AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Applied Psychology

ISSN: 0021-9010

2021, Vol. 106, No. 1, 48–61
https://doi.org/10.1037/apl0000855

Anxiety Responses to the Unfolding COVID-19 Crisis: Patterns of Change in the Experience of Prolonged Exposure to Stressors

Sherry (Qiang) Fu, Lindsey M. Greco, Anna C. Lennard, and Nikolaos Dimotakis
Department of Management, Oklahoma State University

An immense amount of work has investigated how adverse situations affect anxiety using chronic (i.e., average) or episodic conceptualizations. However, less attention has been paid to circumstances that unfold continuously over time, inhibiting theoretical testing and leading to possible erroneous conclusions about how stressors are dynamically appraised across time. Because stressor novelty, predictability, and patterns are central components of appraisal theories, we use the COVID-19 crisis as a context to illustrate how variation in the phenomenon's patterns of change (specifically, total cases [average level] but also the rate of linear [velocity] and nonlinear growth [acceleration] in cases) influence anxiety. We also show the implications of anxiety for next-day functioning at work. These effects are tested in data drawn from a sample of employed adults in a daily diary study conducted in four overlapping waves. The data span the emergence, exponential rise, and initial tapering of the virus in the United States (February 10, 2020 to April 28, 2020). Our results show that although the impact of level of COVID-19 cases on anxiety decreases over time, the effect of change in cases (velocity and acceleration) increases over time. Anxiety is then associated with next-day work functioning (engagement, performance, and emotional exhaustion).

Keywords: transactional model of stress, COVID-19, anxiety, experience sampling, stressors

Supplemental materials: https://doi.org/10.1037/apl0000855.supp

> March 13th, 2020: We're waiting until an announcement is made about coronavirus. Nobody is really working, just mass panicking.

> April 24th, 2020: I am concerned that with the economy opening back up so soon that we may see a surge in COVID-19 cases . . . that would only set us back in our fight. . . . You would see an increase in numbers if it gets out of hand like it did in the beginning stages. Numbers are just starting to go down.

A substantial amount of research has investigated how exposure to stressors influences affect and, ultimately, attitudes and behaviors (Brief & Weiss, 2002; Lazarus, 1991a; Lazarus & Folkman, 1984; Weiss & Cropanzano, 1996). Although many negative affective reactions to stressors are possible, exposure to stressors characterized by uncertainty and existential threat lead specifically to anxiety (Lazarus, 1991a). Anxiety is a pernicious state, as it is persistent, irresolvable, and consumes attentional and cognitive resources, thus inhibiting individuals' functioning (Kagan, 1972). It is unique in that it is anticipatory (future-looking), and has no action tendencies except for avoidance or escape, as the circumstances it arises from are ambiguous, ongoing, and have no clear way out (Lazarus, 1991a). The COVID-19 pandemic is a grim but illustrative anxiety-inducing stressor; an uncertain and ongoing threat that cannot be resolved via avoidance or escape. That is, whereas individual coping strategies are possible (e.g., social distancing), the spread of the virus at a state level is still beyond any given individual's control, which can inhibit coping and self-regulatory processing (Cheng & McCarthy, 2018).

However, there are differing perspectives as to what particular features of an ongoing stressor might give rise to anxiety, and how these effects unfold over time. Situations can evolve temporally in complex ways; for example, a situation can be grim but improving, or mild but deteriorating. In addition, arguments have been made both for individuals feeling less anxious with continued exposure to a stressor (Diener & Diener, 1996; Selye, 1976; Suh et al., 1996), as well as the opposite (Hobfoll, 1989; McEwen, 1998; also see Ritter et al., 2016). A resolution to these conflicting arguments can emerge from a more nuanced perspective of how stressors are experienced. To date, theoretical insights come mostly from either *chronic* or *episodic* views of the focal stressor (Sonnentag & Frese, 2012). The former discusses the effects of stable features of one's life (e.g., life with chronic pain; employment in a high risk occupation; Craig & Jacobsen, 1984; Eckenrode, 1984; Kanner et al., 1981) while the latter relates to how particular stressful events might lead to anxiety (e.g., role overload on a given day, a negative interaction with a supervisor; Anshel, 2000; Barling, 1990; Restubog et al., 2011). Although providing invaluable insights, the underlying conceptualizations of stressors are, to some extent, deficient.

This article was published Online First December 3, 2020.
Sherry (Qiang) Fu https://orcid.org/0000-0001-5975-2184
We thank our department chair, James Pappas, for his invaluable support of this research.
Correspondence concerning this article should be addressed to Sherry (Qiang) Fu, Department of Management, Oklahoma State University, 449 Business Building, Stillwater, OK 74078, United States. Email: sherry.fu@okstate.edu or sherryqfu@gmail.com

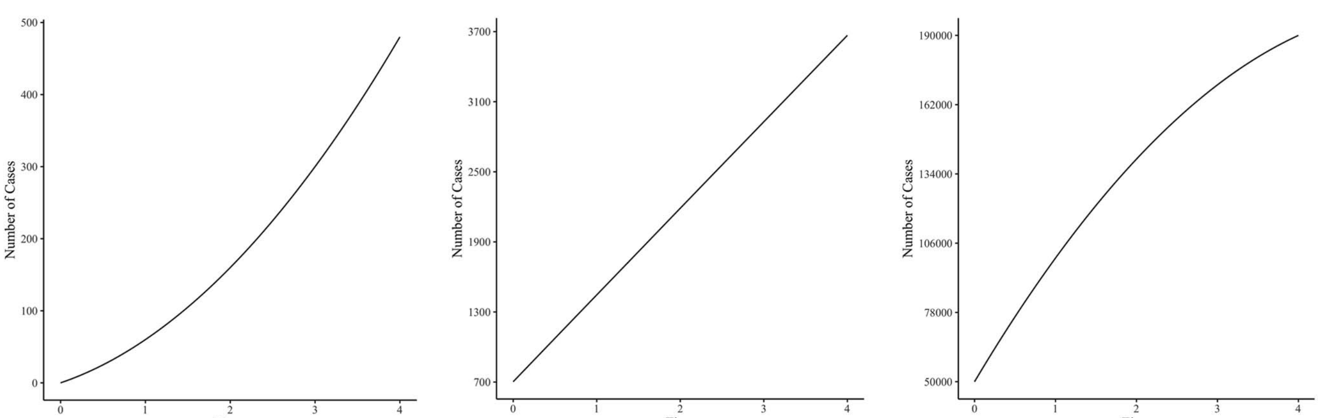
Chronic views fail to consider that situations can vary over time. For example, one person with a chronic heavy workload may experience days of higher or lower workload whereas another's experience may be more stable. Episodic conceptualizations recognize such variation in events, however, they seldom take into account that such events do not occur in a vacuum. Rather, experienced events are seen within the lens of past experience, something referred to as *past as prologue* (Rosen et al., 2020). Because events can persist, deteriorate, or improve over time, it is necessary to assess trajectories—patterns of change over time. For example, a person's experiences with their leader in the workplace might involve acts of abuse represented by a few severe episodes that wane in frequency and severity over time, while another person's experience might be represented by a steady level of infrequent episodes. These two situations represent different temporal contexts and, as a result, they should affect individuals differently. However, neither chronic nor episodic conceptualizations would capture and explain them adequately.

In the COVID-19 pandemic, employees are continuously experiencing a severe stressor, but, importantly, are doing so in different patterns that themselves vary over time. These patterns of change can be conceptualized as both velocity (i.e., rate of change, positive or negative), and acceleration (i.e., change in velocity—whether the rate of change is increasing [positive] or decreasing [negative]; Carver & Scheier, 1990). For example, deteriorating health, marked by increasing symptoms of illness (positive velocity), may be anxiety-inducing on its own, yet whether this velocity is stable (symptoms increasing at a constant rate) or changing (increase getting faster or slower) can lead to distinct affective reactions (see Figure 1 for an illustration and expanded explanation). The same is true for the COVID-19 crisis; the news is full of information about different patterns of change quantified by metrics including the total number of confirmed cases, the daily increase in cases, and the degree of exponential growth (i.e., growth estimates and trajectory dashboards; calls to "flatten the curve"). These discrete metrics point to distinct ways in which things are getting better or worse—an increase of thousands of cases may portend dire outcomes by signifying record or exponential growth on a given day, whereas on a later day the same increase may be positive development if it signifies a flatter curve.

