

# Longitudinal changes in COVID-19 concern and stress: Pandemic fatigue overrides individual differences in caution

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## Abstract

**Background:** Pandemic fatigue describes a phenomenon whereby individuals experience a decrease in COVID-19 concern over time, despite their risk for infection remaining stable, or even increasing. Individual differences in the experience of pandemic fatigue may have important implications for people's adherence to public health recommendations.

**Design and methods:** Using data collected from a large community cohort in McLennan County, TX, longitudinal changes in COVID-19-related concern, stress, and affect across three appointments separated by approximately 4 weeks (July–November 2020) were examined. About 495, 349, and 286 participants completed one, two, and three appointments, respectively. Changes to stress physiology and local travel over time were also analyzed.

**Results:** Results of a latent class growth analysis revealed four distinct classes of individuals: (a) low concern, low stress, (b) moderate concern, moderate stress, (c) moderate concern, low stress, and (d) high concern, high stress. Despite differences between latent classes in initial levels of concern, stress, and negative affect, levels of each variable decreased over time for all groups. While this reduction of concern did not coincide with changes in local travel, it was reflected in heart rate and blood pressure.

**Conclusions:** Together, these results suggest a general trend of pandemic fatigue in the sample, even for those with moderate-to-high levels of initial COVID-19 stress and concern. Such findings may provide insights into the expected challenges of promoting compliance with public health recommendations as the pandemic continues.

## Keywords

Pandemic fatigue, COVID fatigue, COVID-19, growth mixture modeling, latent class analysis

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## Introduction

Since the beginning of the COVID-19 pandemic, research has revealed a striking degree of variability among individuals in pandemic-related vigilance, stress, and concern.<sup>1–5</sup> Such individual differences in psychological responses to the pandemic appear to have important implications for engagement in health-protective behaviors. That is, people reporting high levels of pandemic-related concern, stress, and anxiety are often more likely to comply with public health recommendations, such as social distancing and the use of face coverings in public.<sup>4,6–9</sup>

The tendency for individuals to exhibit decreases in pandemic-related vigilance and concern is often referred

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to in the scientific literature as “pandemic fatigue” (or colloquially as “COVID fatigue”).<sup>10–14</sup> Pandemic fatigue is hypothesized to stem from dissatisfaction with pandemic-related uncertainty and protracted disruptions to normal routines, interpersonal relationships, and economic activity.<sup>5,15,22,32,36</sup> Despite a growing number of studies reporting patterns of pandemic fatigue in diverse populations,<sup>10,16,17</sup> there is still a paucity of research examining whether certain groups of individuals are more susceptible to this than others. Also yet to be explored is whether pandemic fatigue is manifested in physiological markers of stress, such as blood pressure<sup>18,19</sup> and resting heart rate.<sup>20–22</sup> Longitudinal studies are well-suited to redress these gaps and provide novel insights into the nature of pandemic fatigue.

One useful statistical tool for modeling trajectories of change over time, and patterns of individual differences thereof, is latent class growth analysis (LCGA).<sup>23–29</sup> LCGA utilizes structural equation modeling to classify individuals into latent, or unobserved, groups through the detection of similarities in their initial levels of, and rates of change in, a variable or set of variables.<sup>25</sup> For example, in a dataset where concern about the government’s response to COVID-19 and anxiety levels are both measured longitudinally, there may be a subgroup of individuals reporting high initial concern but low anxiety, another subgroup with low initial concern and high anxiety, and yet another subgroup with moderate levels of both measures. Many other permutations are also possible, including differences between subgroups in how these variables change over time, which is of particular relevance to the study of individual differences in pandemic fatigue. Logistic regression can also be used to examine factors that predict class membership.

The current research explored aspects of pandemic fatigue and travel in longitudinal data collected from a community cohort between July–November 2020. Using an LCGA framework, participants were categorized into latent groups based on their self-reported levels of concern about lifting restrictions, stress, and affect across three appointments separated by approximately 4 weeks each. Data were collected against the backdrop of consistent increases in COVID-19 cases and deaths in the county (Supplemental Figure S1). Accordingly, we interpreted reductions in COVID-19-related distress as indicative of pandemic fatigue. Follow-up analyses were conducted to assess whether several demographic, health, and risk perception variables emerged as independent predictors of group membership. A final set of exploratory analyses tested whether physiological markers of stress and frequency of travel outside of the home changed across the study using linear mixed effects models.

## Design and methods

### Procedure

Data were collected as part of the Waco COVID Survey, a longitudinal study testing for the presence of anti-SARS-CoV-2 immunoglobulin G (IgG) in the sera of asymptomatic participants living in McLennan County, TX. Additional information about the project and participant sample, as well as the demographic characteristics of the county, is available in a previous publication.<sup>3</sup> The Waco COVID Survey was approved and endorsed by the Waco-McLennan County Public Health District, and as a public health surveillance study, met the exclusion criteria for institutional review board approval at 45 CFR 46.102(e) and (l) for all Baylor University researchers, staff, and volunteers. Waco Family Medicine researchers, staff, and volunteers were approved to assist with data collection by the institutional review board at Ascension Providence Hospital and Medical Center of Waco, TX. All participants provided informed consent and were at least 18 years of age, lived in McLennan County since December 2019, were fluent in English or Spanish, and did not have any signs or symptoms of COVID-19 between March 13, 2020, and their dates of participation.

