Received: 2 July 2021 | Revised: 4 September 2021 | Accepted: 4 October 2021

DOI: 10.1002/jts.22763

RESEARCH ARTICLE

Trajectories of posttraumatic stress symptoms following the September 11, 2001, terrorist attacks: A comparison of two modeling approaches

Kayla A. Huber[1] | **Patricia A. Frazier**[1] | **Howard E. Alper**[2] | **Robert R. Brackbill**[2]

[1] Department of Psychology, University of Minnesota, Twin Cities, Minneapolis, Minnesota, USA

[2] New York City Department of Health and Mental Hygiene, Queens, New York, USA

Correspondence
Robert M. Brackbill, New York City Department of Health and Mental Hygiene, Division of Epidemiology, 42-09 28th Street Long Island City, Queens, New York 11101.
Email: rbrackbi@health.nyc.gov

This material is based on work supported by the National Science Foundation Graduate Research Fellowship Program (00074041 to Kayla A. Huber). The opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. The authors have no conflicts of interest to report.

Funding information
National Science Foundation, Grant/Award Number: 00074041

Abstract

Several studies have analyzed longitudinal data on posttraumatic stress symptoms (PTSS) from individuals who were proximal to the September 11, 2001, terrorist attacks (9/11) in an attempt to identify different trajectories of mental health in the years following mass trauma. The results of these studies have been heterogeneous, with researchers who used latent growth mixture modeling (LGMM) tending to identify four trajectories and those who used group-based trajectory modeling (GBTM) identifying five to seven trajectories. Given that no study has applied both GBTM and LGMM to their data, it remains unknown which modeling approach and what number of trajectories best fit post-9/11 PTSS data. The present study aimed to address that question by applying both LGMM and GBTM to data from the largest sample of survivors to date, comprising 37,545 New York City community members. When analyzing four waves of PTSS, reflecting participants' mental health up to 15 years post-9/11, LGMM fit the data better than GBTM. Our optimal solution consisted of four trajectories: low-stable (72.2% of the sample), decreasing (12.8%), increasing (9.5%), and high-stable (5.5%) symptoms. Covariate analyses indicated that economic factors (i.e., having a household income less than $25,000 and experiencing job loss due to 9/11) increased the odds of belonging to the high-stable symptom trajectory group to the greatest degree, *OR*s = 4.93–6.08. The results suggest that providing financial support, including affordable mental health care, could be an important intervention in the wake of future mass traumatic events.

On September 11, 2001 (9/11), the citizens of the United States were exposed to an act of terrorism of unprecedented proportions that killed nearly 3,000 individuals and injured thousands more. The impact of the attacks was lasting, with 16.3% of highly exposed persons reporting symptoms consistent with posttraumatic stress disorder (PTSD) when assessed 2–3 years later (Farfel et al., 2008). Although most longitudinal studies have found decreases in rates of probable PTSD over time (see Neria et al., 2011, for a review), other analyses have suggested that highly exposed people may not be a homogenous group with regard to their mental health trajectories (Brackbill et al., 2009). Specifically, among individuals who did not have a PTSD diagnosis prior to 9/11, Brackbill and colleagues (2009) found that 9.6% exhibited "chronic" symptoms (i.e., probable PTSD at both 2–3 years posttrauma and 5–6 years posttrauma), 4.7% exhibited "resolved" symptoms (i.e., probable PTSD at 2–3 years posttrauma only), 9.5% exhibited "late-onset" symptoms (i.e., probable PTSD at 5–6 years posttrauma only), and the remaining 76.2%

exhibited a "resilient" course (i.e., low levels of PTSD symptoms at both assessments). Such heterogeneity in symptom course over just two time points highlights the importance of exploring varying trajectories of symptom change in the years following 9/11.

The World Trade Center (WTC) Health Registry (WTCHR) is the largest postdisaster health registry in U.S. history as well as the longest-running study of post-9/11 health outcomes. To date, three studies have used PTSD symptom data from the WTCHR to explore the possibility that there may be unobserved groups (i.e., latent classes) of people whose mental health was differentially affected over time by the events of 9/11 (see Supplementary Table S1). Despite analyzing the same three waves of PTSD symptom data, the three studies each identified a different number of classes that best fit the data. Specifically, in an analysis of 16,488 adults who were involved in rescue and recovery work, Maslow et al. (2015) reported five classes: consistently low symptoms of PTSD (~53% of the sample), consistently moderate symptoms (29%), initially high symptoms with a downward trend over time (8%), initially moderate symptoms with an increasing trend over time (6%), and consistently high symptoms (4%). In a study of adults who were not involved in rescue and recovery work but were still proximal to the events of 9/11 (N = 17,062), Welch et al. (2016) identified six classes (i.e., the five classes mentioned previously along with a small class that consistently exhibited very high levels of PTSD symptoms). Finally, in a smaller sample of adults who were located in the WTC but did not have physician-diagnosed PTSD before 9/11 (N = 2,355), Adams et al. (2019) identified four classes of individuals who exhibited either consistently low levels of PTSD symptoms (~67%), increasing symptoms over time (14%), decreasing symptoms over time (11%), or consistently high symptom levels (8%).

Heterogeneity in the number of classes selected is not unique to analyses of WTCHR data (see Supplementary Table S1). Indeed, in analyses of police officers who were enrolled in the WTC Health Program, a separate program that provides free medical monitoring and treatment for 9/11-related health conditions, four classes of PTSD symptoms were selected (Feder et al., 2016; Pietrzak et al., 2014). These classes were congruent with the consistently low, increasing, decreasing, and consistently high trends identified by Adams et al. (2019). However, for nontraditional responders (e.g., construction workers), five- (Feder et al., 2016) and six-class (Pietrzak et al., 2014) solutions were selected. Norris et al. (2009) selected an even larger number of PTSD symptom classes in their analysis of a random sample of 1,267 adults in the New York City metropolitan area. Specifically, seven classes appeared to fit the data best, characterized by consistently low symptoms, consistently high symptoms, and five trajectories in between that were categorized by a variety of increasing or decreasing trends.

