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REGULAR ARTICLE

What Drives Preventive Health Behavior During a Global Pandemic? Emotion and Worry

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Abstract

Background & Purpose Primary prevention of COVID-19 has focused on encouraging compliance with specific behaviors that restrict contagion. This investigation sought to characterize engagement in these behaviors in U.S. adults early during the pandemic and to build explanatory models of the psychological processes that drive them.

Methods US adults were recruited through Qualtrics Research Panels (N = 324; 55% female; M_{age} = 50.91, SD = 15.98) and completed 10 days of online reports of emotion, COVID-19 perceived susceptibility and worry, and recommended behaviors (social distancing, hand washing, etc.). Factor analysis revealed behaviors loaded on two factors suggesting distinct motivational orientations: approach and avoidance.

Results Changes in approach and avoidance behaviors over the 10 days indicated large individual differences consistent with three types of participants. Discrete emotions, including fear, guilt/shame, and happiness were associated with more recommended behaviors. Fear and COVID-19 worry indirectly influenced each other to facilitate more behavioral engagement. While emotions and worry strongly predicted individual differences in behavior across the 10 days, they did not predict as well why behaviors occurred on one day versus another.

Conclusions These findings suggest how daily affective processes motivate behavior, improving the understanding of compliance and efforts to target behaviors as primary prevention of disease.

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> Now is the time, if ever there was one… for us to care selflessly about one another.
>
> -Dr. Anthony Fauci, May, 2020

As of December 20, 2020, the novel coronavirus known as COVID-19 had infected 75 million and claimed nearly 1.6 million lives across 216 countries [1, 2]. World Health Organization (WHO, 2020) recommendations for reducing the spread of COVID-19 have focused on engaging in personal preventive health behaviors (e.g., hand washing, social distancing, etc.). However, despite evidence that individuals recognized the increasing threat of COVID-19, the lack of certainty and the increase of fear did not necessarily result in an increase in preventive behaviors [3] but rather an increase in psychological distress [4] and aggressive spread of COVID-19.

Given the critical importance of preventive health behaviors in mitigating the spread of COVID-19, there is a dire need to apply social and behavioral science [5] to understand patterns of behavioral engagement over time in daily life. To date, research on COVID-19 has captured a moment in time via survey, documenting reports of engagement in behaviors and considering the influence of emotion and cognitions about COVID-19 on health behaviors separately [4, 6]. However, emotions and cognitions are intrinsically intertwined [7]. Hence, the present study had two aims: (1) To characterize engagement in recommended COVID-19 preventive health behavior in daily life over time, and (2) To build explanatory models that capture interactions among COVID-19-related emotion, health cognitions, and preventive behaviors by applying methodology sensitive to within-and between-person variation.

According to functional theories of emotion, discrete emotions–such as fear, anger, or disgust–evolved to address specific environmental threats, challenges, and opportunities [8–10]. Within this framework, specific contexts elicit specific emotional responses that facilitate physiological, cognitive, and behavioral action to promote survival. In the context of a global pandemic, discrete emotions may play an important role in momentary behavioral efforts to avoid contracting the disease (c.f. fear's relevance in threat detection and disgust's relevance in contamination avoidance). Other emotions like guilt/shame or happiness may also be important given that COVID-19-related public health messages heavily focused on the impact of one's actions on others (e.g., "Stay Home. Save Lives" [11]).

Past research has examined the role of discrete emotions in health behaviors [12, 13]. Generally, positive emotions, such as joy or happiness, are associated with approach behaviors–those motivationally oriented towards rewards–including related to care of oneself [14] and others [15]. For instance, positive emotions may drive selfless health behaviors such as organ donation [16]. In contrast, fear is generally associated with behavior motivationally oriented towards avoidance of aversive outcomes [10], although this can manifest behaviorally in diverse ways. For example, in some contexts, elevated fear positively predicts health screening (e.g., prostate cancer: [17]), but in others, fear negatively predicts treatment information seeking [18]. Guilt and shame operate to support social norms and to guide behavior in the service of expectations that *could* facilitate health behavior through a sense of responsibility [19].

Health behavior models posit that health cognitions, such as *perceived susceptibility*, or beliefs about one's likelihood of encountering or being susceptible to harm [20], are a dominant factor in health behavior [21]. In the context of the SARS pandemic, higher perceived susceptibility was associated with reports of engaging in more protective behaviors [22]. Data collected during the COVID-19 pandemic are consistent with these earlier findings [23]. In addition, worry about disease, or an individual's *affective* concern about developing a disease, is a reliable predictor of engagement in health behavior [24]. Disease worry is typically not included in health behavior theories (for an exception see [25]). However, worry may be relevant in the context of COVID-19 given the substantial ambiguity about risk factors and disease prognosis. Indeed, research on worry-related cognition (e.g., rumination, negative repetitive thinking: [26]) in clinical contexts has suggested that worry about phenomena in daily life is largely driven by ambiguity around perceived threats [27].

Finally, there is a growing body of research examining how discrete emotions influence cognition that may also be relevant to the COVID-19 crisis. In particular, dominant theories suggest that emotions influence judgments and decision-making, that in turn *could* influence behavioral outcomes (e.g., [8, 28, 29]). For example, fear may increase perceived severity of a risk, which in turn increases willingness to get vaccinated [30]. In contrast, cognitions can also generate affective responses which then motivate behavior like health screening [31]. However, this prior research has been limited to highly controlled experiments in the lab and/or a focus on one specific emotion within a specific context. Thus, although the interactive effects of cognition and emotion are relevant to understanding health behavior during COVID-19, there is a gap in understanding how this could manifest in conditions of uncertainty in daily life.

Current Investigation

To investigate the psychological processes driving preventive health behaviors specific to the COVID-19 pandemic, we collected data from a national sample of U.S. adults during the period of March 24–April 9, 2020 (the onset of stay-at-home orders in the US) as part of a larger parent investigation ([32] under review: https://psyarxiv.com/hukyv/) testing a math intervention to improve understanding of COVID-19 health statistics. We employed an experience sampling diary to index emotions, COVID-19 health cognitions, and behavior in daily life over 10 days. Unique benefits of intensive sampling include modeling dynamic processes underlying behavioral enactment occurring within an individual over time [33].