The effect of COVID-19-related stress on levels of general state anxiety over time should thus be conceptualized as a holistic pattern of continuing experience, not just chronic (i.e., average) or episodic effects. Grasping the various patterns of change across anxiety-inducing events can help clarify effects of the pandemic on workplace functioning and also help illuminate the potential effect of lesser, but more common, stressors that are experienced in a similar way. Thus, this can offer important contributions to our understanding of responses to stressors that emerge, fluctuate, or vary over time (Ganster & Rosen, 2013; McGrath & Beehr, 1990). Stressor characteristics such as predictability or novelty are a central component of theories focusing on stressor responses (Lazarus, 1991a; Lazarus & Folkman, 1984). We specifically rely on such a core perspective, the transactional model of stress (Lazarus & Folkman, 1984) to discuss how various facets of the COVID-19 crisis relate to general state anxiety over time. Importantly, we draw attention to integral but infrequently examined parts of the model that address the dynamism of the stressor-strain process (Lazarus, 1991a). We then integrate these with ideas of stressor change over time derived from cybernetic (Edwards, 1992) and cognitive and affective processing (Ariely & Carmon, 2000; Watson, 2000) views. These frameworks suggest that change (both velocity and acceleration) have meaningful consequences for state anxiety.

Figure 1

Exemplar Trajectories Considering Average Cases, Velocity, and Acceleration



Note. These exemplar trajectories show various combinations of average case levels, slopes, and curves. From left to right, they illustrate the following: (a) a trajectory in which the confirmed cases range from 0 to 500 (low average cases), increasing at Day 1 (positive velocity), and this increase itself grows (positive acceleration); (b) a situation in which the number of cases ranges from 700 to 3,700 (medium average cases), and the trajectory has a positive linear change at baseline (positive velocity) but increases at a relatively constant rate over time (no acceleration); (c) a situation in which the number of cases ranges from 50,000 to 190,000 (high average cases), and the trajectory is one in which the linear change at baseline is positive (positive velocity), but this increase (change) decreases over time (negative acceleration). In other words, these exemplars represent relatively low, medium, and high positive velocity coupled with positive, null, and negative acceleration, and low, medium, and high average cases, respectively.

Anxiety in Response to Stressor Exposure—A Transactional Model View

The transactional model posits that stress responses emerge from appraisal processes that begin when individuals experience a stressor (Lazarus & Folkman, 1984). During primary appraisal, perceptions of elements of the focal stressor are used to determine the degree of threat or harm that this stressor represents; during secondary appraisal, individuals consider if and how they can resolve the underlying stressor (Lazarus & Folkman, 1984; Lyon, 2000). Stress responses thus emerge only from situations appraised as harmful and difficult to resolve; the particular response depends on the appraisal (with anxiety, as noted, being a core response to stressors characterized by existential threat and uncertainty). In this work, we focus on primary appraisal, as resolution of the COVID-19 crisis is outside any given individual's control.

Importantly, the appraisal process is ongoing, and functioning requires people to account for that, as "encounters with the environment are continually changing" (Lazarus, 1991a, p. 134). This requires the appraisal processes to follow suit. Moreover, the stressor features that are visible and important vary over time (Lazarus, 1991a). Features signifying unpredictability, novelty, change, or future implications, for example, demand more attention and are more important to appraisal (Lazarus & Folkman, 1984; Sapolsky, 1999). Integrating a holistic view of the dynamic patterns in which a stressor unfolds over time can thus help clarify its links to anxiety.

Characteristics of COVID as an Ongoing Stressor

The most straightforward characteristic of a stressor is its intensity (Bledow et al., 2011). However, in the current pandemic, there are several other stressor characteristics including not only total cases (intensity), but also dynamic features such as linear and nonlinear change—daily increases, degree of exponential growth, and so forth. Such stressor aspects have been oft discussed in other parts of the literature. For example, cybernetic views (which the transactional model is similar to; Edwards, 1992) provide insights on how it is not only the level of a disturbance or discrepancy that matters, but also its rate of change (velocity; Beck et al., 2017; Howe et al., 2013; Johnson et al., 2013). Such views emerged from work on how affect results from distance from an end state, coupled with rates of movement toward or away from that state (velocity), and increases or decreases in the latter (acceleration; Carver & Scheier, 1990, 2000).

While these propositions were introduced primarily to measure deviations between experienced and actual goal states, similar ideas have emerged in other literatures involving situational judgments. For example, these views are discussed in the gestalt view of situational perceptions (Ariely & Carmon, 2000), foundational models on emotion emergence (Watson, 2000), as well as perhaps more straightforward views in the subjective well-being literature on the effects of whether things are getting better or worse (Sapolsky, 1999). They also speak to foundational characteristics of the transactional model. Although less attention is paid to the dynamic properties of stressors, this is not an omission of the model itself: "What is important to remember is that the appraisal of a chronic persistent event is not static; threat will fluctuate over the course of an event as a function of coping and reappraisal processes and as a function of changes in the environment" (Lazarus & Folkman, 1984, p. 100). Such ideas were more formally encapsulated in discussions of how stressor unpredictability and duration affect the appraisal process (Lazarus & Folkman, 1984). Thus, it is increasingly clear that a fuller understanding of the effect of ongoing stressors on anxiety requires a more comprehensive conceptualization of stressors that go beyond simply their level and also include ways in which they are growing or speeding up over a given time frame. We therefore utilize each of these criteria to outline a model of employee anxiety reactivity to COVID-19, build theory about how that reactivity changes over time, and how anxiety relates to important next-day work outcomes.

Hypothesis Development

As previously noted, anxiety is a response to experiencing a threatening and potentially harmful stimulus that consumes attentional and cognitive resources (Kagan, 1972). Anxiety manifests when "the uncertainty about what will happen and when obviates any clear idea on the part of the person of what to do to prevent or ameliorate it" (Lazarus, 1991a, p. 235). It is also an "anticipatory emotion," deriving out of contexts with no clear resolution or escape (Lazarus, 1991b, p. 829). Whereas anxiety can manifest in many ways, in this paper we will examine general state anxiety. Such state anxiety is likely to emerge in a context like the COVID-19 pandemic, which involves a shifting, unavoidable, multifaceted threat beyond any individual's control.

We posit that, in any given time point, this crisis can be described using the (a) average level, (b) velocity, and (c) acceleration of the COVID-19 case number over the preceding days. This information is available to individuals via the constant coverage of this phenomenon, and, as with previous events, they are likely paying close attention (Althaus & Tewksbury, 2002; Boyle et al., 2004; Casero-Ripollés, 2020; Chao et al., 2020; Heath & Gay, 1997). As such, the appraisal process initiates as usual. Moreover, this process will be ongoing as individuals try to make sense of the daily changes in the crisis (Lazarus, 1991a; Lazarus & Folkman, 1984).

More COVID-19 cases within one's most relevant environment (operationalized in this article as the U.S. state of residence) will result in greater appraisals of threat.[1] Not only do more cases signify greater risk of one getting sick, but they might also portend increased disturbances for both one's personal life (i.e., family, work, and other valued outcomes) as well as macro outcomes (e.g., economic turmoil). Combined, all these factors point to higher levels of uncertainty and threat, leading to anxiety. Beyond averages, however, both velocity as well as acceleration of COVID-19 cases should also imply more unfavorable appraisals. Specifically, the facts that the cases are increasing (positive velocity), and the increases are speeding up (positive acceleration), point to a more threatening development of the undesirable outcomes mentioned above; simply put, the situation is getting worse. As anxiety is an anticipatory emotion (Lazarus, 1991b), an increase in any of these indicators of change portends greater future threats. Thus, at a

[1] We focus on the local U.S. level but acknowledge that the pandemic is a global issue. The location of the sample should not threaten the external validity of this study, as appraisal processes are universal in character.

given time period, all three descriptors of crisis pattern should be associated with anxiety (Sapolsky, 1999).

> *Hypothesis 1:* The (a) average level, (b) velocity, and (c) acceleration of the number of COVID-19 cases over the preceding days are, on average, positively related to daily anxiety.

It is important to note that appraisal is a dynamic phenomenon (Eschleman et al., 2012), meaning that these characteristics might not be equally salient at all points of the ongoing pandemic. As mentioned above, arguments have been made both for an increase in stressor impact over time, such that continued or cumulative stressor exposure will eventually overwhelm the individual (Hobfoll, 1989; McEwen, 1998), as well as for a decrease in stressor impact over time, such that individuals react less strongly to experienced stressors (Brickman & Campbell, 1971; Frederick & Loewenstein, 1999; Helson, 1948; Selye, 1956).

We posit that these two positions are less in opposition than they seem. The key is stressor salience. That is, it is only continued exposure to a salient stressor that threatens to overwhelm an individual—if a stressor is not salient anymore, the associated emotion is "made moot" (Lazarus, 1991a, p. 354). Stressors become less salient over time if their novelty fades, if they become more predictable, and as they are seen as more of an established (as opposed to emerging) environmental feature (Lazarus & Folkman, 1984; Selye, 1976; Watson, 2000).

This habituation is adaptive as it allows constant stimuli to fade into the background, leaving resources available to deal with novel circumstances or stimuli, which are most likely to require immediate attention (Frederick & Loewenstein, 1999) to protect the organism (Herman, 2013; Miller et al., 2007). In this context, average confirmed case levels represent the more static feature of the crisis. Average cases are events that have already occurred (with fewer anticipatory implications), are monotonic, and, overall, carry less salient information for the individual. Thus, their presence becomes more familiar and predictable, requiring less processing and attention (McGrath & Beehr, 1990). This allows adjusting to "the new normal" over time (Brickman & Campbell, 1971). Thus, whereas we argued in the preceding text that COVID-19 cases will be associated with anxiety in general, we expect this effect to decrease over time as average case salience weakens.

