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Using Machine Learning to Investigate the Public's Emotional Responses to Work From Home During the COVID-19 Pandemic

Hanyi Min[1], Yisheng Peng[2], Mindy Shoss[1, 3], and Baojiang Yang[4]
[1] Department of Psychology, University of Central Florida
[2] Department of Organizational Sciences & Communication, The George Washington University
[3] Peter Faber Business School, Australian Catholic University
[4] Católica Lisbon School of Business and Economics, Universidade Católica Portuguesa

According to event system theory (EST; Morgeson et al., *Academy of Management Review*, *40*, 2015, 515–537), the coronavirus disease 2019 (COVID-19) pandemic and resultant stay-at-home orders are novel, critical, and disruptive events at the environmental level that substantially changed people's work, for example, where they work and how they interact with colleagues. Although many studies have examined events' impact on features or behaviors, few studies have examined how events impact aggregate emotions and how these effects may unfold over time. Applying a state-of-the-art deep learning technique (i.e.,the fine-tuned Bidirectional Encoder Representations from Transformers [BERT] algorithm), the current study extracted the public's daily emotion associated with working from home (WFH) at the U.S. state level over four months (March 01, 2020–July 01, 2020) from 1.56 million tweets. We then applied discontinuous growth modeling (DGM) to investigate how COVID-19 and resultant stay-at-home orders changed the trajectories of the public's emotions associated with WFH. Our results indicated that stay-at-home orders demonstrated both immediate (i.e., intercept change) and longitudinal (i.e., slope change) effects on the public's emotion trajectories. Daily new COVID-19 case counts did not significantly change the emotion trajectories. We discuss theoretical implications for testing EST with the global pandemic and practical implications. We also make Python and R codes for fine-tuning BERT models and DGM analyses open source so that future researchers can adapt and apply the codes in their own studies.

Keywords: COVID-19, machine learning, discontinuity growth models, emotion trajectory, event system theory

Supplemental materials: https://doi.org/10.1037/apl0000886.supp

> We are forced into the world's largest work-from-home experiment.
> —Saikat Chatterjee, Senior Director, Advisory at Gartner

On March 11, 2020, the World Health Organization declared the coronavirus disease 2019 (COVID-19) a global pandemic. As of November 9, 2020, there were over 50 million confirmed cases worldwide and over 10 million in the United States. The majority of states in the United States (42 states and some cities in other states) ordered their residents to stay at home or shelter in place beginning in late March or early April (The New York Times, 2020), which directly and drastically changed the working environment for many employees. As organizations closed their physical offices, employees shifted to working from home (WFH). On one hand, WFH during the COVID-19 pandemic lowered employees' health risks, increased their time with families, and reduced their normal commuting time (Bloom, 2014). On the other hand, this disruptive change was difficult to implement for organizations as necessary resources for WFH employees may not be readily available (e.g., technology and communication tools; Allen et al., 2015). At a societal level, stay-at-home orders impacted not only individual employees who were forced to adjust to this new way of working, but also their families/roommates, others who interact with WFH employees (e.g., customers and clients), and those in businesses that would be frequented less now that worksites were closed (e.g., the office building coffee shop). WFH also has served as a salient symbol of the pandemic's significant impact on the way of life.

Building on event system theory (EST; Morgeson et al., 2015), this study utilizes data from Twitter to examine macrolevel (e.g., state-level) emotional reactions to WFH during the COVID-19 pandemic over time. EST theorizes that events marked by novelty, disruption from past routine, and criticality should garner employees' attention and shape their experiences. Moreover, events can have impacts that go beyond the scope of those initially impacted (e.g., the Enron crisis impacted the broader society beyond only those involved). While this macrolevel effect has been noted qualitatively, quantitative research is needed (Hällgren et al., 2018). As novel, disruptive, and critical events, the COVID-19 pandemic and resultant stay-at-home orders pose excellent opportunities to test these effects proposed by EST. They also present an opportunity to expand EST

Hanyi Min https://orcid.org/0000-0002-0095-8513
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Correspondence concerning this article should be addressed to Hanyi Min, Psychology Department, University of Central Florida, Orlando, FL 32816, United States. Email: Hanyi.min@ucf.edu

to consider the emotional impact of events as well as the effects of events as they unfold over time. By examining aggregate emotions directed toward WFH during the COVID-19 pandemic, our study provides insight into how people emotionally react to two particularly disruptive, critical, and novel events as well as whether people gradually adapt to these events as time progresses as indicated by aggregate emotion trajectories. Investigation of aggregate emotion trajectories also helps researchers and decision-makers better understand how people respond to COVID-19-related events, such as stay-at-home orders and number of daily confirmed cases, and can therefore facilitate decision-making in this regard.

This study has three primary theoretical and practical implications. Given the rareness and unexpectedness of global pandemics, EST provides a unique framework to investigate the impact of these types of sudden and disruptive events. The first contribution of the current study is to test and extend EST by examining emotional reactions to two environmental events—daily new COVID-19 confirmed case counts and resultant stay-at-home orders. Though not included in EST, emotions are proximal outcomes to events, especially to events threatening individuals' survival (Keltner & Gross, 1999). Emotions are also of core interest to organizations and societies as they associate with critical organizational outcomes, such as employee engagement (Ouweneel et al., 2012) and intentions to leave (Kiefer, 2005), and societal consequences, such as irrational behaviors (e.g., Sinaceur et al., 2005) and risk perceptions (Xie et al., 2011).

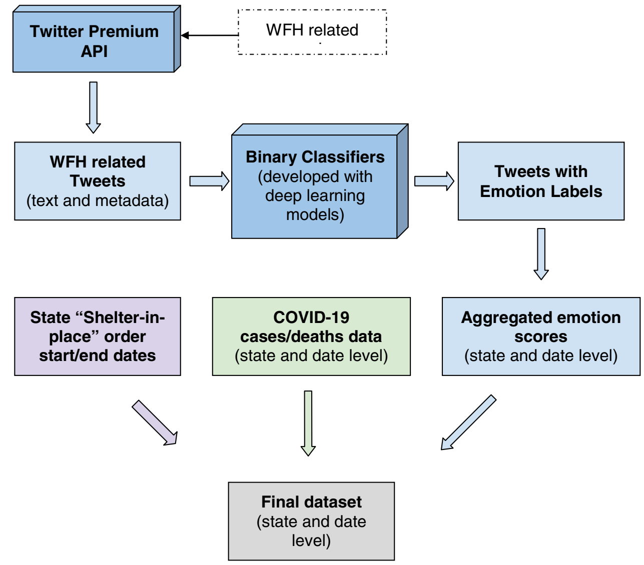
The current study also contributes to EST by examining the longitudinal effects of two events (i.e., stay-at-home orders and COVID-19 confirmed case counts), providing a more comprehensive account of these societal phenomena. As these events are continuously occurring and shaping the public's emotions, they offer an opportunity to examine the dynamic effects of COVID-19 and resultant stay-at-home orders. Thus, by attending to the dynamic and evolutionary nature of the public's emotions, we extend EST to advance scholarly understanding of the temporal progression of these two events and their emotional consequences over time.

Finally, this study offers methodological contributions to organizational research. We use a state-of-the-art deep learning technique (i.e., the fine-tuned Bidirectional Encoder Representations from Transformers [BERT] algorithm) to learn public's emotions toward WFH from social media during the pandemic. Given the intense and short-living nature of discrete emotions (Barsade & Gibson, 2007), it is extremely difficult, if not impossible, to map the longitudinal trajectories (e.g., 4 months) of the public's emotions using traditional survey methods. Machine learning techniques, however, provide a relatively objective way to extract emotions at an aggregated level using large datasets. Additionally, researchers can adapt and use our open-source Python codes for fine-tuning BERT models in future studies.[1]

COVID-19 Stay-at-Home Orders and Daily Confirmed Case Counts as Events

Morgeson et al. (2015) claimed that events are bounded in a particular time and space. Events are defined as "discrete, discontinuous 'happenings,' which diverge from the stable or routine features" of the environment (Morgeson et al., 2015, p. 519). As a globally occurring disaster (World Health Organization, 2020), the COVID-19 pandemic has disrupted nearly every aspect of daily life and continues to occupy attention as indicated by the continuous media coverage devoted to the pandemic's toll on individuals' lives and livelihoods (Liu & Liu, 2020). Particularly relevant for our purposes, events can co-occur as part of a larger event system and can be long-lasting (Morgeson et al., 2015; Shoss et al, 2020).