Before their first laboratory visit, participants completed an online intake survey that included questions about demographics, health, affect, personality, and COVID-19 risk perceptions and attitudes. At first laboratory visit, anthropometric and routine physiological measurements were taken, followed by an intravenous blood draw. Participants who tested negative for anti-SARS-CoV-2 IgG were invited back for two additional laboratory appointments (each including a blood draw and the same physiological and anthropometric measurements), separated by approximately 4 weeks. Subjects who developed signs or symptoms of COVID-19 between appointments, as well as those who received a positive PCR test during that period, were excluded from further participation. During the week preceding each of their follow-up laboratory appointments, participants completed additional questionnaires that included a subset of items measured in the intake survey. In total, 495 participants completed their first appointment, 349 completed two appointments, and 286 completed all three appointments.

### Materials

#### *Concern about lifting COVID-19 restrictions*

To assess concern about lifting COVID-19 restrictions, participants responded to three items using a 7-point scale (1 = not at all concerned; 7 = very concerned) at each session: (a) “How concerned are you that lifting public restrictions too quickly or early will result in more COVID-19-related deaths in the United States?”; (b) “How

**Table 1.** Intercepts (initial levels) and slopes of each variable by latent class.

Latent class	Concern about lifting restrictions		Stress		Negative affect		Positive affect	
	<i>I</i> (SE)	<i>S</i> (SE)	<i>I</i> (SE)	<i>S</i> (SE)	<i>I</i> (SE)	<i>S</i> (SE)	<i>I</i> (SE)	<i>S</i> (SE)
1. Low concern, low stress ( <i>n</i> = 101)	2.98 (0.17)	-0.51 (0.06)***	2.10 (0.07)	-0.19 (0.04)***	1.56 (0.06)	-0.08 (0.03)**	3.42 (0.07)	0.13 (0.03)***
2. Moderate concern, moderate stress ( <i>n</i> = 168)	5.93 (0.11)	-0.43 (0.07)***	2.83 (0.07)	-0.15 (0.03)***	2.09 (0.06)	-0.11 (0.03)***	2.88 (0.05)	-0.02 (0.04)
3. Moderate concern, low stress ( <i>n</i> = 190)	5.97 (0.11)	-0.46 (0.06)***	1.95 (0.05)	-0.15 (0.03)***	1.45 (0.03)	-0.06 (0.02)***	3.64 (0.07)	0.02 (0.03)
4. High concern, high stress ( <i>n</i> = 36)	6.30 (0.24)	-0.13 (0.12)	3.59 (0.13)	-0.25 (0.07)***	3.14 (0.13)	-0.11 (0.10)	2.36 (0.13)	0.11 (0.09)
Sample overall	5.34 (0.07)	-0.44 (0.03)***	2.40 (0.03)	-0.15 (0.02)***	1.80 (0.03)	-0.08 (0.01)***	3.23 (0.03)	0.04 (0.02)*

*I*: intercept, with time centered at baseline such that intercepts reflect group means at Session 1; *S*: linear time slope; SE: standard error.

\**p* < .05, \*\**p* < .01, \*\*\**p* < .001.

concerned are you that lifting public restrictions too quickly or early will result in more COVID-19-related deaths in McLennan county?"; and (c) "How concerned are you that lifting public restrictions will not happen quickly enough?" Items were combined into mean composites (session 1:  $\alpha=0.88$ ; session 2:  $\alpha=0.89$ , session 3:  $\alpha=0.88$ ).

### Stress and affect

Participants responded to the short-form Perceived Stress Scale (PSS-4) (Herrero and Meneses, 2006)<sup>30</sup> at each time point using a 5-point scale. Mean composites were formed, each of which yielded good reliability (session 1:  $\alpha=0.80$ ; session 2:  $\alpha=0.83$ , session 3:  $\alpha=0.82$ ). Higher scores indicated greater perceived stress.

Positive and negative affect were assessed at each time point using the Positive and Negative Affect Schedule (5-point Likert-type scale) (Watson et al., 1988).<sup>31</sup> Mean composites for positive and negative affect were computed; all yielded good reliability (positive: session 1:  $\alpha=0.90$ ; session 2:  $\alpha=0.91$ , session 3:  $\alpha=0.92$ ; negative: session 1:  $\alpha=0.88$ ; session 2:  $\alpha=0.86$ , session 3:  $\alpha=0.89$ ).

### Physiological measures

At each session, participants' forehead temperature was measured twice using a forehead thermometer (EXERGEN TAT-5000). Data analyzed in the current research included averages of these two measurements at each session. After sitting for several minutes, blood pressure (systolic and diastolic) and pulse (beats per minute) were measured in triplicate using automatic upper arm blood pressure monitors (OMRON HEM-907XL and BP785N). Averages of these measurements were analyzed.

### Travel behavior

At the first session, participants reported how many times they left their home each week during Texas's shelter-in-place

order (March 13–May 1, 2020). Specifically, they were asked how often they left to (a) buy essential supplies, (b) go to a friend's house, (c) go to a gas station, (d) go to a liquor store, (e) pick up food from a restaurant, and (f) go to a public park. At each subsequent session, participants were asked how often each week, on average, they left their home for these reasons in the month prior to their appointment.

### Class membership

Data were collected on several demographic, personality, health, and risk perception variables that may covary with COVID-19 attitudes, stress, and affect. These included age, sex, body mass index (BMI), race and ethnicity, education, whether the participant had health insurance, whether the participant worked as a first responder or healthcare worker, risk tolerance, germ aversion and perceived infectability,<sup>32</sup> pathogen disgust,<sup>33</sup> perceived COVID-19 knowledge, perceived risk of becoming infected with the SARS-CoV-2 virus, and perceived risk of experiencing severe COVID-19 disease if infected. We tested whether each of these variables predicted membership in the latent classes. See Supplemental Materials for more information about these variables.