> *Hypothesis 2:* Time moderates the positive effect of the average level of COVID-19 cases on daily anxiety such that the effect of average cases decreases over time.

However, features of the stressor that indicate change are unlikely to become less salient over time. Changing conditions are something that individual monitoring systems are very sensitive to (Watson, 2000). In this context, the longer the crisis, the greater the threat to one's daily life, especially as the crisis drags on. The positive velocity and acceleration of COVID-19 cases represent, by definition, dynamic and novel circumstances that disallows adaptation (Herman, 2013; Lazarus & Folkman, 1984). Instead, this signals an increasing lack of predictability and uncertainty of the stressor, which is likely to maintain stressor salience or even loom ever larger on an individual's view of their situation (Levine & Wiener, 1989; Sapolsky, 1999). Put more simply, the "perception of events as improving or worsening" (Sapolsky, 1999, p. 459) will be an issue that does not lose salience over time. Rather, because such factors can relate to threat not only now, but also in future instances (Lindsley et al., 1995; Riskind, 1997), their salience will remain stable or increase over time (Lazarus, 1991a). In fact, continued exposure to stimuli can increase sensitization to changes in severity or modality (Herman, 2013).

In addition, persistent positive rates of change over time indicate that this crisis is not going to "blow over" (Kim et al., 2011), further enhancing the salience of the stressor. In simpler terms, whereas 1,000 COVID-19 cases may be less anxiety inducing in April compared with in March, as individuals are accustomed to average levels in the thousands, the degree to which these 1,000 cases represent increasing and exponential rates of growth is more likely to overwhelm individuals' emotional systems and capabilities to adapt (Hobfoll, 1989; Lazarus & Folkman, 1984). These arguments are also in line with allostatic load views (McEwen & Seeman, 2003), which posit that continued exposure to a salient stressor will have graver effects as time goes by; whereas level becomes less salient, rate does not, allowing for individuals' capacity to deal with the stressor to be overwhelmed. As a result, we argue that the overall effects of positive velocity and acceleration have an accumulation affect, and thus their impact will increase over time.

> *Hypothesis 3:* Time moderates the positive effect of the (a) velocity and (b) acceleration of COVID-19 cases on daily anxiety, such that their effect increases over time.

Anxiety, on its own, is a particularly unpleasant aversive state. However, what makes it even more insidious are the effects that it has on individual cognition and attention, and thus, on individual attitudes and behaviors. We examine general state anxiety's effects on engagement, performance, and emotional exhaustion at work. First, anxiety creates a state of hypervigilance (Cheng & McCarthy, 2018; Ellis, 1962), which increases individual attention to threats, as well as making such threats loom larger (Grupe & Nitschke, 2013). The hypervigilance anxiety creates leaves little room for other (especially more positive) states (Beal et al., 2005), in essence pushing them out from the individual's consciousness. Second, the aversive character of anxiety-evoking experiences, as well as the toll they take on attentional processes, can sap individual resources and interfere with recovery (Kagan, 1972; Sonnentag et al., 2017). These disengage the individual from the work context, and prohibit resource mobilization toward the same, resulting in lower levels of work engagement. This is in line with work arguing that persistent or unresolved stressor effects are negatively linked with engagement (Sonnentag et al., 2010).

These disruptions also interfere with attention intensive processes, such as task performance (Eysenck et al., 2007); the focus that performance requires is instead consumed by the hypervigilance and aversiveness associated with the anxious state (Beal et al., 2005). Anxiety can lead to avoidance behaviors (Spector & Fox, 2002) that, while not further impacting one's affect, come at the expense of performance (Johnson et al., 2010). Supporting these points are meta-analytic estimates that show a negative relationship between anxiety and job performance (Ford et al., 2011). Anxious individuals also tend to ruminate more (Thau & Mitchell, 2010) which, in addition to the above, further depletes resources, leading to increased levels of emotional exhaustion (Maslach et al., 2001). Several studies have demonstrated these detrimental effects of anxiety on emotional exhaustion (e.g., McCarthy et al., 2016; Richardsen et al., 1992).

All in all, we propose that the pattern of COVID-19 features will affect next-day functioning (i.e., engagement, job performance, and emotional exhaustion) via general state anxiety. In line with the preceding temporal effects arguments, the indirect effects of average cases on next-day functioning via anxiety will decrease over time as the relationship between number of cases and anxiety weakens. The indirect effects of velocity and acceleration in cases, however, will increase over time as the relationship between rate features and anxiety strengthens.

> *Hypothesis 4:* The indirect effects of COVID-19 case (a) average levels, (b) velocity and (c) acceleration on next-day engagement, performance and emotional exhaustion via anxiety will be moderated by time, such that the indirect effects of average levels will weaken, but the indirect effects of velocity and acceleration will strengthen over time.

Method

Sample and Procedure

Participants came from 35 states and the District of Columbia, representing over 90% of the U.S. population and were recruited using the Qualtrics panel service; such panels have been recently validated as a data collection method (e.g., Eberly et al., 2017). Participants were employed (30+ hr/week) in a wide range of industries and jobs (see Appendix A). Data were collected in an experience sampling methodology (ESM) study (Oklahoma State University's Institutional Review Board approved; Project: BU-19–82; Title: A study on dynamic task motivation and engagement) composed of four partially overlapping waves (which we term a *shingled ESM*). Demographics were collected at sign-up. In the daily phase, participants were sent three surveys each workday for three consecutive weeks, containing multiple daily measures of anxiety and the dependent variables. Surveys were sent at workday start (T1), middle (T2), and near the end (T3).

Across four waves, our final sample was 262 individuals providing 2,332 day-level data points. A step-by-step procedure of obtaining the final sample across waves is provided in Appendix A; sample demographics are given in Table 1. We conducted a series of one-way analyses of variance on nonfocal variables (i.e., age, sex, ethnicity, job tenure, and weekly work hours) and response times across waves to ensure that there were no differences that could distort our findings; no statistically significant pairwise differences were found across waves.

Measures

Unless otherwise noted, all our within-person variables were measured at multiple points during the day and aggregated to the day-level (see Appendix B for all survey-measured items, including anchors and referents). Variables relating to COVID-19 were derived from data provided by Johns Hopkins University (https://github.com/CSSEGISandData/COVID-19).

Time

Time was represented by the log of collection day, ranging from 1 to 79, corresponding to our study period that spanned from February 10, 2020 to April 28, 2020.

Average Levels of State Confirmed Cases

We included the average number of confirmed cases at state level of the prior week (5-day period). We log transformed this variable due to its skewed distribution.

Trajectory of State Confirmed Cases

For each study day, we ran a time series analysis to describe linear (velocity) and curvilinear (acceleration) growth over the preceding 5-day period. Estimates were then extracted to be used as IVs. See the online supplemental material for a full description of this process and example data.

Daily Anxiety

Anxiety was measured in each survey (T1, T2, and T3) and reflected current states. A five-item measure was used (Marteau & Bekker, 1992; Watson & Clark, 1994). Mean coefficient alpha across 15 days was .94 (SD = .01).

Daily Dependent Variables

Engagement reflected current engagement with work tasks and was assessed in T1 and T2 surveys (Bakker & Costa, 2014; mean α = .91, SD = .02). Work task performance reflected performance on T1 and T2 tasks and was assessed in T2 and T3 surveys (Williams & Anderson, 1991; mean α = .92, SD = .02). Emotional exhaustion reflected current states and was assessed in T1 and T3 surveys (Wharton, 1993; mean α = .91, SD = .02).

Control Variables

Due to the potential of other attention-grabbing variables to produce anxiety (Becker, 2005), we controlled for whether a particular day was a record high in either confirmed cases or deaths. Results were unchanged with or without these control variables.