Part of the inconsistency across these six studies with regard to the number of identified trajectories may owe to the type of statistical model applied to the data. Three studies (Maslow et al., 2015; Norris et al., 2009; Welch et al., 2016) used group-based trajectory modeling (GBTM), which assumes, among other things, that all individuals within a particular class endorsed the same degree of PTSD symptoms at baseline and had the same rate of change in PTSD symptoms over time (i.e., intraclass variances around the intercept and slope parameters are fixed to 0). In contrast, three studies (Adams et al., 2019; Feder et al., 2016; Pietrzak et al., 2014) used latent growth mixture modeling (LGMM), which allows individuals within a particular class to endorse slightly different levels of PTSD symptoms at baseline and have different rates of change in PTSD symptoms over time (i.e., intraclass variance around the intercept and slope parameters is allowed). The stricter statistical assumptions of GBTM may be one reason studies that applied this modeling technique to post-9/11 mental health data tended to identify a higher number of classes (i.e., five to seven classes) compared with those that applied LGMM (i.e., typically four classes). Indeed, in a large-scale Monte Carlo simulation study, GBTM was shown to overextract classes 90% of the time when the population was homogeneous (i.e., composed of one class). In contrast, LGMM selected the correct model more than 70% of the time, with accuracy ranging from 90% to 100% when the sample size was large (N = 1,500; Diallo et al., 2016). Similar evidence of GBTM's tendency to overextract classes has also been found in analyses of real-world data (e.g., Infurna & Grimm, 2018). These results suggest that LGMM is the most appropriate approach for analyzing post-9/11 trajectories of mental health, as it leads to more parsimonious results; however, no studies have confirmed that this is the case by applying both GBTM and LGMM to the data and comparing the results, a practice that is highly recommended (van de Schoot et al., 2017).

A majority of studies examining post-9/11 PTSD symptom trajectories have assessed predictors of class membership to identify individuals who may have an increased risk of experiencing prolonged distress (i.e., Adams et al., 2019; Feder et al., 2016; Maslow et al., 2015; Pietrzak et al., 2014; Welch et al., 2016). Most studies have compared a low symptom class to various classes categorized by higher symptom levels. The most common predictors examined fell into three categories: demographic characteristics (e.g., gender, race), pre-9/11 experiences (e.g., prior trauma exposure), and the extent of exposure on 9/11 (e.g., injured on 9/11). Demographic factors that have emerged in multiple studies as significantly related to a higher risk of more

severe symptoms include Hispanic ethnicity; being female; being unemployed; older age; having less than a college degree; and being divorced, widowed, or separated (Feder et al., 2016; Maslow et al., 2015; Pietrzak et al., 2014; Welch et al., 2016). Higher income was found to be associated with more symptomatic PTSD trajectories in only one sample of nontraditional responders (Pietrzak et al., 2014). It is important to note that these factors (e.g., Hispanic ethnicity, female gender) are not causal; rather, they may be correlated with distress due to factors such as discrimination, socialization, and access to mental health care (Helms et al., 2005). With regard to pre-9/11 experiences, having a psychiatric history as well as reporting pre-9/11 stressors and trauma exposure predicted membership in more symptomatic trajectories in more than one study (e.g., Feder et al., 2016; Pietrzak et al., 2014). Finally, a higher degree of exposure to the events of 9/11 was consistently related to being in more symptomatic classes (e.g., Feder et al., 2016; Maslow et al., 2015; Pietrzak et al., 2014; Welch et al., 2016).

The overall purpose of the present study was to contribute to knowledge regarding the long-term mental health effects of 9/11. The first aim was to directly compare the results of two modeling approaches (i.e., LGMM and GBTM) that differ in their treatment of within-class heterogeneity. Previous analyses of 9/11-related data have not considered alternative specifications of within-class heterogeneity, a practice recommended in the Guidelines for Reporting on Latent Trajectory Studies (GRoLTS; van de Schoot et al., 2017). In studies that only used GBTM, overly complex models may have been selected, which complicates covariate analyses and their ability to inform policy decisions regarding the efficient allocation of resources to individuals who are likely to experience difficulty following future acts of mass interpersonal violence. We hypothesized that LGMM would produce a better-fitting model than GBTM, consistent with previous research (e.g., Infurna & Grimm, 2018).

Our second aim was to contribute to research on demographic characteristics, pre-9/11 experiences, and 9/11-related exposures associated with membership in different symptom trajectories (e.g., consistently low vs. consistently high symptoms). Some studies have examined covariates that reflect individuals' experiences long after 9/11 (e.g., purpose in life 11–13 years post-9/11, coping strategies most commonly used in the 11–13 years since 9/11; Feder et al., 2016). Given the time elapsed since 9/11, the accuracy of such variables and their mechanistic role in predicting trajectories is unclear. Thus, we chose to examine covariates that described participants prior to, on, or close to 9/11 because this knowledge can inform resource distribution in the immediate aftermath of future acts of mass violence. Our hypotheses were based on the findings of prior studies that examined covariates of membership in post-9/11 PTSD trajectories (Feder et al., 2016; Maslow et al., 2015; Pietrzak et al., 2014; Welch et al., 2016). With regard to demographic characteristics, we hypothesized that, relative to their comparison groups, individuals with a more symptomatic trajectory would be more likely than those with a low-stable symptom trajectory to be Hispanic, female, unemployed, and older; have less than a college degree; and be divorced, widowed, or separated. However, we did not expect that symptom trajectories would be differentiated on the basis of household income. With regard to pre-9/11 experiences, we hypothesized that having a psychiatric history and a history of pre-9/11 trauma exposure would predict membership in more symptomatic classes. Finally, we hypothesized that, relative to their comparison groups, individuals with a more symptomatic trajectory would be more likely than those with a low-stable symptom trajectory to have had more direct (e.g., injured, 9/11-related job loss) and indirect (e.g., witnessed horrific events) 9/11-related exposures. Three modifications were made to our preregistered hypotheses. Previously, older individuals were not hypothesized to have a relatively higher risk, Black individuals were hypothesized to have a relatively higher risk, and the term "unmarried" was used. Modifications were made due to the narrowing of prior studies considered (i.e., to post-9/11 PTSD trajectory studies) and the use of broader inclusion criteria (i.e., significant findings in at least two studies vs. significant findings in a majority of studies).

