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Cascading disasters and mental health: The February 2021 winter storm and power crisis in Texas, USA

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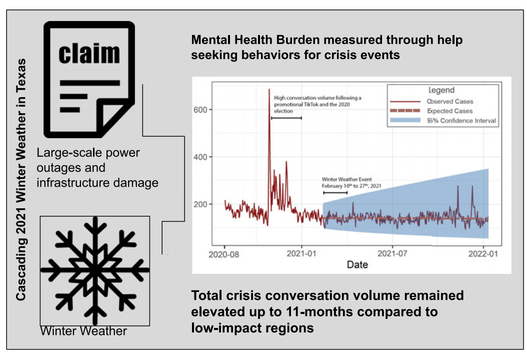
HIGHLIGHTS

- The aim of this study was to investigate crisis outcomes during a cascading winter weather disaster in Texas.
- The volume of total crisis conversations and conversations for thoughts of suicide increased after the inital event.
- Crisis volume remained elevated for up to 11 months.
- Depression-related conversations declined after the initial disaster event.
- Additional research is needed for specific crisis outcomes from cascading disasters.

GRAPHICAL ABSTRACT



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ABSTRACT

In February 2021, the state of Texas and large parts of the US were affected by a severe cold air outbreak and winter weather event. This event resulted in large-scale power outages and cascading impacts, including limited access to potable water, multiple days without electricity, and large-scale infrastructure damage. Little is known about the mental health implications of these events, as most research has predominantly focused on the mental health effects of exposure to hurricanes, wildfires, or other natural disasters that are more commonly found in the summer months. This study aimed to analyze the crisis responses from the 2021 winter weather event in Texas using Crisis Text Line, a text-based messaging service that provides confidential crisis counseling nationwide. To date, Crisis Text Line is the largest national crisis text service, with over 8 million crisis conversations since its inception in 2013. We employed multiple analytic techniques, including segmented regression, interrupted time series, autoregressive integrated moving average (ARIMA), and difference-in-difference (DID), to investigate distinct time periods of exposure for all crisis conversations. ARIMA and DID were further utilized to examine specific crisis outcomes, including depression, stress/anxiety, and thoughts of suicide. Results found increases in total crisis conversations and for thoughts of suicide after the initial winter weather event; however, crisis outcomes varied in time. Thoughts of suicide in high-impact regions were higher across multiple time periods (e.g., 4-weeks, 3-months, 6-months, 9-months and 11-months) compared to low-impact regions and were elevated compared to pre-event time periods for 6-months and 11-months from the initial event. Total crisis volume also remained elevated for high-impact regions compared to low-impact regions up to 11-months after the beginning of the winter event. Our work highlights that cascading winter weather events, like the Texas 2021 Winter storm, negatively impacted mental health. Future research is needed across different disaster types (e.g., cascading, concurrent events) and for specific crisis outcomes (e.g., depression, suicidal ideation) to understand the optimal timing of crisis intervention post-disaster.

Abbreviations: ARIMA, Autoregressive integrated moving average; DID, Difference in difference; CTL, Crisis text line; ITSA, Interrupted time-series analysis; AIC, Akaike information criterion; BIC, Bayesian information criterion.

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1. Introduction

In February 2021, a large US winter storm produced widespread impacts across the US, with >150 million Americans receiving winter weather alerts (CNN, 2021), approximately 195 billion in damages, and nearly 10 million people experiencing power outages (Busby et al., 2021). Some sources deem it the costliest weather disaster in Texas, surpassing even Hurricane Harvey in 2017 (National Weather Service, 2022). The anomalous winter weather event and subsequent power outage in Texas had cascading effects on other services reliant upon electricity, including water, medical services, and indoor heating. While all socio-economic groups were affected, the storm was especially hard on low-income families residing in older, poorly insulated homes with outdated plumbing and limited resources to relocate, repair home damage, or replace spoiled food (Skibell, 2021, Trovall, 2021, Busby et al., 2021).

Historically, a large number of US-declared disasters have been linked to climatic and weather extremes (FEMA (Federal Emergency Management Agency), 2019). Emergent research has demonstrated that any exposure to a climate or weather-related event yields psychological dysfunction in the affected population and specific segments of the population, such as the very young and old, pregnant women, individuals with pre-existing mental illness, and first responders, are more vulnerable to distress and the development of more detrimental mental health outcomes (Watts et al., 2017; Dodgen et al., 2016). The mental health consequences of disasters have been documented in directly exposed populations revealing higher rates of post-traumatic stress disorder, depression, and other mental health problems (Sprang and Silman, 2013, Dyregrov et al., 2018, Weems and Overstreet, 2008). Research suggests that those who are the most at risk for poor mental health after the disaster, in terms of health and socioeconomic status, will be less likely to rebound between disasters due to the inability to replenish economic and social capital following each incident (Lowe et al., 2015), leading to decreased resilience with each disaster and the potential for more adverse crisis outcomes (Malmin, 2021).

As global climate change projections show increases in the frequency and intensity of disasters, multi-hazard and cascading events like the unprecedented Texas Winter Storm are more likely (USGCRP, 2018). To date, little is known about the mental health impacts of cascading disasters (when one disaster results in more significant secondary impacts), although our prior work has examined the effects of concurrent disasters (or when disasters co-occur in both location and timing), finding mixed results; with a higher incidence of mental health conditions for hurricanes that co-occur with the COVID-19 pandemic (Wertis, 2023) and no statistical increases in mental health conditions for wildfires that co-occur in the COVID-19 pandemic (Sugg et al., 2022). The Texas winter storm event offers a unique opportunity to examine a cascading disaster as unprecedented cold conditions resulted in widespread power outages and unsuitable living conditions for many Texas residents. The aim of our study was to examine the mental health impacts of the Texas power outage using one of the largest repositories of mental health data, Crisis Text Line (CTL). Crisis Text Line is a global not-for-profit organization with free, text-based, mental health support and crisis intervention. Crisis Text Line has engaged in over 8 million conversations since August 2013 with support from over 55,000 trained live volunteers (Crisis Trends 2022). Results will provide new knowledge on the mental health impacts of a cascading disaster of winter weather and subsequent unprecedented power outage for the state of Texas, US.

2. Methods

This study's general methodology leveraged quasi-experimental designs to analyze longitudinal changes in crisis response data in the aftermath of the winter storm using time-series and difference-in-difference modeling approaches. Due to the unique nature of 2020 and 2021 with multiple events (e.g., 2020 November presidential election) and to ensure the robustness of our results, we employed four modeling techniques to assess the association between the winter storm event and crisis response volume for highly impacted communities in Texas under the assumption that if the results agreed across models, one could have more confidence in the findings. The four data analytic procedures employed were (1) interrupted time-series analysis with an ANCOVA model (i.e., ITSA), (2) piecewise linear regression, (3) an intervention analysis in the context of an ARIMA model, and (4) difference-in-difference. All pre-event or baseline analyses were performed from January 1, 2021 to February 10, 2021 with the exception of the ARIMA models, which were extended to capture larger trends from August 1, 2020 to February 10, 2021. All analysis was conducted using R statistical computing software (v 4.2.0) (R Core Team, 2022).