Figure 1
Data Collection and Processing Framework



Note. See the online article for the color version of this figure.

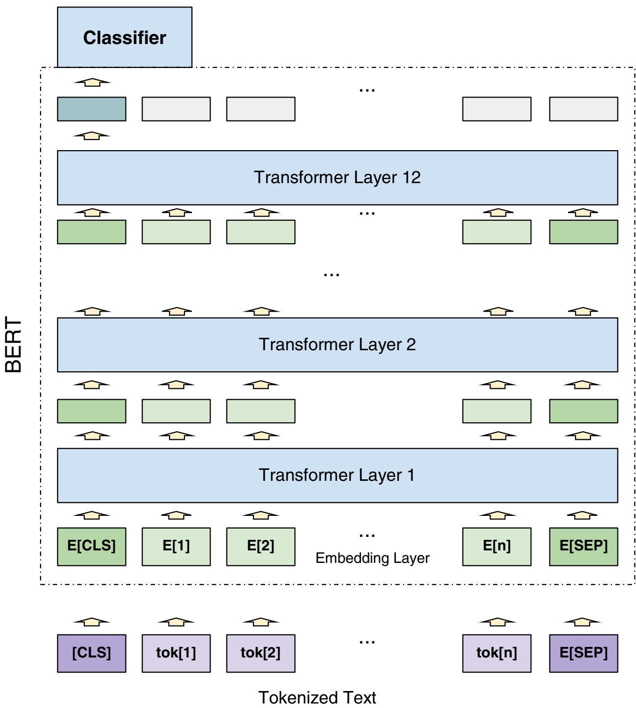
The current study investigates two events related to COVID-19—(a) state stay-at-home or "shelter-in-place" orders and (b) the number of daily new confirmed case counts in each state. Beyond differences in their meaning (a legal directive from a government entity restricting travel and gatherings outside the home vs. indicators of health risk), stay-at-home orders and COVID-19 case counts reflect two different types of events from a temporal perspective. Bliese et al.'s (2017) methodological discussion of event research offered a number of examples of events suggesting that events have an acute (i.e., time-demarcated) onset but may vary in the nature of their subsequent temporal dynamics. Expanding this work, we suggest that COVID-19 case counts reflect a temporally varying event (the Great Recession is another example), whereas the stay-at-home orders reflect events that are temporally delineated (e.g., either present or not).

According to EST, the strength of an event is reflected in the extent to which the event is (a) new and unexpected, (b) creates discontinuity from "normal" or "routine," and (c) has impacts that are important and essential to people. Strong environmental events are very likely to change or create behaviors, features, and new events (Morgeson et al., 2015). We extend EST by suggesting that emotions are proximal reactions that occur in the direct aftermath of an event (Akkermans et al., 2018). For example, studies on public disasters (e.g., the 9/11 attack in the United States, the Sewol Ferry disaster in South Korea) suggest that these events shock

[1] Please find our codes for fine-tuning BERT models, along with other codes used in this study, in the OSF repository: https://osf.io/mnaud

Figure 2

Fine-Tuning Pre-Trained Bidirectional Encoder Representations From Transformers (BERT) Model For Classification Task



Note. Figure adapted from Figure 1 of Devlin, J., Chang, M. W., Lee, K., and Toutanova, K. (2018). See the online article for the color version of this figure.

the public and cause intense emotional reactions from the public (e.g., Schlenger et al., 2002; Woo et al., 2015). Emotions can transfer to other people via emotional contagion through in-person interactions (Totterdell et al., 1998) or the social media (e.g., Facebook; Kramer et al., 2014). Emotional contagion leads people to experience similar emotions and results in collective emotions (Barsade & Gibson, 2007). Past research suggests that public expressions of emotions after events through social media is a valid way of capturing aggregate real-time reactions to events. For example, Javadian (2007) used machine learning techniques to analyze tweets after earthquakes. This study found a peak of fear and anxiety on Twitter immediately after an earthquake happened, and these emotions then quickly decreased a few hours after the earthquake.

The Current Study

This study examines the trajectories of the public's emotions associated with WFH on social media during the pandemic and how they are shaped by (a) stay at home orders and (b) daily new confirmed case counts. Specifically, we analyzed the public's emotional reactions toward WFH on Twitter, a widely used social media platform in the United States. We searched for tweets including keywords related to WFH from March 01, 2020, to July 01, 2020, which resulted in about 1.56 million tweets posted by 706,142 Twitter users. A large number of tweets helps us obtain a reliable estimate of aggregate-level emotions and increase the generalizability of our findings. We adopt a state-of-the-art deep learning technique (i.e., fine-tuned BERT algorithm) to estimate emotions toward WFH from tweets, which are then extracted to test the two events' effects on the public's emotions.

This study examines six basic emotions, namely, anger, sadness, fear, joy, disgust, and surprise. Although there is still debate on which human emotions should be included in the basic set, these six basic emotions are relatively universal across cultures and have important implications for human evolution and survival according to Ekman's basic emotion model (Ekman, 1992, 1999). These emotions have unique functional and adaptive roles in influencing individuals' cognition and behaviors (Fredrickson, 2001; Izard, 1991; Kahneman & Tversky, 1979). Moreover, research has successfully identified these basic emotions on social media using machine learning techniques (Becker et al., 2019; Chatterjee et al., 2019).

Bliese et al. (2017) suggested the EST be paired with discontinuous growth modeling (DGM) as an empirical framework to generate testable hypotheses about event transitions (i.e., the immediate effect of an event onset or offset) and event recovery (i.e., trends during or after an event). In line with their suggestions, we examine if stay-at-home orders change the public's emotions toward WFH, specifically, the relative change of emotions during and after the stay-at-home order, compared to the emotion trajectories before the order. We suggest that the stay-at-home orders are strong events because they are disruptive, critical, and novel. The state stay-at-home orders directly disrupt the working environment for many people. They not only have disruptive and critical impacts on the workers themselves but also on families, roommates, businesses (e.g., restaurants that serve primarily office locations), etc. Further, because stay-at-home orders are atypical in the United States, except in major disasters, they can be perceived as novel. As such, we anticipate an immediate change in the public's sentiment toward WFH at the onset of this event (i.e., a significant transition effect; Bliese et al., 2017). We extend EST, which focuses more on the onset of an event rather than its ending, by also viewing the lifting of the stay-at-home orders as a significant transition. When stay-at-home orders are lifted, individuals have to navigate a new context for work, including uncertainty over reopening, potential virus exposure, and new changes in their job prospects. Thus, the lifting of a stay-at-home order also reflects a novel, critical, and disruptive event that has a significant transition effect.

> *Hypothesis 1:* There are significant intercept (i.e., transition) parameters for the public's emotional reactions to WFH at the beginning and end of stay-at-home orders.

However, the impact of stay-at-home orders may decline over time as people are shocked at the beginning but then adapt to the changing work environment gradually. From an EST perspective, although initially disruptive and novel, WFH should become less novel and disruptive as time goes on and this way of operating becomes more routine. Similarly, it becomes less critical in that individuals mobilize less resources in coping with WFH either as the employee or as someone else impacted (e.g., family member, customer). Adaptation theory likewise suggests that people adapt to stressors after a period of time (Matthews et al., 2014). Accordingly, the impacts of stay-at-home orders and their lifting on the public's emotions may be the strongest right after they are implemented and then slowly diminish over time.

Table 1
Model Accuracy Comparison Based on a Hold-Out Balanced Test Set

Emotions	Fine-tuned BERT	Baseline 1: SVM based on LIWC features	Baseline 2: EmoLex with Syuzhet package
Anger	87%	73% (−14%)	69% (−18%)
Disgust	86%	84% (−2%)	65% (−21%)
Fear	96%	79% (−17%)	74% (−22%)
Joy	88%	83% (−5%)	72% (−16%)
Sadness	88%	71% (−17%)	64% (−24%)
Surprise	95%	68% (−27%)	50% (−45%)

> *Hypothesis 2:* There are significant slope (i.e., recovery) parameters for emotional reactions to WFH during and after the stay-at-home orders.