Analytic Strategy

Given the nested nature of the data (days within people), we tested our hypotheses using multilevel path analysis in Mplus 8 (Muthén & Muthén, 1998-2017) with maximum likelihood estimation. Though the exogenous variables are all at Level 1, we used raw scores instead of the more common group-centering as average level, velocity, and acceleration of COVID-19 cases are all objective and meaningful indicators, instead of reflecting a person's reported mean levels. Time (day) was centered at the date that the first state (California) enacted stay-at-home orders (on March 19, 2020, near the midpoint of data collection). This eases interpretation of main effects and allows sufficient space to model moderation (±25 days, starting when the United States first reached 100 cases and ending with a point equidistantly past the middle—these dates closely align to typical ±1 standard deviation

Table 1
Descriptive Statistics and Intercorrelations Among Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Level 1																									
1. Record day (cases)	0.16	0.34	—	.18	.18	.10	.27	−.02	−.03	−.09	−.03	.05	−.05	.01	.04										
2. Record day (deaths) day	0.09	0.27	.40	—	.23	.32	.09	−.05	.22	.09	.03	.04	−.03	−.01	.00										
3. Time	3.36	0.42	.34	.48	—	.78	.17	−.03	.74	.24	.00	.01	.00	−.07	.02										
4. Average level	4.03	0.86	.17	.61	.80	—	.14	−.14	.90	.35	.08	.02	.03	−.10	.00										
5. Velocity	0.07	0.17	.57	.30	.25	.13	—	−.62	−.08	−.68	.45	.07	−.02	.03	.03										
6. Acceleration	0.00	0.04	.23	−.25	−.06	−.29	−.28	—	−.10	.42	−.81	.00	.03	.01	.01										
7. Average Level × Time	1.93	0.67	−.01	.46	.75	.93	−.12	−.23	—	.46	.07	−.02	.06	−.10	−.02										
8. Velocity × Time	0.01	0.04	−.17	.23	.37	.55	−.66	.11	.70	—	−.53	−.05	.02	−.04	−.01										
9. Acceleration × Time	0.00	0.01	−.27	.12	−.04	.11	.18	−.90	.12	−.16	—	−.02	.01	.00	−.05										
10. Daily anxiety	1.36	0.39	.01	.06	.02	.01	.03	.01	−.01	−.02	−.05	—	−.22	−.16	.55										
11. Daily engagement	3.05	0.57	−.02	.01	.03	.06	−.05	.02	.08	.12	.01	−.25	—	.24	−.41										
12. Daily performance	4.23	0.54	.02	−.12	−.08	−.13	.03	.02	−.13	−.07	.00	−.21	.24	—	−.21										
13. Daily emotional exhaustion	1.77	0.53	.03	−.03	−.04	.01	.01	.06	.00	.01	−.11	.61	−.42	−.30	—										
Level 2																									
14. Age	44.73	9.42	−.19	−.08	−.01	.05	−.18	.04	.10	.14	−.03	.01	.17	.04	−.08	—									
15. Sex	0.24	0.43	.09	.08	.14	.09	.01	.04	.07	.04	−.08	.03	.07	.01	−.04	.14	—								
16. White	0.77	0.42	.06	−.02	.04	.05	−.01	.03	.07	.04	−.03	.08	−.02	−.07	.12	.06	−.05	—							
17. African American	0.11	0.31	.04	.01	.09	.06	.01	.07	.06	.07	−.08	−.06	.05	.11	−.10	.00	.09	−.64	—						
18. Hispanic/Latin	0.04	0.20	−.08	−.06	−.07	−.07	.06	−.08	−.09	−.14	.09	−.08	−.03	.07	−.07	−.04	−.03	−.38	−.07	—					
19. Asian	0.05	0.22	−.11	−.03	−.09	−.08	−.07	−.02	−.07	−.03	.06	.00	.04	−.06	.01	−.01	.08	−.41	−.08	−.05	—				
20. West Asian	0.00	0.06	−.05	−.04	.01	−.06	−.04	−.01	−.04	−.01	.02	.02	−.07	−.04	.00	−.04	−.03	−.11	−.02	−.01	−.01	—			
21. Other race	0.03	0.16	.05	.15	−.07	−.03	.04	−.07	−.08	−.02	.06	.00	−.02	−.02	−.05	−.09	−.09	−.30	−.06	−.03	−.04	−.01	—		
22. Job tenure	9.22	8.44	−.06	−.09	−.03	−.04	−.04	.03	−.02	−.02	.01	−.04	.09	.04	−.04	.47	−.02	−.02	.02	−.02	.04	.06	−.04	—	
23. Weekly work hours	42.25	6.26	.14	.16	.09	.10	.02	.00	.07	.06	−.01	−.11	.04	−.02	−.03	.02	.13	.02	−.02	−.03	.01	−.02	.02	.00	—

Note. $N = 2{,}332$ observations derived from 262 participants. Time was centered at the midpoint of the study (March 19, 2020) and was natural log transformed for the interaction terms. For within-individual variables, standard deviations are reported at the within-individual level. Correlations in the upper diagonal are at the within-individual level. Correlations in the lower diagonal are at the between-individual level. Between-individual correlations that are greater than .13 are statistically significant at $p < .05$; within-individual correlations that are greater than .05 are statistically significant at $p < .05$.

levels). Time was transformed via natural log as typical with long time frames. We modeled time effects as random to accommodate the moderation analyses (Snijders & Bosker, 2011). Indirect effects were tested via a 20,000 replication Monte Carlo parametric bootstrap procedure (Preacher & Selig, 2012) to create 95% bias-corrected confidence intervals (CIs).[2]

We also ran several supplementary analyses by (a) using national instead of state-level confirmed cases; (b) using a 7-day instead of 5-day timeframe for COVID-19 patterns; (c) including, as controls, relevant demographics, state-level dummy codes or characteristics such as active stay-at-home orders or economic issues and whether individuals were working from home; (d) raw time instead of the natural log of time; and (e) a three-level model that accounted for nesting within states.[3] Results are all similar in size and scope (see the online supplemental material for these as well as for analyses excluding the record day controls).

Results

In our shingled ESM design, daily responses were nested within person. Within-person variables (Level 1) included the average confirmed case level for the preceding five days in the person's state, the velocity and acceleration of change in COVID-19 cases, daily anxiety, and next-day engagement, task performance, and emotional exhaustion. Variance components analysis indicated that all endogenous variables had a notable proportion of within-person variance: 29.85% for anxiety, 29.44% for engagement, 54.94% for performance, and 28.90% for emotional exhaustion, suggesting that the use of multilevel modeling is appropriate.

We conducted a multilevel confirmatory factor analysis to assess the fit of our measurement model (Byrne, 2001). Our proposed four-factor model demonstrated a good fit to the data, $\chi^2(71) = 284.71$, $p < .01$; CFI = .99; RMSEA = .04; SRMR = .03. In addition, it performed better than alternative models in which (a) emotional exhaustion and anxiety were collapsed, (b) engagement and performance were collapsed, and (c) all items were combined (see Table 2).

Table 1 shows means, standard deviations, and correlations. Hypothesis 1, which predicted that the (a) average level, (b) velocity, and (c) acceleration of the number of COVID-19 cases over the past days are positively related to daily anxiety, was supported (see Table 3), in that all these features of the crisis were positively associated with anxiety at the study midpoint (March 19, 2020; $\gamma_{\text{average level}} = .02$, $p = .04$; $\gamma_{\text{velocity}} = .32$, $p = .04$; $\gamma_{\text{acceleration}} = 1.34$, $p = .04$).

Hypotheses 2 and 3 predicted that, over time, the effect of (a) average level of COVID-19 cases on anxiety would decrease (Hypothesis 2), but the effect of the (b) velocity and (c) acceleration of COVID-19 cases would increase (Hypothesis 3). The interaction of average cases and time was negative ($\gamma = -.07$, $p < .01$), suggesting that, over time, the effect of average levels of COVID-19 cases on anxiety did indeed decrease (slope = .06, $p < .001$ and slope = .00, $p = .77$ for early and late stages, respectively). In contrast, the interaction of time and velocity ($\gamma = .93$, $p = .05$) and acceleration ($\gamma = 4.16$, $p = .03$) were positive, suggesting that over time, the effects of velocity (slope = −.21, $p = .23$ and slope = .71, $p = .03$ for early and late stages, respectively) and acceleration (slope = −1.05, $p = .10$ and slope = 3.06, $p = .03$ for early and late stages, respectively) on anxiety increased (see Table 3). Hypotheses 2 and 3 were thus supported.

Hypothesis 4 stated that time would moderate the indirect effects (IEs) of COVID-19 (a) level (negatively), (b) velocity, and (c) acceleration (positively) on the dependent variable's via anxiety. The IEs of case levels (see Table 4) on next-day engagement, performance, and emotional exhaustion via anxiety were indeed stronger in earlier (vs. later) stages (for early vs. middle: $\Delta IE_{\text{engagement}} = -.0054$, 95% CI [–.0101, −.0022]; $\Delta IE_{\text{performance}} = -.0042$, 95% CI [–.0083, −.0015]; $\Delta IE_{\text{emotional exhaustion}} = .0100$, 95% CI [.0053, .0158]; for middle vs. late: $\Delta IE_{\text{engagement}} = -.0039$, 95% CI [–.0074, −.0016]; $\Delta IE_{\text{performance}} = -.0031$, 95% CI [–.0060, −.0011]; $\Delta IE_{\text{emotional exhaustion}} = .0073$, 95% CI [.0039, .0115].