Our study contributed to the literature in some additional ways. First, in contrast to studies that have examined rescue and recovery workers (e.g., Feder et al., 2016; Maslow et al., 2015; Pietrzak et al., 2014), we analyzed data from community members, which increases the generalizability of the results to community samples. This also is important because trajectories of general distress post-9/11 have been shown to differ between community members and rescue and recovery workers, with the former more likely to be in higher distress classes (Ko et al., 2021). Second, we analyzed data from the largest sample to date ($N = 37{,}545$ enrollees in the WTCHR). Other studies have had smaller initial samples (e.g., Norris et al., 2009) or, even if they used WTCHR data from community members, restricted the samples in various ways (Adams et al., 2019; Welch et al., 2016). Analyzing data from a larger sample improved the precision with which we were able to estimate effect sizes and increases the generalizability of our findings. Finally, we used the most recent data available from the WTCHR, which assessed participants up to 15 years post-9/11, and, thus, have the longest follow-up period of any 9/11-related PTSD trajectory study published to date (see Supplementary Table S1).

METHOD

Participants and procedure

Participants verbally consented to be enrolled in the WTCHR, which has monitored the health of 71,431 individuals who were proximal to the events of 9/11 (i.e., residents, students and staff, occupants and passersby, rescue and recovery workers; see Murphy et al., 2007, for additional details). To date, participants have been invited to complete four waves of surveys: Wave 1 (W1; conducted from September 2003–November 2004), Wave 2 (W2; November 2006–December 2007), Wave 3 (W3; June 2011–March 2012), and Wave 4 (W4; March 2015–January 2016). Our study was preregistered with the Open Science Framework and approved by the University of Minnesota's Institutional Review Board. Our analyses were restricted to the 37,545 individuals who were not involved in rescue and recovery work and were 18 years of age or older on 9/11. We chose this sample to increase the generalizability of the results to adult community samples. The majority of participants were non-Hispanic White (57.6%), female (53.6%), married or cohabitating on 9/11 (60.4%), between 25–and 44 years of age on 9/11 (50.1%), and had earned a college or postgraduate degree by W1 (60.3%). The modal household income was between $75,000 (USD) and $149,999 annually (28.9%). Additional demographic information can be found in Table 1.

TABLE 1 Demographic characteristics

Variable	Valid %	*n*
Eligibility group[a]	100.0	37,545
Area workers	61.6	23,121
Residents	29.4	11,035
Passers-by	8.8	3,297
Students/school staff	0.2	92
Race/ethnicity	100.0	37,545
Non-Hispanic White	57.6	21,611
Non-Hispanic Black	14.6	5,493
Hispanic or Latino	12.8	4,802
Non-Hispanic Asian	10.7	4,008
Multiracial/"other"	4.3	1,631
Gender	100.0	37,545
Female	53.6	20,109
Male	46.4	17,436
Marital status on 9/11	62.8	23,593
Married or cohabitating	60.4	14,250
Never married	25.3	5,980
Divorced, widowed, or separated	14.3	3,363
Wave 1 educational attainment	98.1	36,823
College or postgraduate degree	60.3	22,217
Less than a college degree	39.7	14,606
Employment status on 9/11	98.5	36,996
Employed	90.5	33,465
Unemployed	9.5	3,531
Age on 9/11 (years)	100.0	37,545
18–24	7.3	2,730
25–44	50.1	18,800
45–64	37.3	14,005
≥ 65	5.4	2,010
Household income in 2002 (USD)	86.7	32,536
< $25,000	14.0	4,549
$25,000–$49,999	23.1	7,510
$50,000–$74,999	17.8	5,807
$75,000–$149,999	28.9	9,412
≥$150,000	16.2	5,258

Note: 9/11 = September 11, 2001, terrorist attacks. .
[a]A hierarchical system of classification was used.

Measures

PTSD symptoms

Symptoms of PTSD were measured using the PTSD Checklist–Specific Version (PCL; Weathers et al., 1993) during Waves 1–4. This version of the PCL was intended to cohere with the fourth edition of the *Diagnostic and Statistical Manual of Mental Disorders* (*DSM-IV; American Psychiatric Association, 2013*). The PCL is a 17-item, self-report measure that asks participants to rate much they have been bothered by symptoms of PTSD within a designated time frame, with responses scored on a scale of 1 (*not at all*) to 5 (*extremely*). WTCHR participants were asked to report symptoms they experienced during the past 30 days. Items related to the PTSD symptom clusters of reexperiencing and avoidance were worded to reference 9/11 (e.g., "Repeated, disturbing dreams of the events of 9/11"). Scores were summed (possible range: 17–85), with higher scores indicating a higher degree of posttraumatic stress symptoms. Although various PCL cutoff scores have been used in studies of PTSD prevalence following 9/11, a cutoff score of 44 is most common (Hamwey et al., 2020). Scores on the specific version of the PCL have exhibited adequate internal consistency in samples of NYC residents post-9/11, and evidence for convergent and discriminant validity has been found in samples of adults with a variety of trauma exposures (see Wilkins et al., 2011, for a review).

