strength were centered on each participant's mean and scaled by each participant's standard deviation. Effects therefore reflect how a person's emotions respond when an event is more positive or stronger than is typical for that person, separating within-person processes from stable between-person differences. Unlike in H1 and H2, emotion ratings in H3 were not centered within-person, so that between-person differences in emotional level could be captured by the person-specific parameters.

Because emotion ratings contained a large proportion of zeros, we used two-part (i.e., hurdle) generalized additive models (GAMs; Wood, 2017) to test nonlinearity (H1). The occurrence part modeled whether each emotion was present (rating > 0) with a binomial GAM including a random intercept per participant. The intensity part modeled emotion intensity when present with a Gaussian GAM, with intensity centered and scaled within person using only active episodes; participants with fewer than two active episodes were excluded from this part. For each part and emotion, we compared a linear model, an additive GAM with smooth terms for valence and strength, and a GAM adding a tensor-product interaction between them, all fitted by maximum likelihood. Nonlinearity was assessed through the deviance explained, ΔAIC, and likelihood-ratio tests of the GAM against the linear model.

To test for bifurcation and abrupt shifts (cusp catastrophe models in H2), we fitted Cobb's (1978) stochastic cusp model by maximum likelihood (Grasman et al., 2009). Event valence was specified as the asymmetry factor (α) and event strength as the bifurcation factor (β) drawing on the Bifurcation Model of Affect Structure (Li et al., 2010). The state variable was the full 0–10 emotion rating, centered and scaled within person; participants who never reported the emotion were excluded. Each model was fitted from multiple starting values, retaining the solution with the highest likelihood. Following Grasman et al. (2009), we evaluated the cusp against two alternatives: a linear model and a logistic model, which produces abrupt but non-bifurcating change. Because these models are not nested, they were compared by BIC. We also report Cobb's pseudo-R^2, the significance of the control parameters and, following common empirical heuristics in catastrophe modeling (e.g., Grasman et al., 2009), we examined whether a non-trivial share of observations (≥ 10%) fell within the bifurcation set. This criterion is necessary but not sufficient for bistability: it does not show that individuals switch between states or that their responses depend on their previous state (hysteresis), which a static cusp model cannot test.

Finally, to test whether participants differ in their control parameters (nonergodicity; H3), we extended the cusp model following the logic of Butner et al. (2014), whereby control parameters vary across individuals. We added person-specific intercepts to α and β, estimated as fixed effects with sum-to-zero contrasts, and compared three nested models: a common model (M_0), a model adding person-specific asymmetry (M_α), and a model also adding person-specific bifurcation ($M_{\alpha\beta}$). Unlike in H2, the state variable was the 0–10 emotion rating scaled by its overall standard deviation but not centered within person, so that between-person differences in level are captured by the person-specific parameters. Because the cusp package does not converge with this number of parameters, we programmed Cobb's likelihood with an analytic gradient and maximized it with the *nlminb* optimizer; for the common model, this implementation reproduced the cusp package estimates. With relatively few records for many participants (*Mdn* = 13.5), AIC and likelihood-ratio tests are biased toward models with person-specific parameters (incidental-parameter problem; see Neyman & Scott, 1948). The primary criterion was therefore the out-of-sample log-likelihood from 5-fold cross-validation within persons, with AIC, BIC, and likelihood-ratio tests reported as secondary information. These analyses included participants with at least five records and at least two non-zero ratings of the emotion, the minimum required to identify person-specific parameters.

Together, these analyses distinguish linear, smoothly nonlinear, and discontinuous (bifurcating) responses of discrete emotions to workplace events, and assess whether such responses are shared across individuals or person-specific.

Results

Descriptive and Correlational Results

A total of 1,479 valid daily records were collected from 100 participants. Events were slightly positive on average (M = 5.29, SD = 3.32) and of medium strength (M = 4.49, SD = 2.60). Among discrete emotions, happiness showed the highest mean intensity (M = 4.27, SD = 3.72), followed by surprise (M = 2.46, SD = 2.98) and anger (M = 2.03, SD = 3.12). The remaining negative emotions (sadness, fear, and disgust) had lower means (Ms < 1.5) and were absent in most records (see Table 1). ICCs ranged from .22 to .30 for all emotions except fear (ICC = .38), so that between 62% and 78% of the variance in emotions lay within persons. The non-negligible between-person variance nevertheless indicates that records from the same participant are not independent (Bliese, 2000), which is why all analyses accounted for the nesting of daily records within participants.

Table 1
Descriptive Statistics and Intraclass Correlation Coefficients

Variable	M	SD	Mdn	Trimmed M	Skewness	Kurtosis	ICC
Anger	2.03	3.12	0	1.41	1.32	0.29	.30
Disgust	0.68	1.85	0	0.16	3.43	11.90	.29
Happiness	4.27	3.72	5	4.08	0.14	-1.51	.30
Sadness	1.36	2.61	0	0.69	1.98	2.69	.27
Surprise	2.46	2.98	1	2.00	0.95	-0.38	.22
Fear	0.92	2.03	0	0.36	2.53	5.88	.38
Event valence	5.29	3.32	5	5.36	-0.22	-1.16	.32
Event strength	4.49	2.60	5	4.53	-0.19	-0.74	.36
Note: N = 100 participants; n = 1,479 daily records.							

Table 2 presents Spearman rank correlations at both levels of analysis. Several patterns are worth highlighting. First, within-person associations between discrete emotions and event appraisals were consistent with theoretical expectations. Event valence showed its strongest positive within-person association with happiness (r = .69, p < .001) and negative associations with anger (r = − .41), sadness (r = − .39), disgust (r = − .29), and, more weakly, fear (r = − .16), all ps < .001. Surprise was the emotion least associated with valence at both levels (r_{within} = .02, $r_{between}$ = .06). Event strength, in contrast, showed its strongest association with surprise (r_{within} = .41, $r_{between}$ = .56), all ps < .001, consistent with its conceptual overlap with novelty and disruption (Morgeson et al., 2015).