Data for this investigation were extracted from the control sample of the parent study who received *no* math intervention, and the current investigation constitutes the second of two investigations from these dataset. Note that the first manuscript from the parent study tested the effect of the math intervention on COVID-19-related math problem solving and explored its effect on health cognitions, emotions, and behaviors as a secondary goal. Health behaviors investigated here were recommended at the U.S. federal and state level and accompanied stay-at-home orders (e.g., social distancing, working at home, hand washing, etc.). The emphasis in public health messaging during this period was to "flatten the curve," or slow the spread of COVID-19. Outbreaks were typically in urban, densely populated areas (e.g., New York [34]).

We employed a discrete emotion framework to investigate associations between emotions and COVID-19-specific cognitions and behavior. Research investigating discrete emotional responses (e.g., fear versus anger and perceived risk following terrorist attacks on November 9, 2001 [35]) provided insight on how individuals reacted to highly aversive events, including national threats. However, no research has investigated discrete emotions collectively, as opposed to fear in isolation, while employing daily sampling during a health crisis. Accordingly, we applied an *exploratory* or *non-confirmatory* approach throughout the investigation [36].

Our first aim was to characterize how COVID-19 preventive behaviors are enacted in daily life. Prior surveys have indicated variability in preventive behavior use [3, 37], but none have evaluated how these specific behaviors operate in relation to each other within and between people. Our second aim was to build explanatory models exploring how emotion and COVID-19 cognition influence behavioral enactment in real-time within each day and from day to day. We also explored specific mediation and moderation models, based on prior research suggesting transactional interplay between emotion and cognition broadly [29], as well as the interacting components of fear and anger with risk perception [35]. For example, prior research has suggested an inverse transactional response between anger and risk perception: as anger increases, perceived risk decreases [8, 35]. Conversely, fear has a positive association with risk perception, which given the clear association between fear and avoidance, would presumably contribute to greater avoidance behavior. There is also prior evidence suggesting a positive association between perceived susceptibility and preventive behaviors broadly [21, 38]. However, because COVID-19 is an unprecedented, global challenge, the extent to which prior research can inform current predictions and hypotheses is unclear [39]. Indeed, experience sampling methodology captures *reports in the midst of daily living*, increasing sensitivity to contextual parameters, greatly influencing how emotion and cognition drive behavior [40, 41]. Accordingly, we did not make a priori hypotheses, but instead relied broadly on theories of discrete emotion and health behavior to guide our exploratory, non-confirmatory analytic frame, consistent with recent recommendations [36]. No prior research has evaluated associations among discrete emotions, health cognitions, and behavior simultaneously via daily sampling, particularly not with the degree of uncertainty and dynamic nature of this crisis context.

Method

Participants

U.S. adults, over 18 and fluent in English, were recruited via Qualtrics panels for the parent project investigating the influence of a math intervention on COVID-19 risk. Recruitment was stratified by age, gender, and education to match the distribution in the U.S. (note the lowest level of education was under-represented in the final sample). The investigation was approved by the Kent State University Institutional Review Board, and all participants provided informed consent. Of the 627 participants from the parent project who completed two or more diaries, n = 324 were in the control condition and comprise the sample here.

The sample mean age was 50.91, SD = 15.98, range 18–82, and 55% female. As expected, educational attainment was stratified across the sample: 26% had a high school diploma or less, 27% had at least some college education, and 37% had graduated from college. The majority of participants (79%) were White (7% Black; 5% Asian, 4% multi-racial, 1% Native American/Alaskan Native, 4% other or did not report) and largely non-Hispanic (98%). Based on zip codes, individuals were assigned a score reflecting population density and geography of their residence [42]. Fifty-three percent of the sample lived in large metropolitan areas (population: >/= 1 million); 22% lived in small metropolitan areas (population: 250,000–1 million); 13% lived in metro-adjacent areas (population: 20,000–250,000); and the remaining 11% lived in rural areas (population: 2,500–20,000, with two participants in fully rural areas with populations less than 2,500). Median annual household income was between $50,000.00–74,999.00, with 10% of participants reporting income under $15,000 and 20% reporting income over $75,000. Most participants were employed (51%: self-employed or working for wages) or retired (29%). Eight percent of participants reported being out of work, 3% were students, and 8% described themselves as parents at home.

Procedure

Details on the parent study design and procedures are reported in [32] under review (https://psyarxiv.com/hukyv/ and at https://osf.io/9hc7d). Of the n = 324 participants who completed the diary, n = 315 (97%) participants completed demographic questionnaires and an index of trait anxiety during one online baseline session. All 324 participants were also shown case fatality information relating to global COVID-19 and U.S. flu deaths and number of total cases (CDC, 2020), and solved three COVID-related math problems. These participants received no guidance, support, or feedback on the problems. After completing the online session, participants were invited to respond to 10 days of daily diary prompts within Qualtrics. Diaries were sent each day, late afternoon or early evening, and included the same set of questions about emotional experience, health cognition, and behaviors each day. Commonly recommended attention checks were embedded in all assessments [43] (e.g., participants were asked to make a specific response such as "*please select C*"). Diary entries with failed attention checks were excluded from analyses. After the 10-day sampling period, participants were compensated. Only demographics, trait anxiety, and diary data were included in this investigation.

Materials

Trait Anxiety

Participants trait items from the State-Trait Anxiety Inventory [44]. Internal consistency was adequate, $\alpha = 0.76$, and mean = 45.45, $SD = 7.66$, between non-clinical and clinical levels [45].

Daily Diary

Over ten consecutive days, participants were prompted each day to report current emotional experiences, cognitions about COVID-19 (perceived susceptibility and worry) and report yes/no whether they engaged in each of a list of recommended health behaviors that day. Items were randomized to minimize order effects. Reliability for all diary emotion and cognition indices was assessed based on recommendations [35] including within- (R_C) and between- (R_{KF}) person reliability. Daily diary compliance was good at 82%, $M = 8.2$, $SD = 2.55$, range 2–10, suggesting that analyses would include ~2,583 diary reports across $n = 324$ people. Given the range in compliance, we completed sensitivity analyses using a more exclusive sample of $n = 229$ individuals with at least 6 or more diary responses, within 1 sd of the mean. The main effect results were entirely consistent with the $n = 324$ sample that included individuals within 2 sd so we maintained the larger sample.

Emotion

First in each diary, participants were prompted to rate "how they were feeling now" on a list of emotion words presented in random order using a 1–5 Likert scale. Discrete emotions of anger ($R_{kf} = 0.92$), fear ($R_{kf} = 0.92$), sadness ($R_{kf} = 0.99$), and disgust ($R_{kf} = 0.93$) were single item ratings, whereas guilt and shame were aggregated as one index of self-conscious emotion ($R_{kf} = 0.98$; $R_c = 0.44$), and happiness and joy were aggregated as one index of positive emotion ($R_{kf} = 0.99$; $R_c = 0.69$). These discrete emotions were selected based on dominant theory and evidence supporting unique action and motivational tendencies [8–10, 12].