We also examine the trajectories of specific emotions as a research question. According to appraisal theories of emotions, individuals' interpretations of an event or situation determine the specific emotion felt (Frijda, 1986; Lazarus, 1991; Roseman, 1984; Roseman et al, 1996; Smith & Ellsworth, 1985). During the COVID-19 pandemic, people may experience anger due to WFH's perceived interference with one's goal attainment because they feel social isolation and increased job insecurity (Rudolph et al., 2020), which are unpleasant experiences that thwart their personal aims. People may also feel a lack of ability and resources to cope with the pandemic and the associated unpleasant, stressful situations (Sinclair et al., 2020), leading them to experience fear. Additionally, individuals may feel sadness because they appraise the pandemic as something affected by situational circumstances beyond their control (Ellsworth & Smith, 1988). However, as previously noted, WFH may also associate with positive emotions as individuals reduce commuting time and spend more time with their nuclear families. Given the contagious nature of COVID-19, WFH during this time reduces the risk of getting COVID-19 and threats to health. In this sense, WFH during the COVID-19 pandemic is likely to associate with increased joy (Dubey & Tripathi, 2020) and decreased fear, sadness, and anger. Given the limited evidence in the literature, we explore each emotion as a research question.

> *Research Question 1:* How do stay-at-home orders' transition and recovery effects differ by emotion?

In addition to stay-at-home orders, daily new COVID-19 confirmed case counts may also associate with fluctuations in the public's emotions toward WFH. State-level daily new COVID-19 confirmed case counts are indicators of COVID-19 severity in each state. Smaller numbers of confirmed cases reflect lower criticality and may be perceived as less threatening. Based on EST, the public's emotional reactions toward WFH are likely to increase over time as daily new COVID-19 confirmed case counts increase. However, it may also be the case that the novelty of daily new COVID-19 confirmed case counts decreases over time. The public's emotional reaction may decrease as the novelty decreases. Thus, we explore the relationship between daily new COVID-19 confirmed case counts and the public's emotion toward WFH as a research question.

> *Research Question 2:* What are the relationships between states' daily new COVID-19 confirmed case counts and the transition and recovery parameters of the public's emotions toward WFH?

Method

Data

Three datasets were combined from different sources (see Figure 1). First, we obtained information on confirmed COVID-19 cases for each of the 50 U.S. states and the District

Table 2
Change Variables in the Discontinuous Mixed-Effects Growth Models

	March													May											
	1	2	3	4	. . .	19	20	21	22	23	24	25	. . .	14	15	16	17	18	. . .	24	25	26	27	28	29
Change variables																									
Preorder slope	0	1	2	3		18	19	20	21	22	23	24		74	75	76	77	78		84	85	86	87	88	89
During-order intercept[a]																									
CA	0	0	0	0		0	1	1	1	1	1	1		1	1	1	1	1		1	1	0	0	0	0
NY	0	0	0	0		0	0	0	0	1	1	1		1	1	0	0	0		0	0	0	0	0	0
During-order slope[a]																									
CA	0	0	0	0		0	0	1	2	3	4	5		55	56	57	58	59		65	66	0	0	0	0
NY	0	0	0	0		0	0	0	0	0	1	2		52	53	0	0	0		0	0	0	0	0	0
After-order intercept[a]																									
CA	0	0	0	0		0	0	0	0	0	0	0		0	0	0	0	0		0	0	1	1	1	1
NY	0	0	0	0		0	0	0	0	0	0	0		0	0	1	1	1		1	1	1	1	1	1
After-order slope[a]																									
CA	0	0	0	0		0	0	0	0	0	0	0		0	0	0	0	0		0	0	0	1	2	3
NY	0	0	0	0		0	0	0	0	0	0	0		0	0	0	1	2		8	9	10	11	12	13

Note. The stay-at-home order started on March 19, 2020, in CA and March 22, 2020, in New York. The coding of the change variables assumes one-day-lagged effect. That is, the first discontinuity point is one day after the order is effective and the second discontinuity point is one day after the order ends. We also examined DGM assuming immediate effect and two-day-lagged effect, but these two models demonstrated worse model fit. [We thank the associate editor and anonymous reviewers for suggesting us compare models assuming immediate effect and lagged effects.] Our results are consistent in all three models. Results of the other two DGMs are available in the supplemental materials.
[a] The coding for these change variables depends on the starting and ending date of the stay-at-home orders in each state, and thus differs for each state.

Table 3
Means, Standard Deviations, and Correlations of Predicted Emotions and Daily New COVID-19 Confirmed Case Counts

Variable between-state level	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Anger (preorder, non-WFH)	15.05	1.40																				
2. Anger (during order, WFH)	12.69	1.83	.40**																			
3. Anger (after order, non-WFH)	15.20	1.88	−.14	−.07																		
4. Disgust (Preorder, non-WFH)	25.01	2.68	.52**	.35*	−.03																	
5. Disgust (during order, WFH)	20.66	1.85	.26	.80**	−.24	.30																
6. Disgust (after order, non-WFH)	23.50	2.08	.01	−.09	.73**	.18	−.18															
7. Joy (preorder, non-WFH)	29.28	3.05	−.24	.03	.03	−.34*	−.15	−.11														
8. Joy (during order, WFH)	32.01	2.10	−.17	−.43**	.42**	−.36*	−.58**	.30*	.35*													
9. Joy (after order, non-WFH)	29.79	2.83	.11	.23	−.15	.15	.12	−.34*	.59**	.10												
10. Fear (preorder, non-WFH)	3.89	.99	−.24	−.16	−.35*	−.16	.15	−.39**	−.23	−.18	−.02											
11. Fear (during order, WFH)	2.88	.53	.30	.18	−.39**	.50**	.19	−.12	−.12	−.34*	.02	.13										
12. Fear (after order, non-WFH)	4.58	1.11	.01	−.18	.06	.20	.13	.26	−.17	−.17	.09	.23	−.02									
13. Sadness (Preorder, non-WFH)	27.96	2.42	.43**	.11	.19	.38*	−.11	.18	−.24	.18	.02	−.41**	.13	−.07								
14. Sadness (during order, WFH)	24.82	1.41	.29	.48**	.36*	.17	.48**	.23	−.36*	−.06	−.12	.01	−.13	−.06	.38*							
15. Sadness (after order, non-WFH)	26.86	2.23	.08	.39**	.45**	−.01	.17	.26	.25	.13	.12	−.36*	−.30	−.18	.34*	.42**						
16. Surprise (preorder, non-WFH)	.69	.21	.09	.24	.28	−.01	.02	.40**	.03	.14	−.25	−.35*	−.06	−.30*	.04	.31*	.29					
17. Surprise (during order, WFH)	.73	.23	−.09	.16	−.16	−.24	−.02	−.13	.18	.14	−.11	−.18	−.17	−.61**	.02	−.03	.32*	.29				
18. Surprise (after order, non-WFH)	.59	.21	−.05	−.23	−.57**	−.28	−.04	−.49**	.09	.10	.07	.39**	.16	−.11	.01	−.17	−.32*	−.14	.05			
19. Cases by popu. (preorder, non-WFH)	.8	.69	.25	.28	−.13	.06	.26	−.05	−.05	−.28	−.12	−.01	.17	−.14	−.03	−.04	−.07	.02	−.06	.08		
20. Cases by popu. (during order, WFH)	7.61	7.32	.40**	.25	−.39**	.22	.24	−.26	−.32*	−.48**	−.15	.30*	.28	−.19	−.17	.00	−.18	−.12	−.01	.10	.59**	
21. Cases by popu. (after order, non-WFH)	6.64	3.69	.10	.06	.05	−.14	−.22	−.05	.14	−.02	−.05	.06	−.01	−.24	−.03	−.09	.05	.21	−.01	−.02	.13	.25

Within-state (daily) level	*M*	*SD*	ICC	1	2	3	4	5	6
1. Anger	14.39	9.83	.01						
2. Sadness	26.43	11.52	.01	.41**					
3. Joy	30.35	12.20	.02	−.32**	−.26**				
4. Disgust	22.92	11.42	.01	.66**	.44**	−.40**			
5. Fear	3.76	6.86	.00	.38**	.34**	−.16**	.29**		
6. Surprise	.65	1.35	.00	.00	−.03*	.01	−.02	−.04**	
7. Cases by popu.	5.85	7.70	—	−.01	−.03*	.01	−.05**	.00	.01

Note. Cases by popu. = new confirmed cases by population. Between-state level $k = 51$ (50 states and the District of Columbia); within-state level $N = 6{,}222$. M = mean, ICC = intraclass correlation coefficient.
$^{*} p < .05$. $^{**} p < .01$ (two tailed).