## Results

### Latent class determination

The latent class growth analysis was conducted using MPlus statistical software.<sup>34</sup> Data analysis plan and additional information about the LCGA is available in the Supplemental Materials. The results of the multivariate LCGA yielded an optimal four class solution (Supplemental Table S1 for results of LCGA; Table 1 for slopes and intercepts by class; Supplemental Figure S2 for individual slopes). Based on patterns of responding among these groups, we henceforth refer to Class 1

**Table 2.** Descriptive statistics for predictors of latent class membership.

Variable	Class 1 Low concern, low stress (n=101, 76, 62)	Class 2 Moderate concern, moderate stress (n=168, 116, 94)	Class 3 Moderate concern, low stress (n=190, 137, 113)	Class 4 High concern, high stress (n=36, 20, 17)	Predicted class membership
Age (years)	45.76 (14.29)	40.79 (12.93)	48.92 (14.50)	34.03 (8.45)	*
Sex (female) (%)	46.5	67.9	66.8	63.9	*
Body mass index (kg/m <sup>2</sup> )	27.69 (5.45)	28.75 (6.52)	29.28 (6.59)	32.73 (6.65)	
Hispanic (%)	8.9	18.0	24.2	30.6	*
Education (1–10)	5.71 (1.97)	5.87 (2.08)	6.00 (2.10)	5.86 (2.09)	*
Has insurance (%)	97.0	92.3	94.2	86.1	
First responder/healthcare worker (%)	28.7	39.9	39.5	17.1	*
General risk tolerance (1–7)	4.39 (1.55)	3.40 (1.64)	3.50 (1.76)	2.83 (1.92)	*
Germ aversion (1–7)	4.23 (1.14)	5.37 (1.07)	5.17 (0.95)	5.56 (1.20)	*
Perceived infectability (1–7)	2.69 (1.22)	3.42 (1.24)	2.85 (1.20)	3.53 (1.17)	*
Pathogen disgust (1–7)	4.35 (1.54)	4.62 (1.34)	4.66 (1.22)	5.23 (1.12)	
Perceived COVID-19 knowledge (1–7)	5.93 (0.91)	6.13 (0.97)	6.20 (0.90)	5.81 (1.14)	
Perceived risk for COVID-19 infection (1–7)	3.94 (1.71)	4.35 (1.45)	3.84 (1.56)	4.25 (1.78)	
Perceived risk for severe COVID-19 (1–7)	2.95 (1.47)	3.81 (1.46)	3.65 (1.46)	4.50 (1.50)	*

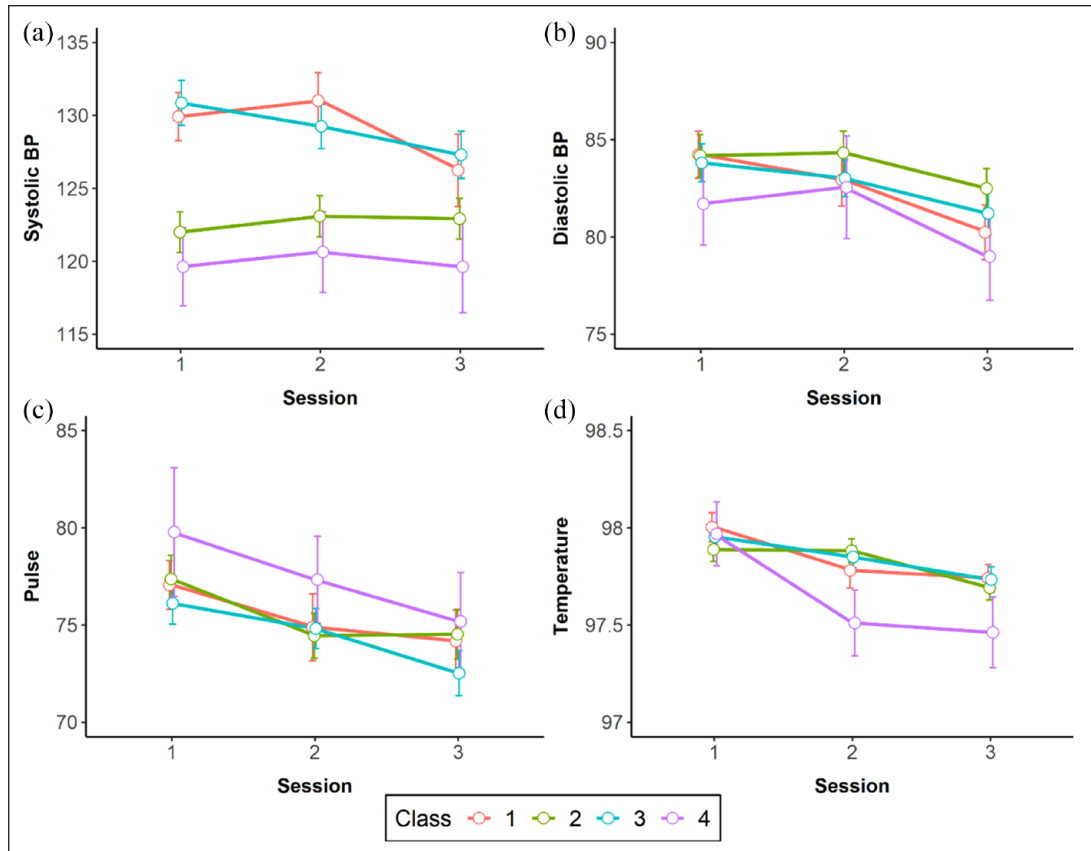
Shown here for continuous variables are means and standard deviations (parentheses).

\*Indicates that the variable significantly predicted likelihood of belonging in a class relative to the reference class (Class 3) in a multinomial logistic regression analysis.