2.1. Data

Crisis Text Line is among the US's largest crisis prevention services that offers crisis support through text messaging. Crisis Text Line users are connected with a trained volunteer Crisis Counselor via SMS text message, and following each conversation, counselors complete a report to identify the crisis issue discussed during the text message conversation. Anonymized Crisis Text Line data has been previously used to assess mental health responses from celebrity suicides (Sugg et al., 2019a), psychosocial issues (Szlyk et al., 2020), spatial trends (Thompson et al., 2018), as well as the effects of natural disasters such as Hurricane Florence (Runkle et al., 2021a), high temperatures (Sugg et al., 2019b), COVID-19 (Runkle et al., 2021b), and the Western US Wildfires (Sugg et al., 2022). For this analysis, secondary data from CTL conversations were identified for Texas-based area codes for the following crisis concerns: Any text, Thoughts of Suicide, Depression, and Stress/Anxiety. Any text conversation includes any crisis concerns, including self-harm, relationship, bullying, eating disorders, or forms of abuse (Sugg et al., 2022, Runkle et al., 2021a). Crisis outcomes are identified by crisis counselors using issue tags that relate to over 15 crisis outcomes that are either mental health (e.g., depression) or interpersonal issues (e.g., abuse) (Gould et al., 2022). Daily counts for each crisis response outcome were provided as a binary outcome (yes/no). Prior analysis of CTL crisis outcomes post-climate hazard (e.g., Hurricane Florence) has shown similar positive trends among impacted locations with electronic medical records like emergency department visits, highlighting its strength as a mental health surveillance dataset for climate disasters (Runkle et al., 2021a). In addition, this study also examined the potential explanatory effects of other stressors on mental health outcomes, including temperature and underlying COVID-19 rates. COVID-19 death and incidence rates were obtained from USA Facts (https://usafacts.org/visualizations/coronavirus-covid-19-spread-map). Daily maximum and minimum temperatures were obtained from the epiNOAA R package.

2.2. Exposure

Population exposure to the winter weather event was determined using county-level FEMA declarations for individual and public assistance. FEMA provides aid distribution based on grant eligibility on damage densities within communities, and emergency and trauma needs, among other factors, through the US Stafford Act (Malmin, 2021). The use of FEMA disaster declarations, and specifically the Individual and Public Assistance as an exposure metric, has been utilized in other studies as well (Bell et al., 2020; McCann et al., 2022; Quast and Feng et al., 2019; Horney et al., 2020; Runkle et al., 2021a). In general, individual assistance occurs when primary assistance levels of damages are determined beyond the response capability of the state government, whereas public assistance is for less-affected areas (Quast and Feng 2019).

Within the public assistance funding, there are different classifications ranging from 1) Emergency Work with Category A: Debris Removal, Category B: Emergency Protective Measures, to 2) Permanent Work with Category C: Roads and Bridges, Category D: Water control facilities, Category E: Public Buildings and contents, Category F: Public utilities, and Category G: Parks, recreation and other facilities (FEMA (Federal Emergency Management Agency), 2019). Based on these criteria, we defined highly-impacted area codes as those that received both individual and public FEMA assistance (Categories C-G). In contrast, the two western Texas area codes (915 and 432) were considered lower-impacted areas and were classified as the counterfactual or control group due to the overall lack of Individual assistance and Public assistance (Categories C-G) (Fig. 1). A sensitivity analysis was also conducted with area code 806 (e.g., Northern Texas, 806), where it was included as lower impact exposure location with western Texas area codes (915 and 432). The sensitivity analysis was conducted as area code 806 had generally less total area with Individual and Public Assistance (Category C-G) designations than other eastern Texas area codes. The use of counterfactual groups was only implemented in the Difference-in-Difference sub-analysis. However, only high-impact locations (e.g., eastern Texas) were modeled in other analyses.

2.3. Time periods of analyses

Little is known about the timing of poor mental health response after cold weather events, particularly following severe cold air outbreaks like the cascading 2021 winter weather event, which brought multiday road closures, power outages, loss of indoor heat, and broken pipes for the Texas region (National Weather Service, 2022; Day et al., 2022). Multiple intervention time points were investigated in this study to examine changes in crisis concern volume across different time periods. This severe cold storm event was triggered initially when the ambient temperature fell below freezing in early February and remained below freezing for several days (Glazer et al., 2021). Therefore, the post-event time periods examined included:

1. Beginning of the initial disaster event (2/10–2/27),
2. Four weeks after the beginning of the event (2/10 to 3/10),
3. Six weeks after the beginning of the event (2/10 to 3/24),
4. Three months after the beginning of the event (2/10 to 5/10),
5. Six months after the beginning of the event (2/10 to 8/10),
6. Nine months after the beginning of the event (2/10- to 1/20), and
7. 11 months after the beginning of the event (2/10 to 1/10/2022).

Our time periods of analyses were limited to 11 months after the event due to data availability from Crisis Text Line. This study was exempt from the Appalachian State University's IRB review board (protocol#: 23563).

2.4. ITSA modeling

Interrupted time-series analysis (ITSA) modeling was used to statistically evaluate the effect of the winter storm by assessing the underlying trend of a time series interrupted by a specific intervention (e.g., natural disaster) (Bernal et al., 2017 et al., 2017). Using the "its.analysis" package, we used a Type-2 Sum of Squares ANCOVA lagged dependent variable model to assess the mean difference between non-interrupted (pre) and interrupted (post) time-periods (i.e., before and after the winter weather event) (English, 2019). Unlike other ITS methods, the "its.analysis" package is designed for small sample sizes (typically under 45-time points), which was optimal for our event after the 2020 December holidays and the 2020 presidential election, where high CTL usage was also observed. ITSA outputs include a trimmed median F-value from which a bootstrapped *p*-value is derived for both the intervention and autocorrelation terms. Bootstrapped models were run using 1000 iterations and $\alpha = 0.05$. These analyses were made using the its.analysis package for directly exposed locations (all Texas area codes except 432 and 915) (English 2019) (R Core Team, 2022).