Second, within-person correlations among discrete emotions revealed the expected structure of hedonic co-activation. Negative emotions were positively intercorrelated, with the strongest associations for anger-sadness (r = .57), anger-disgust (r = .54), and sandess-fear (r = .51). Happiness was negatively correlated with anger (r = − .37) and sadness (r = − .33), but only weakly with disgust (r = − .19) and fear (r = − .12), suggesting partial rather than complete hedonic opposition.

Third, several within- and between-person correlations diverged. Because significance tests at each level rest on very different sample sizes (1,479 records vs. 100 participants), we focus on differences in magnitude. Anger was more strongly related to event valence within-persons (r = − .41) than between-persons (r = − .23), and a similar pattern held

for anger-happiness (-.37 vs. − .23) and sadness-happiness (-.33 vs. − .20). More often, however, associations were stronger between persons. Surprise correlated only weakly with negative emotions within-persons (*r* = .12 to .19) but moderately between-persons (*r* = .33 to .48), and event valence and strength were more closely related between- (*r* = .43) than within-persons (*r* = .17). Between-person correlations may therefore partly reflect stable individual differences, such as a general tendency toward emotional reactivity (Davidson, 1998), that do not operate at the level of daily events. These divergences show that relations observed across individuals cannot be assumed to describe within-person processes (Hamaker, 2012; Molenaar & Campbell, 2009), supporting the within-person focus adopted here; whether these processes also differ across individuals is tested directly in H3.

Table 2
Within-Person and Between-Person Spearman Rank Correlations Among Study Variables

Variable	1	2	3	4	5	6	7	8
1. Anger	-	.66***	− .23	.58***	.39**	.36**	− .23	.35**
2. Disgust	.54***	-	− .17	.69***	.39**	.56***	− .26	.27
3. Happiness	− .37***	− .19***	-	− .20	.14	− .20	.85***	.37**
4. Sadness	.57***	.57***	− .33***	-	.48***	.62***	− .29*	.35**
5. Surprise	.15***	.12***	.02	.19***	-	.33*	.06	.56***
6. Fear	.32***	.46***	− .12***	.51***	.16***	-	− .32*	.28*
7. Event valence	− .41***	− .29***	.69***	− .39***	.02	− .16***	-	.43***
8. Event strength	.31***	.24***	.14***	.34***	.41***	.34***	.17***	-

Note. N = 100 participants; n = 1,479 observations. Within-person Spearman correlations appear below the diagonal. Between-person Spearman correlations appear above the diagonal. p values in both triangles are Holm-adjusted.

* p < .05. ** p < .01. *** p < .001.

Generalized Additive Models (GAMs)

Table 3 summarizes the two-part GAMs (and Figs. 1 and 2 display the estimated partial effects). Nonlinearity was evaluated by comparing each GAM with a linear model fitted to the same observations (ΔAIC and likelihood-ratio test); the significance of individual smooth terms indicates only that an effect differs from zero, not that it is nonlinear.

Regarding the onset of emotions (Table 3a), the GAM improved on the linear model for anger (ΔAIC = 7.8, p = .008), disgust (ΔAIC = 9.8, p = .004), and happiness (ΔAIC = 5.8, p = .011). In all three cases, nonlinearity stemmed mainly from event valence (*edf* = 3.61–4.39). Most notably, the probability of experiencing happiness shifted sharply around the person's typical valence, from about .20 for clearly negative events to near certainty for events only somewhat more positive than usual, whereas disgust was likely only for events well below the person's average valence. For disgust, event strength also showed a nonlinear effect (*edf* = 2.13). Evidence for sadness was weaker (ΔAIC = 2.5, p = .068), and the occurrence of surprise and fear was adequately described by linear effects (ΔAIC = 0.0). Event strength was linearly related to the occurrence of anger, sadness, and fear (*edf* = 1.00, all *ps* < .001) and unrelated to the occurrence of happiness (*p* = .129), whereas surprise depended on strength (*p* < .001) but not on valence (*p* = .176). Gains in deviance explained over the linear model were small (0.3–1.4 percentage points); the relatively high overall

values (39.0%-61.8%) largely reflect the random intercept, that is, stable between-person differences in the propensity to experience each emotion.

In additional models, adding a tensor-product interaction (valence-strength interaction) most clearly improved the models for the intensity of fear (ΔAIC = 14.7) and disgust (ΔAIC = 6.1) and for the occurrence of happiness (ΔAIC = 4.0), indicating that, for these emotions, the response to event strength depended on event valence.

These patterns bear on the two exploratory expectations. First, where nonlinearity appeared, the estimated functions changed near or beyond each person's typical values (zero on the centered predictors), consistent with thresholds anchored in a personal frame of reference. Second, the expected valence asymmetry was clearest for anger and happiness, whose intensity responded mainly to events worse and better than usual, respectively, and for the occurrence of disgust. It did not extend to the other negative emotions: the intensity of sadness was linearly related to valence, and the thresholds for the intensity of disgust and fear lay in event strength rather than valence.

Overall, these results partially support Hypothesis 1. The GAM was preferred over the linear model in 7 of the 12 emotion-by-part comparisons by unadjusted likelihood-ratio tests (and also, by ΔAIC alone, for the occurrence of sadness). After Holm adjustment for the 12 tests, nonlinearity remained significant for 4 of them: the intensity of happiness, disgust, and anger, and the occurrence of disgust. Nonlinearity was thus more robust for intensity than for occurrence, whereas sadness and surprise followed essentially linear patterns. These threshold-like and asymmetric patterns are consistent with the threshold account; whether they also reflect bistability is addressed by the cusp models. Two caveats apply. First, the models allow person-specific intercepts but not person-specific curves, so the estimated functions describe the typical within-person response. Second, the intensity models for disgust and fear rest on fewer observations (277 and 354 records from 44 and 52 participants, respectively), so their curves should be interpreted with caution.