**Table 3.** Logistic regression analysis for demographic predictors of latent class membership.

Variable	b	SE	t	p	OR	CI <sub>s</sub>
<b>Age</b>						
Low concern, low stress (Class 1)	-0.02	0.01	-1.55	0.12	0.98	(0.95, 1.01)
Moderate concern, moderate stress (Class 2)	-0.07	0.02	-5.07	<0.001	0.93	(0.90, 0.96)
High concern, high stress (Class 4)	-0.19	0.04	-4.54	<0.001	0.83	(0.76, 0.90)
<b>Sex</b>						
Low concern, low stress (Class 1)	0.76	0.36	2.11	0.04	2.13	(1.06, 4.29)
Moderate concern, moderate stress (Class 2)	-0.05	0.31	-0.17	0.86	0.95	(0.52, 1.74)
High concern, high stress (Class 4)	0.97	0.50	1.92	0.06	2.63	(0.98, 7.07)
<b>BMI</b>						
Low concern, low stress (Class 1)	-0.05	0.03	-1.46	0.15	0.96	(0.90, 1.02)
Moderate concern, moderate stress (Class 2)	-0.03	0.03	-1.06	0.29	0.97	(0.52, 1.74)
High concern, high stress (Class 4)	0.03	0.05	0.53	0.60	1.03	(0.94, 1.12)
<b>Hispanic</b>						
Low concern, low stress (Class 1)	-1.50	0.54	-2.78	0.01	0.22	(0.08, 0.64)
Moderate concern, moderate stress (Class 2)	-0.91	0.36	-2.55	0.01	0.40	(0.20, 0.81)
High concern, high stress (Class 4)	-0.25	0.67	-0.38	0.71	0.78	(0.21, 2.89)
<b>Education</b>						
Low concern, low stress (Class 1)	-0.25	0.09	-2.90	<0.001	0.78	(0.66, 0.92)
Moderate concern, moderate stress (Class 2)	-0.05	0.08	-0.69	0.49	0.95	(0.82, 1.10)
High concern, high stress (Class 4)	0.16	0.18	0.92	0.36	1.18	(0.83, 1.67)
<b>Has insurance</b>						
Low concern, low stress (Class 1)	1.13	0.81	1.40	0.16	3.10	(0.64, 15.00)
Moderate concern, moderate stress (Class 2)	0.27	0.71	0.37	0.71	1.30	(0.32, 5.27)
High concern, high stress (Class 4)	-0.22	1.05	-0.21	0.83	0.80	(0.10, 6.26)
<b>First responder or healthcare worker</b>						
Low concern, low stress (Class 1)	-0.88	0.43	-2.04	0.04	0.41	(0.18, 0.97)
Moderate concern, moderate stress (Class 2)	-0.31	0.31	-1.01	0.31	0.73	(0.40, 1.34)
High concern, high stress (Class 4)	-1.83	0.89	-2.07	0.04	0.16	(0.03, 0.91)

Shown here are unstandardized regression coefficients (b), standard errors (SE), t-values (t), p-values (p), odds ratios (OR), and confidence intervals for the ORs (CI<sub>s</sub>).



**Figure 1.** Longitudinal trajectories for physiological measures separated by latent class: low concern, low stress (Class 1), moderate concern, moderate stress (Class 2), moderate concern, low stress (Class 3), and high concern, high stress (Class 4). Systolic blood pressure (BP) shown in panel (a), diastolic BP in (b), pulse in (c), and forehead temperature in (d).

( $n=101$ ) as the “Low Concern, Low Stress” category, Class 2 ( $n=168$ ) as the “Moderate Concern, Moderate Stress” category, Class 3 ( $n=190$ ) as the “Moderate Concern, Low Stress” category, and Class 4 ( $n=36$ ) as the “High Concern, High Stress” category. For all comparisons, the largest class (Moderate Concern, Low Stress; Class 3) was the reference group.

For the sample, overall, concern about lifting pandemic restrictions significantly decreased across time,  $b=-0.44$ ,  $SE=0.03$ ,  $t=-14.32$ ,  $p<0.001$ , as did negative affect,  $b=-0.08$ ,  $SE=0.01$ ,  $t=-6.05$ ,  $p<0.001$ , and stress,  $b=-0.15$ ,  $SE=0.02$ ,  $t=-10.06$ ,  $p<0.001$ . In comparison, positive affect slightly increased,  $b=0.04$ ,  $SE=0.02$ ,  $t=1.98$ ,  $p=0.047$ .

Similar changes were observed for all latent classes over time (Table 1). That is, all groups exhibited a decrease in stress across the study, and all but the High Concern, High Stress category reported a decrease in concern and negative affect. Together, these results suggest that even though the four latent classes varied considerably in their mean levels of concern and distress, these variables tended to decrease at a similar rate over time for each group.

### Predictors of class membership

See Table 2 for descriptive statistics stratified by latent class. Logistic regression was used to test predictors of class membership. Regarding demographic characteristics (Table 3), results revealed that the Moderate Concern, Moderate Stress class, and High Concern, High Stress class were younger on average. The Low Concern, Low Stress class contained more men than the reference class, and also reported lower education. Those in both the Low Concern, Low Stress and Moderate Concern, Moderate Stress classes were also less likely to identify as Hispanic than those in the Moderate Concern, Low Stress reference class. Healthcare workers were more likely to be in the Moderate Concern/Stress classes.

Furthermore, individuals in the High Concern, High Stress class reported lower general risk tolerance than the reference class, as well as higher perceived risk for severe COVID-19-related illness if infected (see Table 4 for full statistics). The Low Concern, Low Stress class had lower germ aversion scores and lower perceived risk for severe COVID-19 compared to the reference group. The Moderate Concern, Moderate Stress class only differed from the reference class in that they reported higher general perceived infectability.