2.5. Segmented regression

We extended our preliminary ITSA analysis by incorporating simplistic breakpoint models to evaluate the trends in all crisis outcomes at specific time periods (e.g., four weeks after, six weeks after, etc.). Breakpoint models assume a piecewise linear relationship between the response and explanatory variables and can therefore detect breakpoint relationships (Muggeo, 2003). These models were estimated using the R package, segmented (version 3.0; R Development Core Team) (Muggeo, 2003, 2008), which utilizes generalized linear models to estimate the piecewise regression and associated breakpoints. The median slope prior to and post-event is used to assess the overall interruption effect in an immediate and sustained (i.e., >1 day) response. Compared to other analytic techniques, segmented regression provides an easy-to-interpret post-event trend from the baseline.

2.6. Autoregressive integrated moving average (ARIMA) Methodology

An interrupted time series (ITS) analysis using ARIMA was also performed to capture the crisis text volume for individuals in Texas before and after the impact of the storm; unlike other data analytical procedures (e.g., segmented regression, itsa modeling), a longer pre-intervention period increased the power to detect secular trends. In addition, ARIMA models address autocorrelation common in time series, thereby providing a flexible time series model for pre-and post-event hypothesis testing (Schaffer et al., 2021). In ARIMA (*p*, *d*, *q*), *p*, *d*, and *q* represent the autoregressive order, the number of differences, and the moving average order, respectively. Various ARIMA models were examined, and the best

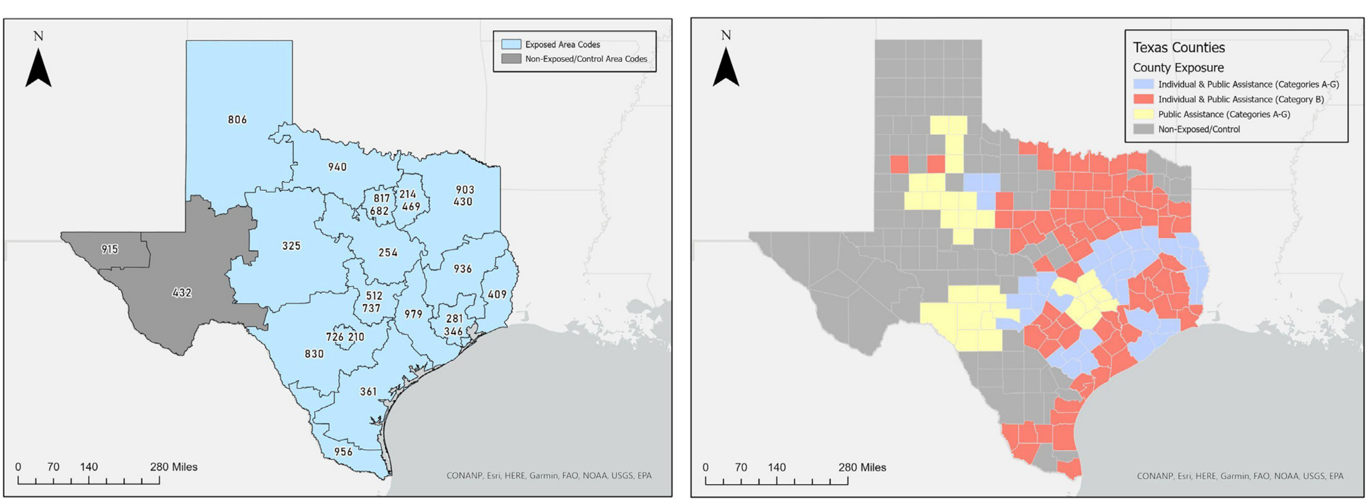

Fig. 1. Map of FEMA declarations and corresponding area codes of exposed and non-exposed locations. Only low-exposure area codes were used in the Difference-in-Difference Analysis.

fit was decided based on a multi-step process that included the 1) Evaluation of the autocorrelation function and partial autocorrelation function and 2) Use of the auto.arima algorithm (Hyndman et al., 2022). And then, after model completion, (3) the Ljung-Box test to evaluate the standardized residuals of the model to ensure that white noise has been removed and that the null hypothesis can be rejected, and 4) the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) scores to manually adjust the models for the most parsimonious model. Transfer functions were used to quantify the complex impact of the intervention, with model fit statistics (AIC, BIC) used to select the most appropriate transfer function (e.g., Pulse, Ramp, or Step) (Schaffer et al., 2021). ARIMA forecasts provide predicted text volumes, allowing for the comparison of the observed volume of texts versus predicted volume of texts. Analysis was done in R packages *astsa* (Stoffer, 2021) and *forecast* (Hyndman et al., 2022).

In addition to ARIMA, the Autoregressive Integrated Moving Average with Explanatory Variables (ARIMAX) model was used to assess the impact of temperature and/or COVID-19 rates. Prior to ARIMAX model, the cross-correlation function between the COVID-19, weather variables, and crisis outcomes was calculated to determine the significant time lag periods of 0, 7, 14, and 21 days. The coefficients of the ARIMAX were assessed for statistical significance to determine key determinants in crisis text volume. The values of RMSE (prediction error or the measure of how much a dependent series varies from its predicted value), MAE (average of the absolute errors/residuals between observed vs. predicted values), MAPE (prediction accuracy of a developed model), AIC and BIC, were used to assess ARIMAX model performance and were found to be higher than ARIMA models (Saigal and Mehrotra, 2012).

2.7. DiD methodology

Difference-in-difference (DID) is a separate quasi-experimental design methodology for longitudinal data from high-impact locations (i.e., treatment group; most of Texas) and a control or counterfactual locations (i.e., control group; 915 and 432; both West Texas-based area codes) to estimate the causal effect of an intervention on an impacted population (Wing et al., 2018). Unlike the ARIMA analysis, DID allows for the inclusion of the counterfactual groups (i.e., control groups), or in the instance of our study, low-exposure locations (i.e., counterfactual) (Callaway and Sant'Anna, 2021a).

We used the Callaway and Sant'Anna difference-in-difference approach with multiple time periods because, unlike the traditional difference-in-difference method, this method allows for multiple staggered time periods to be examined at once. In our study, The Average Treatment Effect on Treated (ATT) was constructed for each crisis concern separately, as well as, the total crisis text volume. Pre-test of the parallel trends assumption of the high-impact versus low-impact locations were significant (p-value >0.10) for all outcomes except depression and therefore the DID association are not considered causal (Supplemental Fig. 1, Callaway and Sant'Anna, 2021a). A sensitivity analysis of low-impact and high-impact areas was also conducted to include area code 806 as a low-exposure location, despite multiple counties in the FEMA designation of Permanent work (Category D - G) and Individual Assistance. Pretest for the parallel trends assumption of this updated high impact versus low impact locations (e.g., area codes 806, 915, 432) were insignificant (p-value <0.10) for all outcomes, and therefore potentially highlighting a causal association (Supplemental Fig. 2, Callaway and Sant'Anna, 2021a). Analysis was completed in the R package did (Callaway and Sant'Anna, 2021b).