Table 3

a: GAM Results for the Occurrence of Discrete Emotions (Binomial, Logit Link)

Emotion	**n obs.**	**n persons**	**Predictor**	***edf***	***χ²***	***p***	**Dev. expl. linear (%)**	**Dev. expl. GAM (%)**	**ΔAIC (lin - GAM)**	**p LRT**	**ΔAIC (GAM - GAM + ti)**
Anger	1479	100	Event valence	3.70	195.28	< .001	45.6	46.3	7.8	.008	1.1
			Event strength	1.00	83.28	< .001					
Disgust	1479	100	Event valence	3.61	88.54	< .001	60.4	61.8	9.8	.004	-2.6
			Event strength	2.13	19.16	< .001					
Happiness	1479	100	Event valence	4.39	266.52	< .001	55	56.3	5.8	.011	4
			Event strength	1.59	4.38	.129					
Sadness	1479	100	Event valence	3.76	133.91	< .001	44.7	45.2	2.5	.068	1.3
			Event strength	1.00	62.98	< .001					
Surprise	1479	100	Event valence	1.00	1.83	.176	38.7	39	0	.162	2.8
			Event strength	2.30	172.84	< .001					
Fear	1479	100	Event valence	1.00	27.01	< .001	54.4	54.4	0	-	0.4
			Event strength	1.00	80.84	< .001					

Note. All observations included (emotion present = 1, absent = 0). Models include a random intercept per participant. *edf* = effective degrees of freedom of the smooth term (*edf* ≈ 1 indicates a linear effect). p tests whether the smooth term differs from zero, not whether it is nonlinear; nonlinearity is assessed with ΔAIC and the likelihood-ratio test (LRT) of the GAM against the linear model fitted to the same observations. ΔAIC > 0 favors the more complex model. Models estimated by maximum likelihood.

Table 3
b: GAM Results for the Intensity of Discrete Emotions When Present (Gaussian)

Emotion	n obs.	n persons	Predictor	*edf*	*F*	*p*	Dev. expl. linear (%)	Dev. expl. GAM (%)	ΔAIC (lin - GAM)	p LRT	ΔAIC (GAM - GAM + ti)
Anger	576	79	Event valence	4.00	9.25	< .001	10.1	13	10.9	.002	2.7
			Event strength	1.00	38.43	< .001					
Disgust	277	44	Event valence	1.59	11.96	< .001	13.4	21.4	15.4	< .001	6.1
			Event strength	4.55	7.98	< .001					
Happiness	966	84	Event valence	5.83	61.19	< .001	30.2	33.8	40.1	< .001	0.8
			Event strength	1.00	0.44	.507					
Sadness	446	66	Event valence	1.00	49.25	< .001	13.7	13.7	0	-	-1.1
			Event strength	1.00	21.84	< .001					
Surprise	785	91	Event valence	1.00	0.64	.423	10.8	10.8	0	-	-1.9
			Event strength	1.00	92.20	< .001					
Fear	354	52	Event valence	1.00	4.83	.029	6.4	11	7.5	.008	14.7
			Event strength	4.91	5.52	< .001					

Note. Only observations in which the emotion was present (intensity ≥ 1). Intensity was centered and scaled within person using only active episodes; participants with fewer than 2 active episodes or no within-person variance were excluded. *edf* = effective degrees of freedom of the smooth term (*edf* ≈ 1 indicates a linear effect). p tests whether the smooth term differs from zero, not whether it is nonlinear; nonlinearity is assessed with ΔAIC and the likelihood-ratio test (LRT) of the GAM against the linear model fitted to the same observations. ΔAIC > 0 favors the more complex model. Models estimated by maximum likelihood.

Unilevel Cusp Models

Table 4 summarizes the unilevel cusp models. Following Grasman et al. (2009), support for a cusp requires that the model outperform both the linear and the logistic alternatives, that the control parameters be significant in the expected direction (β > 0 for event strength)In addition, we adopted the empirical heuristic that a non-trivial share of observations (≥ 10%) should fall within the bifurcation set.

By BIC, the cusp model outperformed the linear model for five of the six emotions (ΔBIC = 151–824), whereas for happiness both the linear and the logistic models were preferred (ΔBIC = -101 and − 146, respectively). However, the advantage of the cusp closely tracked the proportion of zero ratings (Spearman ρ = .83, across the six emotions). The

three emotions with the most zeros (disgust, 78.9%; fear, 73.0%; sadness, 67.5%) showed the largest BIC advantages (585–824) and the largest gains in pseudo-R^2 (e.g., from .13 to .53 for disgust). In these three emotions, however, the bifurcation set covered 69%-92% of observations, the Hessian was near-singular so that standard errors were unreliable, and for fear and sadness the logistic model did not converge, precluding the most stringent comparison. This pattern suggests that the cusp density captured the bimodality between the absence (= 0) and presence (> 0) of the emotion rather than bistability driven by event characteristics, and we therefore do not interpret it as support for a cusp. In other words, the cusp model effectively picked up emotional onset (presence vs. absence) rather than catastrophic shifts in intensity.

Among the emotions with reliable estimates, the cusp outperformed both alternatives for anger (ΔBIC = 371 vs. linear and 505 vs. logistic) and, more modestly, for surprise (ΔBIC = 151 and 153). For anger, event valence was a significant asymmetry factor (α = -0.73, $p < .001$), and event strength was significantly related to the bifurcation factor (β = -0.44, $p < .001$), but in the opposite direction to that predicted. Moreover, only 7.6% of observations fell within the bifurcation set, and the cusp's pseudo-R^2 was identical to that of the linear model (.24), indicating that the BIC advantage reflected a better description of the shape of the distribution rather than a better prediction of emotion levels. For surprise, valence was unrelated to the asymmetry factor (α = 0.01), strength was again negatively related to bifurcation (β = -0.78, $p < .001$), the bifurcation set was small (4.3%), and pseudo-R^2 did not exceed the linear value (.18 vs. .19). For happiness, valence acted as a strong asymmetry factor (α = 2.26, $p < .001$), but strength was unrelated to bifurcation (β = 0.27, *ns*), and no observations fell within the bifurcation set.

Notably, the strength coefficient on the bifurcation factor was negative for five of the six emotions, although it could be reliably estimated only for anger and surprise: events stronger than usual were associated with less, not more, bistability. Taken together, these results do not support Hypothesis 2. Event valence behaved as an asymmetry factor in the expected directions where it could be reliably estimated, consistent with the GAM results, but we found no evidence that event strength opens a bifurcation region in which two emotional states coexist.