The IEs of COVID-19 velocity on next-day engagement, performance, and emotional exhaustion via anxiety were inversely strengthened at later (vs. earlier) stages (for early vs. middle: $\Delta IE_{\text{engagement}} = .0774$, 95% CI [.0088, .1955]; $\Delta IE_{\text{performance}} = .0604$, 95% CI [.0067, .1625]; $\Delta IE_{\text{emotional exhaustion}} = -.1431$, 95% CI [–.3097, −.0078]; for middle vs. late: $\Delta IE_{\text{engagement}} = .0560$, 95% CI [.0063, .1414]; $\Delta IE_{\text{performance}} = .0438$, 95% CI [.0048, .1175]; $\Delta IE_{\text{emotional exhaustion}} = -.1037$, 95% CI [–.2239, −.0056]. Likewise, the indirect effects of COVID-19 acceleration on engagement, performance, and emotional exhaustion via anxiety were stronger at later stages (for early vs. middle: $\Delta IE_{\text{engagement}} = .3476$, 95% CI [.0622, .8467]; $\Delta IE_{\text{performance}} = .2714$, 95% CI [.0446, .6994]; $\Delta IE_{\text{emotional exhaustion}} = -.6429$, 95% CI [−1.3287, −.0873]; for middle vs. late: $\Delta IE_{\text{engagement}} = .2514$, 95% CI [.0450, .6124]; $\Delta IE_{\text{performance}} = .1963$, 95% CI [.0323, .5057]; $\Delta IE_{\text{emotional exhaustion}} = -.4649$, 95% CI [–.9608, −.0632]. Overall, IEs were significant for early and middle (but not for late) stages for average cases; they were significant for middle and late stages (but not for early) for velocity and acceleration. These results are thus supportive of our hypotheses.

Discussion

We investigated anxiety associated with the current COVID-19 pandemic, a context characterized by an uncertain and changing threat over time. Grounded in appraisal theories, we focused on the experience of the stressor as it unfolded over time. We proposed and found that, within a given time frame, the overall level of a crisis (current average COVID-19 cases) and the rate of change (velocity and acceleration of case growth) have independent effects on individual experiences of general state anxiety, which in turn relates to next-day functioning. Moreover, we showed that these effects change over time; the impact of average levels on state anxiety lessened, but the impact of both rate variables increased as the crisis continued to unfold.

[2] Full code and output appear in the Open Science Framework repository (https://osf.io/tpbu3).

[3] State accounted for a trivial percentage (i.e., less than .20%) of the variance for endogenous variables (all daily: anxiety = .20%, engagement = .09%, performance = .19%, emotional exhaustion = .11%), making it unlikely that shared state-level experiences might create analytical issues not addressed in our two-level model (see online supplemental material).

Table 2
Confirmatory Factor Analysis

Model	χ^2	*df*	CFI	RMSEA	SRMR	AIC
Four-factor model: Proposed	284.71	71	.99	.04	.03	44567.65
Three-factor model: Emotional exhaustion and anxiety collapsed	2962.56	74	.84	.13	.10	51692.41
Three-factor model: Engagement and performance collapsed	3248.33	74	.82	.13	.18	53324.08
One-factor model: All variables collapsed	10231.16	77	.42	.23	.22	69035.61

Note. CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean squared residual; AIC = Akaike information criterion.

Implications

Our findings have important implications for appraisal theories (Lazarus & Folkman, 1984) and related frameworks (Edwards, 1992). First, we show that contexts should be evaluated holistically. Ongoing stressors unfold over time in nuanced ways, all of which are important in predicting anxiety. Thus, a bad situation that is steadily worsening differs from one that is improving and different from one where the deterioration is itself accelerating. Considering differing appraisals of ongoing stressors over time adds nuance and predictive ability to the temporal aspect of the theory (Lazarus & Folkman, 1984). Integration of concepts from cybernetic views allows for more complex and interesting effects to be tested in the future.

We showed that the impact of the various aspects of the stressor change over time. The more static aspects diminish in magnitude, whereas the dynamic aspects increase. This temporal perspective may be the first step in resolving seemingly contradictory theoretical perspectives related to adaptation (i.e., the effects of ongoing stressors decreasing over time [Brickman & Campbell, 1971; Frone & McFarlin, 1989; Helson, 1948]) versus accumulation effects (i.e., ongoing stressors becoming overwhelming over time [Lazarus, 1999; McEwen & Seeman, 2003]). Whereas these views might appear to have opposite predictions, we find that they can, in fact, operate in tandem, based on how different facets of a context are evaluated over time. This work not only enhances theory, but also provides an analytical roadmap for testing the updated predictions from theoretical perspectives that integrate changes over time.

Our study also has implications for practice, both within and outside of the COVID-19 context. Our findings imply that people are likely to acclimate to anxiety over time if stressors are constant (e.g., level of crime for police officers, number of patients for medical staff), yet changes in the rate (velocity or acceleration) that indicate the situation is worsening will still have an impact. This can guide decision makers to consider the trajectory of a stressor unfolding over time, as interventions may be more effective if they focus on changing, rather than static, stressors. This also argues against allowing situations to continually deteriorate (as such deterioration would be anxiety generating). Likewise, our study can guide practitioners in allocating resources to individuals who might be personally experiencing anxiety due to ongoing stressors—people do not "get used to" contexts involving problematic rates, especially over time.

Limitations

Our study is not without limitations. First, we only used self-reported measures of anxiety and next-day functioning. Whereas no reasonable alternative exists for some of these variables (anxiety and engagement), if the behavioral variables were measured via more objective reports our concerns about common method

Table 3
Results of Multilevel Analyses Predicting Daily Anxiety, Next Day Engagement, Task Performance, and Emotional Exhaustion

	Daily anxiety			Next day engagement			Next day performance			Next day emotional exhaustion		
Variables	γ	*SE*	*t*	γ	*SE*	*t*	γ	*SE*	*t*	γ	*SE*	*t*
Intercept	1.37	.06	23.17	3.01	.08	36.73	4.23	.06	73.21	1.81	.08	23.80
Record day for confirmed	.03	.02	1.17	−.09	.05	−1.75	−.02	.05	−.37	.01	.05	.24
Record day for deaths	.04	.03	1.32	−.10	.07	−1.45	.03	.07	.41	−.01	.07	−.19
Average level	$.02^{*}$	.01	2.02	.00	.01	.05	−.01	.01	−1.50	−.00	.01	−.36
Velocity	$.32^{*}$	.15	2.11	−.04	.16	−.26	$.29^{*}$	.15	2.02	.16	.15	1.09
Acceleration	1.34^{*}	.66	2.01	−.28	.63	−.44	.77	.58	1.33	.88	.58	1.54
Time	.03	.05	.70	−.02	.04	−.52	−.01	.03	−.43	−.01	.03	−.20
Average Level × Time	$-.07^{**}$	.02	−4.43									
Velocity × Time	$.93^{*}$	.47	1.98									
Acceleration × Time	4.16^{*}	1.92	2.17									
Daily anxiety				$-.15^{**}$	.04	−3.56	$-.11^{**}$	.04	−3.05	$.27^{**}$	.04	7.29
Pseudo R^2		7.30			1.90			1.20			4.20	

Note. N = 2,332 observations derived from 262 participants. All coefficients are unstandardized. Time was centered at the midpoint of the study (March 19, 2020) and was natural log transformed.
$^{*}\ p < .05$. $^{**}\ p < .01$.

Table 4
Results of Indirect Effects at Different Stages

	Next day engagement			Next day task performance			Next day emotional exhaustion		
		95% CI			95% CI			95% CI	
Indirect effect	Estimate	Lower limit	Upper limit	Estimate	Lower limit	Upper limit	Estimate	Lower limit	Upper limit
Average level of cases									
Early stages	**−.0089**	**−.0177**	**−.0032**	**−.0070**	**−.0146**	**−.0022**	**.0165**	**.0072**	**.0278**
Middle stages	**−.0035**	**−.0086**	**−.0004**	**−.0027**	**−.0071**	**−.0003**	**.0065**	**.0005**	**.0137**
Late stages	.0004	−.0026	.0041	.0003	−.0021	.0033	−.0008	−.0067	.0049
Differences									
Early versus middle	**−.0054**	**−.0101**	**−.0022**	**−.0042**	**−.0083**	**−.0015**	**.0100**	**.0053**	**.0158**
Middle versus late	**−.0039**	**−.0074**	**−.0016**	**−.0031**	**−.0060**	**−.0011**	**.0073**	**.0039**	**.0115**
Velocity of cases									
Early stages	.0301	−.0142	.0985	.0235	−.0101	.0815	−.0556	−.1573	.0316
Middle stages	**−.0474**	**−.1162**	**−.0065**	**−.0369**	**−.0958**	**−.0049**	**.0875**	**.0068**	**.1786**
Late stages	**−.1034**	**−.2512**	**−.0155**	**−.0807**	**−.2073**	**−.0115**	**.1912**	**.0183**	**.3867**
Differences									
Early versus middle	**.0774**	**.0088**	**.1955**	**.0604**	**.0067**	**.1625**	**−.1431**	**−.3097**	**−.0078**
Middle versus late	**.0560**	**.0063**	**.1414**	**.0438**	**.0048**	**.1175**	**−.1037**	**−.2239**	**−.0056**
Acceleration of cases									
Early stages	.1527	−.0086	.4231	.1192	−.0044	.3514	−.2824	−.6712	.0387
Middle stages	**−.1949**	**−.4887**	**−.0205**	**−.1522**	**−.4031**	**−.0158**	**.3605**	**.0124**	**.7511**
Late stages	**−.4463**	**−1.0765**	**−.0718**	**−.3485**	**−.8885**	**−.0529**	**.8254**	**.0920**	**1.6584**
Differences									
Early versus middle	**.3476**	**.0622**	**.8467**	**.2714**	**.0446**	**.6994**	**−.6429**	**−1.3287**	**−.0873**
Middle versus late	**.2514**	**.0450**	**.6124**	**.1963**	**.0323**	**.5057**	**−.4649**	**−.9608**	**−.0632**

Note. $N = 2{,}332$ derived from 262 participants. Confidence intervals that do not include zero appear in boldface type. Early stage refers to date March 2, 2020, middle stage refers to date March 19, 2020, and late stage refers to date April 8, 2020.

variance would be lessened. However, we separated the variables over time and used multiple measurements for each variable (which renders them more reliable), somewhat assuaging these concerns; in addition, the results are, broadly speaking, in line with other investigations of the effects of anxiety on such measures of functioning.