3. Results

The daily number of mean CTL conversations was highest for the later time intervals (e.g., 9-month, 11-month) for high-impact locations (i.e., predominately eastern Texas). In contrast, in low-exposure locations (i.e., area codes 915 and 432, both West Texas-based area codes), the daily mean number of mean CTL conversations decreased at later time intervals (e.g., 9-month, 11-month), compared to early time intervals (e.g., 4-week, 6-week). Mean conversations related to thoughts of suicide and depression peaked during shorter time periods (e.g., 4 weeks) for high-impact locations compared to longer intervals (e.g., 11-months) (Table 1). Despite widespread power outages from the event, average daily CTL conversations remained similar to 2019 numbers in the 4-week time period (average daily conversations: 134.7, 2019 average daily conversations for the same 4-week period: 136.7).

Table 2 demonstrates the demographic information available for crisis conversations in high impact regions (e.g., eastern Texas). Of the CTL-users who provided age information (26.5 % of the total sample), 18.7 % were under the age of 13 (5 % of the total sample), 33.2 % were between the age of 14 and 17 (8.8 % of the total sample), and 23.0 % were between 18 and 24 (6.1 % of the total sample). CTL-users who provided demographic information predominately identified as White (54.7 % of those users who provided racial information, 10.4 % of the total sample), Black (13.7 % of those users who provided racial information, 2.6 % of the total sample), and Female (68.8 % of those users who provided racial information, 18.8 % of total sample).

3.1. ITSA-short time series and segmented regression results for all crisis conversations

ITSA-short time series analysis in high-impact locations found significant variability in CTL total conversation volume during the initial event, 6 weeks, 3 months, 6 months, and 9 months after the beginning of the storm as compared to before the event (Table 3). Segmented piecewise linear regression found similar results in high-impact locations, with total CTL conversation volume higher in the post-event time period compared to the pre-event time period for the 4 weeks (β:0.4468), 3-months (β:0.0817), 9-months (β:0.0051), and 11-months (β:0.0334) after the beginning of storm (Supplemental Table 1).

3.2. ARIMA for all crisis conversations, thoughts of suicide, stress/anxiety, and depression

Four ARIMA models were selected; one for each crisis-event topic based on AIC, RMSE, MAE, using August 1, 2020, to February 10, 2020, as the pre-event time period (Table 4). The ramp ARIMA model (ramp intervention p-value <0.096) was the best fit to examine changes in daily text volume for all crisis texts (1,1,1) and for stress and anxiety (0,1,3) (ramp intervention p-value<0.01) (Table 5). The step ARIMA model was the best-fit model for examining pre-post Texas winter storm changes in daily depression-related text volume (1,0,4, step intervention p-value<0.09) and for thoughts of suicide (1,1,1, step intervention p-value<0.12) (Table 5). No seasonal lag was observed in daily crisis text volume within the period examined, and seasonality was not adjusted for in the models.

The impact model results for each outcome for the different event scenarios are shown in Fig. 1. Increases in observed crisis text volume compared to forecasted crisis text volume were generally higher for 9-months and 11-month time periods across all crisis outcomes. We observed a 15.4 % increase in crisis texts for thoughts of suicide in 6 months compared to the forecasted daily amount and a 22.5 % increase in crisis texts for thoughts of suicide in 11 months compared to the forecasted daily amount. Crisis texts for stress and anxiety remained elevated across all time periods with a 9.0 % increase 4-weeks post event, 8.6 % increase in 6-weeks post-event, 8.4 % increase in the 3-months post-event, 3.9 % increase in the 6-months post-event, 6 % increase in 9-months post-event and 4.5 % increase in the 11-months post-event.

Total crisis text volume had marginal changes between forecasted and observed values, with the largest increases in 9 months (1.6 %) and 11 months post-event (1.1 %). Comparatively, decreases in crisis text volume were maximized in the 6-weeks post event (−2 %) and were marginal at 4-weeks post-event (<0.02 %), 3-months post-event (<0.02 %) and 9-months post-event (<0.02 %). Unlike other crisis outcomes, declines for depression crisis texts in observed text volume compared to forecasted text volume were noted in 4-week (−10.3 %), 6-week (−11.0 %), 3-

Table 1
Mean number of daily conversations across different post-event time periods from the onset on the winter weather event (February 10, 2021) for CTL-users from high-impact locations.

	4-week	6- week	3-month	6-month	9-month	11-month
	02/10–03/10	02/10–03/24	02/10–05/10	02/10–08/10	02/10–11/10	02/10/21–02/10/22
Crisis outcomes for high impact locations						
Total CTL (mean (SD))	134.69 (17.28)	132.88 (16.25)	134.78 (16.54)	133.02 (15.72)	136.06 (17.24)	136.44 (22.14)
Depression (mean (SD))	50.45 (7.88)	49.07 (7.69)	50.40 (8.55)	48.35 (8.52)	48.73 (8.74)	49.19 (10.91)
Thoughts of Suicide (mean (SD))	37.07 (6.52)	36.63 (6.47)	36.94 (6.17)	35.95 (6.49)	36.15 (6.94)	35.60 (7.29)
Stress and Anxiety (mean (SD))	45.03 (8.81)	45.56 (7.87)	45.81 (8.12)	44.49 (7.84)	46.01 (8.73)	45.45 (9.61)
Crisis outcomes for low impact locations						
Total CTL (mean (SD))	12.14 (3.42)	11.26 (3.43)	11.26 (3.43)	10.60 (3.53)	10.80 (3.70)	10.98 (3.92)
Depression (mean (SD))	4.69 (1.98)	4.53 (1.98)	4.53 (1.98)	4.01 (2.05)	3.92 (2.11)	4.08 (2.26)
Thoughts of Suicide (mean (SD))	3.86 (2.00)	3.11 (1.86)	3.11 (1.86)	2.96 (1.77)	3.03 (1.92)	3.00 (1.89)
Stress and Anxiety (mean (SD))	2.28 (1.56)	1.82 (1.31)	1.82 (1.31)	1.71 (1.26)	1.70 (1.27)	1.63 (1.27)

months (−7.7 %), 6-months (−3.3 %), 9-months (−3.1 %) and remained unchanged at 11-months (0.0 %) (Fig. 2).

3.3. ARIMAX results for all crisis conversations, thoughts of suicide, stress/anxiety, and depression

Several ARIMAX models were developed using different combinations of potential explanatory variables (e.g., maximum temperature, average temperature, minimum temperature, and COVID-19 incidence) and different lag periods (e.g., 0, 7, 14, and 21 days) to assess the total number of crisis conversations as well as select crisis outcomes (Supplemental Table 2).