Table 4
Cusp Catastrophe Models (Theoretical Specification) for Discrete Emotions

Emotion	Zeros (%)	n	R^2 linear	R^2 cusp	ΔBIC vs. linear	ΔBIC vs. logistic	α: valence	β: strength	Bifurcation set (%)
Disgust	78.9	892 / 56	.13	.53	705	728	-0.45†	-0.22†	91.7
Fear	73.0	1059 / 70	.12	.36	585	-	-0.21†	-0.42†	89.3
Sadness	67.5	1330 / 87	.20	.43	824	-	-0.49†	-0.30†	68.8
Anger	59.6	1402 / 92	.24	.24	371	505	-0.73***	-0.44***	7.6
Surprise	45.2	1422 / 95	.19	.18	151	153	0.01	-0.78***	4.3
Happiness	31.5	1444 / 97	.45	.46	-101	-146	2.26***	0.27	0.0

Note. Cobb's stochastic cusp model with event valence as the asymmetry factor (α) and event strength as the bifurcation factor (β). The state variable is the full 0–10 emotion rating, centered and scaled within person; participants who never reported the emotion were excluded. n = observations / participants. R^2 for the cusp model is Cobb's pseudo-R^2. ΔBIC = BIC of the comparison model minus BIC of the cusp model (positive values favor the cusp). Bifurcation set = percentage of observations for which the model predicts bistability. Rows are ordered by the percentage of zero ratings. † Standard errors unreliable (near-singular Hessian); significance not reported. - = logistic model did not converge or was degenerate. *p < .05. **p < .01. ***p < .001.

Figure 3 displays the position of the observations on the cusp surface for each emotion. For disgust, fear, and sadness, observations clustered on both the upper and the lower sheets within the folded region, a pattern consistent with the separation between zero ratings and active episodes rather than with transitions between two emotional states. For anger and surprise, observations lay mostly along the edge of the fold, with few cases inside the bifurcation set, and for happiness they fell entirely outside it, on the region of the surface where the response changes smoothly with event valence.

Overall, the unilevel cusp analyses converge on a consistent conclusion. Although the cusp often achieved a better BIC than the linear and logistic alternatives, this advantage was largest, and pseudo-R^2 highest, precisely for the emotions with the most zero ratings, where estimates were unstable; where estimates were reliable, the defining features of a cusp (a positive effect of strength on bifurcation and a non-trivial bifurcation set) were absent. These analyses, however, assume that all participants share the same control parameters. The next section examines whether allowing the asymmetry and bifurcation factors to vary across individuals reveals a different picture.

Cusp Models With Person-Specific Control Parameters

Table 5 reports the cusp models with person-specific control parameters. Because these models were fitted to participants with at least five records and two non-zero ratings, sample sizes and baseline estimates can differ from those in Table 4. Following the analytic plan, we relied primarily on within-person cross-validation (ΔCV); AIC, BIC, and likelihood-ratio tests are reported for completeness.

Allowing the asymmetry factor to vary across participants (M_α vs. M_0) improved out-of-sample prediction for all six emotions (ΔCV = 3.5–237.2), most clearly for happiness and least for disgust. AIC and likelihood-ratio tests agreed, whereas BIC favored the person-specific model only for happiness. Person-specific asymmetry estimates varied

considerably (*SD* = 1.2–8.2 across emotions), although the largest values likely also reflect imprecise estimation for participants with few non-zero ratings. Because the state variable was not centered within person, these differences largely reflect stable between-person differences in the level of each emotion, including the propensity to report its absence, consistent with the ICCs reported above. Participants thus differed in which emotional state they tended toward for events of similar valence and strength relative to their own typical events.

In contrast, adding person-specific bifurcation parameters ($M_{\alpha\beta}$ vs. M_{α}) markedly worsened out-of-sample prediction for all six emotions (ΔCV = -76.4 to -753.3), even though AIC and likelihood-ratio tests favored the more complex model (all *ps* < .001). This divergence illustrates the incidental-parameter problem: with relatively few records for many participants, in-sample criteria reward person-specific parameters that do not generalize to new observations from the same person. Thus, we found no evidence that participants differed in the bifurcation parameter that governs bistability. Hypothesis 3a was therefore supported: participants differed in the asymmetry of their emotional responses, mainly reflecting between-person heterogeneity in emotional level. However, hypothesis 3b was not supported: we found no evidence that participants differed in the bifurcation parameter, and thus no evidence of person-specific thresholds for abrupt emotional change.

Table 5
Cusp Models With Person-Specific Control Parameters: Tests of Nonergodicity (H3)

Emotion		**Person-specific asymmetry (M_{α} vs. M_{o})**				**Person-specific bifurcation ($M_{\alpha\beta}$ vs. M_{α})**			
	n	**ΔCV**	**ΔAIC**	**ΔBIC**	**χ^2 (df)**	**ΔCV**	**ΔAIC**	**ΔBIC**	**χ^2 (df)**
Disgust	735 / 47	3.5	114	-97	206 (46)***	-753.3	119	-92	211 (46)***
Fear	870 / 56	89.0	252	-10	362 (55)***	-356.1	189	-73	299 (55)***
Sadness	1097 / 68	93.3	234	-101	368 (67)***	-480.1	102	-233	236 (67)***
Anger	1263 / 81	70.0	274	-138	434 (80)***	-676.8	184	-228	344 (80)***
Surprise	1394 / 91	51.8	209	-262	389 (90)***	-532.3	112	-359	292 (90)***
Happiness	1383 / 89	237.2	554	94	730 (88)***	-76.4	292	-168	468 (88)***

Note. Cobb's cusp model with event valence (asymmetry, α) and event strength (bifurcation, β) both centered and scaled within person, and the 0–10 emotion rating scaled by its overall SD. M_{o} = common parameters for all participants; M_{α} = adds a person-specific intercept in α; $M_{\alpha\beta}$ = additionally adds a person-specific intercept in β. n = observations / participants. ΔCV = gain in out-of-sample log-likelihood from 5-fold within-person cross-validation. ΔAIC and ΔBIC = criterion of the simpler model minus that of the more complex model. Rows are ordered by the percentage of zero ratings, as in Table 4. *p < .05. **p < .01. ***p < .001.