Preventive health behaviors

Participants reported enactment of 13 behaviors (e.g., social distancing, hand washing, wearing masks) recommended by public health experts and agencies as yes/no each day. We performed a multilevel exploratory factor analysis to identify groups of behaviors that clustered together instead of assuming a single dimension (see supplemental materials, Tables S1–S3). Ten of the 13 behaviors loaded onto two primary factors corresponding to avoidant- and approach-related motivational orientation [46]. Specifically, avoiding public transportation, avoiding people/social distancing, avoiding public spaces, working from home, washing hands, and covering coughs loaded onto one factor labeled, "Avoidant Behaviors," because they facilitate direct avoidance of disease or contagion. In contrast, buying cleaning supplies, storing extra food, speaking to a physician, and wearing a mask loaded onto one factor labeled, "Approach Behaviors," because they facilitate approach toward safety and security. Additional behaviors assessed, (i.e., looking up/sharing information about COVID-19) loaded onto their own factor and were excluded from the primary analyses. However, growth modeling indicating their relative frequency and distribution across the sample is presented in the supplemental materials (Tables S9-S10).

For each factor, we summed the number of behaviors endorsed each day so that each participant had a daily score of avoidant (0–6), and approach behaviors (0–4). On average, individuals reported engaging in more than four avoidance behaviors daily and less than one approach behavior daily (Table 1). This could be due to differences the number of behaviors measured and opportunity as data collection occurred when many individuals were home due to stay-at-home orders, avoidance could be easier to accomplish than approach behaviors. Although behavioral outcome data derived during sampling can be non-normal due to over-dispersion, the distributions here met assumptions of normality so no transformations were applied.

COVID-19 cognition

We indexed perceptions of susceptibility (or likelihood of contracting COVID-19) and perceived worry about COVID-19 daily. *COVID-19 Susceptibility* (adapted from [47]) was assessed by participants rating the likelihood of developing COVID-19 with two absolute cognitive risk items (i.e., risk for oneself and close others). These items were highly correlated at both the within- ($r = 0.66$, 95% CI [.64, .68]) and between-person ($r = 0.81$, 95% CI [.77, .84]) levels and were averaged. To reduce potential bias in risk perceptions, participants could select "I don't know" for the two

Table 1 Zero-order correlations across primary study variables (n = 324 =)

	M(*SD*)	1.	2	3	4	5	6	7	8	9	10	11	12
1. Age	50.91 (15.98)	–											
2. Trait Anxiety	45.45 (7.66)	**.30**	–										
3. Urban-Rural	2.15 (1.72)	.11	.10	–									
4. COVID-19 Susceptibility	2.72 (1.08)	**−.14**	**.35**	.09	–								
5. COVID-19 Worry	2.62 (0.87)	**−.13**	**.33**	−.02	**.65**	–							
6. Approach Behavior	0.84 (0.89)	**−.20**	.11	−.11	.08	**.19**	–						
7. Avoidance Behavior	4.24 (1.16)	−.09	.10	**−.21**	**.15**	**.36**	**.33**	–					
8. Anger	1.83 (1.03)	**−.13**	**.30**	−.04	**.38**	**.41**	**.27**	**.14**	–				
9. Fear	2.29 (1.20)	**−.13**	**.43**	−.05	**.41**	**.69**	**.31**	**.35**	**.69**	–			
10. Disgust	1.78 (1.01)	−.10	**.31**	−.02	**.37**	**.42**	**.26**	**.13**	**.89**	**.68**	–		
11. Sadness	2.16 (1.06)	−.11	**.45**	−.05	**.37**	**.55**	**.28**	**.26**	**.73**	**.82**	**.72**	–	
12. Guilt/Shame	1.33 (0.67)	−.33	**.37**	−.05	**.32**	**.28**	**.46**	.11	**.57**	**.48**	**.57**	**.54**	–
13. Happiness	2.24 (0.93)	−.02	**-.38**	.10	**−.21**	**−.32**	.10	−.03	**−.29**	**−.36**	**−.30**	**−.37**	−.02

NOTE: Correlations from diary variables are based on person means; correlations in bold are significant at p < .05; Urban population centers are coded as 1 to most rural coded as 9.

susceptibility items; "I don't know" reports (14% of 2,583) were not included in analyses. Failure to include a "don't know" option leads to lower reported perceived risk than when a "don't know" option is not included [48]. *COVID-19 Worry* (adapted from [49]) was assessed with two items (i.e., worry about themselves or their family/ friends being infected with COVID-19). These items were highly correlated at the within- (r = 0.58, 95% CI [.55, .60]) and between-person (r = 0.80, 95% CI [.76, .84]) levels and were averaged.

Data Analytic Strategy

First, to characterize variability in the use of recommended preventive health behaviors over time, we applied latent growth mixture models (LGMM), which is an exploratory clustering technique that allows for qualitatively different profiles of growth within a sample. This approach provides richer information about how behaviors are enacted within samples as compared to descriptive statistics derived by the central tendency. Analysis of variance (ANOVA) for continuous outcomes and chi-square tests of independence for dichotomous outcomes were conducted to identify any meaningful differences in behavioral enactment profiles by key demographic and trait variables. Post-hoc pairwise comparisons were conducted for each model with a Bonferroni correction within each demographic/trait and behavior combination (e.g., sex and avoidant behaviors).

Second, we built explanatory models that captured real-time associations between psychological factors and behavioral engagement. In all analyses, we evaluated each behavior factor independently (i.e., avoidant vs. approach) and considered key demographic characteristics. We began by examining zero-order correlations for all key variables using person means extracted from the daily diaries. Then, we applied linear mixed-effects models to examine the role of within- versus between-person variability in emotion and cognition contributing to behavioral enactment. We applied a step-wise approach, examining emotion first then adding COVID-19 cognition, in models testing for concurrent effects, as well as models applying a lagged framework (predicting the next day's report of behaviors while covarying the current day) in order to test for processes uniquely contributing to day-to-day variability in behaviors. A false discovery rate correction was applied within each model framework to reduce risk of Type 1 error. Specifically, we corrected the threshold for significance by dividing the conventional threshold $p < .05$ by the number of incremental models tested per outcome. Each outcome was testing by 3 incremental models so the threshold of $p < .0.017$ was used. Except, we also tested an additional moderation in the model testing day-to-day change in approach behaviors and thus $p < .0.013$ was used.