The maximum temperature was found to be a significant predictor of CTL conversations (p-value<0.05) rather than minimum and average temperature and therefore was used in subsequent analysis. In addition, COVID-19 cases (p-value = 0.16) rather than COVID-19 deaths (p-value = 0.75) were more likely to predict CTL conversations. Total CTL conversations were significantly predicted by COVID-19 cases (p-value<0.10) when assessed with maximum temperature at lag 0. For depression, maximum temperature (p-value<0.05) rather than COVID-19 cases were a driver of crisis trends at Lag 0. For stress/anxiety, maximum temperature (p-value<0.05) and COVID-19 cases (p-value<0.10) were drivers of crisis trends at Lag 0. Longer lag periods (7 to 21 days) and crisis outcomes did not result in significant explanatory variables (Supplemental Table 2).

3.4. Difference-in-difference for all crisis conversations, thoughts of suicide, stress/anxiety, and depression

Difference-in-Difference analysis was used to examine the temporal changes in daily crisis text volume of the high-impact locations compared to low impact locations. Unlike the other data analytic strategies, the DID analysis includes a counterfactual location (i.e., lower impact regions of western Texas). Overall, the average treatment effect on the treated (ATT) for total crisis volume (i.e., any text) remained elevated across all the time periods of analyses (e.g., four weeks, six weeks, three months, six months, nine months, and 11 months). Thoughts of suicide also remained significantly higher for ATT values for all time periods of analyses except six weeks after the initial disaster event (Table 6). The ATT was significant for stress/anxiety at six weeks (ATT: 0.221, CI: 0.109–0.334) and nine months (ATT: 0.208, CI: 0.043–0.374). ATTs for crisis texts for depression were insignificant across all time periods of analyses, although the assumption of parallel trends was met for this specific crisis outcome (Table 6).

The Difference-in-Difference sensitivity analysis included the area code 806 (e.g., northern Texas) in the low-impact regions, which reflects an area with less coverage of Individual or Public Assistance (Categories: D-G) designations compared to eastern Texas. The sensitivity analysis met the assumption of parallel trends across all crisis outcomes (e.g., Any Text, Thoughts of Suicide, Depression, and Stress/anxiety). Significant ATT

Table 2
Demographics of CTL users in exposed locations who completed post-conversation survey from Crisis Text Line from January 2021 to January 2022.

	Strata	Overall
n		51,637
	No response	37,999 (73.6)
	13 or younger	2571 (5.0)
	14–17	4534 (8.8)
	18–24	3136 (6.1)
	25–34	2075 (4.0)
	35–44	606 (1.2)
	45–54	404 (0.8)
	55–64	217 (0.4)
Age (%)	65+	95 (0.2)
	No response	39,295 (76.1)
	LGBTQ+	6986 (13.5)
Sexuality (%)	Straight	5356 (10.4)
	No response	37,442 (72.5)
	Male	1876 (3.6)
	Female	9704 (18.8)
Gender (%)	Nonconforming	2615 (5.1)
	No response	41,805 (81.0)
	Black	1324 (2.6)
	Indigenous American	374 (0.7)
	Middle Eastern	62 (0.1)
	Asian	599 (1.2)
	Other/Mixed Race	2056 (4.0)
	Pacific Islander	21 (0.0)
Race (%)	White	5396 (10.4)
	No response	8612 (16.7)
	Hispanic	4141 (8.0)
Hispanic (%)	No Answer	38,884 (75.3)
	No	34,453 (66.7)
Anxiety and Stress (%)	Yes	17,184 (33.3)
	No	33,000 (63.9)
Depression (%)	Yes	18,637 (36.1)
	No	38,200 (74.0)
Thoughts of Suicide (%)	Yes	13,437 (26.0)
	No	50,662 (98.1)
Mention COVID-19 (%)	Yes	975 (1.9)

Table 3
ITSA model outputs of time periods after the initial Texas winter weather event (February 10, 2021). The pre-event time period was from January 1, 2021 to February 10, 2021.

Intervention parameter	Sum of squares	F-value[a]	p-Value[b]
High impact locations in Texas[c]			
Initial event (2/10 to 2/27)	1104.1	4.29 (0.26–15.28)	0.048
4-weeks after (2/10 to 3/10)	734.6	3.05 (0.13–11.24)	0.086
6-weeks after (2/10 to 3/24)	1210.9	5.29 (0.48–15.40)	0.025
3-months after (2/10 to 5/10)	1288.6	4.97 (0.22–17.50)	0.022
6-months after (2/10 to 8/10)	2409	10.21 (1.90–26.66)	0.001
9-month after (2/10 to 11/10)	2048	8.56 (1.28–22.95)	0.003
11-month after (2/10 to 2/10)	711	2.18 (0.03–10.15)	0.145

[a] F-value is the interruption variable.
[b] p-value for the interruption variable (F-value).
[c] All Texas area codes except 915 and 432; both west Texas based area codes.

Table 4
Autoregressive integrated moving average (ARIMA) parameters, coefficients, and performance accuracy to determine best fit models; best fit models are selected in bold.

	Base Model			Pulse			Ramp			Step		
	ARIMA (p,d,q)	RMSE, MAE, MAPE	AIC	ARIMA (p,d,q)	RMSE, MAE, MAPE	AIC	ARIMA (p,d,q)	RMSE, MAE, MAPE	AIC	ARIMA (p,d,q)	RMSE, MAE, MAPE	AIC
Any text	1,1,1	31.3, 18.0, 10.8	520.7	1,1,1	31.3, 17.9, 10.8	519.1	**1,1,1**	**31.3, 18.0, 10.8**	**518.7**	1,1,1	31.3, 18.0, 10.8	518.7
Suicidal thought	1,1,1	7.7, 5.8, 15.1	242.3	1,1,1	7.7, 5.8, 15.1	241.0	1,1,1	7.7, 5.8, 15.0	240.6	**1,1,1**	**7.7, 5.8, 15.1**	**240.6**
Stress and anxiety	0,1,3	12.7 8.2, 15.9	179.9	0,1,3	12.7, 8.2, 15.9	178.2	**0,1,3**	**12.7, 8.2, 15.8**	**177.9**	0,1,3	12.7, 8.2, 15.9	178.0
Depression	1,0,4	16.7, 9.4, 15.2	202.0	1,0,4	16.7, 9.4, 15.2	200.5	1,0,4	16.7, 9.4, 15.2	200.0	**1,0,4**	**16.7, 9.4, 15.2**	**200.0**

RMSE: Root mean square error.
MAE: Mean absolute error.
MAPE: Mean absolute percentage error.
AIC: Akaike Information Criterion.

values were observed for Any Text (Total crisis text volume) at 11 months (ATT: 0.243, CI: 0.066, 0.421) and for Depression at six months (ATT: -0.170, CI: −0.319, −0.020) after the initial disaster event (Supplemental Table 3).