Cronbach's alphas in this sample ranged from .94 to .95 across the four waves. PCL scores changed little over time on average (Wave 1: $M = 31.90$, $SD = 13.32$; Wave 2:

M = 32.03, SD = 14.17; Wave 3: M = 31.17, SD = 13.66; Wave 4: M = 29.47, SD = 13.02). The PCL score distribution was positively skewed at all time points, γ_1 = 1.20, 1.21, 1.29, and 1.48, for Waves 1–4, respectively. The percentage of participants with missing data on the PCL increased with each wave (i.e., 4.8%, 37.6%, 43.7%, and 53.2% of the original sample had an incomplete PCL measure in Waves 1–4, respectively). All missingness at W1 was due to incompleteness (i.e., missing one or more items on the measure). The vast majority (i.e., 92.2%–92.8%) of missingness in the remaining waves was due to attrition and intermittent missingness (i.e., being lost to follow-up or inconsistently participating in waves), with a minority of missingness due to incompleteness (i.e., 7.2%–7.8%; see Supplemental Materials).

Demographic characteristics

All demographic characteristics except marital status were assessed at W1. Race/ethnicity was categorized according to the methods used by the 2000 U.S. Census. Categories included White (non-Hispanic), Black or African American (non-Hispanic), Hispanic or Latino (of any racial background), Asian (non-Hispanic; including Native Hawaiian and Pacific Islander), multiracial, and "other" (e.g., American Indian, Alaska Native). The multiracial and "other" categories were small and were combined to protect confidentiality. Gender was assessed in a binary fashion (i.e., male, female). Participant age on 9/11 was collapsed into four brackets (0–17 years, 18–24 years, 45–64 years, and 65 years or older) to reflect the groupings used in the U.S. Census tables. Educational attainment was measured as the highest grade or year of school the participant had completed at W1. The educational attainment variable was collapsed into "less than a college degree" and "college or postgraduate degree" to be consistent with the most comparable study in the literature (Welch et al., 2016). Whether participants were employed (i.e., working at a job or business or self-employed) on 9/11 was assessed in a binary fashion (i.e., yes, no). Participant's total household income in 2002 before taxes was collapsed into five brackets ($24,999 or less, $25,000–$49,999, $50,000–$74,999, $75,000–$149,999, $150,000 or more), similar to Welch et al. (2016). Marital status on 9/11 was assessed at W2 and was collapsed into three categories: married or living with a partner; widowed, divorced, or separated; and never married, consistent with Welch et al. (2016).

Pre-9/11 experiences

At W3, participants were asked to indicate their pre-9/11 exposure to eight potentially traumatic events, including experiences that could have threatened the participant's life (e.g., serious accident, life-threatening illness, sexual assault) or those during which they witnessed someone being seriously injured or violently killed. This variable was collapsed into "yes," indicating the participant endorsed one or more events, and "no," indicating they did not endorse any events, to be consistent with Maslow et al. (2015). Psychiatric history was assessed at both W2 and W3. Participants were asked whether they had ever been diagnosed with depression, anxiety, or PTSD and, if so, if it was before 9/11. The psychiatric history variable was collapsed into "yes" (i.e., endorsement of a pre-9/11 diagnosis at both waves) and "no" (i.e., no endorsement of a lifetime diagnosis or indicated the diagnosis was made post-9/11 at both waves). Individuals who endorsed a lifetime diagnosis but did not specify whether it was pre- or post-9/11 and individuals who provided inconsistent information across waves were classified as missing.

9/11-related exposures

The following exposures (i.e., yes, no) were assessed at W1: whether participants (a) were outdoors within a dust or debris cloud resulting from the collapse of the WTC towers, (b) evacuated from a building or area below Chambers Street, (c) had to evacuate from their home, (d) were injured (e.g., concussed, burned), and (e) witnessed horrific events (i.e., airplanes hitting the WTC, buildings collapsing, people running away, people injured/killed, or people jumping or falling from the towers). Participants who witnessed three or more events were placed in one group, and those who witnessed two or fewer events were placed in another, consistent with Welch et al. (2016). The following exposures (i.e., yes, no) were assessed at W2: whether participants (a) thought they might be injured or killed, (b) lost their job as a result of 9/11, and (c) knew anyone who died as a result of the WTC disaster.

Data analysis

Trajectory analyses

The GRoLTS Checklist (van de Schoot et al., 2017) was used to guide our analytic approach and reporting. As recommended, a series of unconditional growth curve models, GBTMs, and LGMMs was run in *M*plus (Version 8.2) to determine the optimal number of trajectories to describe the data. For the GBTMs, the intraclass variance and covariance estimates for the growth parameters were fixed to 0. For the LGMMs, the intraclass variance around the growth parameters was estimated. Residual

variances were initially estimated freely (i.e., the amount of intraclass variance was allowed to differ across classes) but fixed to be equal if convergence issues were encountered. We ran GBTMs and LGMMs with between two and eight classes, as eight classes is one more than the maximum number of classes identified in past 9/11 trajectory studies (i.e., Norris et al., 2009). Both linear and quadratic models were run because four waves of data were available.

All models were run with 500 random sets of starting values, 20 initial rounds of optimizations, and 20 final rounds of optimizations to avoid local maxima; however, these values were increased if convergence issues were encountered. The metric of time was determined by calculating the number of months between September 2001 and the midpoint of each wave of data collection (i.e., factor loadings were 31, 68, 122, and 167 months post-9/11 for W1–W4, respectively). This was intended to represent that the process of interest began on 9/11, not at W1, and that the time between waves was not equal. Participants who provided complete PCL data in at least one wave were included in the analyses; 2.3% of the sample was excluded for having incomplete PCL data at all waves. Missing data were accommodated with full-information maximum likelihood estimation, consistent with recommendations for handling missing data in longitudinal studies (e.g., Buhi et al., 2008; Enders, 2011). Both GBTM and LGMM models assume that data are missing at random.