Another limitation is that we did not account for some important factors that may be impacting people's daily life during this crisis; of note are home factors such as work-family conflict and family demands. Part of the unfolding nature of COVID-19 has been a record shift to working from home. While the enactment of stay-at-home orders resulted in only around 50% of our sample shifting to working from home (at the highest point), and our model was robust to controlling for such shifts, inability to control for such variables directly is a limitation. Another limitation is that the composition of our sample is not nationally representative in gender or race.

Our operationalization of COVID-19 variables also requires that individuals are, to some extent, aware of the broad shapes of this crisis. Absent this, it would be difficult to explain our results. We do, however, see this assumption as reasonable; people follow crises closely (as noted above), and knowledge of this crisis was widespread early. Further, the COVID-19 crisis persisted past the end of data collection in April, generating periods of slowing (negative velocity/deceleration) not seen prior, in addition to the growth and plateauing (null velocity/acceleration) previously observed. Whereas growth and plateauing are contexts that we were able to link to reduced anxiety, our data did not include major periods of deceleration, limiting our ability to draw conclusions about anxiety when bad situations improve, as opposed to worsen or persist. Last, although our work contributes to the transactional theory of stress, this contribution, at least for the time being, relates only to adverse situations, as we cannot automatically extend these findings to positive situations over time. This is, however, an opportunity for future work to investigate unfolding positive contexts (such as changes in compensation) over time.

Conclusion

The trajectories of unfolding crises can be characterized in a variety of ways. Using the transactional theory of stress, we illustrate the importance of looking at these holistically. We demonstrated that the impact of these various trajectory aspects can strengthen or diminish effects on work outcomes via anxiety over time. Future work can provide a contribution by integrating these insights into many investigations on the effects of persistent adverse situations.

References

Althaus, S. L., & Tewksbury, D. (2002). Agenda setting and the "new" news: Patterns of issue importance among readers of the paper and online versions of the New York Times. *Communication Research*, *29*(2), 180–207. https://doi.org/10.1177/0093650202029002004

Anshel, M. H. (2000). A conceptual model and implications for coping with stressful events in police work. *Criminal Justice and Behavior*, *27*(3), 375–400. https://doi.org/10.1177/0093854800027003006

Ariely, D., & Carmon, Z. (2000). Gestalt characteristics of experiences: The defining features of summarized events. *Journal of Behavioral Decision Making*, *13*(2), 191–201. https://doi.org/10.1002/(SICI)1099-0771(200004/06)13:2<191::AID-BDM330>3.0.CO;2-A

Bakker, A. B., & Costa, P. L. (2014). Chronic job burnout and daily functioning: A theoretical analysis. *Burnout Research*, *1*(3), 112–119. https://doi.org/10.1016/j.burn.2014.04.003

Barling, J. (1990). *Employment, stress and family functioning*. Wiley. https://doi.org/10.1002/job.4030120409

Beal, D. J., Weiss, H. M., Barros, E., & MacDermid, S. M. (2005). An episodic process model of affective influences on performance. *Journal of Applied Psychology*, *90*(6), 1054–1068. https://doi.org/10.1037/0021-9010.90.6.1054

Beck, J. W., Scholer, A. A., & Hughes, J. (2017). Divergent effects of distance versus velocity disturbances on emotional experiences during goal pursuit. *Journal of Applied Psychology*, *102*(7), 1109–1123. https://doi.org/10.1037/apl0000210

Becker, T. E. (2005). Potential problems in the statistical control of variables in organizational research: A qualitative analysis with recommendations. *Organizational Research Methods*, *8*(3), 274–289. https://doi.org/10.1177/1094428105278021

Bledow, R., Schmitt, A., Frese, M., & Kühnel, J. (2011). The affective shift model of work engagement. *Journal of Applied Psychology*, *96*(6), 1246–1257. https://doi.org/10.1037/a0024532

Boyle, M. P., Schmierbach, M., Armstrong, C. L., McLeod, D. M., Shah, D. V., & Pan, Z. (2004). Information seeking and emotional reactions to the September 11 terrorist attacks. *Journalism & Mass Communication Quarterly*, *81*(1), 155–167. https://doi.org/10.1177/107769900408100111

Brickman, P., & Campbell, D. T. (1971). Hedonic relativism and planning the good society. In M. H. Appley (Ed.), *Adaptation level theory: A symposium* (pp. 287–301). Academic Press.

Brief, A. P., & Weiss, H. M. (2002). Organizational Behavior: Affect in the Workplace. *Annual Review of Psychology*, *53*(1), 279–307. https://doi.org/10.1146/annurev.psych.53.100901.135156

Byrne, B. M. (2001). Structural equation modeling with AMOS, EQS, and LISREL: Comparative approaches to testing for the factorial validity of a measuring instrument. *International Journal of Testing*, *1*(1), 55–86. https://doi.org/10.1207/S15327574IJT0101_4

Carver, C. S., & Scheier, M. F. (1990). Origins and functions of positive and negative affect: A control-process view. *Psychological Review*, *97*(1), 19–35. https://doi.org/10.1037/0033-295X.97.1.19

Carver, C. S., & Scheier, M. F. (2000). On the structure of behavioral self-regulation. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 41–84). Academic Press. https://doi.org/10.1016/B978-012109890-2/50032-9

Casero-Ripollés, A. (2020). Impact of Covid-19 on the media system. Communicative and democratic consequences of news consumption during the outbreak. *El Profesional de la Información*, *29*(2), e290223. https://doi.org/10.3145/epi.2020.mar.23

Chao, M., Xue, D., Liu, T., Yang, H., & Hall, B. J. (2020). Media use and acute psychological outcomes during COVID-19 outbreak in China. *Journal of Anxiety Disorders*, *74*, 102248. https://doi.org/10.1016/j.janxdis.2020.102248

Cheng, B. H., & McCarthy, J. M. (2018). Understanding the dark and bright sides of anxiety: A theory of workplace anxiety. *Journal of Applied Psychology*, *103*(5), 537–560. https://doi.org/10.1037/apl0000266

Craig, E. A., & Jacobsen, K. (1984). Mutations of the heat inducible 70 kilodalton genes of yeast confer temperature sensitive growth. *Cell*, *38*(3), 841–849. https://doi.org/10.1016/0092-8674(84)90279-4

Diener, E., & Diener, C. (1996). Most people are happy. *Psychological Science*, *7*(3), 181–185. https://doi.org/10.1111/j.1467-9280.1996.tb00354.x

Eberly, M. B., Holley, E. C., Johnson, M. D., & Mitchell, T. R. (2017). It's not me, it's not you, it's us! An empirical examination of relational attributions. *Journal of Applied Psychology*, *102*(5), 711–731. https://doi.org/10.1037/apl0000187

Eckenrode, J. (1984). Impact of chronic and acute stressors on daily reports of mood. *Journal of Personality and Social Psychology*, *46*(4), 907–918. https://doi.org/10.1037/0022-3514.46.4.907

Edwards, J. R. (1992). A cybernetic theory of stress, coping, and well-being in organizations. *Academy of Management Review*, *17*(2), 238–274. https://doi.org/10.5465/amr.1992.4279536

Ellis, A. (1962). *Reason and emotion in psychotherapy*. Stuart.