Finally, we explored mediation and moderation models suggested by prior research. Specifically, we investigated whether COVID-19 worry or COVID-19 susceptibility *mediated* or was mediated by fear, anger, and happiness in relation to behavior. Due to diary data being nested, multilevel structural equation modeling was conducted to decompose the within-person and between-person effects and their standardization. We also explored specific *moderation* effects. Given considerable evidence linking fear to avoidance motivation, and anger to approach motivation [50], we explored whether fear might increase the impact of COVID-19 susceptibility on avoidance behaviors, while anger might increase the impact on approach behaviors.

Results

Descriptive Analysis and Associations Between all Key Study Variables

Table 1 presents descriptive statistics using person-means for all diary variables and bivariate correlations among key study variables. There were positive associations between trait anxiety, COVID-19 perceived susceptibility and worry, and *all* negative emotions. In addition, there was an association between geography and avoidance behaviors, such that individuals in more densely populated regions reported more avoidance behavior. Despite most health messaging emphasizing risk to older adults, age was negatively associated with COVID-19 perceived susceptibility, worry, and report of approach behaviors. There were strong associations amongst *all* negative emotion variables (including inverse associations with happiness). Approach and avoidance behavior had a moderate positive association with each other and with negative emotions including fear, anger, disgust, and sadness (with guilt/shame associated with approach behaviors only, and happiness with neither).

Latent Growth Modelling of Behavioral Enactment over Time

LGMM was applied to detect variable trajectories of behavioral enactment across the sample over time (see supplemental materials, p S19-21). For both avoidance and approach behaviors, three profiles were selected with one profile capturing over two-thirds of the sample (Figure 1). Means and standard deviations of intercept and slope factors in each model are in Table 2. Time was scaled so that 0 was the first day of the diary and 9 was the tenth and last day, such that intercepts represented estimated scores on the first day of the diary and slopes represent estimated change across one day of the diary. Profiles differed by intercepts with only minor differences in slopes, suggesting few participants with consistent change over time.

We compared participant demographic and trait differences across profiles using ANOVA (see Table 2). There were no differences in trajectory of avoidant behaviors for any demographic or trait variables. For approach behaviors, significant differences were found for age, race, ethnicity, and employment. Participants reporting the *most* approach behaviors at the start and

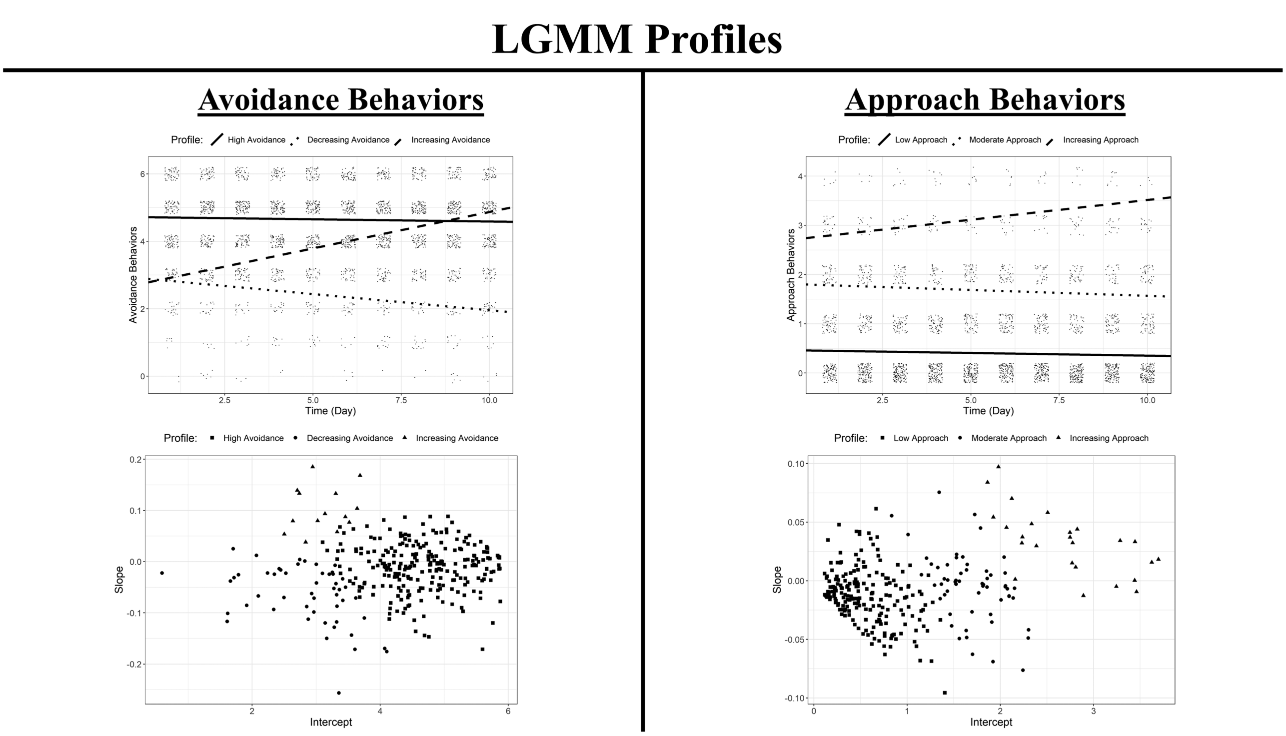

Figure 1 Graphs of the final latent growth mixture models (LGMM) for avoidance and approach behaviors. The top graphs display the profile mean growth curves superimposed on a jittered scatter plot of the behaviors across the 10 days of the diary. The bottom graphs display the intercept and slope factor scores by their modal profile assignment.