**Table 4.** Logistic regression analysis for risk perception predictors of latent class membership.

Variable	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>	OR	CI <sub>s</sub>
General risk tolerance						
Low concern, low stress (Class 1)	0.19	0.10	1.91	0.06	1.21	(1.00, 1.48)
Moderate concern, moderate stress (Class 2)	-0.04	0.09	-0.52	0.60	0.96	(0.81, 1.13)
High concern, high stress (Class 4)	-0.58	0.25	-2.28	0.02	0.56	(0.34, 0.92)
Germ aversion						
Low concern, low stress (Class 1)	-1.04	0.17	-5.97	<0.001	0.35	(0.25, 0.50)
Moderate concern, moderate stress (Class 2)	0.11	0.15	0.73	0.47	1.12	(0.83, 1.51)
High concern, high stress (Class 4)	-0.02	0.34	-0.05	0.96	0.98	(0.51, 1.90)
Perceived infectability						
Low concern, low stress (Class 1)	0.03	0.17	0.16	0.87	1.03	(0.74, 1.44)
Moderate concern, moderate stress (Class 2)	0.31	0.12	2.49	0.01	1.36	(1.07, 1.74)
High concern, high stress (Class 4)	0.33	0.29	1.13	0.26	1.39	(0.78, 2.47)
Pathogen disgust						
Low concern, low stress (Class 1)	0.08	0.16	0.52	0.60	1.09	(0.80, 1.48)
Moderate concern, moderate stress (Class 2)	-0.07	0.12	-0.58	0.56	0.93	(0.74, 1.18)
High concern, high stress (Class 4)	0.66	0.35	1.89	0.06	1.94	(0.98, 3.86)
Perceived COVID-19 knowledge						
Low concern, low stress (Class 1)	-0.26	0.21	-1.25	0.21	0.77	(0.51, 1.16)
Moderate concern, moderate stress (Class 2)	0.11	0.17	0.66	0.51	1.12	(0.80, 1.57)
High concern, high stress (Class 4)	-0.61	0.31	-1.96	0.05	0.54	(0.29, 1.00)
Perceived risk for COVID-19 infection						
Low concern, low stress (Class 1)	0.03	0.12	0.27	0.79	1.03	(0.82, 1.29)
Moderate concern, moderate stress (Class 2)	0.14	0.10	1.35	0.18	1.15	(0.94, 1.41)
High concern, high stress (Class 4)	-0.02	0.21	-0.07	0.94	0.99	(0.65, 1.49)
Perceived risk for severe COVID-19						
Low concern, low stress (Class 1)	-0.29	0.13	-2.17	0.03	0.75	(0.58, 0.97)
Moderate concern, moderate stress (Class 2)	0.17	0.13	1.32	0.19	1.19	(0.92, 1.53)
High concern, high stress (Class 4)	0.74	0.23	3.24	<0.001	2.10	(1.34, 3.30)

Shown here are unstandardized regression coefficients (*b*), standard errors (*SE*), *t*-values (*t*), *p*-values (*p*), odds ratios (OR), and confidence intervals for the ORs (CI<sub>s</sub>).

### Class differences in physiological changes

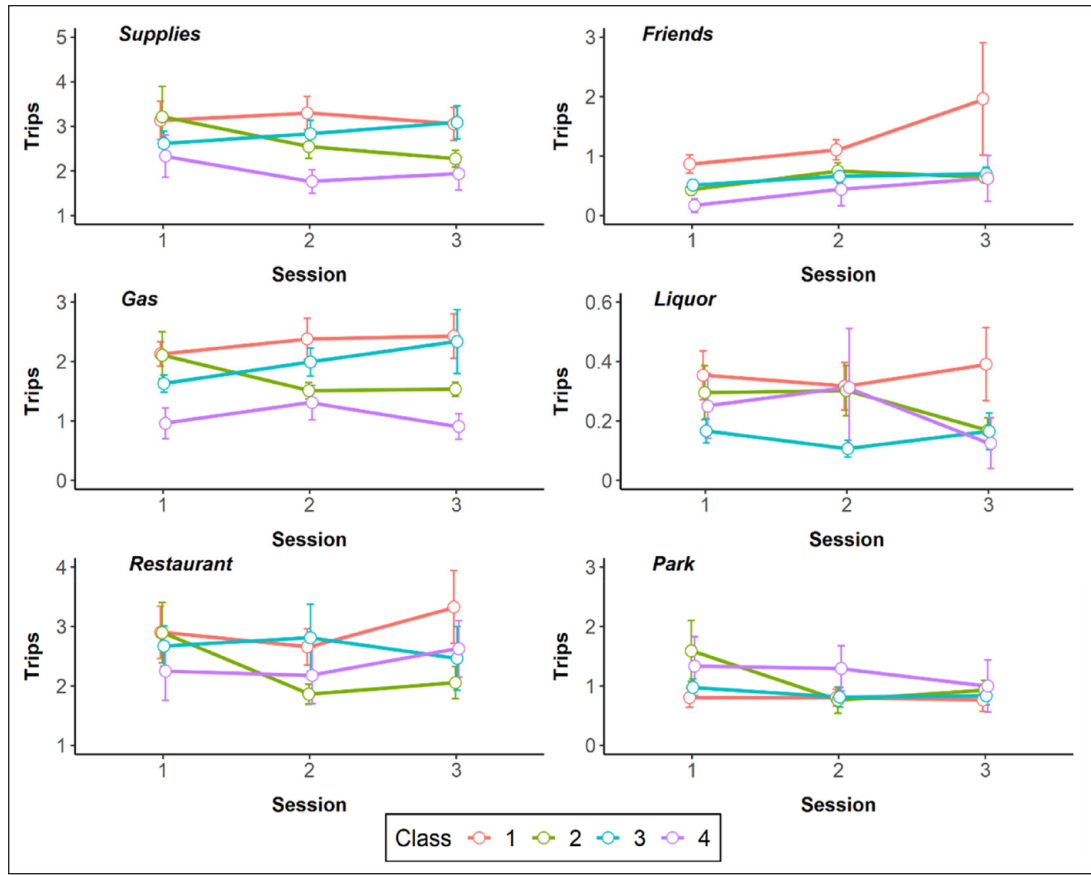
Longitudinal changes in physiology and travel were analyzed using linear mixed-effects models in R.<sup>35</sup> See Supplemental Materials for full statistics. For systolic blood pressure, results revealed a significant main effect of time,  $b = -1.03$ ,  $SE = 0.41$ ,  $t = -2.54$ ,  $p = 0.01$ , indicating that, for the sample as a whole, participants experienced a modest decrease in systolic blood pressure over the course of the study. Similar decreases were found for diastolic blood pressure,  $b = -1.11$ ,  $SE = 0.29$ ,  $t = -3.86$ ,  $p < 0.001$ , pulse,  $b = -1.51$ ,  $SE = 0.32$ ,  $t = -4.71$ ,  $p < 0.001$ , and forehead temperature,  $b = -0.10$ ,  $SE = 0.5$ ,  $t = -2.08$ ,  $p = 0.04$ . Together, these results indicate that like concern about lifting pandemic restrictions, negative affect, and self-reported stress, physiological correlates of stress declined across study sessions for the sample. These effects were largely uniform across classes, with only minimal differences observed among the four groups (Figure 1).