Discussion

This study tested whether discrete emotions respond to the valence and strength of everyday events proportionally, through thresholds relative to a personal frame of reference, or discontinuously, as the BMAS proposes, and whether people differ in the parameters that govern these responses. Workplaces offered an ecologically valid context for this test, because work events are frequent and goal-relevant (e.g., Navarro et al., 2026), yet research on them has typically assumed that emotional intensity scales proportionally with event characteristics.

Overall, the results favor the threshold account over both the proportional and the discontinuous accounts. Hypothesis 1 was partially supported: nonlinear relations appeared in 7 of the 12 emotion-by-part comparisons before adjustment and in 4 after Holm adjustment, and were more robust for the intensity of emotions than for their occurrence. Where nonlinearity appeared, emotions changed near or beyond each person's typical values, and the expected valence asymmetry was clear for anger and happiness, although it did not extend to all negative emotions. Hypothesis 2 was not supported. Cusp models did not reveal bistability, and event strength did not act as a bifurcation factor; where it could be reliably estimated, its coefficient was negative. The cusp's better fit than linear models was concentrated in emotions with many zero ratings, which suggests that it captured the boundary between the absence and the presence of an emotion rather than abrupt switches between two stable states in the emotional intensity. Finally, Hypothesis 3a was supported and Hypothesis 3b was not: participants differed in the asymmetry parameter, largely reflecting differences in emotional level, but we found no evidence that they differed in the bifurcation parameter.

Whether: The Onset of Discrete Emotions

Whether an emotion arose depended on event appraisals in emotion-specific ways, but the evidence for thresholds in occurrence was modest. For anger, disgust, and happiness, the probability of occurrence was a nonlinear function of event valence, although only for disgust did this survive adjustment for multiple comparisons, and gains over linear models were small. The shape of these functions is nonetheless informative. The probability of happiness rose steeply around the person's typical valence, from about .20 for clearly negative events to near certainty for events only somewhat better than usual, whereas disgust became likely only for events well below the person's usual valence. Both patterns are consistent with emotions being elicited by departures from a personal frame of reference (Frijda, 1988), and the contrast between a low threshold for happiness and a high one for disgust is consistent with the positivity offset proposed by the evaluative space model (Cacioppo et al., 1997). Surprise was the only emotion whose occurrence was unrelated to valence and depended on event strength instead, in line with its role in signaling novelty and disruption (Meyer et al., 1997), although this association partly reflects the inclusion of novelty in the strength composite.

These results also clarify why the cusp model fitted best for the emotions with the most zero ratings. What the Cobb density captured in these emotions was the boundary between the absence and the presence of an emotion, not bistability in its intensity. This distributional pattern does not by itself show that emotions emerge once events cross a threshold, but the occurrence models help locate where such a threshold, if present, lies. The BMAS proposes that discrete emotions emerge when the perceived intensity of an event exceeds a critical value (Li et al., 2010), and the threshold account makes the same prediction for occurrence. In our data, however, where occurrence was nonlinear, the nonlinearity lay in event valence, whereas event strength was linearly related to the occurrence of anger, sadness, and fear. If emergence thresholds exist, they may therefore be governed by whether an event is better or worse than usual rather than by how strong it is. Finally, most of the variance explained in occurrence (39%–62%) came from the random intercept, indicating that whether an emotion arises depends largely on each person's general propensity to experience it.

How Much: Nonlinear Intensity Without Bistability

Once an emotion was present, its intensity followed emotion-specific patterns that were nonlinear for some emotions but continuous, with no evidence of bistable jumps. For anger and happiness, nonlinearity in intensity was driven by valence and was asymmetric: anger intensified only as events became worse than usual and was unaffected by better-than-usual events, whereas happiness changed little across worse-than-usual events and rose steeply once events were better than usual. This asymmetry is consistent with the evaluative space model (Cacioppo et al., 1997), in which

positive and negative responses follow distinct activation functions rather than lying at opposite ends of a single continuum, although our single bipolar measure of valence cannot test the separability of the two systems directly.

For disgust and fear, event strength rather than valence produced a threshold-like pattern: intensity changed little for events weaker than usual and increased once events exceeded the person's typical strength. This pattern matches the threshold logic of appraisal theories, in which intensity reflects the excess of emotion potential over a threshold (Ortony et al., 1988), and partly supports EST's claim that only sufficiently strong events affect individual responses (Morgeson et al., 2015), although only for particular emotions. These curves should nonetheless be interpreted with caution, because they rest on fewer participants, their confidence bands were wide, and the effect for fear did not survive adjustment for multiple comparisons. In contrast, the intensity of sadness and surprise was linearly related to event appraisals, indicating that nonlinearity is not a general property of emotional responses.

The cusp models provided no evidence of bistability in emotional intensity. For the two emotions with reliable estimates, anger and surprise, event strength had a negative coefficient on the bifurcation factor, and few observations fell within the bifurcation set (7.6% and 4.3%). Stronger events were thus associated with less, not more, bistability. This result admits several explanations. It may partly reflect the distribution of the data: weaker events were more often associated with the absence of an emotion, so that the mixture of zero and non-zero ratings is greater at low strength. It may also reflect a restricted range of events, because the DRM asked participants to report an important event of the day. A substantive, post hoc interpretation is offered by situational strength theory (Meyer et al., 2010): strong events may provide clearer cues that channel people toward a more uniform response, whereas weak or ambiguous events leave more room for divergent responses. Our data cannot distinguish among these explanations, but none of them supports the claim that strong events destabilize emotional responses.

For Whom: Different Levels, No Evidence of Different Dynamics

The divergence between within- and between-person correlations shows that relations observed across people cannot be assumed to describe how each person responds (Molenaar & Campbell, 2009). The association between anger and event valence, for example, was considerably stronger within persons ($r = -.41$) than between persons ($r = -.23$). Whether the underlying processes also differ across people, however, is a separate question, which the theoretical framework addressed at two levels.