Table 2 Descriptive statistics and demographic/trait differences across profiles of behavioral engagement

Statistic	Avoidance Behaviors				Approach Behaviors			
	Full Sample	**High Avoid-ance**	**Decreasing Avoidance**	**Increasing Avoidance**	**Full Sample**	**Low Approach**	**Moderate Approach**	**Increasing Approach**
Subsample Size	324	259	51	14	324	240	59	25
Intercept Mean	4.313	4.718	2.916	2.712	0.883	0.464	1.808	2.715
Slope Mean	−0.014	−0.013	−0.096	0.216	−0.006	−0.011	−0.024	0.080
Intercept *SD*	1.048	0.706	0.706	0.706	0.814	0.359	0.359	0.359
Slope *SD*	0.084	0.055	0.055	0.055	0.045	0.032	0.032	0.032
Demographic/Trait	**Omnibus Test**	**High Avoidance**	**Decreasing Avoidance**	**Increasing Avoidance**	**Omnibus Test**	**Low Approach**	**Moderate Approach**	**Increasing Approach**
Female (Sex)	$\chi^2 = 5.02$	.585	.431	.429	$\chi^2 = 4.24$	.588	.466	.440
White (Race)	$\chi^2 = 2.72$	.795	.843	.643	$\chi^2 = 9.69$**	.838[a]	.678[b]	.680[a,b]
Hispanic (Ethnicity)	$\chi^2 = 2.62$	.027	.000	.071	$\chi^2 = 4.03$	.017	.034	.080
Employed	$\chi^2 = 0.02$	.517	.510	.500	$\chi^2 = 14.04$***	.454[a]	.678[b]	.720[b]
Age	$F = 0.03$	50.9	50.4	50.6	$F = 7.36$***	52.7[a]	47.1[b]	42.0[b]
Education	$F = 0.15$	2.65	2.65	2.86	$F = 0.59$	2.67	2.53	2.88
Income	$F = 0.40$	63,400	62,500	75,700	$F = 5.90$**	59,100[a]	69,500[a]	94,300[b]
Rural (Geography)	$F = 1.61$	2.07	2.54	1.93	$F = 1.03$	2.22	1.89	1.90
Anxiety	$F = 2.72$	45.9	44.7	41.4	$F = 2.37$	45.1	46.0	48.5

Note. The final model selected for both avoidant and approach behaviors had equal variances (i.e., *SD*s) across profiles. Different superscripts across means or proportions in the same section and row combination indicate significant pairwise differences (a v. b). F = omnibus analysis of variance test; χ^2 = omnibus chi-square test of independence; * = $p < .05$; ** = $p < .01$; *** = $p < .001$.

throughout were more likely to be young, and/or racial minorities, and/or identify as Hispanic, and/or hold high-income jobs. Participants reporting the fewest approach behaviors at the start and throughout the diary were more likely to be older and/or White and/or not working.

Modelling Discrete Emotion and Cognition in Daily Behavioral Enactment

To build explanatory models that capture real-time associations between psychological factors and behavioral engagement, we ran a total of four linear-mixed effects models. We applied an incremental approach to understand individual and aggregate associations between emotion and COVID-19 cognition as associated with both concurrent reports of avoidant or approach behaviors and future, or next-day, reports (using a lagged model framework). In the lagged models, we included both behavioral factors to explore how behavioral enactment one day might impact behaviors on the next. Finally, given the range of diary compliance, we did consider whether diary compliance was a potential moderator of effects, but models yielded no evidence of moderation, thus compliance was maintained as a covariate. All equations, and analytic details are provided in supplemental materials, (Tables S11–S13). Effects that did not survive the false discovery rate (FDR) correction are explicitly noted.

Modelling Concurrent Avoidant Behavior

To model enactment of same day avoidant behavior, we began with a model that included discrete emotions only, then added cognitions in the next step. In the final model (Table 3), we added covariates and model fit improved significantly (AIC/BIC decreases >360 with 7 Δdf). Results were between-person effects for happiness, $B = .17$, SE= .09, p= .045; worry, $B = .35$, $SE = .12$, p =.004; and fear, $B = .29$, $SE = .11$, $p = .007$ each associated with greater avoidant behavior across the diary. Notably, effect sizes for worry and fear were nearly twice the size as that for happiness, and the effect for happiness did not survive the FDR correction ($p < .017$). Moreover, to confirm effects for happiness and fear were not a product of multicollinearity, we reran models for each emotion alone. The between-person effects were unchanged. In addition, there was a significant between-person effect of rural geography, $B = -.13$, $SE = .04$, $p < .001$, such that individuals living in more rural areas reported fewer behaviors. There was also an effect of

Table 3 Solution for final model fixed effects: concurrent avoidance and approach behaviors.

	Avoidance Behaviors					Approach Behaviors				
	B	*SE*	*t*	*p*	*Effect*[1]	*B*	*SE*	*t*	*p*	*Effect*[1]
Susceptibility*	−.01	.04	−.29	.78	.01	.02	.04	.53	.60	.01
Worry*	.03	.05	.54	.59	.01	.02	.04	.54	.59	.01
Anger*	.04	.03	1.12	.26	.02	.02	.03	.77	.44	.01
Fear*	.04	.03	1.14	.26	.02	.00	.03	.07	.95	.00
Sadness*	.02	.03	.59	.56	.01	.01	.03	.21	.83	.00
Disgust*	.01	.03	.30	.76	.01	.04	.03	1.41	.16	.02
Happy*	.00	.04	.04	.97	.00	.10	.03	2.88	.004	.16
Guilt/Shame*	−.07	.07	−.99	.33	.03	.00	.05	.03	.97	.00
Mean Susceptibility	−.05	.08	−.62	.54	.05	−.08	.06	−1.35	.18	.08
Mean Worry	.35	.12	2.87	.004	.30	.05	.09	.57	.57	.04
Mean Anger	−.12	.14	−.89	.37	.12	.01	.10	.07	.94	.01
Mean Fear	.29	.11	2.70	.007	.35	.20	.08	2.62	.009	.25
Mean Sadness	.02	.12	.14	.89	.02	.07	.09	.74	.46	.07
Mean Disgust	.00	.14	.02	.99	.00	−.04	.10	−.43	.67	.04
Mean Happy	.17	.09	2.04	.045	.16	.04	.07	.57	.57	.03
Mean Guilt/Shame	−.20	.13	−1.50	.13	.13	.49	.10	4.95	<.001	.32
Age	−.00	.00	−.17	.87	.01	−.00	.00	−.77	.44	.04
Sex	.12	.14	.82	.41	.06	−.06	.10	−.60	.55	.03
Education	.08	.05	1.76	.08	.11	−.02	.03	−.72	.47	.03
Race	−.00	.04	−.03	.98	.00	.04	.03	1.48	.14	.07
Ethnicity	1.04	.42	2.49	.013	.16	.80	.29	2.70	.007	.12
Trait Anxiety	.01	.01	.60	.55	.05	−.01	.01	−.61	.54	.03
Geography	−.13	.04	−3.49	.001	.22	−.04	.03	−1.34	.18	.06
Time (day)	−.02	.01	−1.82	.07	.05	.00	.01	.48	.64	.01
Diary Compliance	.00	.03	0.13	.90	.01	−.04	.02	−2.14	.033	.07

*Within-person component (person mean-centered); [1]Effect size as the standardized raw score of the fixed effect [49].

ethnicity, $B = 1.04$, $SE = .42$, $p = .013$, which appeared to be driven by the small number of Hispanic individuals in the sample ($n = 8$). These individuals reported high levels of both avoidance and approach behaviors across the diary period.