As recommended by the GRoLTS Checklist (van de Schoot et al., 2017), a variety of indices were examined to select the most appropriate model. Our main index was the Bayesian information criterion (BIC); better-fitting models have a lower BIC. The BIC was selected as it outperformed other information criteria in identifying the correct model in Monte Carlo simulations (Nylund et al., 2007). Indeed, accuracy worsened as sample size increased when using Akaike's information criterion (AIC), which reaffirms the importance of using a criterion that adjusts for sample size, such as BIC. Additional considerations included entropy, with higher values indicating more distinct classes and values above .80 typically preferred (Lubke & Muthén, 2007); class size, with classes that comprise at least 5% of the sample preferred to ensure the stability of results (Infurna & Luthar, 2017); parsimony, with more parsimonious models preferred; and theoretical meaningfulness, whereby classes that account for only minor variations would not be considered meaningful, such as two classes with approximately the same slope but slightly different intercepts. The results from likelihood ratio tests (LRTs) were not considered, as trivial effects are likely to be statistically significant in a sample of our size, which would encourage the selection of models with too many classes (Grimm et al., 2017).

Covariate analyses

Multinomial logistic regressions were run to determine what demographic characteristics, pre-9/11 experiences, and 9/11-related exposures were associated with higher odds of belonging to more symptomatic classes. Recommendations from the GRoLTS Checklist (van de Schoot et al., 2017) were followed in conducting these analyses. Specifically, we selected the best-fitting model without the inclusion of covariates. We then ran the multinomial logistic regressions using the auxiliary command (R3STEP) in *M*plus, which accounted for uncertainty in class membership (Asparouhov & Muthén, 2013). Odds ratios were considered significant if their 95% confidence intervals did not contain 1.00. In our preregistration, we specified that all covariates would be included in a single multinomial logistic regression. However, upon inspection of the data, two variables had a large amount of missingness (i.e., pre-9/11 trauma exposure, home evacuation). To avoid a substantial reduction in sample size, these two covariates were analyzed separately. The remaining 15 variables were included in a single regression; 16,261 participants had complete data on the 15 covariates (43.3% of the original sample) and were included in the regression analyses.

RESULTS

Trajectory analyses

In an initial linear growth curve model (GCM), there was significant variance around the intercept and slope parameters, $ps < .001$, suggesting the appropriateness of mixture modeling. We proceeded to run 14 GBTMs with PCL sum scores at each wave (i.e., two through eight class linear and quadratic models; see Table 2). Steep declines in BIC were found until five classes, after which point the declines were relatively small for our sample (i.e., less than 2,000). After five classes, classes were also extracted that comprised a small proportion of the sample (i.e., less than 5%), and class separation generally decreased. A five-class quadratic model was deemed better-fitting than a five-class linear model because three of the five classes had a significant quadratic term, the quadratic model had a lower BIC, and class proportions and entropy values were nearly identical across the two models. Thus, using GBTM, a five-class quadratic model was the best fit, which included a large group of participants who endorsed a low level of PTSD symptoms over time ("low-stable;" 57.0% of the sample), a group that endorsed a moderate level of symptoms over time ("moderate-stable;" 23.8%), a group that endorsed fewer symptoms over time ("decreasing;" 8.3%), a group

TABLE 2 Model Fit Criteria

Number of classes and class shape	GBTM			LGMM		
	BIC	Entropy	Class proportion range[a] (%)	BIC	Entropy	Class proportion range[a] (%)
1						
Linear	737,582	n/a	100.0	737,582	n/a	100.0
Quadratic	—	—	—	—	—	—
2						
Linear	743,776	.88	79.0–21.0	728,517	.84	85.5–14.5
Quadratic	743,340	.87	79.0–21.1	727,758	.84	85.0–15.0
3						
Linear	730,212	.83	67.2–8.9	724,876	.83	81.0–9.3
Quadratic	729,440	.83	67.1–9.4	723,871	.84	80.0–9.1
4						
Linear	726,125	.79	61.4–4.6	721,478	.82	73.1–6.6
Quadratic	725,116	.78	60.8–4.9	***720,181***	***.82***	***72.2–5.5***
5						
Linear	723,272	.78	58.0–4.8	720,064	.80	70.5–2.3
Quadratic	**722,211**	**.78**	**57.0–4.9**	717,787	.81	72.8–4.1
6						
Linear	721,423	.78	61.5–3.8	—	—	—
Quadratic	720,050	.79	59.0–3.9	716,465	.81	72.7–2.5
7						
Linear	719,612	.75	53.4–2.5	—	—	—
Quadratic	718,207	.75	52.3–2.7	715,402	.81	68.4–1.8
8						
Linear	718,524	.75	55.4–2.1	—	—	—
Quadratic	716,764	.76	52.5–2.5	714,237	.79	63.8–1.6

Note: The best-fitting model from each modeling approach is bolded, and the overall best-fitting model is in bold italics. Dashes indicate that model estimation errors were encountered that could not be resolved. LGMM models that estimated residual variances freely consistently produced errors and are not shown here. GBTM = group-based trajectory modeling; LGMM = latent growth mixture modeling; BIC = Bayesian information criterion.

[a]Class proportions are based on participants' most likely latent class membership.

that endorsed worsening symptoms over time ("increasing;" 6.0%), and a group that endorsed a high level of symptoms over time ("high-stable;" 4.9%).

We initially ran seven linear LGMMs that estimated residual variances freely. However, errors were consistently encountered—either model estimation did not terminate normally, even after increasing the number of starts and iterations, or the models produced latent variable covariance matrices that were not positive definite. We then ran 14 LGMMs (i.e., seven linear, seven quadratic) that fixed residual variances to be equal. Estimation errors could not be resolved for three of these models (i.e., six- to eight-class linear models; see Table 2). Variance around all quadratic terms was fixed to 0 to address additional estimation errors, consistent with prior trajectory studies (Adams et al., 2019).

As shown in Table 2, large decreases in BIC were found until four classes. After four classes, some class proportions became small (i.e., less than 5% of the sample) and entropy values decreased. A four-class quadratic model was deemed better-fitting than a four-class linear model because all the classes had a significant quadratic term, the quadratic model had a lower BIC, and class proportions and entropy values were nearly identical across the two models. Thus, using LGMM, a four-class quadratic model was the best fit for PTSD, which included low-stable (72.2%), decreasing (12.8%), increasing (9.5%), and high-stable (5.5%) symptom groups. Unlike the best-fitting GBTM, the LGMM did not include a moderate symptom class.