The first level concerns each person's frame of reference. Because event appraisals were centered within persons, the GAMs located thresholds relative to each person's typical events, and the functions changed near or beyond these values. This is consistent with people evaluating events against their own reference point (Frijda, 1988), although the GAMs estimated common rather than person-specific curves and thus cannot show that everyone follows the same function. The second level concerns the parameters of the process itself, tested in H3. Allowing person-specific asymmetry parameters (M_{α}) improved out-of-sample prediction for all six emotions ($\Delta CV = 3.5$ to 237.2). Because emotion ratings were not centered within persons in these models, this mainly indicates that people differ in their typical emotional levels, which may reflect both stable emotional tendencies and the events each person typically encounters (e.g., job context). In contrast, person-specific bifurcation parameters ($M_{\alpha\beta}$) markedly impaired out-of-sample prediction ($\Delta CV = -76.4$ to -753.3), even though within-sample indices favored the more complex model, as expected from the incidental-parameter problem (Neyman & Scott, 1948).

These results are consistent with a weak form of nonergodicity: people differed in their typical emotional levels, but we found no evidence that they differed in their susceptibility to abrupt emotional change. This does not mean that such differences are absent. With relatively few reports for many participants, many of them zero, our data may lack the information needed to estimate person-specific bifurcation parameters reliably; studies with denser sampling and

physiological measures have found considerable individual variation in recurring affective patterns (Hoemann et al., 2020). Moreover, person-specific effects were limited to intercepts in the control parameters, so we did not test whether people differ in their sensitivity to event valence and strength, and cross-validation folds were assigned at random, so they did not test whether individual patterns remain stable over time.

Theoretical and Practical Implications

We can point out three main implications for emotion theory. First, they support the threshold account of appraisal theories over the proportional assumption that underlies most empirical tests. For several emotions, intensity changed little until events departed from what was typical for the person and increased beyond that point, as expected if intensity reflects the excess of emotion potential over a threshold (Ortony et al., 1988) and if thresholds are set by a personal frame of reference (Frijda, 1988). Treating occurrence and intensity separately was essential to see this, because the two parts of the response followed different functional forms; models that conflate them may misrepresent how appraisals translate into emotion. Second, the form of the relation was emotion-specific. The asymmetric responses of anger and happiness to worse- and better-than-usual events are consistent with distinct activation functions for negative and positive affect (Cacioppo et al., 1997), whereas for disgust and fear the threshold lay in event strength, and sadness and surprise responded linearly. A general account of event-emotion relations should therefore specify which appraisal dimension governs each emotion rather than assume a common form. Third, the findings qualify dynamical accounts of emotion. They are compatible with the BMAS claim that discrete emotions emerge beyond a critical level of event intensity (Li et al., 2010), but not with its stronger claim of bistability: stronger events did not open a region in which two emotional states coexist, and where emergence thresholds appeared, they were located in valence rather than in event strength. For research on workplace affect, these results suggest that tests of AET and EST should examine not only which event features elicit emotions, but also the functional form of these effects.

Two methodological implications also follow. Bounded emotion ratings with many zeros can mimic the bimodality of a cusp catastrophe, so that cusp models should be compared with logistic alternatives, evaluated by the share of observations within the bifurcation set, and complemented by two-part models that separate absence from intensity. In addition, with short series per person, within-sample criteria favor person-specific parameters that do not generalize, which makes within-person cross-validation advisable when testing nonergodicity.

In practical terms, if emotional responses depend on thresholds relative to each person's typical experience, small improvements in daily events that do not move them beyond that point may go unnoticed. The asymmetry between anger and happiness further suggests that reducing negative events and promoting positive ones may need to be addressed as distinct goals.

Limitations and Future Research

Several limitations should be considered when assessing these results. First, the study was based on non-probabilistic (snowball) sampling of employees from various sectors. Although this professional heterogeneity enhances the ecological variability of everyday work events, the sample is not representative of any specific working population, voluntary participation without compensation may have favored participants with greater interest in reflecting on their emotions, and the results may not generalize to other cultural and linguistic contexts. Second, the Day Reconstruction Method reduces recall biases compared with global surveys, but recalling events the following day and selecting a single important event per day restrict the range of observed events and may dampen momentary peaks. Because participants reported salient events, weak and routine events are likely underrepresented, which may have limited our ability to detect responses across the full range of event strength. Future studies could use experience sampling with multiple daily reports, although such protocols are demanding for employee samples. Third, the hypotheses were not

preregistered, H1 involved 12 comparisons, and the expectations about the location of thresholds and valence asymmetries were examined in an exploratory way; these findings should therefore be tested in confirmatory, preregistered studies. Fourth, Cobb's stochastic model is static and cannot capture hysteresis or transitions between states over time. Establishing whether emergence thresholds are steep or truly discontinuous would require continuous measures of emotional activation, less affected by zero ratings, and dynamic models of how emotions unfold across successive events. Finally, incorporating additional appraisal dimensions, such as agency, legitimacy, and controllability, would help explain not only how intense an emotion becomes, but which discrete emotion a given work event elicits.

Conclusion

Rather than following proportional or catastrophic dynamics, emotional responses to everyday work events were best described by emotion-specific nonlinear thresholds. Whether an emotion arose and how intense it became followed different functional forms, and the clearest nonlinearities appeared in intensity, where several emotions changed little until events departed from what was typical for the person and increased beyond that point. These thresholds were emotion-specific and, for anger and happiness, asymmetric with respect to valence, whereas cusp models provided no evidence that stronger events make emotions bistable. People differed in their typical emotional levels, but we found no evidence that they differed in their susceptibility to abrupt change. By testing proportional, threshold, and discontinuous accounts against each other with naturally occurring events, the study supports appraisal-based thresholds anchored in a personal frame of reference as a more accurate description of how events translate into emotion than the proportional assumption that underlies most empirical tests.