4. Discussion

This study examined the association between the unprecedented 2021 winter weather event and changes in help-seeking behaviors for mental health crises in Texas. This cascading event, where cold temperatures and winter weather led to a large power failure across most of the state of Texas, resulted in a number of secondary impacts, including limited potable water access, damage to infrastructure, broken pipes/waterlines, water system failures, and a massive electrical grid failure (Glazer et al., 2021, National Weather Service, 2022, Day et al., 2022). Our study leveraged a quasi-experimental design with multiple analytic approaches to examine different crisis text volumes across various time spans (e.g., 4-weeks, 6-weeks, 3-months, 6-months, 9-months, 11-months). We found overall increases in crisis text volume and thoughts of suicide; increases were generally higher at longer time spans (e.g., 9-months and 11-months) compared to both low-impact regions and pre-event time periods. Other specific outcomes like stress/anxiety and depression either had significant increases at select time periods (stress/anxiety) or decreasing numbers of crisis texts (depression) after the beginning of the disaster event.

Our work provides a unique contribution as the only study focused on mental health to investigate the crisis response following a severe cold, extreme weather event rather than the typically studied heatwave (Liu et al., 2021), hurricane (Neria and Shultz, 2012; Runkle et al., 2021a), or wildfire events (Sugg et al., 2022). In general, we noted an increase in crisis concerns following the cascading winter weather event in high-impact locations compared to lower impact locations. Across all analytic methods, the total volume of crisis texts increased following the winter event over longer time periods of analyses, with significant increases for DID at 9 and 11-months (compared to low-impact regions) and higher observations than forecasted values for ARIMA at 9 months and 11 months (compared to time period before the event). Results were confirmed at 9 months with the ITSA short time series and segmented piecewise regression (shorter baseline time period than ARIMA). All crisis concerns included a variety of

Table 5
The final ARIMA coefficients for crisis outcomes across the six post-event intervention periods in the ITS analysis. Margins of error are reported in parenthesis. Model 1: (Febuary 10 - Mar 10); Model 2: (Febuary 10 - March 24); Model 3: (Febuary 10 - May 10); Model 4: (Febuary 10 - August 10); Model 5: (Febuary 10 - November 10); Model 6: (Febuary 10 - Jan 10). The baseline or pre-event time period was August 1, 2020 to February 10, 2021.

Crisis event	Four weeks[a]	Six weeks[b]	Three months[c]	Six months[d]	Nine months[e]	11-months[f]
Total crisis volume						
AR1	0.66 (0.08)***	0.65 (0.07)***	0.63 (0.07)***	0.55 (0.06)***	0.53 (0.05)***	0.57 (0.05)***
MA1	−0.93 (0.04)***	−0.93 (0.04)***	−0.93 (0.04)***	−0.93 (0.03)***	−0.92 (0.03)***	−0.93 (0.0243)***
Ramp Function	0.002 (0.01)	−0.0004 (0.01)	0.001 (0.004)	−0.0004 (0.002)	0.001 (0.002)	−0.0001 (0.001)
Thoughts of suicide						
AR1	0.38 (0.08)***	0.38 (0.08)***	0.38 (0.07)***	0.32 (0.06)***	0.25 (0.06)***	0.28 (0.05)***
MA1	−0.91 (0.04)***	−0.92 (0.04)***	−0.92 (0.04)***	−0.91 (0.03)***	−0.92 (0.03)	−0.91 (0.03)***
Step Function	−0.06 (0.12)	−0.06 (0.12)	−0.06 (0.11)	−0.05 (0.10)	−0.05 (0.10)	−0.05 (0.10)
Stress and anxiety						
MA1	−0.41 (0.06)***	−0.42 (0.06)***	−0.48 (0.06)***	−0.53 (0.05)***	−0.54 (0.04)***	−0.53 (0.04)***
MA2	−0.16 (0.08)*	−0.15 (0.08)*	−0.16 (0.08)***	−0.12 (0.07)***	−0.12 (0.06)**	−0.14 (0.05)**
MA3	−0.21 (0.07)**	−0.22 (0.07)***	−0.18 (0.06)***	−0.18 (0.05)***	−0.20 (0.05)***	−0.18 (0.04)***
Ramp Function	0.01 (0.01)	0.004 (0.01)	−0.001 (0.005)	−0.0002 (0.003)	0.0005 (0.002)	−0.0003 (0.002)
Depression						
AR1	0.96 (0.03)***	0.97 (0.03)***	0.97 (0.03)***	0.97 (0.03)***	0.97 (0.02)***	0.95 (0.03)***
MA1	−0.30 (0.07)***	−0.32 (0.07)***	−0.33 (0.06)***	−0.41 (0.06)***	−0.44 (0.05)***	−0.4 (0.05)***
MA2	−0.1 (0.07)	−0.10 (0.07)	−0.17 (0.07)**	−0.11 (0.06)	−0.12 (0.05)*	−0.13 (0.05)**
MA3	−0.22 (0.07)*	−0.12 (0.07)*	−0.09 (0.06)	−0.13 (0.06)*	−0.13 (0.05)**	−0.13 (0.05)**
MA4	−0.22 (0.07)***	−0.23 (0.07)***	−0.19 (0.06)**	−0.16 (0.06)**	−0.12 (0.05)*	−0.12 (0.05)*
Intercept	4.18 (0.09)***	4.17 (0.1)***	4.17 (0.09)***	4.14 (0.10)***	4.16 (0.08)***	4.17 (0.07)***
Step Function	−0.09 (0.15)	−0.12 (0.15)	−0.14 (0.13)	−0.20 (0.14)	−0.21 (0.11)	−0.24 (0.08)**

Significance: * <0.05, ** <0.01, *** <0.001.
[a] Model 1: (Feb 10 - Mar 10).
[b] Model 2: (Feb 10 - Mar 24).
[c] Model 3: (Feb 10- May 10).
[d] Model 4: (Feb 10 - Aug 10).
[e] Model 5: (Feb 10- Nov 10).
[f] Model 6: (Feb 10 - Jan 10).