Eschleman, K. J., Alarcon, G. M., Lyons, J. B., Stokes, C. K., & Schneider, T. (2012). The dynamic nature of the stress appraisal process and the infusion of affect. *Anxiety, Stress, and Coping*, *25*(3), 309–327. https://doi.org/10.1080/10615806.2011.601299

Eysenck, M. W., Derakshan, N., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: Attentional control theory. *Emotion*, *7*(2), 336–353. https://doi.org/10.1037/1528-3542.7.2.336

Ford, M. T., Cerasoli, C. P., Higgins, J. A., & Decesare, A. L. (2011). Relationships between psychological, physical, and behavioural health and work performance: A review and meta-analysis. *Work and Stress*, *25*(3), 185–204. https://doi.org/10.1080/02678373.2011.609035

Frederick, S., & Loewenstein, G. (1999). Hedonic adaptation. In D. Kahneman, E. Diener, & N. Schwarz (Eds.), *Well-being: The foundations of hedonic psychology* (pp. 302–329). Russell Sage Foundation.

Frone, M. R., & McFarlin, D. B. (1989). Chronic occupational stressors, self-focused attention, and well-being: Testing a cybernetic model of stress. *Journal of Applied Psychology*, *74*(6), 876–883. https://doi.org/10.1037/0021-9010.74.6.876

Ganster, D. C., & Rosen, C. C. (2013). Work stress and employee health:A multidisciplinary review. *Journal of Management*, *39*(5), 1085–1122. https://doi.org/10.1177/0149206313475815

Grupe, D. W., & Nitschke, J. B. (2013). Uncertainty and anticipation in anxiety: An integrated neurobiological and psychological perspective. *Nature Reviews Neuroscience*, *14*(7), 488–501. https://doi.org/10.1038/nrn3524

Heath, R. L., & Gay, C. D. (1997). Risk communication: Involvement, uncertainty, and control's effect on information scanning and monitoring by expert stakeholders. *Management Communication Quarterly*, *10*(3), 342–372. https://doi.org/10.1177/0893318997010003004

Helson, H. (1948). Adaptation-level as a basis for a quantitative theory of frames of reference. *Psychological Review*, *55*(6), 297–313. https://doi.org/10.1037/h0056721

Herman, J. (2013). Neural control of chronic stress adaptation. *Frontiers in Behavioral Neuroscience*. Advance online publication. https://doi.org/10.3389/fnbeh.2013.00061

Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist*, *44*(3), 513–524. https://doi.org/10.1037/0003-066X.44.3.513

Howe, M., Chang, C.-H., & Johnson, R. E. (2013). Understanding affect, stress, and well-being within a self-regulation framework. In P. L. Perrewé, C. C. Rosen, & J. Halbesleben (Eds.), *The role of emotion and emotion regulation in job stress and well-being (research in occupational stress and well-being* (Vol. 11, pp. 1–34). Emerald Group Publishing. https://doi.org/10.1108/S1479-3555(2013)0000011005

Johnson, R. E., Howe, M., & Chang, C. H. (2013). The importance of velocity, or why speed may matter more than distance. *Organizational Psychology Review*, *3*(1), 62–85. https://doi.org/10.1177/2041386612463836

Johnson, R. E., Tolentino, A. L., Rodopman, O. B., & Cho, E. (2010). We (sometimes) know not how we feel: Predicting job performance with an implicit measure of trait affectivity. *Personnel Psychology*, *63*(1), 197–219. https://doi.org/10.1111/j.1744-6570.2009.01166.x

Kagan, J. (1972). Motives and development. *Journal of Personality and Social Psychology*, *22*(1), 51–66. https://doi.org/10.1037/h0032356

Kanner, A. D., Coyne, J. C., Schaefer, C., & Lazarus, R. S. (1981). Comparison of two modes of stress measurement: Daily hassles and uplifts versus major life events. *Journal of Behavioral Medicine*, *4*(1), 1–39. https://doi.org/10.1007/BF00844845

Kim, T. G., Hornung, S., & Rousseau, D. M. (2011). Change-supportive employee behavior: Antecedents and the moderating role of time. *Jour-*

nal of Management, *37*(6), 1664–1693. https://doi.org/10.1177/0149206310364243

Lazarus, R. S. (1991a). *Emotion and adaptation*. Oxford University Press.

Lazarus, R. S. (1991b). Progress on a cognitive-motivational-relational theory of emotion. *American Psychologist*, *46*(8), 819–834. https://doi.org/10.1037/0003-066X.46.8.819

Lazarus, R. S. (1999). The cognition-emotion debate: A bit of history. In T. Dalgleish & M. J. Power (Eds.), *Handbook of cognition and emotion* (pp. 3–19). Wiley. https://doi.org/10.1002/0470013494.ch1

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer. https://doi.org/10.1007/978-1-4419-1005-9_215

Levine, S., & Wiener, S. G. (1989). Coping with uncertainty: A paradox. In D. Palermo (Ed.), *Coping with uncertainty: Behavioral and developmental perspectives* (pp. 1–16). Lawrence Erlbaum.

Lindsley, D. H., Brass, D. J., & Thomas, J. B. (1995). Efficacy-performing spirals: A multilevel perspective. *Academy of Management Review*, *20*(3), 645–678. https://doi.org/10.5465/amr.1995.9508080333

Lyon, B. L. (2000). Stress, coping, and health. In V. H. Rice (Ed.), *Handbook of stress, coping and health: Implications for nursing research, theory, and practice* (pp. 2–20). SAGE.

Marteau, T. M., & Bekker, H. (1992). The development of a six-item short-form of the state scale of the Spielberger State–Trait Anxiety Inventory (STAI). *British Journal of Clinical Psychology*, *31*(3), 301–306. https://doi.org/10.1111/j.2044-8260.1992.tb00997.x

Maslach, C., Schaufeli, W. B., & Leiter, M. P. (2001). Job burnout. *Annual Review of Psychology*, *52*(1), 397–422. https://doi.org/10.1146/annurev.psych.52.1.397

McCarthy, J. M., Trougakos, J. P., & Cheng, B. H. (2016). Are anxious workers less productive workers? It depends on the quality of social exchange. *Journal of Applied Psychology*, *101*(2), 279–291. https://doi.org/10.1037/apl0000044

McEwen, B. S. (1998). Stress, adaptation, and disease. Allostasis and allostatic load. *Annals of the New York Academy of Sciences*, *840*(1), 33–44. https://doi.org/10.1111/j.1749-6632.1998.tb09546.x

McEwen, B. S., & Seeman, T. (2003). Stress and affect: Applicability of the concepts of allostasis and allostatic load. In *Handbook of affective sciences* (pp. 1117–1137). Oxford University Press.

McGrath, J. E., & Beehr, T. A. (1990). Time and the stress process: Some temporal issues in the conceptualization and measurement of stress. *Stress Medicine*, *6*(2), 93–104. https://doi.org/10.1002/smi.2460060205

Miller, G. E., Chen, E., & Zhou, E. S. (2007). If it goes up, must it come down? Chronic stress and the hypothalamic-pituitary-adrenocortical axis in humans. *Psychological Bulletin*, *133*(1), 25–45. https://doi.org/10.1037/0033-2909.133.1.25

Muthén, L. K., & Muthén, B. O. (1998–2017). *Mplus user's guide* (8th ed.).

Parke, M. R., Weinhardt, J. M., Brodsky, A., Tangirala, S., & DeVoe, S. E. (2018). When daily planning improves employee performance: The importance of planning type, engagement, and interruptions. *Journal of Applied Psychology*, *103*(3), 300–312. https://doi.org/10.1037/apl0000278

Preacher, K. J., & Selig, J. P. (2012). Advantages of Monte Carlo confidence intervals for indirect effects. *Communication Methods and Measures*, *6*(2), 77–98. https://doi.org/10.1080/19312458.2012.679848

Restubog, S. L. D., Scott, K. L., & Zagenczyk, T. J. (2011). When distress hits home: The role of contextual factors and psychological distress in predicting employees' responses to abusive supervision. *Journal of Applied Psychology*, *96*(4), 713–729. https://doi.org/10.1037/a0021593

Richardsen, A. M., Burke, R. J., & Leiter, M. P. (1992). Occupational demands, psychological burnout and anxiety among hospital personnel in Norway. *Anxiety, Stress, and Coping*, *5*(1), 55–68. https://doi.org/10.1080/10615809208250487

Riskind, J. H. (1997). Looming vulnerability to threat: A cognitive paradigm for anxiety. *Behaviour Research and Therapy*, *35*(8), 685–702. https://doi.org/10.1016/S0005-7967(97)00011-9

Ritter, K.-J., Matthews, R. A., Ford, M. T., & Henderson, A. A. (2016). Understanding role stressors and job satisfaction over time using adaptation theory. *Journal of Applied Psychology*, *101*(12), 1655–1669. https://doi.org/10.1037/apl0000152

Rosen, C. C., Dimotakis, N., Cole, M. S., Taylor, S. G., Simon, L. S., Smith, T. A., & Reina, C. S. (2020). When challenges hinder: An investigation of when and how challenge stressors impact employee outcomes. *Journal of Applied Psychology*, *105*(10), 1181–1206. https://doi.org/10.1037/apl0000483

Sapolsky, R. M. (1999). The physiology and pathophysiology of unhappiness. In D. Kahneman, E. Diener, & N. Schwartz (Eds.), *Well-being: The foundations of hedonic psychology* (p. 453). Russell Sage Foundation.

Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The measurement of work engagement with a short questionnaire: A cross-national study. *Educational and Psychological Measurement*, *66*(4), 701–716. https://doi.org/10.1177/0013164405282471

Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, *3*(1), 71–92. https://doi.org/10.1023/A:1015630930326

Selye, H. (1956). *The stress of life*. McGraw-Hill.

Selye, H. (1976). Stress without distress. In G. Serban (Ed.), *Psychopathology of human adaptation* (pp. 137–146). Springer. https://doi.org/10.1007/978-1-4684-2238-2_9

Snijders, T. A. B., & Bosker, R. J. (2011). *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. SAGE.

Sonnentag, S., Dormann, C., & Demerouti, E. (2010). Not all days are created equal: The concept of state work engagement. In A. B. Bakker & M. P. Leiter (Eds.), *Work engagement: Recent developments in theory and research* (pp. 25–38). Psychology Press.

Sonnentag, S., & Frese, M. (2012). Dynamic performance. In S. W. J. Kozlowski (Ed.), *Oxford handbook of industrial and organizational psychology* (Vol. 1, pp. 548–575). Oxford University Press.

Sonnentag, S., Venz, L., & Casper, A. (2017). Advances in recovery research: What have we learned? What should be done next? *Journal of Occupational Health Psychology*, *22*(3), 365–380. https://doi.org/10.1037/ocp0000079

Spector, P. E., & Fox, S. (2002). An emotion-centered model of voluntary work behavior: Some parallels between counterproductive work behavior and organizational citizenship behavior. *Human Resource Management Review*, *12*(2), 269–292. https://doi.org/10.1016/S1053-4822(02)00049-9

Suh, E., Diener, E., & Fujita, F. (1996). Events and subjective well-being: Only recent events matter. *Journal of Personality and Social Psychology*, *70*(5), 1091–1102. https://doi.org/10.1037/0022-3514.70.5.1091

Thau, S., & Mitchell, M. S. (2010). Self-gain or self-regulation impairment? Tests of competing explanations of the supervisor abuse and employee deviance relationship through perceptions of distributive justice. *Journal of Applied Psychology*, *95*(6), 1009–1031. https://doi.org/10.1037/a0020540

Watson, D. (2000). *Mood and temperament*. Guilford Press.

Watson, D., & Clark, L. A. (1994). *The PANAS-X: Manual for the Positive and Negative Affect Schedule—Expanded form*. https://doi.org/10.17077/48vt-m4t2

Weiss, H. M., & Cropanzano, R. (1996). Affective events theory: A theoretical discussion of the structure, causes and consequences of affective experiences at work. In B. M. Staw & L. L. Cummings (Eds.), *Research in organizational behavior: An annual series of analytical essays and critical reviews* (Vol. 18, pp. 1–74). JAI Press.

Wharton, A. S. (1993). The affective consequences of service work: Managing emotions on the job. *Work and Occupations*, *20*(2), 205–232. https://doi.org/10.1177/0730888493020002004

Williams, L. J., & Anderson, S. E. (1991). Job satisfaction and organizational commitment as predictors of organizational citizenship and in-role behaviors. *Journal of Management*, *17*(3), 601–617. https://doi.org/10.1177/014920639101700305

Appendix A

Sample and Procedure

This study was conducted in four partially overlapping waves. For each wave, participants were asked to complete three surveys a day for three consecutive weeks. Surveys were sent at the start (T1), middle (T2), and near the end (T3) of the workday; average completion times were 9:30 a.m., 1:12 p.m., and 5:26 p.m., respectively.

The first wave started on February 6, 2020, and 205 participants completed the sign-up survey. The daily phase started on February 10, 2020. On the fourth day of the study, we stopped the participation of 45 people because they (a) missed attention checks embedded in the survey for 3 days in a row or (b) carelessly responded to some qualitative questions (included as part of a broader data collection). In addition, a few participants had responded to the survey more than once. After removing these duplicated daily surveys, our initial Wave 1 sample was 934 day-level observations from 130 participants. Of these day-level observations, 27 were excluded because they were completed outside the required timeframe and 376 were excluded because they missed responses in one of the three daily surveys on a study day. We were left with 75 individuals providing 531 day-level observations for the first wave.

Similarly, our second wave started on February 19, 2020 with 225 individuals in the initial survey with the daily phase starting on February 24, 2020. Of these individuals, 53 were removed for the same reasons as above (i.e., attention checks and careless responses). Excluding missed responses within a particular study day and incorrectly timed responses left us with 92 individuals providing 731 day-level observations for the second wave.

The third wave started on March 5, 2020 with 90 individuals, and the daily phase starting on March 9, 2020. This was reduced to 73 individuals (after exclusions) providing 410 day-level observations. Missing response and incorrectly timed responses brought the sample to 39 individuals providing 244 day-level observations.

The fourth wave started on April 4, 2020 and included 224 individuals who completed the initial survey; the daily phase started on April 8, 2020. The sample was reduced to 180 individuals providing 1,618 observations after exclusions (duplicated surveys). Of this sample, 60 observations were excluded because they were not completed within the required timeframe. Accounting for missing daily surveys left us with a sample of 113 individuals with 962 day-level observations.

Our initial combined sample across four waves therefore was composed of 319 individuals providing 2,468 day-level observations. After removing 48 individuals with a single daily observation (our design required participants with at least two consecutive days without missing data), we had 271 individuals providing 2,420 daily observations.

Missing item-level data (21 observations) on our dependent variables (i.e., engagement, performance, and emotional exhaustion) reduced the total sample to 2,399 observations from 271 individuals. In addition, we were not able to definitively determine the locations of eight individuals (who had provided 65 observations) from this subset, leaving us with 2,334 observations from 263 individuals. Two other observations (belonging to one individual) were not usable due to being from a state that had no other observations. Therefore, our final sample for analysis includes 2,332 observations within 262 individuals. These individuals were all full-time employees (working 42.5 hr per week on average) in a varied set of industries and jobs. (summarized in Table A1).

(*Appendices continue*)

Table A1
Participants' Employment Across Industries

Industry	%	Example job
Agriculture, forestry, fishing, and hunting	1.15	Biologist
Utilities	1.53	Water operator
Construction	1.53	Foremen
Manufacturing	9.16	Operations director
Wholesale trade	3.05	Territory manager
Retail trade	3.82	Store design
Transportation and warehousing	3.44	Dispatch manager
Information	2.67	Electronics Engineer
Finance and insurance	9.16	Equities analyst
Real estate and rental and leasing	3.05	Accounting manager
Professional, scientific, and technical services	9.54	Contract specialist
Management of companies and enterprises	0.76	Analyst
Administrative and support/waste management	1.53	Legal assistant
Educational services	14.12	School principal
Health care and social assistance	17.18	Physical therapist
Arts, entertainment, and recreation	1.91	Director of artist residencies
Accommodation and food services	0.76	Motel manager
Other services (except public administration)	12.60	Receptionist
Central administrative office activity	3.05	Federal government contractor

(*Appendices continue*)

Appendix B

Survey Measures

Task Engagement (Bakker & Costa, 2014; Schaufeli et al., 2002; Schaufeli et al., 2006)

Measured on T1 and T2 surveys and aggregated to the day level.

Referent: Engagement with current task

(1= *strongly disagree*, 2 = *disagree*, 3 = *neither*, 4 = *agree*, 5 = *strongly agree*)

1. I feel bursting with energy working on this task.
2. I am enthusiastic about this task I am doing.
3. I feel happy working intensely on this task.

Task Performance (Parke et al., 2018; Williams & Anderson, 1991)

Measured on the T2 and T3 surveys and aggregated to the day level.

Referent: Performance in work tasks during morning and afternoon, respectively

(1= *strongly disagree*, 2 = *disagree*, 3 = *neither*, 4 = *agree*, 5 = *strongly agree*)

1. I fulfilled the responsibilities specified in my job description for that task.
2. I consistently met the formal performance requirements for that task.
3. I adequately completed all my assigned duties in that task.

Emotional Exhaustion (Wharton, 1993)

Measured on the T1 and T3 surveys and aggregated to the day level.

Referent: Emotional exhaustion experienced currently

(1= *not at all*, 2 = *a little*, 3 = *moderately*, 4 = *quite a bit*, 5 = *very much).*

1. I feel emotionally drained.
2. I feel burned out.
3. I feel used up.

Anxiety (Marteau & Bekker, 1992; Watson & Clark, 1994)

Measured on the T1, T2, and T3 surveys and aggregated to the day level.

Referent: Anxiety experienced currently

(1 =*very slightly*, 2 = *a little*, 3 = *moderately*, 4 = *quite a bit*, 5 = *extremely*)

1. Nervous
2. Anxious
3. Upset
4. Tense
5. Worried

Received June 18, 2020
Revision received September 17, 2020
Accepted October 4, 2020 ■