Declarations

Author Contribution

All authors contributed to the study conception and design. Material preparation, data collection, and statistical analyses were performed by JN and VT. The first draft of the manuscript was written by JN and VT, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data Availability

Data and Code Availability: The datasets and analysis scripts generated and analyzed during the current study are available in the Open Science Framework (OSF) repository: https://osf.io/sudc3/overview?view_only=074554031a674ee5beb9afc4591b5819

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Figures

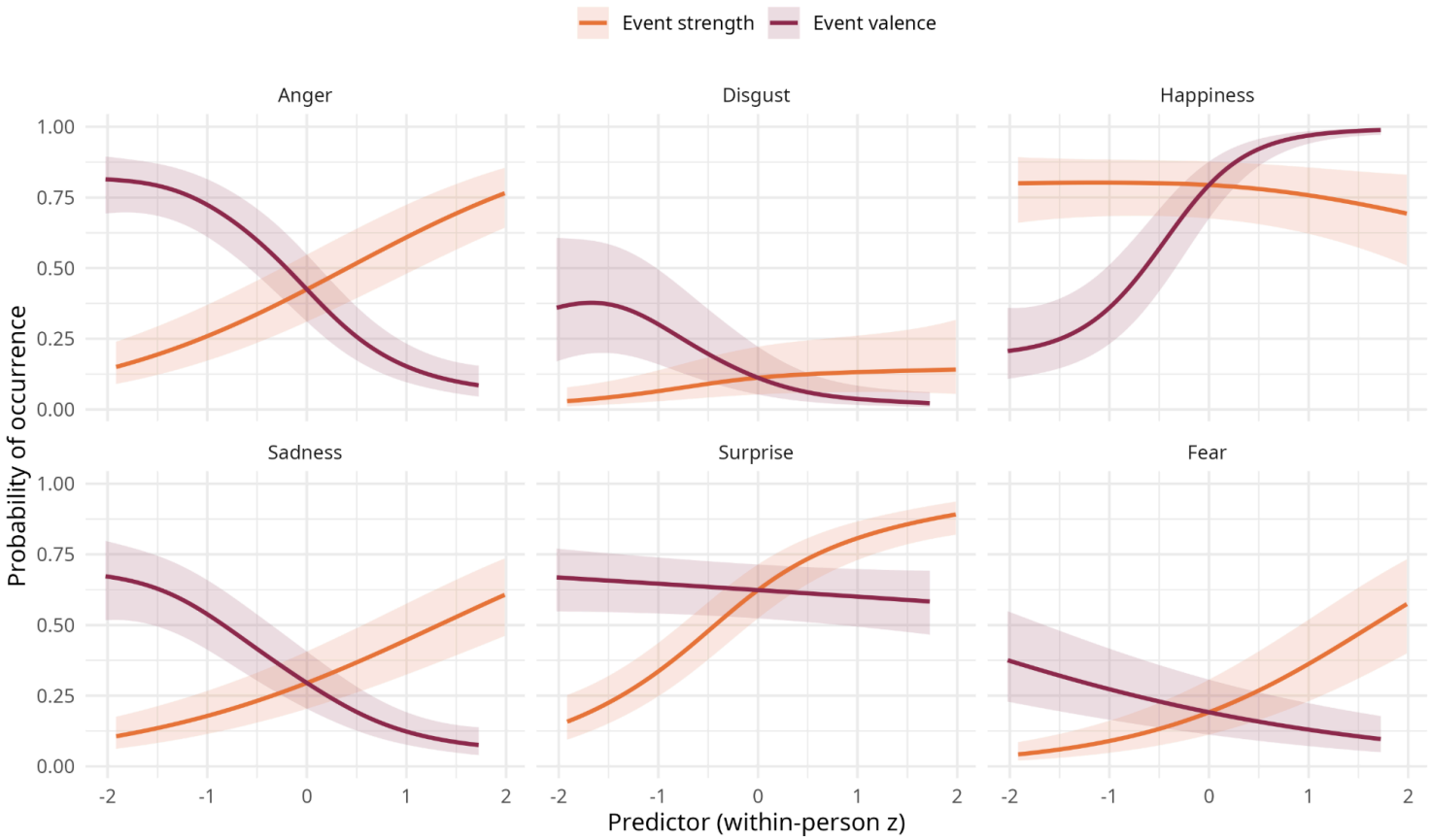


Figure 1

Estimated partial effects of event valence and event strength on the probability of occurrence of each discrete emotion (binomial GAMs). Predictors are centered and scaled within person, so 0 corresponds to the participant's average event. Each curve is computed with the other predictor held at the participant's mean and excludes the random intercept (i.e., for a typical participant). Shaded areas are 95% confidence intervals. Because curves are shown on the probability scale, a linear effect on the logit scale also appears S-shaped.