Table 4

Discontinuity Growth Model Results for Anger Assuming One-Day Delayed Effect

Variable	Model 1 Coef.	Model 1 Coef. *SE*	Model 1 *t*	Model 2 Coef.	Model 2 Coef. *SE*	Model 2 *t*	Model 3 Coef.	Model 3 Coef. *SE*	Model 3 *t*
Preorder									
Intercept π_{0i}	13.81	.35	39.97***	14.66	.48	30.41***	14.71	.48	30.38***
Slope π_{1i} (Time^{pre})				−.03	.01	−2.80**	−.04	.01	−3.10**
During order									
Relative intercept π_{2i} (TRANS1)				−4.57	.49	−9.40***	−4.35	.49	−8.82***
Relative slope π_{3i} (RECOV1)				.16	.02	8.15***	.17	.02	8.14***
After order									
Relative intercept π_{4i} (TRANS2)				5.64	.70	8.08***	6.31	.77	8.15***
Relative slope π_{5i} (RECOV2)				−.09	.02	−5.79***	−.09	.02	−5.02***
CASE π_{6i}							.00	.03	.09
Control variables									
Weekday dummies	Controlled			Controlled			Controlled		
Random effects									
Preorder									
Intercept				2.48	1.57		2.47	1.57	
Slope (Time^{pre})				.00	.04		.00	.04	
During order									
Relative intercept (TRANS1)				.77	.88		.25	.50	
Relative slope (RECOV1)				.00	.06		.00	.06	
After order									
Relative intercept (TRANS2)				.35	.59		1.58	1.26	
Relative slope (RECOV2)				.00	.05		.01	.07	
CASE							.01	.12	
Residual				90.23	9.50		89.86	9.48	
−2*loglikelihood (*df*)	46384.87 (9)			46141.93 (34)			46144.14 (42)		
AIC	46402.87			46209.93			46228.14		
BIC	46463.55			46439.16			46511.30		
R^2_{LR}	.015			.056			.056		

Note. $k = 51$ (50 states and the District of Columbia); $n = 122$ days; $N = 51 * 122 = 6{,}222$. The results are consistent including or excluding the control variable (weekday dummies). Pseudo-R^2, R^2_{LR}, was calculated using $1 - \exp(-2/N * [L_0 - L_M])$ where L_0 refers to the log-likelihood for a null model without any fixed or random effects and L_M refers to the model of interest (Lang et al, 2019; Magee, 1990; Niessen & Lang, 2020).

$^{*} p < .05$. $^{**} p < .01$. $^{***} p < .001$.

of Columbia for the period of March 01, 2020–July 01, 2020, from the COVID-19 Data Repository at Johns Hopkins University. Given the magnitude of a state's confirmed cases that may greatly relate to the state's population, we combined the confirmed cases measures with the state population from the U.S. Census website, after dividing the state population by 100,000 (e.g., Sergent & Stajkovic, 2020). Meanwhile, because many states report their daily confirmed cases by the end of the day, we used the number of last day confirmed case counts to predict the public's emotions toward WFH on the next day.[2] Second, we collected the information about state-level stay-at-home orders from the NBC News website.[3] This website included the start and end dates for 43 states and the District of Columbia. The rest of the states, to the best of our knowledge, did not have a state-level stay-at-home order during the period of interest.[4]

Finally, our text data for emotion analysis were collected via the Twitter API. We queried all available tweets related to WFH (i.e., tweets including the following seven keywords: "*WFH*," "*work from home*," "*working from home*," "*work remotely*," "*working remotely*," "*remote work*," and "*remote working*") over a four-month period (March 01, 2020–July 01, 2020) by searching through the historical tweets database. In total, we collected 1.56 million tweets posted by 706,142 distinct Twitter users. We leveraged the information on Twitter profile locations to match tweets to states. The tweet data were used to extract state-level daily emotions toward WFH. Particularly, for each tweet, we predicted the emotion labels for each type of emotion using the classification models we built with state-of-the-art deep learning techniques. We then aggregated the emotions by state and date to obtain the state-level sentiment measures. The above three sources of data on the state–date level in our final dataset were then combined ($N = 51$ states * 122 days = 6,222). To ensure appropriate use of tweets and the protection of Twitter users, we followed with the existing ethical guidance discussed in recent literature (Ahmed et al., 2017; Murphy, 2017; Williams et al., 2017). Before accessing tweets, we obtained approval by Twitter, as well as the first author's affiliated university Institutional Review Board (IRB), which determined that the project was exempt from IRB review.

[2] For example, the number of confirmed cases on March 01, 2020, is used to predict the public's emotion on March 02, 2020.

[3] https://www.nbcnews.com/health/health-news/here-are-stay-home-orders-across-country-n1168736

[4] These states include Arkansas, Iowa, Nebraska, North Dakota, Oklahoma, South Dakota, and Utah.

Table 5
Discontinuity Growth Model Results for Disgust Assuming One-Day Delayed Effect

Variable	Model 1 Coef.	Model 1 Coef. *SE*	Model 1 *t*	Model 2 Coef.	Model 2 Coef. *SE*	Model 2 *t*	Model 3 Coef.	Model 3 Coef. *SE*	Model 3 *t*
Preorder									
Intercept π_{0i}	21.62	.40	53.65***	25.12	.65	38.67***	25.14	.65	38.51***
Slope π_{1i} (Time^{pre})				−.12	.02	−5.60***	−.12	.02	−5.54***
During order									
Relative intercept π_{2i} (TRANS1)				−4.79	.70	−6.84***	−4.71	.70	−6.72***
Relative slope π_{3i} (RECOV1)				.22	.04	6.10***	.22	.04	6.17***
After order									
Relative intercept π_{4i} (TRANS2)				8.88	1.19	7.46***	8.96	1.20	7.47***
Relative slope π_{5i} (RECOV2)				.00	.03	−.01	.00	.03	.02
CASE π_{6i}							−.01	.02	−.66
Control variables									
Weekday dummies	Controlled			Controlled			Controlled		
Random effects									
Preorder									
Intercept				7.93	2.82		8.11	2.85	
Slope (Time^{pre})				.01	.10		.01	.10	
During order									
Relative intercept (TRANS1)				6.82	2.61		6.00	2.45	
Relative slope (RECOV1)				.04	.19		.04	.19	
After order									
Relative intercept (TRANS2)				8.62	2.94		8.99	3.00	
Relative slope (RECOV2)				.02	.13		.02	.13	
CASE							[a]		
Residual				120.94	11.00		120.97	11.00	
−2*loglikelihood (*df*)	48284.55 (9)			48014.99 (34)			48020.29 (35)		
AIC	48302.55			48082.99			48090.29		
BIC	48363.24			48312.22			48326.26		
R^2_{LR}	.012			.056			.056		

Note. $k = 51$ (50 states and the District of Columbia); $n = 122$ days; $N = 51 * 122 = 6{,}222$. The results are consistent including or excluding the control variable (weekday dummies). Pseudo-R^2, R^2_{LR}, was calculated using $1 - \exp(-2/\mathrm{N} * [\mathrm{L_0} - \mathrm{L_M}])$ where L_0 refers to the log-likelihood for a null model without any fixed or random effects and L_M refers to the model of interest (Lang et al, 2019; Magee, 1990; Niessen & Lang, 2020).
[a] This component created convergence problem and is not estimated.
*** $p < .001$. ** $p < .01$. * $p < .05$.

Obtaining the Public's Emotions Using Deep Learning Models

For each WFH-related tweet, we obtain its emotion representations in the six emotion dimensions with six respective deep-learning-based classification models.[5] The six binary classifiers were constructed by fine-tuning six BERT models. BERT, or Bidirectional Encoder Representations for Transformers, is an open-source deep learning model that has shown state-of-the-art performance in a wide variety of natural language processing tasks, including text classifications, question answering, and named-entity recognition. (BERT; Devlin et al., 2018). BERT was architected as a multilayer bidirectional transformer encoder pretrained on a large corpus (including Wikipedia and the Toronto Book Corpus).