### Class differences in travel

Only minimal changes in average weekly trips were reported across the study period. While these behaviors did not consistently differ across classes, those in the Low Concern, Low Stress group did tend to report more visits to friends' houses,  $b = 0.66$ ,  $SE = 0.20$ ,  $t = 3.40$ ,  $p < 0.001$ , and trips to the liquor store,  $b = 0.19$ ,  $SE = 0.07$ ,  $t = 2.59$ ,  $p = 0.01$ , than the reference group (Figure 2).

## Discussion

The current research examined the landscape of differences in COVID-19 concern and stress, as well as patterns of pandemic fatigue, in a large community, longitudinal cohort. For the study sample overall, concern about lifting pandemic restrictions, negative affect, and self-reported stress decreased across the three study sessions (separated by approximately 4 weeks each), while positive affect increased. Considering these



**Figure 2.** Longitudinal trajectories for travel measures separated by latent class: low concern, low stress (Class 1), moderate concern, moderate stress (Class 2), moderate concern, low stress (Class 3), and high concern, high stress (Class 4). The y-axis represents typical number of reported trips of that type in an average week.

findings alongside the general increases in COVID-19 cases, hospitalizations, and deaths locally, statewide, and globally during this period suggests the development of a general pandemic fatigue among many study participants. This interpretation is further supported by the longitudinal stress physiology measurements which revealed decreases in blood pressure, pulse, and forehead temperature across the study.

Regarding the four latent classes extracted by the LCGA, the largest group reported moderate concern about restrictions, but low levels of stress. That pandemic restrictions were at the forefront of many community members' minds, yet most did not have direct interactions with COVID-19 illness (i.e. all had remained asymptomatic), may explain why a large portion reported some concern about restrictions, yet low levels of stress and negative affect. The possibility that this low reported experience with COVID-19-related issues influenced patterns of pandemic fatigue should be considered when interpreting the results of the current research.

Regarding age and other predictors of class membership, one surprising set of findings revealed that the Moderate Concern, Moderate Stress and High Concern, High Stress

groups were younger than the reference group. Moreover, the High Concern, High Stress group, despite being younger on average than the reference class, also had higher perceived risk for severe COVID-19 disease. These findings identify a unique group of individuals who, although younger and thus likely to have a relatively low risk for severe COVID-19 disease compared to older individuals, expressed high levels of concern and stress throughout the study, as well as high perceived risk for serious illness if infected. Elevated COVID-19 anxiety in younger adults compared to older adults has been previously documented.<sup>3,36</sup>

Also of interest is that the individuals working in healthcare settings or as first responders tended to have moderate levels of concern and stress. This finding may reflect habituation that occurs in such contexts. That is, although SARS-CoV-2 exposure risk is higher in healthcare settings, day-to-day exposure to COVID-19 cases, hospitalization, and/or deaths may cause a desensitization to these situations over time.<sup>37</sup> Another possible explanation is that variability in SARS-CoV-2 exposure is just higher in the general population relative to people working in healthcare. For example, people working outside of healthcare settings (compared to those working in

healthcare) may be more likely to have either high (e.g. person has a close relative seriously ill with COVID-19) or low (e.g. person does not know anyone who was infected) SARS-CoV-2 exposure, increasing their representation in the High Concern, High Stress and Low Concern, Low Stress classes, respectively.

As with any study, there are limitations to consider when interpreting and generalizing the results of the current research. First, the study participants were not randomly selected from McLennan County's population, and the current sample reported higher level of education and a more Democratic political lean than county averages.<sup>3</sup> Further, less than 20% of the sample reported being Hispanic or Latina/Latino members, which is lower than county population estimates (<https://www.census.gov/quickfacts/mclennancountytexas>). Accordingly, the current results cannot be interpreted as representative of McLennan County as a whole.