When comparing the best-fitting models across the two methods, the four-class quadratic LGMM had the best fit overall given its lower BIC value, slightly higher entropy value, and more parsimonious solution. See Figure 1 for a graph of the classes and Table 3 for additional information on this model, including parameter estimates, mean

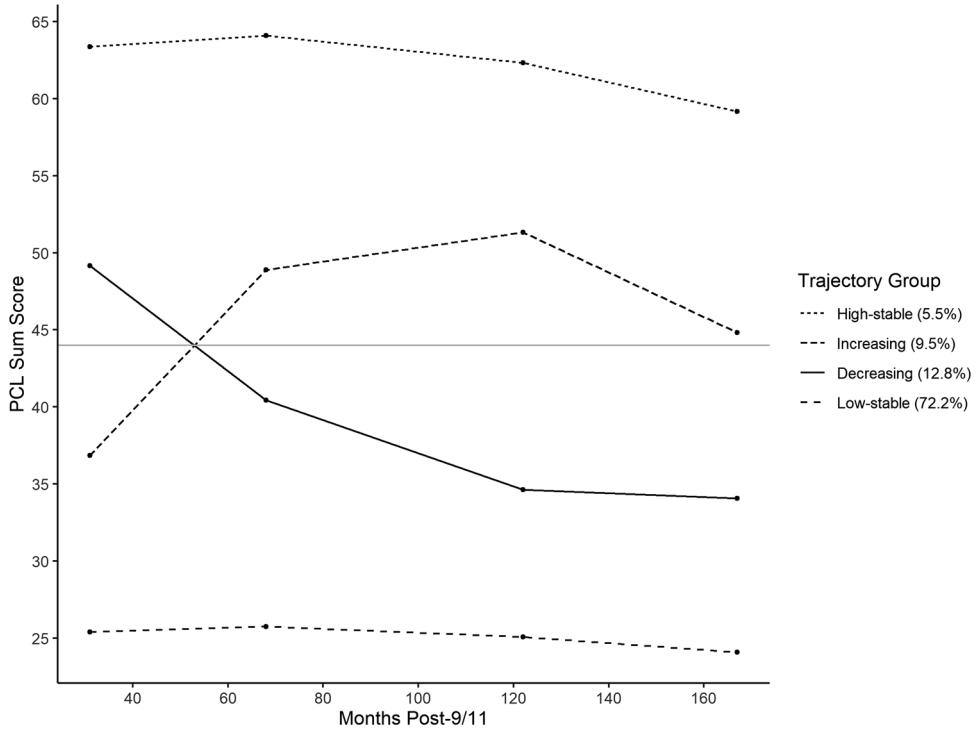

FIGURE 1 Plot of best-fitting model. Note: Factor loadings were 31, 68, 122, and 167 months following the September 11, 2001, terrorist attacks (9/11). The horizontal line at 44 is a commonly used cutoff score for probable posttraumatic stress disorder (PTSD) on the PTSD Checklist (PCL). PCL sum scores range from 17 to 85

posterior probabilities by class, and mean PCL scores for each class by wave. Other popular selection criteria (e.g., AIC, LRTs), plots of individual trajectories, and plots of the unselected models can be found in the Supplementary Materials; additional preregistered analyses that are outside the scope of the current paper can also be found in the Supplementary Materials.

Covariate analyses

The findings supported the majority of our hypotheses with regard to variables that would predict membership in more symptomatic trajectory classes (see Table 4). Consistent with our hypotheses regarding demographic characteristics, Hispanic ethnicity, female gender, older age, and having less than a college education were associated with a higher likelihood, relative to their comparison groups, of being categorized in more symptomatic classes than in the low-symptom class. In contrast to our hypotheses, being unemployed or being divorced, widowed, or separated were not associated with being in a more symptomatic class. Also in contrast to our hypotheses, individuals with lower income levels had higher odds of belonging to more symptomatic classes. Indeed, a gradient was seen whereby odds increased as income decreased. The only other finding that was contrary to our hypotheses regarding demographic predictors of class membership was that Black, multiracial, and participants of another race/ethnicity—and, to a lesser extent, Asian participants—also tended to have a higher risk of membership in classes characterized by more severe symptoms as compared with just Hispanic participants, as hypothesized. The findings also support our hypotheses regarding pre-9/11 experiences and 9/11-related exposures such that a psychiatric history, a history of trauma exposure prior to 9/11, and higher degrees of 9/11-related exposures, with the exception of being evacuated from a building or one's home, were associated with a higher likelihood, relative to their comparison groups, of being in more symptomatic classes than in the low-symptom class.

DISCUSSION

This study contributed to the literature on post-9/11 PTSD trajectories in several ways. For example, we used the largest sample and the longest follow-up period to date, directly compared the results of two modeling approaches that differed in their assumptions about within-class heterogeneity, and predicted membership in more symptomatic PTSD trajectories using covariates that described

TABLE 3 Class proportions, mean Posttraumatic Stress Disorder Checklist (PCL) scores, and parameter estimates

				Mean PCL score[c]					Parameter estimates			
Group	***n***[a]	**%**[a]	**Mean posterior probability**[b]	**W1**	**W2**	**W3**	**W4**		**Intercept**	**95% CI**	**Linear**	**95% CI**
High-stable	2,032	5.5	.87	63.37	64.09	62.33	59.18		**61.61**	[60.04, 63.18]	**0.08**	[0.03, 0.12]
Increasing	3,482	9.5	.78	36.84	48.89	51.33	44.81		**22.44**	[20.84, 24.04]	**0.54**	[0.49, 0.60]
Decreasing	4,685	12.8	.78	49.17	40.42	34.62	34.07		**58.53**	[56.88, 60.18]	**− 0.34**	[−0.38, −0.30]
Low-stable	26,488	72.2	.94	25.39	25.74	25.07	24.09		**24.94**	[24.68, 25.20]	**0.02**	[0.02, 0.03]

Note: PCL = PTSD Checklist; W = wave. Bolded estimates are significantly different from 0 at an alpha level of .05. Quadratic estimates have been omitted; however, all quadratic terms were significant and small (i.e., $p < .01$).