Fine-tuning BERT refers to the method of adding one additional output layer on top of the pretrained BERT structure to align with a specific task (see Figure 2). It is a method of transfer learning, which takes knowledge the neural network learned from one large (in data) and expensive (in training budget) task and applies that knowledge to a separate task (Pan & Yang, 2009). Thus, fine-tuning BERT requires relatively modest size training data to achieve satisfactory performance. This is practically helpful for social and psychology studies because the labels of text data (in our case the emotions) are usually costly to obtain at scale (Mohammad & Turney, 2010). The training data we used to fine-tune BERT are a dataset published for the "SemEval-2018" project (Mohammad et al, 2018). In the dataset, a tweet was manually classified by human raters as either "neutral or no emotion" or as "has emotion" for the six given emotions, respectively, which completely aligns with the classification tasks in our study.

Our fine-tuned BERT models achieved 86%–96% accuracy in predicting all of the six emotions on a balanced test set (for each emotion 50% with label 1 and 50% with label 0, such that a coin-flip model achieves 50% accuracy; Table 1). Across all the emotions on the balanced test datasets, the fine-tuned BERT models achieve 2%~27% higher accuracy than Linguistic Inquiry and Word Count (LIWC)-based SVMs and 16%~45% higher

[5] Mathematically, let x_i be the tweet text from the ith tweet, and represent a binary classifier for emotion e. Then the predicted label of x_i for emotion e becomes $\hat{y}_i^e = f^e(x_i)$, where $\hat{y}_i^e = 1$ indicates that tweet x_i was classified as positive in emotion e, and $\hat{y}_i^e = 0$ otherwise.

Table 6
Discontinuity Growth Models Results for Joy Assuming One-Day Delayed Effect

Variable	Model 1 Coef.	Model 1 Coef. *SE*	Model 1 *t*	Model 2 Coef.	Model 2 Coef. *SE*	Model 2 *t*	Model 3 Coef.	Model 3 Coef. *SE*	Model 3 *t*
Intercept π_{0i}	31.46	.47	67.20***	28.44	.72	39.55***	28.45	.72	39.24***
Slope π_{1i} (Time^{pre})				.15	.03	6.02***	.15	.03	6.04***
During order									
Relative intercept π_{2i} (TRANS1)				4.44	.65	6.81***	4.60	.67	6.83***
Relative slope π_{3i} (RECOV1)				−.33	.03	−11.64***	−.33	.03	−11.62***
After order									
Relative intercept π_{4i} (TRANS2)				−12.44	1.62	−7.68***	−12.36	1.66	−7.45***
Relative slope π_{5i} (RECOV2)				.03	.03	.94	.03	.03	.93
CASE π_{6i}							−.04	.03	−1.17
Control variables									
Weekday dummies	Controlled			Controlled			Controlled		
Random effects									
Preorder									
Intercept				10.67	3.27		11.03	3.32	
Slope (Time^{pre})				.01	.12		.01	.12	
During order									
Relative intercept (TRANS1)				1.49	1.22		2.41	1.55	
Relative slope (RECOV1)				.01	.09		.01	.10	
After order									
Relative intercept (TRANS2)				57.19	7.56		63.78	7.99	
Relative slope (RECOV2)				.02	.13		.02	.14	
CASE							.01	.09	
Residual				135.96	11.66		135.78	11.65	
−2*loglikelihood (*df*)	49072.62 (9)			48762.74 (34)			48765.88 (42)		
AIC	49090.62			48830.74			48849.88		
BIC	49151.30			49059.97			49133.05		
R^2_{LR}	.017			.067			.067		

Note. $k = 51$ (50 states and the District of Columbia); $n = 122$ days; $N = 51 * 122 = 6{,}222$. The results are consistent including or excluding the control variable (weekday dummies). Pseudo-R^2, R^2_{LR}, was calculated using $1 - \exp(-2/N * [L_0 - L_M])$ where L_0 refers to the log-likelihood for a null model without any fixed or random effects and L_M refers to the model of interest (Lang et al, 2019; Magee, 1990; Niessen & Lang, 2020).
$^{*} p < .05$. $^{**} p < .01$. $^{***} p < .001$.

accuracy than the NRC Emotion Lexicon (EmoLex) based models. This may be attributed to not only the exceptional understanding of the relations between words, but also the contextual information of the original sentences that BERT has understood. The tweet data with predicted emotions were then aggregated by taking the average on the state and date level such that each state–date combination represents an observation in the aggregated dataset.[6] We open sourced the code for constructing the deep learning models and a step-by-step description in the code repository.

Analytic Strategies

The discontinuity growth model (DGM) is appropriate for hypotheses testing for repeated measures at numerous times punctuated with discontinuities (e.g., Bliese & Lang, 2016; Bliese & Ployhart, 2002). The daily emotions toward WFH extracted from tweets using deep learning models are nested within states. We model stay-at-home orders as an event that happened during this period that can potentially cause discontinuities in the emotion trajectories. Emotions from March 01, 2020, to the order start date are modeled as the basal emotion trajectory using the basic growth model (see Table 2). The start and end of orders (i.e., TRANS parameters; Bliese et al., 2017) result in transits in the emotion trajectories, relative to the basal emotion trajectory if the order had not occurred. The relative trend of emotion trajectories during and after the order compared to that before the order is reflected as relative slopes in DGM (RECOV parameter; Bliese et al., 2017). Additionally, we included daily new COVID-19 confirmed case counts as a within-state predictor in DGM. The R code is provided in the code repository.

We started with the basic linear DGM where Level 1 change variables were added. The Level 1 change variables are preorder slope (*Time^{pre}*), intercept difference at the start (*TRANS1*) and end (*TRANS2*) of orders compared to preorder, relative slope during (*RECOV1*) and after (*RECOV2*) "stay-at-home" orders relative to the slope before the order, and the number of last day confirmed cases (*CASE*). The outcome variable (Y_{ti}) is the score for one emotion extracted and aggregated from tweets of state t on date

[6] Mathematically, the tweet emotion data were aggregated as follows. Let s represent a state and t represent a day, l_i be the location of tweet i and t_i be the date it was posted, then $Y^e_t = \frac{1}{n_s(t)} \sum_{l_i=s,t_i=t} \hat{y}^e_i * 100$. Y^e_{ts} can be regarded as the average number of tweets that show positive in emotion e per 100 tweets from the state on a given date.

Table 7
Discontinuity Growth Model Results for Fear Assuming One-Day Delayed Effect

Variable	Model 1 Coef.	Model 1 Coef. *SE*	Model 1 *t*	Model 2 Coef.	Model 2 Coef. *SE*	Model 2 *t*	Model 3 Coef.	Model 3 Coef. *SE*	Model 3 *t*
Preorder									
Intercept π_{0i}	4.28	.23	18.57***	4.32	.31	13.77***	4.34	.31	13.89***
Slope π_{1i} (Time^{pre})				.00	.01	−.80	−.01	.01	−.85
During order									
Relative intercept π_{2i} (TRANS1)				−1.27	.32	−4.00***	−1.31	.33	−3.92***
Relative slope π_{3i} (RECOV1)				.03	.01	2.33*	.03	.01	2.49*
After order									
Relative intercept π_{4i} (TRANS2)				.91	.40	2.27*	.94	.42	2.23*
Relative slope π_{5i} (RECOV2)				.01	.01	.78	.01	.01	.92
CASE π_{6i}							.00	.02	−.02
Control variables									
Weekday dummies	Controlled			Controlled			Controlled		
Random effects									
Preorder									
Intercept				.47	.69		.43	.65	
Slope (Time^{pre})				.00	.02		.00	.01	
During order									
Relative intercept (TRANS1)				.00	.03		.24	.49	
Relative slope (RECOV1)				.00	.00		.00	.01	
After order									
Relative intercept (TRANS2)				.26	.51		.09	.30	
Relative slope (RECOV2)				.00	.04		.00	.04	
CASE							.01	.11	
Residual				45.29	6.73		45.03	6.71	
−2*loglikelihood (*df*)	41826.10 (9)			41780.97 (34)			41782.50 (42)		
AIC	41844.10			41848.97			41866.50		
BIC	41904.79			42078.20			42149.67		
R^2_{LR}	.024			.035			.035		