Additionally, it is possible that patterns of pandemic fatigue found in the current research, especially the decline in blood pressure and pulse, were influenced by participants' habituation to the study site.<sup>38</sup> However, that a continued decrease in some of these markers was observed from the second to third session (in addition to the decrease from the first to second session) seems to suggest these results cannot merely be reduced to familiarity with the study's setting and personnel. Lastly, while the presence of pandemic fatigue is inferred from the general decreases in concern and stress found in the current research, we did not directly ask participants if they felt that they were experiencing this phenomenon, nor did we explicitly measure changes in compliance with health recommendations. Future research might benefit from examining whether individuals' perceptions of experiencing pandemic fatigue are consistent with psychological, biological, and behavioral markers of concern and stress.

Another potentially fruitful direction for future research would be to examine whether there are hormonal and immunological correlates of pandemic fatigue. It may be particularly interesting to explore any immunological shifts that co-occur with changes in COVID-19-related stress, as these may have implications for vaccine responsiveness and susceptibility to severe illness.<sup>39,40</sup>

In sum, the current research revealed changes in psychological and physiological markers of stress over time that were consistent with the development of pandemic fatigue. While latent class-based differences in concern, stress, and negative affect did explain some variance in patterns of pandemic fatigue, levels of each decreased in nearly all groups identified by the LCGA. The current project builds on a wealth of recent research examining psychological and behavioral changes throughout the current pandemic and may lay the groundwork for future research to further explore how these shifts are manifested in physiological, immunological, and hormonal markers.

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## Author contributions

MPM and EJB conceived the Waco COVID Survey and implemented it with SPW; MPM wrote the survey, designed the study, and obtained the funding; EJB designed and managed the websites; TJN, JG, and MPM managed the enrollment; JG and TJN lead the data collection; MPM and JG conceived the paper; TJN and JG conducted the statistical analyses; ADH contributed to data collection and manuscript preparation; JG, TJN, ADH, and MPM wrote the manuscript.

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## Ethical approval and consent to participate

The Waco COVID survey was approved and endorsed by the Waco-McLennan County Public Health District, and as a public health surveillance study, met the exclusion criteria for institutional review board approval at 45 CFR 46.102(e) and (l) for all Baylor University researchers, staff, and volunteers. Waco Family Medicine researchers, staff, and volunteers were approved to assist with data collection by the institutional review board at Ascension Providence Hospital and Medical Center of Waco, TX. All participants provided informed consent prior to participation.

## Informed consent

Written informed consent was obtained from participants for anonymized data to be published in scientific journals.



## Significance for public health

There exist stark differences in people's distress and concern about the COVID-19 pandemic. Moreover, these differences have important implications for individuals' engagement in behaviors that help prevent the spread of SARS-CoV-2. The current manuscript contributes to the literature by demonstrating that, despite wide between-person differences in initial levels of COVID-19 related concern, the majority of participants exhibited decreases in negative affect, stress, and concern about pandemic restrictions between July and November 2020. Declining COVID-19 related concern occurred against the backdrop of steady increases in daily COVID-19 cases, hospitalizations, and deaths in the county, suggesting a general trend of pandemic fatigue. The manuscript also examines a variety of factors that predict levels of COVID-19 related concern over time. Understanding the antecedents to, and consequences of, pandemic fatigue will lend key insights into how people's health behaviors are expected to change as the pandemic continues and new variants of concern emerge.

## Availability of data and materials

De-identified data can be made available to researchers upon reasonable request.

## Supplemental material

Supplemental material for this article is available online.