Modelling Day-to-Day Change in Avoidant Behavior

To test factors that predicted change in avoidant behavior, we reran the analyses applying a lagged model framework (Table S13 in supplemental materials). The dependent variable was avoidant behaviors reported the next day, and predictors were emotion, cognition, and behaviors that current day. This approach reduces the risk of reverse causation and allows for detection of unique effects driving changes in reported behaviors *from day to day*. Results suggested that current report of avoidance behaviors was the primary driver of next day avoidance behaviors, $B = .50$, $SE = .02$, $p < .0001$. Notably, both geography and compliance, had small effects. Individuals in more rural/less-densely populated areas reported fewer avoidance behaviors, $B = -.05$, $SE = .02$, $p = .007$. Finally, diary compliance was inversely associated with avoidance behavior, $B = -.04$, $SE = .02$, $p = .021$ but this did not survive FDR correction ($p < .017$). There were no other significant associations.

Modelling Concurrent Approach Behavior

We conducted the same series of analyses for approach behaviors. In the final step (Table 3), we added all covariates and model fit significantly improved (AIC/BIC decreases >350 with 7 Δdf). Results indicated that within-person increases in happiness were associated with greater concurrent approach behavior, $B = .10$, $SE = .03$, $p = .004$, and between-person levels of fear, $B = .20$, $SE = .08$, $p = .009$, and guilt/shame, $B = .49$, $SE = .10$, $p < .0001$, were positively associated with approach behavior across the sampling period. The between-person effects for fear and guilt/shame were nearly double in size, relative to the within-person effect of happiness. To confirm effects for emotions were not a product of multicollinearity, we reran models for each emotion alone. The between-person effects were unchanged for fear and guilt/shame, however the within person effect of happiness did not reach significance. Finally, there were no effects of cognition. As with avoidance behaviors, those individuals (n = 8) who identified as Hispanic reported greater approach behaviors, B = .80, SE = .30, p = .007. In addition, there was a small inverse association with compliance, such that individuals who completed more diaries reported fewer behaviors, B = −.04, SE = .02, p = .033 but this did not survive FDR correction (p < .017). There were no other effects.

Modelling Day-to-Day Changes in Approach Behaviors

To model factors predicting change in approach behaviors from one day to the next, we applied the same lagged model framework as above (Table S13). The dependent variable was approach behaviors reported in the next day. Predictors were emotion, cognition, and behaviors reported that current day. Approach behaviors on the current day were the strongest predictor of approach behaviors the next day, B = .26, SE = .02, p < .001. In addition, avoidance behaviors on the current day predicted approach behaviors the next day, B = .04, SE = .02, p = .023 but this did not survive the FDR correction. Moreover, the between-person association of guilt/shame to approach, B = .39, SE = .07, p < .0001 was consistent with the prior model as were the effects of ethnicity, B = .48, SE = 20, p = .016, and time, B = .02, SE = .01, p = .003. Finally, there was an inverse association between diary compliance and approach behavior, B = −.06, SE = .02, p < .001 suggesting that perhaps as time went on, engagement in behaviors may have been less necessary.

Given these findings, we considered the possibility that guilt/shame was meaningful in motivating next day approach behaviors in part because of the interaction with behaviors (approach or avoidance) enacted that same day. We explored moderation and found an interaction of guilt/shame with current avoidance behaviors, B = .06, SE = .03, p = .027, suggesting that the positive association between guilt/shame and next day approach was strengthened for participants who reported greater avoidance the current day (see Figure S1 for the simple slopes). However, the relative impact of the interaction would be small and did not survive the FDR correction for these analyses (p < .013).

Modelling Emotion by Cognition Pathways to Behavioral Enactment

To evaluate the possibility of a chain of associations connecting emotion and cognition with behavioral enactment at both the within-person and between-person levels, we applied a *mediation* framework. We examined bi-directional pathways between the emotions of anger, fear, and happiness with COVID-19 cognitions of perceived susceptibility and worry, in relation to avoidance or approach behaviors. For *both* avoidant and approach behaviors, there were no significant indirect effects at the within-person level from either concurrent or lagged analyses (i.e., all 95% CI included 0). However, there were significant within-person associations between emotion and cognition in the a-path models that were largely consistent with correlations reported above. These are reported in detail in supplemental materials (p.S40-S42).

At the between-person level, there were significant indirect effects for *both* avoidance and approach behaviors. See Figure 2 for the standardized coefficients and their associated 95% CI, which indicate moderate to large effect sizes. COVID-19 worry was a significant mediator of the association between fear and avoidant behaviors (indirect effect = .216, 95% CI = [.063, .379]; stdyx = .235; 95% CI = [.072, .409]). The percent mediation was 40.7%, and the direct effect of fear was still significant (c’-path = .330, se = .149, z = 2.22, p = .027). When the direction was reversed, fear remained a mediator of the COVID-19 worry and avoidant behavior association (indirect effect = .185, 95% CI = [.014, .379]; stdyx = .146; 95% CI = [.014, .293]). The percent mediation was 35.8% and the direct effect of COVID-19 worry was still significant (c’-path = .343, se = .129, z = 2.67, p = .008). For *approach* behaviors at the between-person level, COVID-19 worry was not a significant mediator of the fear and approach behaviors association but fear did have a significant direct effect (c’-path = .225, se = .088, z = 2.56, p = .011). When the direction was reversed, fear was a significant mediator of the COVID-19 worry and approach behavior association (indirect effect = .119, 95% CI = [.015, .236]; stdyx = .123; 95% CI = [.016, .244]). The percent mediation was 75.6%, and the direct effect of COVID-19 worry was not significant (p = .681). After parsing out overlap with COVID-19 worry, COVID-19 susceptibility had unusual significant *negative* indirect effects through fear for both avoidant (indirect effect = −.045, 95% CI = [−.110, −.001]; stdyx = −.043; 95% CI = [−.106, −.002]; percent mediation = 44.8%) and approach (indirect effect = −.029, 95% CI = [−.070, −.001]; stdyx = −.037; 95% CI = [−.088, −.002]; percent mediation = 23.4%) behaviors. The remaining direct effects of COVID-19 susceptibility were not significant (ps > .235).