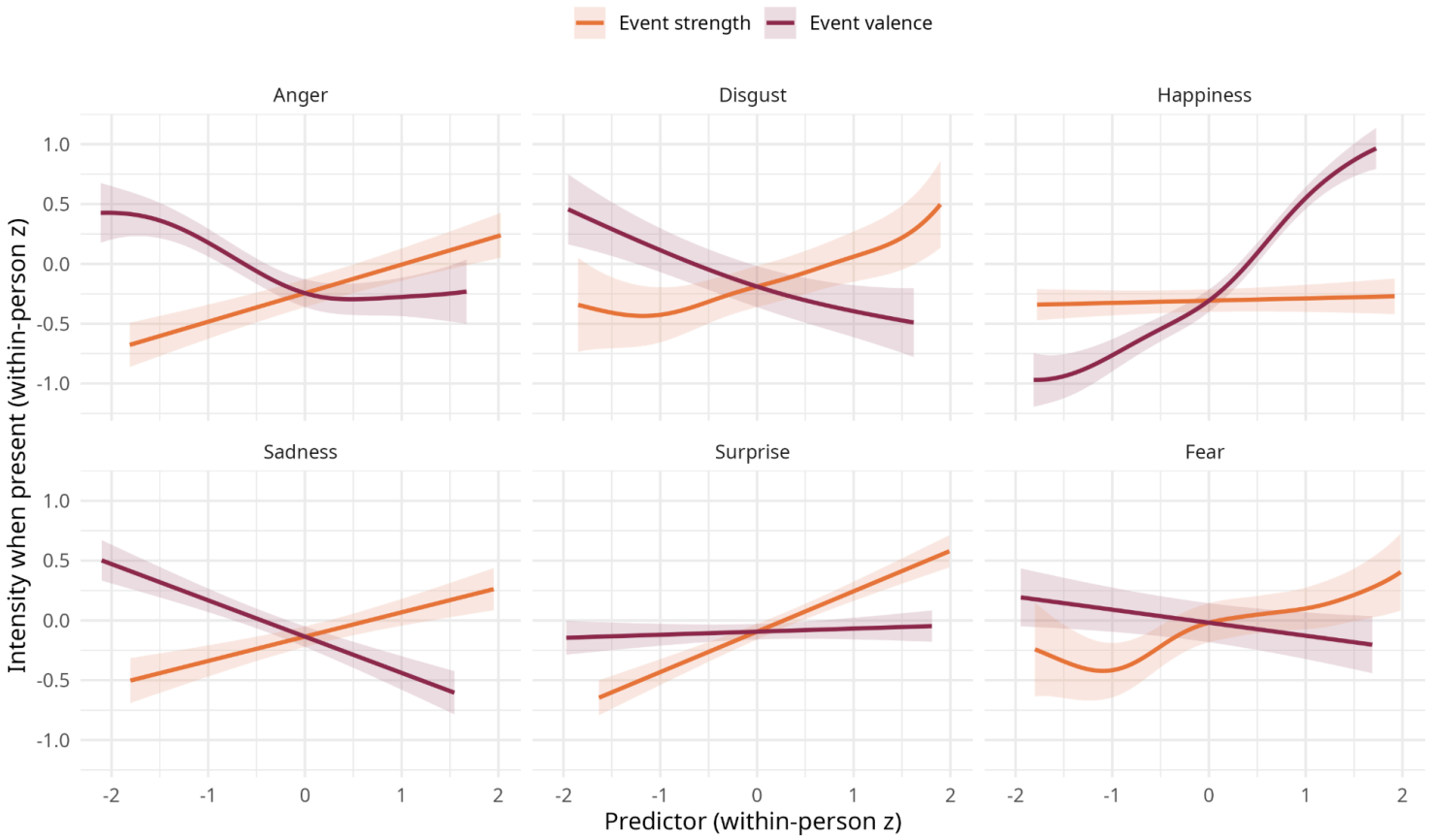


Figure 2

Estimated partial effects of event valence and event strength on the intensity of each discrete emotion when present (Gaussian GAMs). Intensity and predictors are centered and scaled within person. Each curve is computed with the other predictor held at the participant's mean. Shaded areas are 95% confidence intervals.

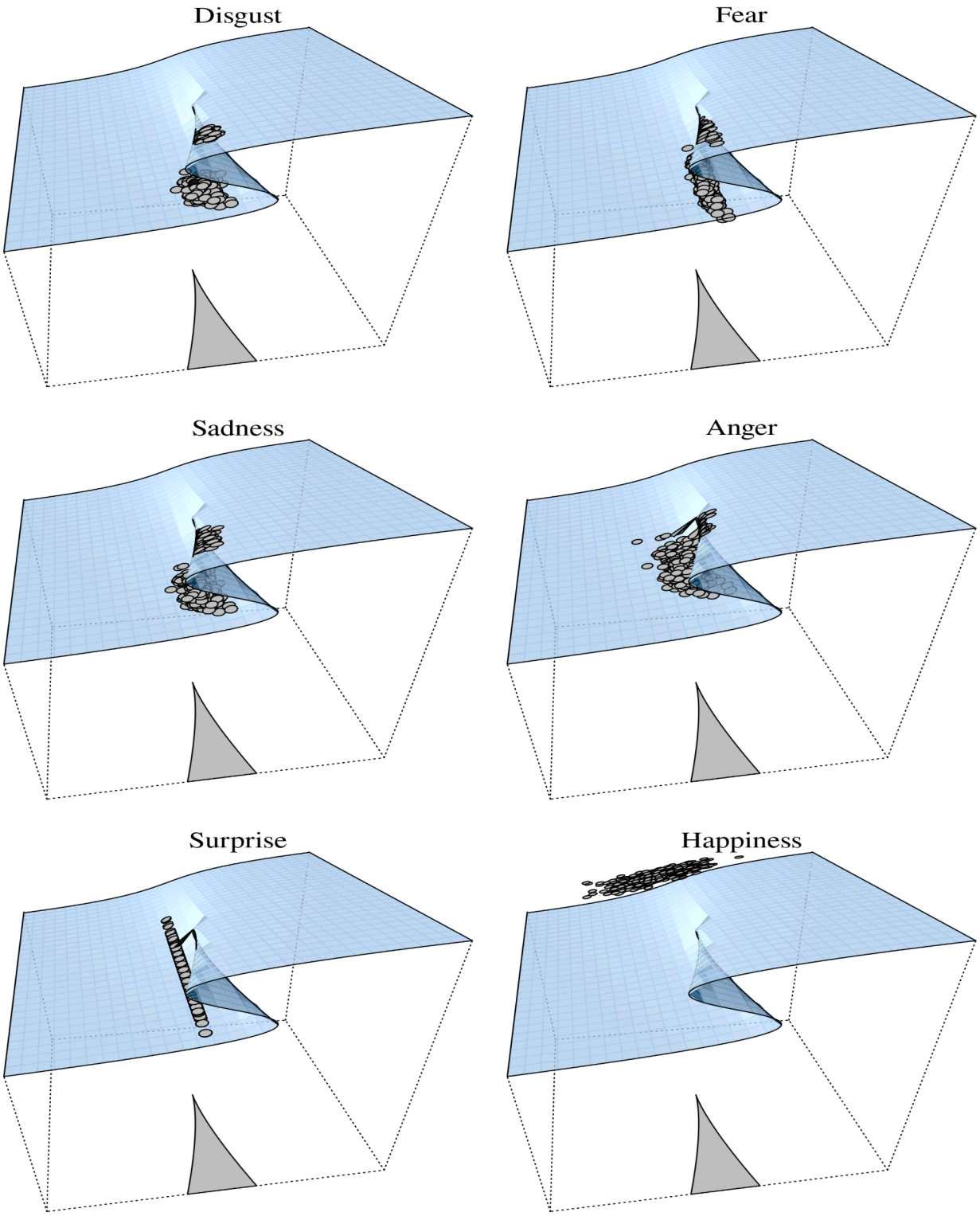


Figure 3

Observations on the Estimated Cusp Catastrophe Surface for Each Discrete Emotion.