[a]Class counts and proportions are based on participants' most likely latent class membership. [b]Average latent class probabilities for most likely latent class membership by latent class. [c]Mean scores were weighted by estimated class probabilities for each class.

participants prior to, on, or close to the terrorist attacks on 9/11. Herein, we discuss key findings, limitations, and future directions.

Our finding that LGMM produced a better-fitting model of PTSD trajectories, relative to GBTM, supported our hypothesis and was consistent with the results of studies that have directly compared LGMM to GBTM (e.g., Diallo et al., 2016; Infurna & Grimm, 2018). For PTSD symptoms, LGMM led to the selection of the ubiquitous four-class model (Galatzer-Levy et al., 2018), whereas GBTM led to the extraction of an additional moderate–stable class, as has been found in previous analyses of WTCHR data (Maslow et al., 2015; Welch et al., 2016). This result supports the notion that overly complex models may be selected when modeling approaches do not allow for within-class heterogeneity. Model complexity has important implications for the estimated prevalence of various classes and for covariate analyses. For example, there was a large difference in the number of individuals assigned to the low-stable symptom class when using GBTM (57.0% of the sample) versus LGMM (72.2%), suggesting that GBTM may underestimate the prevalence of "resilience" (i.e., consistently reporting a low level of symptoms). In addition, given that the low-stable symptom class is often used as a reference category in covariate analyses, the modeling approach selected may substantially affect the results of these analyses.

With regard to the covariate analyses, a large number of our hypotheses were supported. For example, most of the hypothesized demographic characteristics (e.g., female gender, Hispanic ethnicity, having less than a college degree) were associated with a higher likelihood of membership in more symptomatic classes relative to the low-symptom class, consistent with prior research (e.g., Feder et al., 2016; Maslow et al., 2015). Similarly, individuals who had higher degrees of exposure to 9/11 and a prior trauma or psychiatric history were more likely to be in the more symptomatic classes (e.g., Feder et al., 2016; Pietrzak et al., 2014). With regard to the absolute magnitude of the relations between the covariates and group membership, the highest odds of belonging to the high-stable symptom group were associated with economic factors (i.e., having a household income of less than $25,000, having lost a job due to 9/11). These factors were associated with higher odds of belonging to the increasing and decreasing groups as well, albeit to a lesser degree. Based on prior studies that used fewer income categories, we had not hypothesized that income would predict trajectories (e.g., Feder et al., 2016). However, the more fine-grained measure used in the present study revealed that the risk of belonging to more symptomatic trajectories progressively increased as income decreased.

TABLE 4 Odds of trajectory group membership by enrollee characteristics and exposure related to the September 11, 2001, terrorist attacks (9/11)

		Decreasing		Increasing		High-stable	
Category		***OR***	**95% CI**	***OR***	**95% CI**	***OR***	**95% CI**
Race/ethnicity	37,545						
Black	5,493	1.59	[1.40, 1.80]	*0.91*	*[0.77, 1.07]*	1.49	[1.25, 1.78]
Hispanic	4,802	**2.05**	**[1.80, 2.33]**	1.25	[1.07, 1.47]	**2.83**	**[2.40, 3.34]**
Asian	4,008	1.19	[1.01, 1.41]	*1.19*	*[0.99, 1.43]*	*0.85*	*[0.64, 1.15]*
Multiracial/"other"	1,631	1.77	[1.42, 2.21]	1.58	[1.23, 2.04]	**2.62**	**[2.02, 3.40]**
Gender	37,545						
Female	20,109	1.74	[1.58, 1.92]	1.14	[1.02, 1.27]	1.49	[1.32, 1.70]
Marital status on 9/11	23,593						
Divorced, widowed, or separated	3,363	*0.92*	*[0.80, 1.07]*	*1.09*	*[0.91, 1.28]*	*0.87*	*[0.73, 1.05]*
Never married	5,980	0.63	[0.55, 0.72]	0.74	[0.65, 0.86]	0.54	[0.45, 0.65]
Wave 1 educational attainment	36,823						
Less than a college degree	22,217	1.57	[1.42, 1.73]	1.76	[1.58, 1.97]	**2.14**	**[1.86, 2.45]**
Employment on 9/11	36,996						
Unemployed	3,531	*0.91*	*[0.75, 1.09]*	*1.22*	*[0.98, 1.51]*	*1.23*	*[0.98, 1.53]*
Psychiatric history	27,396						
Yes	2,408	1.82	[1.53, 2.18]	**2.44**	**[2.05, 2.90]**	**2.25**	**[1.81, 2.81]**
Age on 9/11 (years)	37,545						
25–44	18,800	1.49	[1.23, 1.81]	1.25	[1.02, 1.54]	**2.38**	**[1.78, 3.18]**
45–64	14,005	1.70	[1.39, 2.07]	*1.00*	*[0.80, 1.25]*	**2.53**	**[1.88, 3.41]**
≥ 65	2,010	*1.28*	*[0.97, 1.70]*	*0.78*	*[0.56, 1.08]*	*0.92*	*[0.59, 1.43]*
Household income in 2002 (USD)	32,536						
< $25,000	4,549	**3.07**	**[2.56, 3.68]**	**2.28**	**[1.85, 2.81]**	**6.08**	**[4.82, 7.66]**
$25,000–$49,999	7,510	**2.25**	**[1.94, 2.61]**	1.88	[1.59, 2.22]	**2.64**	**[2.14, 3.26]**
$50,000–$74,999	5,807	1.78	[1.53, 2.08]	1.49	[1.26, 1.76]	1.52	[1.22, 1.91]
$75,000–$150,000	9,412	1.19	[1.03, 1.37]	1.20	[1.04, 1.39]	*0.95*	*[0.77, 1.18]*
Dust exposure on 9/11	37,235						
Yes	23,621	1.38	[1.24, 1.54]	1.26	[1.11, 1.42]	1.67	[1.42, 1.96]
Lost job due to 9/11	22,691						
Yes	2,472	1.96	[1.65, 2.34]	**2.37**	**[2.00, 2.82]**	**4.93**	**[4.18, 5.82]**
Feared being killed on 9/11	24,082						
Yes	16,426	1.21	[1.10, 1.34]	1.92	[1.71, 2.16]	1.28	[1.14, 1.45]
Knew anyone who died on 9/11	24,117						
Yes	13,605	*1.01*	*[0.91, 1.12]*	1.53	[1.36, 1.71]	1.45	[1.28, 1.65]
Injured on 9/11	37,435						
Yes	15,415	**2.55**	**[2.32, 2.80]**	**2.14**	**[1.92, 2.38]**	**4.89**	**[4.25, 5.63]**
Number of horrific events witnessed on 9/11	36,391						
3–5	17,258	1.91	[1.74, 2.09]	2.11	[1.90, 2.35]	2.82	[2.47, 3.21]
Evacuated from a building	32,481						
Yes	25,391	*1.00*	*[0.87, 1.07]*	*0.99*	*[0.88, 1.12]*	*1.07*	*[0.93, 1.23]*
Evacuated from home due to 9/11[a]	10,932						
Yes	6,679	0.71	[0.64, 0.80]	0.76	[0.66, 0.86]	0.67	[0.58, 0.78]