## References

- Achterberg M, Dobbelaar S, Boer OD, et al. Perceived stress as mediator for longitudinal effects of the COVID-19 lockdown on wellbeing of parents and children. *Sci Rep* 2021; 11: 2971.
- Ferreira RJ, Buttell F and Cannon C. COVID-19: immediate predictors of individual resilience. *Sustainability* 2020; 12: 6495.
- Gassen J, Nowak TJ, Henderson AD, et al. Unrealistic optimism and risk for COVID-19 disease. *Front Psychol* 2021; 12: 647461.
- Makhanova A and Shepherd MA. Behavioral immune system linked to responses to the threat of COVID-19. *Pers Individ Dif* 2020; 167: 110221.
- Nkire N, Mrklas K, Hrabok M, et al. COVID-19 pandemic: demographic predictors of self-isolation or self-quarantine and impact of isolation and quarantine on perceived stress, anxiety, and depression. *Front Psychiatry* 2021; 12: 553468.
- Mevorach T, Cohen J and Apter A. Keep calm and stay safe: the relationship between anxiety and other psychological factors, media exposure and compliance with COVID-19 regulations. *Int J Environ Res Public Health* 2021; 18: 2852.
- Moran C, Campbell DJT, Campbell TS, et al. Predictors of attitudes and adherence to COVID-19 public health guidelines in western countries: a rapid review of the emerging literature. *J Public Health Oxf Engl* 2021; 43: 739–753.
- Ning L, Niu J, Bi X, et al. The impacts of knowledge, risk perception, emotion and information on citizens' protective behaviors during the outbreak of COVID-19: a cross-sectional study in China. *BMC Public Health* 2020; 20: 1751.
- Shook NJ, Sevi B, Lee J, et al. Disease avoidance in the time of COVID-19: the behavioral immune system is associated with concern and preventative health behaviors. *PLoS One* 2020; 15: e0238015.
- Crane MA, Shermock KM, Omer SB, et al. Change in reported adherence to nonpharmaceutical interventions during the COVID-19 pandemic, April–November 2020. *JAMA* 2021; 325: 883–885.
- Elia F and Vallelonga F. "Pandemic fatigue" or something worse? *Recenti Prog Med* 2020; 111: 788–789.
- MacIntyre CR, Nguyen P-Y, Chughtai AA, et al. Mask use, risk-mitigation behaviours and pandemic fatigue during the COVID-19 pandemic in five cities in Australia, the UK and USA: a cross-sectional survey. *Int J Infect Dis* 2021; 106: 199–207.
- Murphy JFA. Pandemic fatigue. *Ir Med J* 2020; 113: 90.
- Reicher S and Drury J. Pandemic fatigue? How adherence to covid-19 regulations has been misrepresented and why it matters. *BMJ* 2021; 372: n137.
- Skulmowski A and Standl B. Covid-19 information fatigue? A case study of a German university website during two waves of the pandemic -lundefined information fatigue? A case study of a German university website during two waves of the pandemic. *Hum Behav Emerg Technol* 2021; 3: 350–356.
- Ayre J, Cvejic E, McCaffery K, et al. Contextualising COVID-19 prevention behaviour over time in Australia: patterns and long-term predictors from April to July 2020 in an online social media sample. *PLoS One* 2021; 16: e0253930.
- Fancourt D, Steptoe A and Bu F. Trajectories of anxiety and depressive symptoms during enforced isolation due to COVID-19 in England: a longitudinal observational study. *Lancet Psychiatry* 2021; 8: 141–149.
- Kulkarni S, O'Farrell I, Erasi M, et al. Stress and hypertension. *WMJ* 1998; 97: 34–38.
- Spruill TM. Chronic psychosocial stress and hypertension. *Curr Hypertens Rep* 2010; 12: 10–16.
- Juster R-P, McEwen BS and Lupien SJ. Allostatic load biomarkers of chronic stress and impact on health and cognition. *Neurosci Biobehav Rev* 2010; 35: 2–16.
- Schubert C, Lambertz M, Nelesen RA, et al. Effects of stress on heart rate complexity—a comparison between short-term and chronic stress. *Biol Psychol* 2009; 80: 325–332.
- Torpy JM, Lynn C and Glass RM. JAMA patient page. Chronic stress and the heart. *JAMA* 2007; 298: 1722–1722.
- Becnel JN and Williams AL. Using latent class growth modeling to examine longitudinal patterns of body mass index change from adolescence to adulthood. *J Acad Nutr Diet* 2019; 119: 1875–1881.
- Berlin KS, Parra GR and Williams NA. An introduction to latent variable mixture modeling (part 2): longitudinal latent class growth analysis and growth mixture models. *J Pediatr Psychol* 2014; 39: 188–203.
- Jung T and Wickrama KAS. An introduction to latent class growth analysis and growth mixture modeling. *Soc Personal Psychol Compass* 2008; 2: 302–317.
- Muthén B and Muthén LK. Integrating person-centered and variable-centered analyses: growth mixture modeling with latent trajectory classes. *Alcohol Clin Exp Res* 2000; 24: 882–891.

27. Petersen KJ, Qualter P and Humphrey N. The application of latent class analysis for investigating population child mental health: a systematic review. *Front Psychol* 2019; 10: 1214.
28. Ram N and Grimm KJ. Growth mixture modeling: a method for identifying differences in longitudinal change among unobserved groups. *Int J Behav Dev* 2009; 33: 565–576.
29. van de Schoot R. Latent trajectory studies: the basics, how to interpret the results, and what to report. *Eur J Psychotraumatol* 2015; 6: 27514.
30. Herrero J and Meneses J. Short Web-based versions of the perceived stress (PSS) and Center for Epidemiological Studies-Depression (CESD) Scales: A comparison to pencil and paper responses among Internet users. *Computers in Hum Behav* 2006; 22: 830–846.
31. Watson D, Clark LA and Tellegen A. Development and validation of brief measures of positive and negative affect: The PANAS scales. *J Pers Soc Psychol* 1988; 54: 1063–1070.
32. Duncan LA, Schaller M and Park JH. Perceived vulnerability to disease: development and validation of a 15-item self-report instrument. *Pers Individ Dif* 2009; 47: 541–546.
33. Tybur JM, Lieberman D and Griskevicius V. Microbes, mating, and morality: individual differences in three functional domains of disgust. *J Pers Soc Psychol* 2009; 97: 103–122.
34. Muthén LK and Muthén BO. *Mplus user's guide*. 8th ed., [https://scholar.google.com/scholar\\_lookup?title=Mplus%20user%27s%20guide%3A%20Seventh%20edition&author=L.K.%20Muth%C3%A9n&publication\\_year=1998-2012](https://scholar.google.com/scholar_lookup?title=Mplus%20user%27s%20guide%3A%20Seventh%20edition&author=L.K.%20Muth%C3%A9n&publication_year=1998-2012) (1998, accessed 8 November 2020).
35. R Core Team. *R: a language and environment for statistical computing*. Vienna, Austria: R Foundation Statistics Computing, <https://www.R-project.org/> (2019).
36. Xiong J, Lipsitz O, Nasri F, et al. Impact of COVID-19 pandemic on mental health in the general population: a systematic review. *J Affect Disord* 2020; 277: 55–64.
37. von Delft A, Dramowski A, Khosa C, et al. Why healthcare workers are sick of TB. *Int J Infect Dis* 2015; 32: 147–151.
38. Hughes BM, Lü W and Howard S. Cardiovascular stress-response adaptation: conceptual basis, empirical findings, and implications for disease processes. *Int J Psychophysiol* 2018; 131: 4–12.
39. Glaser R, Sheridan J, Malarkey WB, et al. Chronic stress modulates the immune response to a pneumococcal pneumonia vaccine. *Psychosom Med* 2000; 62: 804–807.
40. Miller GE, Cohen S, Pressman S, et al. Psychological stress and antibody response to influenza vaccination: when is the critical period for stress, and how does it get inside the body? *Psychosom Med* 2004; 66: 215–223.