Note. $k = 51$ (50 states and the District of Columbia); $n = 122$ days; $N = 51 * 122 = 6{,}222$. The results are consistent including or excluding the control variable (weekday dummies). Pseudo-R^2, R^2_{LR}, was calculated using $1 - \exp(-2/N * [L_0 - L_M])$ where L_0 refers to the log-likelihood for a null model without any fixed or random effects and L_M refers to the model of interest (Lang et al, 2019; Magee, 1990; Niessen & Lang, 2020).
* $p < .05$. ** $p < .01$. *** $p < .001$.

i, ranging from 0 to 100. We model each emotion using the following multilevel equation (Bliese & Lang, 2016):

$$Y_{ti} = \pi_{0i} + \pi_{1i}TIME^{pre}_{ti} + \pi_{2i}TRANS1_{ti} + \pi_{3i}RECOV1_{ti} + \pi_{4i}TRANS2_{ti} + \pi_{5i}RECOV2_{ti} + \pi_{6i}CASE_{ti} + e_{ti}$$

Additionally, we included the estimation of variance components (i.e., the amount of between-state variability) in the intercepts and slopes. This helps to account for preexisting between-state differences and understand whether the impacts of two events on the public's emotions vary across states (Lang & Bliese, 2009; McFarland et al, 2020). We also included weekdays as a within-state control variable because weekdays may be associated with different emotions toward WFH (e.g., Hülsheger et al, 2014; Stone et al, 2012).

Results

Table 3 shows the means, standard deviations, and intercorrelations for the six state-level emotions, last day confirmed cases, and the number of tweets divided by population. We tested random effects using log-likelihood ratio tests. Results indicated a significant amount of random variability in three emotions—anger (preorder slope, χ^2 *df*(2) = 12.36, $p = .002$), joy (preorder slope, χ^2 *df*(2) = 8.61, $p = .01$; during-order intercept, χ^2 *df*(3) = 10.61, $p = .01$; after-order intercept, χ^2 *df*(4) = 12.78, $p = .01$), and disgust (after-order slope, χ^2 *df*(6) = 23.18, $p = .017$).

Hypotheses Testing

The linear DGM results (Tables 4–9) showed that five of the six emotions (i.e., anger, disgust, joy, fear, and sadness) had significant transition effects at the beginning of orders, and three of the six emotions (i.e., anger, disgust, and joy) had significant transition effects at the lift of orders, relative to the preorder trajectories.[7] Hypothesis 1 was partially supported. Results revealed that the trajectories of three emotions (i.e., anger, disgust, and joy) during and after stay-at-home orders showed significant slope change relative to the preorder slopes, partially supporting Hypothesis 2.

[7] Following the recommendations of Bliese and Lang (2016) and Bliese and Ployhart (2002), we also examined the curvilinear DGMs. The fit indices indicated that the curve linear models did not fit the data better than the linear model for all six emotions. For parsimoniousness and simplicity of interpretation, we interpreted the results based on the basic linear models. Results of curve linear DGMs are reported in the supplemental material.

Table 8
Discontinuity Growth Model Results for Sadness Assuming One-Day Delayed Effect

Variable	Model 1			Model 2			Model 3		
	Coef.	Coef. *SE*	*t*	Coef.	Coef. *SE*	*t*	Coef.	Coef. *SE*	*t*
Preorder									
Intercept π_{0i}	26.99	.42	64.05***	28.48	.56	51.04***	28.48	.56	50.53***
Slope π_{1i} (Time^{pre})				−.01	.01	−1.15	−.01	.01	−.90
During order									
Relative intercept π_{2i} (TRANS1)				−2.57	.55	−4.70***	−2.53	.57	−4.46***
Relative slope π_{3i} (RECOV1)				.00	.02	.25	.00	.02	.22
After order									
Relative intercept π_{4i} (TRANS2)				−.76	.68	−1.11	−.81	.70	−1.15
Relative slope π_{5i} (RECOV2)				.03	.02	1.38	.03	.02	1.25
CASE π_{6i}							−.02	.03	−.58
Control variables									
Weekday dummies	Controlled			Controlled			Controlled		
Random effects									
Preorder									
Intercept				2.93	1.71		3.26	1.81	
Slope (Time^{pre})				.00	.03		.00	.03	
During order									
Relative intercept (TRANS1)				.07	.26		.63	.80	
Relative slope (RECOV1)				.00	.03		.00	.03	
After order									
Relative intercept (TRANS2)				.04	.20		.00	.00	
Relative slope (RECOV2)				.01	.08		.01	.08	
CASE							.00	.06	
Residual				128.41	11.33		128.25	11.32	
−2*loglikelihood (*df*)	48378.48 (9)			48334.96 (34)			48338.59 (42)		
AIC	48396.48			48402.96			48422.59		
BIC	48457.17			48632.20			48705.75		
R^2_{LR}	.013			.023			.023		

Note. $k = 51$ (50 states and the District of Columbia); $n = 122$ days; $N = 51 * 122 = 6{,}222$. The results are consistent including or excluding the control variable (weekday dummies). Pseudo-R^2, R^2_{LR} was calculated using $1 - \exp(-2/N * [L_0 - L_M])$ where L_0 refers to the log-likelihood for a null model without any fixed or random effects and L_M refers to the model of interest (Lang et al, 2019; Magee, 1990; Niessen & Lang, 2020).
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Research Question 1 explores how stay-at-home orders change the emotion trajectories for specific emotions. The trajectories of anger and disgust showed similar patterns (see Table 4 and 5). Trajectories of anger and disgust both had significant relative drops at the beginning of the order (anger: $\pi_{2i} = -4.35$, $SE = .49$, $p < .001$; disgust: $\pi_{2i} = -4.71$, $SE = .70$, $p < .001$). Relative to the preorder trajectories, anger dropped 4.35 points and disgust dropped 4.71 points when orders started. The during-order slopes of anger and disgust trajectories increased significantly relative to the preorder slopes (anger: $\pi_{3i} = .17$, $SE = .02$, $p < .001$; disgust: $\pi_{3i} = .22$, $SE = .04$, $p < .001$). The lift of stay-at-home orders was associated with large rises in the public's anger and disgust toward WFH (anger: $\pi_{4i} = 6.31$, $SE = .77$, $p < .001$; disgust: $\pi_{4i} = 8.96$, $SE = 1.20$, $p < .001$) relative to the preorder trajectory. Then the public's anger decreased at a steeper rate compared to the preorder slopes (anger: $\pi_{5i} = -.09$, $SE = .02$, $p < .001$), but the public's disgust did not show significant relative change (disgust: $\pi_{5i} = .00$, $SE = .03$, $p = .99$).

The trajectory of the public's joy toward WFH had a significant relative rise when stay-at-home orders started ($\pi_{2i} = 4.60$, $SE = .67$, $p < .001$), indicating when orders started the public's joy was 4.60 points higher than the expected value based on the preorder trajectory (see Table 6). The during-order slope decreased relative to the preorder slope ($\pi_{3i} = -.33$, $SE = .03$, $p < .001$). When the order ended, the trajectory of joy also showed a significant drop ($\pi_{4i} = -12.36$, $SE = 1.66$, $p < .001$) relative to the preorder trajectory. After the order, the slopes of joy trajectory did not significantly differ from the preorder slope ($\pi_{5i} = .03$, $SE = .03$, $p = .35$).

The trajectories of fear and sadness showed significant relative drops at the beginning of orders (fear: $\pi_{2i} = -1.31$, $SE = .33$, $p < .001$; sadness: $\pi_{2i} = -2.53$, $SE = .57$, $p < .001$; see Tables 7 and 8). The trajectory of fear also showed increased during-order slope ($\pi_{3i} = .03$, $SE = .01$, $p = .01$) and increased after-order transit relative to the preorder trajectory ($\pi_{4i} = .94$, $SE = .42$, $p = .03$). The trajectory of surprise did not show significant relative changes in intercepts or slopes (see Table 9). Figures 3 and 4 provide visualization of observed and predicted values for two example states.

Research Question 2 explored the relation between states' daily confirmed case counts and the relative changes in emotion trajectories before, during, and after stay-at-home orders. DGM results indicated that daily confirmed case counts did not significantly change any emotion trajectories.