We conducted sensitivity analyses to see how diary compliance (i.e., number of days of diary data) might have impacted the mediation results. Diary compliance did not moderate any of the within-person or between-person effects in the multilevel mediation models. When only including participants with 6 or

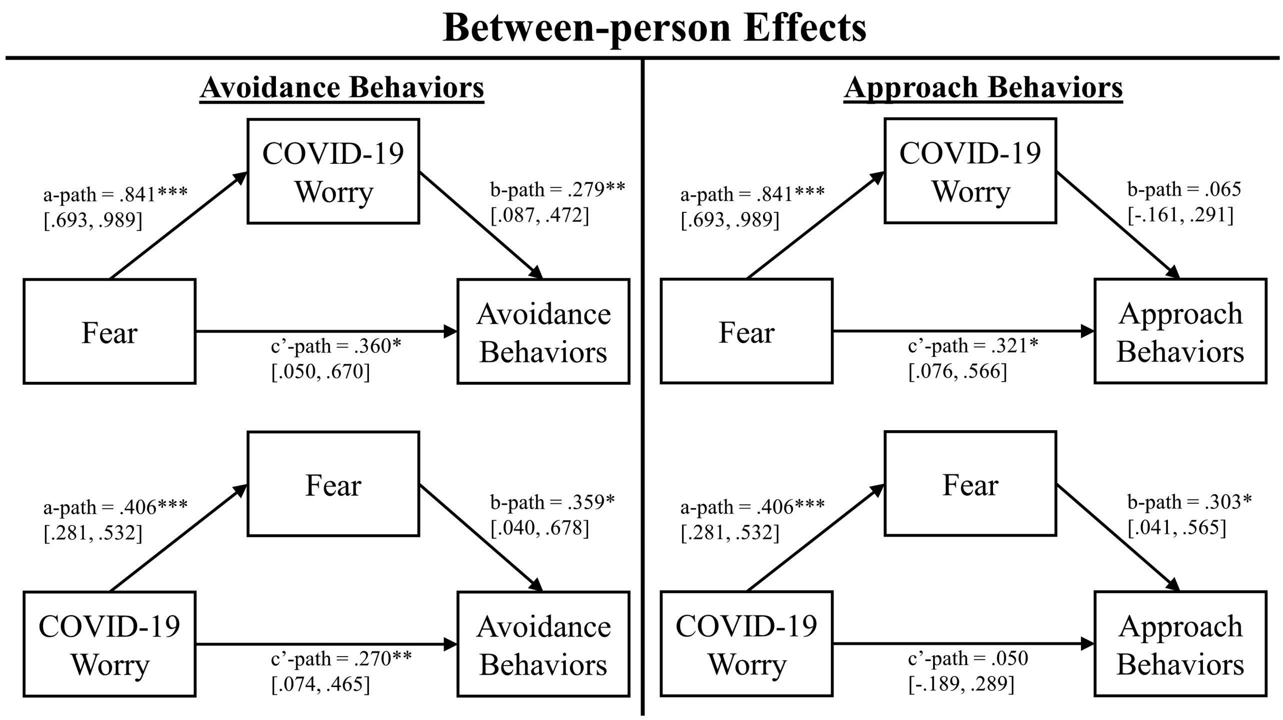

Figure 2 Between-person multilevel mediation path models with Covid-19 related worry and fear.
Note: Standardized regression coefficients and their 95% CI are displayed; * $p < .05$, ** $p < .01$, ***$p < .001$.

more days of diary data, the between-person associations between fear and avoidance behaviors ($b = .242$, se = 1.70, $z = 1.42$, $p = .154$) and fear and approach behaviors ($b = .146$, se = .090, $z = 1.63$, $p = .103$) were no longer significant. This resulted in four indirect effects no longer being significant: 1. COVID-19 worry predicting avoidance behaviors through fear (indirect = .129, 95% CI = [−.048, .323], 2. COVID-19 worry predicting approach behaviors through fear (indirect = .078, 95% CI = [−.017, .183]), 3. COVID-19 susceptibility predicting avoidance behaviors through fear (indirect = −.030, 95% CI = [−.092, .011], 4. COVID-19 susceptibility predicting approach behaviors through fear (indirect = −.018, 95% CI = [−.053, .004]).

Using *moderation* analyses, we investigated whether fear or anger strengthened the association between perceived susceptibility and behavior. For avoidance behaviors, fear did not interact with COVID-19 perceived susceptibility, and for approach behaviors, anger did not (ps < .180). Therefore, the effects of emotion were consistent across ratings of perceived susceptibility.

Discussion

The threat of COVID-19 remains considerable, and primary prevention efforts are focused on encouraging individuals to comply with preventive health behaviors to curb contagion. However, there is notable variability in individual compliance with these behaviors. In this investigation, we sought to characterize engagement in these preventive behaviors over 10 days in a national sample of U.S. adults.

First, our factor analysis and latent growth models suggest two distinct underlying sub-sets of behavior: approach and avoidance. Individuals clustered in their behavior primarily by their starting point at the beginning of the diary (i.e., intercepts) and not as much by their systematic change over time (i.e., slopes). Moreover, people engaged in greater avoidance than approach behaviors perhaps because avoidance behaviors were actions people could do while staying in their homes (e.g., working from home) and many of the approach behaviors (e.g., buying cleaning supplies) would not likely be repeated over 10 days. Finally, demographic factors and trait anxiety did not impact avoidance behaviors and only influenced approach behaviors in a limited way suggesting that other psychological processes could be impactful.

Notably, we found that *emotions* drive the enactment of COVID-19 preventive health behaviors. *Both* fear and happiness/joy were predictive of approach and avoidance health behaviors. Prior research has demonstrated the role of fear in health behaviors and happiness in pro-social behavior. However, that fear was the stronger driver (with a twofold impact) of *both* behavioral factors has not been previously demonstrated. Also notable was that neither disgust nor anger had significant impacts on behaviors. Although disgust functions to facilitate avoidance of contamination, it may need salient sensory cues to be elicited (e.g., sight of dirt; [51]), and the invisibility of a virus could limit reports of disgust. In addition, although anger is associated with approach behavior and decreased risk cognition, this has not been reliably shown in a health context. Finally, that guilt/shame was a key driver of greater approach behavior concurrently and day-to-day change, may be related to the social pressure to conform and act on behalf of others. Indeed, theories of guilt/shame argue for its primary role in maintaining social order and hence that guilt/shame would be related to greater approach behavior is consistent with research suggesting that pro-sociality is a driver of COVID-specific behavior [52].