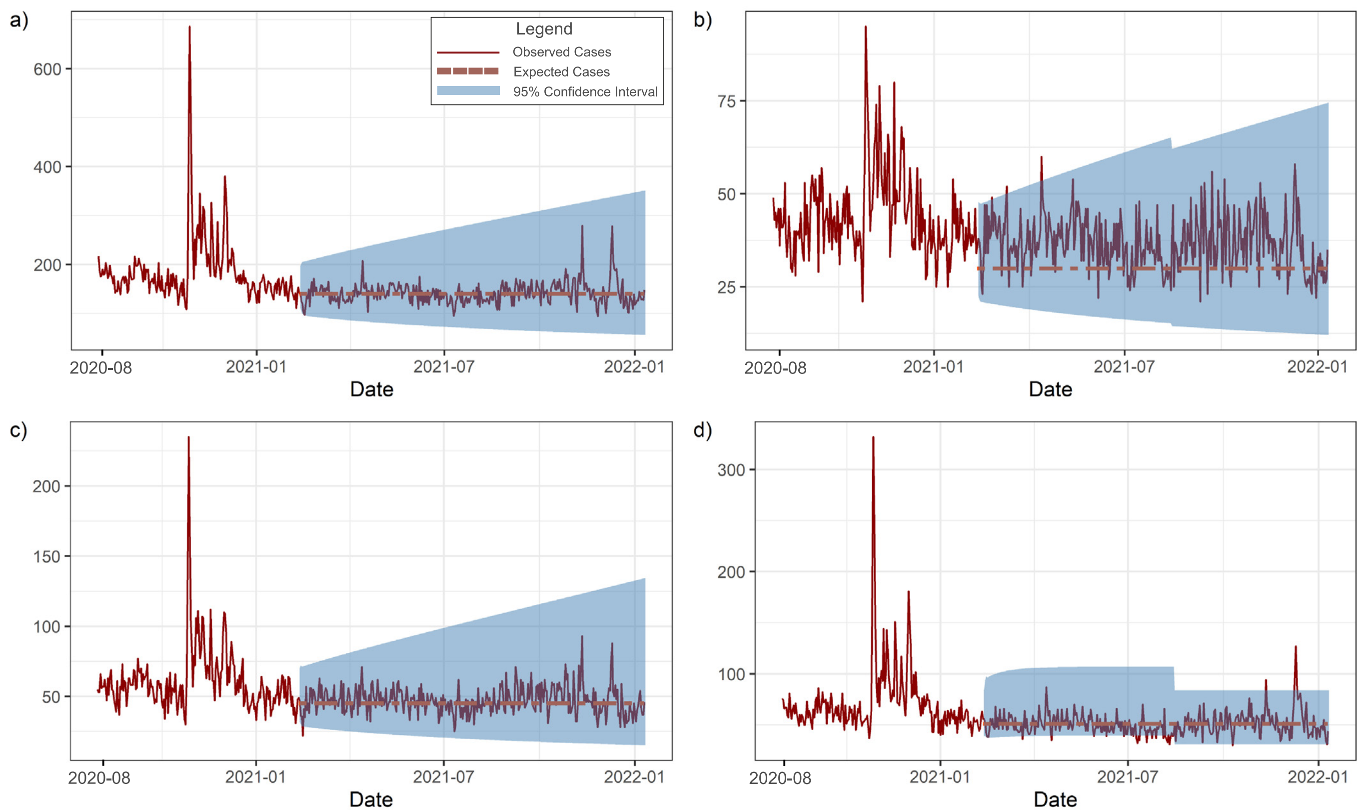

Fig. 2. Forecasted vs. Predicted Crisis Conversations for A) All conversations B) Thoughts of Suicide C) Stress and Anxiety and D) Depression.

conditions, including suicidal behaviors, interpersonal issues, third-party issues, and types of abuse. These crisis concerns have noted increases in other studies focused on hurricanes, with increases observed for domestic violence (Gearhart et al., 2018), stress/anxiety (Mills et al., 2007), and grief (Shear et al., 2011), and our work provides new evidence of the mental health effects of natural hazards outside of hurricane events.

Specific crisis outcomes like suicidal thoughts had the largest increases in crisis concerns in the DID and ARIMA, highlighting a sustained increase in suicidal behaviors through 11 months after the initial event. In particular, we noted a sudden, continual change in CTL conversations after the winter weather event that shifted Thoughts of Suicide conversations upward immediately following the winter weather storm in ARIMA analysis (i.e., step function). Elevated texts for suicidal thoughts compared to lower impact regions were also observed in the DID analysis. Similar CTL-based studies noted larger increases at shorter time intervals, with a 23 % increase in suicidal ideation in the 6-week time period post-hurricane Florence in NC (Runkle et al., 2021a) and a 26.5 % increase in the suicidal thoughts post-hurricane Ida in Louisana (Wertis, 2023). COVID-19 cases and cold temperatures did not significantly predict thoughts of suicide, highlighting that other stressors like power outages or the disaster itself may influence suicidal ideation. Nonetheless, our results confirm the initial and sustained increases in thoughts of suicide and highlight that preventive measures should be put in place in the weeks and months following anomalous winter weather disasters.

Stress and anxiety peaked at irregular intervals compared with other crisis outcomes. In particular, the DID analysis noted significantly higher

Table 6
Average treatment effect on treated (ATT) for high-impact regions (e.g., eastern Texas) and the beginning of the disaster event (February 10–20) after 4-weeks, 6-weeks, 3-months, 6-months, 9-months and 11- months with low-impact regions as counterfactual locations (e.g., western Texas).

Daily text volume	ATT					
	4-weeks	6-weeks	3-month	6-month	9-month	11-month
	(95%CI)	(95%CI)	(95%CI)	(95%CI)	(95%CI)	(95%CI)
	(Feb 10, 2021 - Mar 10, 2021)	(Feb 10, 2021 - Mar 24, 2021)	(Feb 10, 2021 - May 10, 2021)	(Feb 10, 2021 - Aug 10, 2021)	(Feb 10, 2021 - Nov 10, 2021)	(Feb 10, 2021 - Jan 10, 2022)
Any text	0.198* (0.066 0.330)	0.265* (0.071 0.459)	0.122* (0.006 0.237)	0.191* (0.077 0.306)	0.310* (0.231 0.389)	0.219* (0.062 0.377)
Stress and anxiety	0.053 (−0.100 0.208)	0.221* (0.109 0.334)	−0.063 (−0.233 0.106)	0.028 (−0.051 0.108)	0.208* (0.043 0.0374)	0.031 (−0.068 0.131)
Thoughts of suicide	0.246* (0.112 0.380)	0.339 (−0.014 0.694)	0.230* (0.020 0.439)	0.213* (0.088 0.337)	0.269* (0.168 0.370)	0.211* (0.112 0.309)
Depressed	0.082 (−0.044 0.209)	0.095** (−0.053 0.244)	0.064*** (−0.177 0.305)	0.129 (−0.0497 0.3078)	0.187 (−0.046 0.420)	0.081 (−0.049 0.213)

* p-value <0.05.
** p-value <0.01.
*** p-value<0.001.

stress/anxiety outcomes in the immediate aftermath (6 weeks) and at a longer interval (9 months) after the winter storm for high-impact locations (e.g., eastern Texas). In addition, the stress/anxiety conversations from the ARIMA analysis resulted in a change of slope immediately after the intervention (ramp) and the largest increase 9-months following the initial disaster event in forecast vs. predicted conversations. Results parallel a similar CTL analysis of Hurricane Florence with a 17 % increase in stress/anxiety 6-weeks post-hurricane, however, our results find evidence that stress/anxiety can also occur at longer intervals after the initial storm event. Both COVID-19 cases and temperature predicted stress/anxiety crisis conversations in ARMIAX models, with higher COVID-19 cases and lower temperature predicting higher stress/anxiety, highlighting that multiple stressors may trigger abnormally higher levels of stress/anxiety among Crisis Text Line users.