Table 9
Discontinuity Growth Model Results for Surprise Assuming One-Day Delayed Effect

Variable	Model 1			Model 2			Model 3		
	Coef.	Coef. *SE*	*t*	Coef.	Coef. *SE*	*t*	Coef.	Coef. *SE*	*t*
Preorder									
Intercept π_{0i}	.65	.05	14.09***	.70	.06	11.82***	.70	.06	11.62***
Slope π_{1i} (Time^{pre})				.00	.00	–1.50	.00	.00	–1.60
During order									
Relative intercept π_{2i} (TRANS1)				.06	.06	.99	.05	.06	.72
Relative slope π_{3i} (RECOV1)				.00	.00	.14	.00	.00	.14
After order									
Relative intercept π_{4i} (TRANS2)				–.07	.07	–.93	–.07	.07	–.94
Relative slope π_{5i} (RECOV2)				.00	.00	1.42	.00	.00	1.39
CASE π_{6i}							.00	.00	1.37
Control variables									
Weekday dummies	Controlled			Controlled			Controlled		
Random effects									
Preorder									
Intercept				.00	.01		.00	.07	
Slope (Time^{pre})				.00	.00		.00	.00	
During order									
Relative intercept (TRANS1)				.00	.02		.00	.01	
Relative slope (RECOV1)				.00	.00		.00	.00	
After order									
Relative intercept (TRANS2)				.00	.02		.00	.00	
Relative slope (RECOV2)				.00	.00		.00	.00	
CASE							.00	.00	
Residual				1.81	1.35		1.81	1.34	
–2*loglikelihood (*df*)	21569.95 (9)			21598.94 (34)			21607.30 (42)		
AIC	21587.95			21666.94			21691.30		
BIC	21648.64			21896.17			21974.46		
R^2_{LR}	.002			.004			.004		

Note. $k = 51$ (50 states and the District of Columbia); $n = 122$ days; $N = 51 * 122 = 6{,}222$. The results are consistent including or excluding the control variable (weekday dummies). Pseudo-R^2, R^2_{LR}, was calculated using $1 - \exp(-2/N * [L_0 - L_M])$ where L_0 refers to the log-likelihood for a null model without any fixed or random effects and L_M refers to the model of interest (Lang et al, 2019; Magee, 1990; Niessen & Lang, 2020).
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

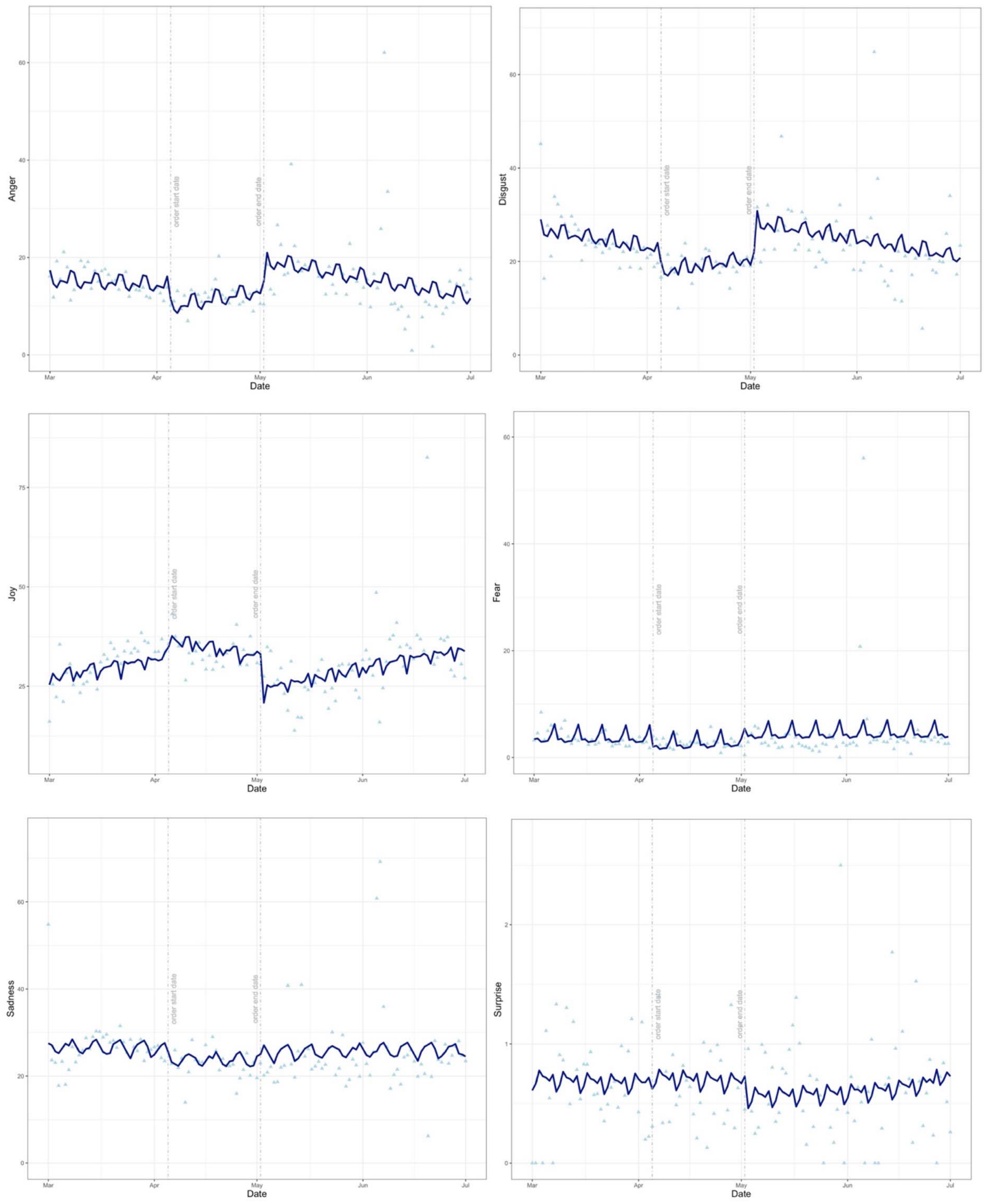
Discussion

Based on EST, we examined the influences of stay-at-home orders and COVID-19 case counts on the trajectories of the public's emotions toward WFH on social media over four months. Our findings extended EST by showing that environmental events (i.e., stay-at-home orders) change the public's emotions and have both transition effects (Bliese et al., 2017) and recovery effects (i.e., relative slope during and after order compared to preorder slope; Bliese et al., 2017), such as the change in slopes of emotion trajectories. Specifically, the public's anger, disgust, fear, and sadness toward WFH showed large declines when stay-at-home orders started (and a large immediate rise in joy); whereas the public's anger and disgust showed a large rise when the orders ended (and a large immediate decline in joy). The slopes of the emotion trajectories during and after the order also indicated the effects of the order diminished as its novelty and disruption decreased over time. The public's anger and disgust toward WFH increased (i.e., returned to baseline) after the immediate decline, whereas the public's joy toward WFH decreased (i.e., returned to baseline) after the immediate rise. Moreover, certain emotions (e.g., anger, disgust, and joy) surpassed preorder levels. It is possible that when approaching the later stages of stay-at-home orders, the public's emotions are influenced by uncertainty over reopening, such as potential virus exposure, adapting to new organization rules related to COVID-19, and high work–family interface due to school closure (Chung et al., 2020).