Another notable finding was the relative importance of COVID-19 related worry and the lack of evidence that perceived susceptibility predicted unique variance in behaviors. Although individuals' perceived susceptibility was related to their avoidance behaviors, there was also considerable shared variance with COVID-19 worry and with negative emotions. Thus, unique aspects of perceived susceptibility had non-significant explanatory power. There is a large literature capturing associations between perceived susceptibility and health behavior, including a recent meta-analysis demonstrating that heightening perceived susceptibility has small-to-medium effects on behavior [21]. However, much of that research has been cross-sectional, including research on susceptibility in the context of COVID-19, and thus, unable to capture more dynamic processes that often lead to behavior. The discrepancy between findings from cross-sectional operationalization and experience sampling assessment is increasingly evident for other key constructs (e.g., emotion regulation: [53]), but certainly warrants confirmation and further explication in this context. Importantly, more individuals also opted out of estimating their susceptibility than in other similar studies [54]. Perhaps participants lacked knowledge needed to estimate their risk [55] given the novelty of COVID-19 and lack of available information [4]. This could explain the counter-intuitive *negative* indirect effects of COVID-19 susceptibility on behaviors through fear.

When simultaneously exploring discrete emotions and COVID-19 cognitions, there was some evidence of bi-directional mediational processes linking worry to fear that were associated with increased behavioral output. Although clinical models of worry and anxiety have argued for this process in theory, there is an absence of evidence due to little prior in-the-moment sampling. Moreover, these data provide the first evidence of these processes in the context of a substantial health risk. Also notable was clear evidence of distinct processes driving each behavioral factor, avoidance versus approach. In particular, the above-mentioned mediational effects appeared most meaningful when predicting avoidance behaviors. Mediational processes, but not moderation, evidenced here were consistent with theoretical models that argue for a chain of processes linking emotion to cognition or cognition to emotion that can translate to behaviors [8]. However, associations between fear and behavior were no longer significant when excluding participants with fewer than 6 days of diaries, indicating these mediation models must be replicated and confirmed.

Additional differences characterized each behavioral factor. For example, rural geography was inversely associated with avoidance behaviors but not approach, suggesting that people living in urban areas engaged in more avoidance behaviors consistent with outbreaks [34] and related ordinances limiting activities in many urban communities. In contrast, approach behaviors appeared to be largely driven by discrete emotions, such as fear, happiness, and guilt/shame, and not geography nor COVID-19 specific cognitions. Moreover, avoidance behaviors had a positive directional association to approach behaviors reported the next day, suggesting that avoidance could serve as a reminder to also engage in approach behaviors (e.g., purchasing cleaning supplies) but this was not evident in the reverse. Also, trait anxiety and education were not significant predictors in any analyses. It could be that anxiety-prone individuals were more worried about the indirect effects of COVID-19 on finances, employment/school, and relationships, muddying associations among trait anxiety and health behavior engagement [56]. Moreover, education, a common factor in scientific or health literacy [57] may have been insignificant given more powerful affective forces.

There were several limitations to this investigation. In particular, the frequency and length of the sampling period were limited and may have made it challenging to detect within-person processes. Indeed, given the variability in compliance (range 2–10) and large intraclass correlations, it is possible that we were underpowered to detect these within-person effects. Moreover, single-item ratings of discrete emotions are not ideal, and those findings will warrant replication with multi-item scales. In addition, risk of error due to Type 1 or Type 2 is present, and thus confirmatory research with larger samples is essential. Finally, we were not able to consider other factors likely to be relevant during this crisis, such as political affiliation. In the US, heightened political polarization has influenced how people respond to health communications [58]. Given the ways in which political affiliation can align with age and geography, both factors in combination with political affiliation will be important to include in a replication study. Many of these design limitations were a result of the challenges of engaging participants for an intensive longitudinal online investigation that could be perceived as burdensome during a still-novel crisis. It will be important to expand and replicate these effects in other samples in relation to COVID-19 and in other health contexts (e.g., seasonal influenza) to see how they can be generalized.

Finally, the exploratory -or- non-confirmatory approach to this investigation warrants some consideration. There is a vast literature relating to the research questions here that could have been applied with more formal hypothesis testing. However, recent recommendations suggest that applying a confirmatory frame to research when there is *in*sufficient precedent and *gaps* in the "derivation chain" [36] is unlikely to be successful. As noted previously, there is no prior research applying experience sampling methodology within a health crisis context to assess the aforementioned associations between health cognition, emotion and behaviors. Accordingly, we approached this project to *first* explore how associations captured in real-time were consistent with prior literature in order to *then* be confirmed and/or replicated in future projects. Our team is currently working toward that goal.

In sum, these findings are relevant both practically in the context of COVID-19 and with respect to health behavior theory. First, the results suggest that COVID-19 recommended health behaviors should not be considered one coherent class, but rather distinct motivational responses (approach, avoidance). Recognizing this distinction may be useful in framing public health messaging to improve compliance, particularly for individuals in the low response trajectories. Second, the strongest predictors of recommended behaviors were *affective* in nature: emotion and worry. Hence, public health messaging that exclusively targets risk perception could fall short. Instead, these findings suggest an opportunity to promote greater compliance by targeting the association between these behaviors and reports of happiness (i.e., feeling good when doing good for others) by harnessing the influence of pro-social emotion. In sum, the threat of COVID-19 remains significant, and primary prevention efforts are still largely focused on behavioral strategies (e.g., social distancing). Results of this investigation provide novel and highly relevant information that could improve health messaging and contribute to broader explanatory models of health behavior.

Supplementary Material

Supplementary material is available at *Annals of Behavioral Medicine* online.

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Compliance with Ethical Standards

Authors' Statement of Conflict of Interest and Adherence to Ethical Standards Authors Karin G. Coifman, David J. Disabato, Pallavi Aurora, T. H. Stanley Seah, Benjamin Mitchell, Nicolle Simonovic, Jeremy L. Foust, Pooja Gupta Sidney, Clarissa A. Thompson, and Jennifer M. Taber declare that they have no conflicts of interest. All procedures, including the informed consent process, were conducted in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2000.

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