Unlike the other crisis outcomes, we did not observe an increase in depression-related conversations across multiple time periods. For instance, a statistically significant decline in slope immediately in our ARIMA followed the storm, highlighting that mental health may vary across crisis outcomes (e.g., depression, thoughts of suicide) after the initial weather disaster, with some crisis events increasing and others decreasing. Low maximum temperatures significantly predicted depression outcomes in ARIMAX models and may highlight a stronger climatic or natural hazard signal than other external stressors on this crisis outcome. Previous analysis across multiple cities in China also found a significant association between low temperatures and depression, with a 5C decrease resulting in a 15.6 % increase in depression (Jiang et al., 2022). Yet, this work and our work contrasts with multiple analyses that find increases in depression during high temperature (Wang et al., 2014) and heat waves (Hansen et al., 2008).

Previous disaster/mental health models have overlooked the variability inherent in the temporal trajectory of mental health, often focusing on univariate disasters and single crisis intervention models (Kaminsky et al., 2007). The Substance Abuse and Mental Health Service Administration's (SAMSHA)'s popular model focus on behavioral and mental health conditions across various time periods; however, this model fails to account for concurrent, cascading, and co-occurring disasters and the variability of effects across individuals in a community. Our work highlights the need for updated frameworks across different crisis outcomes (e.g., depression, stress/anxiety) and for future research to confirm the differences in our findings compared to studies focused on univariate disasters like hurricanes. We hypothesize that the winter storm-mental health association is likely different for specific at-risk populations like minorities, lower-income populations, and those with pre-existing mental health conditions. Future research is needed across different sub-populations to fully understand the differential vulnerability of cascading hazards on mental health. Lastly, our work highlights the utility of using novel data sources like Crisis Text Line to understand these complex trends in near real-time as climate and public health disasters unfold.

4.1. Strengths and limitations

Our study utilized a quasi-experimental design to causally link a severe winter storm event with poor mental health in the impacted population. Quasi-experimental designs like difference-in-difference are underutilized in the literature on climate and health interactions (Massazza et al., 2022), despite their ability to detect causal inference and incorporation of a counterfactual. In addition, our work uses multiple analytic strategies, including ARIMA models, which strengthens the validity of our findings. Our results are further strengthened by the use of an interrupted time series analysis for short time periods (ITSA models) and segmented regression, which improve the interpretation of our results. Our study also uses a large longitudinal sample of crisis text conversations providing more evidence for the climate and mental health relationship, whereas most literature focuses on the use of mental health constructs that are limited to self-reported measures or from health service records (e.g., hospital administrative data).

Our study exhibits several noteworthy limitations. First, our study fails to examine confounders, mediators, or effect measure modifiers in the relationship between the winter weather event and crisis events. As understanding furthers on trends in mental health post-climate disaster, future studies should incorporate complex system methods that allow for measuring interactions between exposure events (Massazza et al., 2022). By including multiple data analytic strategies, some of our findings are contradictory in significance for crisis trends. The difference in significance is likely due to the use of comparison groups (for the Difference-in-Difference analysis),the inability to adjust for spillover effects (e.g., media coverage of the event) or other potential confounders not available in our dataset. However, our results highlight the need for multiple analytic strategies to understand the complicated effects of climate on mental health fully. Other noteworthy limitation includes using ecological data (e.g., area-code measures) to determine population-based exposure to the winter weather event. Differential exposure to natural hazards has a strong association with mental health outcomes at the individual level (Verger et al., 2003); however, the use of ecological data sources for exposure is a well-established approach used to examine the mental health effects of large-scale disasters (e.g., Gearhart et al., 2018; Runkle et al., 2021a) with roughly equivalent outcomes across different classification methods (Grabich et al., 2015). Lastly, the reliance on data from Crisis Text Line may have impacted the results as power outages were noted throughout the state affecting wireless users during the storm (FCC, n.d.). Future research examining the mental health impacts of the event in alternative datasets like administrative hospital data is needed to confirm our findings.

4.2. Implications

Winter weather, including heavy snow and cold air outbreaks, in the US is projected to increase in the coming decades due to climate change (Cohen et al., 2014; Cohen et al., 2018). The mental health implications of natural hazards have largely been restricted to hurricanes (Runkle et al., 2021a), flood events (Verger et al., 2003) or wildfires (Sugg et al., 2022), and climate disasters common in the warmer summer months. Our work highlights the potential mental health implications of the cold exposure climate hazards. The winter weather event in Texas in 2021 had cascading effects with economic repercussions well after the storm and potential economic costs higher than major hurricanes like Harvey (National Weather Service, 2022). Preparedness is key for ensuring an effective response to climate-related hazards (Mason et al., 2020). Despite widespread power outages, Crisis Text Line was still utilized by Texas residents; this highlights the potential of its use as both an immediate and long-term crisis intervention tool. Notable increases in total crisis volume and conversations specific to thoughts of suicide were observed up to 11 months post-storm. Future work should confirm our findings about the timing of specific crisis conditions post-disaster and use results for targeted interventions after disasters like the 2021 winter weather event in Texas.

5. Conclusion

The aim of this study was to examine the effect of crisis outcomes from a cascading winter weather event in Texas in 2021. Unlike previous work, this study was the first to examine the mental health implications of a climate disaster in the winter months, and that resulted in cascading effects such as large-scale infrastructure damage and power outages. We noted sustained increases in all crisis outcomes, thoughts of suicide, and stress/anxiety at shorter and longer-term time intervals after the initial weather disaster. Our work provides evidence for the need for a new framework for mental health conditions post-disasters, especially for specific crisis outcomes and non-univariate or cascading disasters.

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CRediT authorship contribution statement

Margaret M. Sugg: Conceptualization, Methodology, Formal analysis, Investigation,Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. Luke Wertis: Methodology, Formal analysis, Data curation, Writing - original draft, Writing - review & editing. Sophie Ryan: Methodology, Formal analysis, Data curation, Writing - original draft, Writing - review & editing. Shannon Green: Data Curation, Writing - review & editing. Devyani Singh: Duration Curation, Writing - review & editing, Jennifer Runkle: Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Supervision.

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Data availability

The authors do not have permission to share data.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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