The current study sheds light on the temporal dynamics of how environmental events (i.e., stay-at-home orders) influence the public's emotions. Specifically, stay-at-home orders demonstrate strong impacts (i.e., significant transits) on the public's anger, disgust, and joy toward WFH immediately after the order implementation. However, the impacts fade over time. These findings underscore the importance of repeated measures in revealing a lived and accurate reflection of event effects. Nonetheless, considering the burdensome and high cost of repeated survey designs (e.g., experience sampling method, ESM; Gabriel et al., 2019), our approach of investigating emotional reaction to environmental events has methodological implications. Machine learning techniques demonstrate high accuracy in estimating many constructs of interest to organizations, for example, personality (e.g., Bleidorn & Hopwood, 2018) and organization culture (e.g., Li et al, 2020). This study demonstrates that state-of-the-art deep learning techniques help us understand the temporal dynamics of the public's emotions and provide

Figure 3

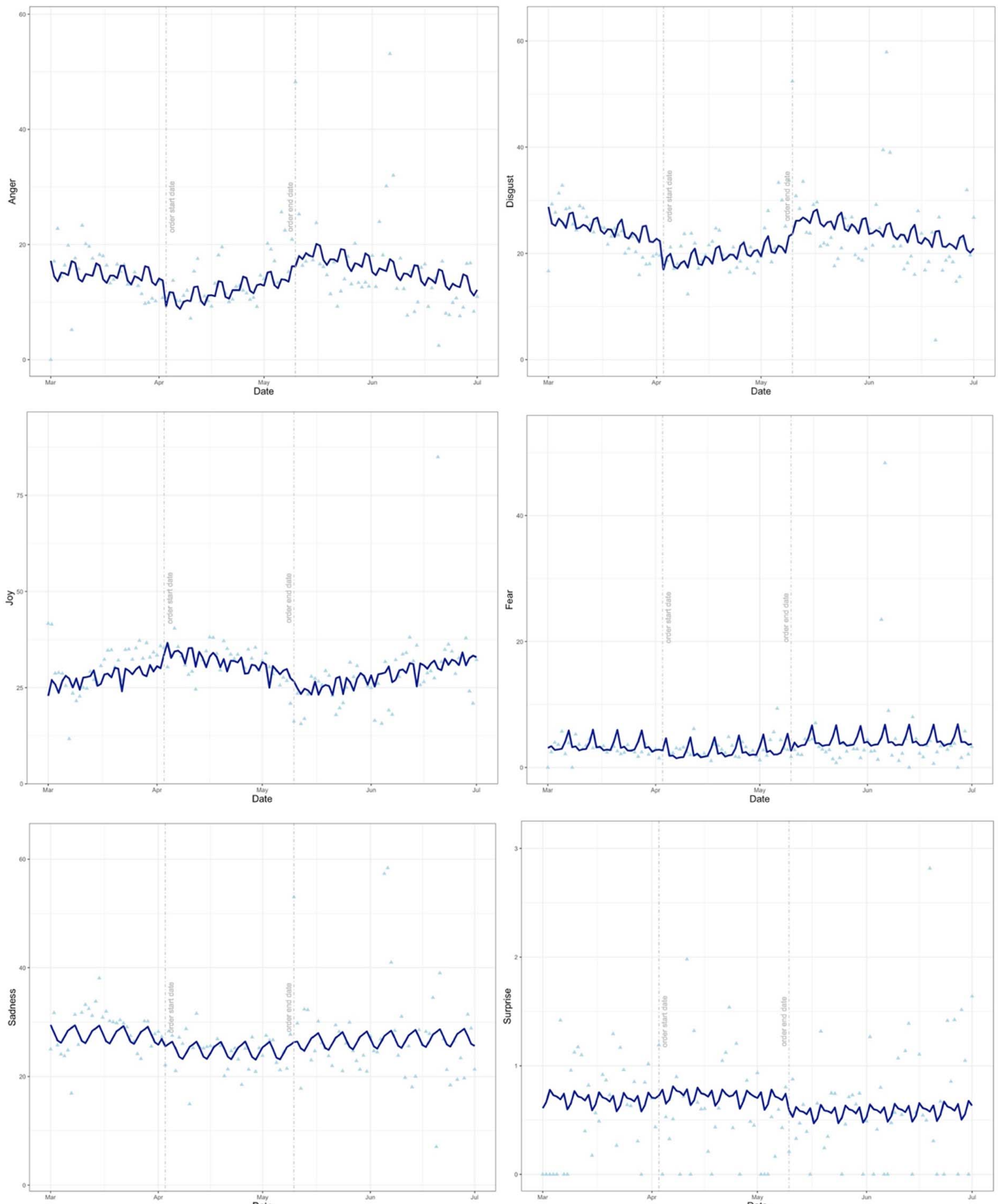
The Trajectories of the Public's Six Emotions Toward Working From Home in Florida Modeled With a Discontinuity Growth Model



Note. Each dot represents the public's surprise score extracted from tweets each day in Florida between March 01, 2020, and July 01, 2020. Each solid line represents the predicted emotion for Florida from the respective discontinuity growth model (DGM) including all predictors and random effects (Model 3 in Tables 4–9). The predicted values are cyclic because we included weekday dummies as control variables in DGM models. See the online article for the color version of this figure.

Figure 4

The Trajectories of the Public's Six Emotions Toward Working From Home in Pennsylvania Modeled With a Discontinuity Growth Model



Note. Each dot represents the public's surprise score extracted from tweets each day in Pennsylvania between March 01, 2020, and July 01, 2020. Each solid line represents the predicted emotion for Pennsylvania from the respective discontinuity growth model (DGM) including all predictors and random effects (Model 3 in Tables 4–9). The predicted values are cyclic because we included weekday dummies as control variables in DGM models. See the online article for the color version of this figure.

evidence for the emotions obtained using fine-tuned BERT models. With 1.56 million tweets, our fine-tuned BERT model showed advantages in model accuracy over traditional techniques (i.e., LIWC and Emolex). Thus, deep learning techniques complement our traditional methods (e.g., daily dairy or ESM) and provide another approach to examine the temporal dynamics of the public's attitudes or behaviors.

This study further extends the research on the aggregate effects of macrolevel events (e.g., Shoss & Penney, 2012). By analyzing the public's emotions toward WFH, we extend the application of EST into a broad, societal, macrolevel context. In testing the macrolevel effects of stay-at-home orders and COVID-19 case counts, we add to a limited but clearly important line of research that, taken together, has offered insight into multilevel effects of the COVID-19 pandemic (e.g., Probst et al., 2020; Shoss et al., 2020). These results may inform governments and organizations of the public's emotional reactions when issuing relevant policies. Moreover, this study extends EST by showing that the lifting of an event also has impacts on emotions.

With regard to the nonsignificant effect of COVID-19 case counts, it is likely that the novelty of a state's number of daily new confirmed cases counts decays over time, and its criticality declines or gets distorted due to misinformation sharing and social media fatigue during the COVID-19 pandemic (Islam et al., 2020). The confirmed cases may also depend on the different test strategies used in each state, and this potential error source may partially explain the nonsignificant effect of COVID-19 case counts. The public may also get used to the increasing confirmed cases as people adapt to stressors over time (Matthews et al., 2014).

During the COVID19 pandemic, many large organizations allowed employees to work from home until summer 2021 (e.g., Facebook and Google); some even offered the option of WFH forever (e.g., Twitter). However, it remains unclear to what extent WFH is beneficial for emotions and how long the positive impacts last, especially when considering aggregate reactions that include not only the emotions of the employees themselves but also the emotions of others in society who may be reacting to these decisions. Practically, we suggest that issuing stay-at-home orders has been accompanied with a number of immediate emotional benefits, which could largely be attributed to the advantages of WFH during the COVID-19 pandemic (Bloom, 2014). However, these emotional benefits seem to fade over time. This suggests that perhaps it is worthwhile for organizations to provide sustained support to WFH employees.

Like any study, ours has limitations. Our analysis of the public's emotions toward WFH was limited to tweets in the United States. Because Twitter users may not represent the full population (Tufekci, 2014), our findings may not be generalizable to segments of the public who do not use Twitter. Research has shown that people who are less sociable, extraverted, emotionally stable, and those who are seeking cognitive stimulation showed a preference for Twitter (Hughes et al., 2012). The link between personality and Twitter preference may be attributed to Twitter's greater user anonymity and emphasis on a user's own thoughts and feelings (Hughes et al., 2012), which is important to emotional expressions and information dissemination, particularly during public crises (e.g., Dubey & Tripathi, 2020; Fu et al., 2016). As such, we deemed Twitter appropriate for our research purpose. However, future research could replicate our findings using a more representative sample from other social media. Another limitation is that we used state-level data. The public's emotion may be more sensitive to county-level policies or confirmed cases, leaving us a conservative examination of the hypotheses. However, conducting the study at county level requires specific location information, which is unavailable for most Twitter users (65% of tweets). Thus, we conducted the study at state level to increase data representativeness.

In short, this study examined the trajectories of the public's emotions toward WFH on social media during the COVID-19 pandemic. The issuing and end of stay-at-home orders significantly affected the trajectories of the public's emotions toward WFH, albeit different impacts were observed for specific discrete emotions.

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