(Continues)

TABLE 4 (Continued)

Category		Decreasing		Increasing		High-stable	
		OR	95% CI	*OR*	95% CI	*OR*	95% CI
Pre-9/11 trauma[a]	9,920						
Yes	7,436	*1.02*	*[0.92, 1.14]*	1.99	[1.80, 2.21]	1.28	[1.13, 1.45]

Note: Sample sizes for categories refer to the number of enrollees who had a valid response for each covariate. Intervals that contain 1.00 are italicized, and odds that are greater than 2.00 are bolded. All estimates are in reference to the low-stable symptom group. The reference category within each variable is omitted from the table; however, they are as follows: White, male, married or cohabitating, college or postgraduate degree, employed, no psychiatric history, 18–24 years old, ≥ $150,000, no dust exposure, no job loss, no fear of being killed, did not know anyone who died, was not injured, witnessed 0–2 horrific events, did not evacuate from a building, did not evacuate from their home, and did not endorse trauma exposure that occurred before the September 11, 2001, terrorist attacks (9/11).
[a]Variable entered into separate logistic regressions due to high amounts of missingness; all other variables were included in the same logistic regression.

There is ample evidence to suggest that unemployed individuals are more distressed than their employed counterparts, and it is likely that unemployment plays a causal role in such distress (Paul & Moser, 2009). Relatedly, decreases in income have been prospectively associated with increased odds of meeting the criteria for a variety of mental illnesses (Sareen et al., 2011). The higher odds of prolonged mental health difficulty among individuals with lower income levels and those who became unemployed may owe, in part, to an inability to access mental health care or other forms of support in the wake of 9/11. Indeed, in prior analyses of WTCHR data, the probability of having a worsening or chronic trajectory of PTSD symptoms was highest among participants who reported having an unmet mental health care need (Welch et al., 2016). These results suggest that connecting newly unemployed individuals, those with lower socioeconomic status, and other at-risk groups (e.g., those who are injured during mass trauma) with affordable mental health care is especially important in the wake of future acts of mass interpersonal violence. The fact that these factors (e.g., job loss) were more strongly associated with the high-stable group than the increasing and decreasing symptom groups also suggests that the timely provision of mental health care may decrease the prevalence of the high-stable trajectory to the greatest degree.

The present study had a number of important limitations. First, the WTCHR is not prospective, which prohibits us from examining the validity of the assumption that the PTSD trajectories identified in this study were triggered by the events of 9/11 as opposed to other traumatic experiences. Additionally, studies that lack prospective data tend to underestimate the prevalence of resilience, indicating that individuals who choose to participate in longitudinal studies may be experiencing higher levels of distress (Galatzer-Levy et al., 2018). Second, the WTCHR is affected by the same limitations as many longitudinal studies, including selection bias, attrition, and intermittent missingness, which can alter the accuracy of models in terms of parameter estimates and the number of classes selected (Bauer, 2007). The prevalence of the four-class "cat's cradle" model in the trauma literature, however, suggests that the trajectories identified in this study are relatively robust (Galatzer-Levy et al., 2018). Third, because the first wave of data collection for the WTCHR occurred 2–3 years post-9/11, recall bias may have compromised the accuracy of the data collected. This is particularly an issue for pre-9/11 trauma exposure, which was not measured until Wave 3. In addition, the large amount of time between waves is a limitation because PTSD symptoms could conceivably recover and then remit between the waves, making a curvilinear association appear linear. Fourth, the WTCHR relied upon self-reports of PTSD symptoms rather than gold-standard clinician assessments. Fifth, our analyses did not account for the time-unstructured nature of the data (i.e., not all WTCHR enrollees were assessed at the same time within each wave of data collection), which may have biased parameter estimates (van de Schoot et al., 2017). Sixth, demographic variables, such as race, were used to predict trajectory membership in this study; however, "race" is socially constructed, and belonging to a particular racial group does not cause one to have a particular mental health trajectory. Rather, structural racism actively produces racial health disparities (Helms et al., 2005). Consistently collecting data on explanatory variables (e.g., barriers to accessing mental health care, experiences of discrimination and culturally incompetent care) is of the utmost importance in future studies of mass trauma. Finally, the present study focused on mixture models and their implications for the number of latent classes selected. However, critiques have been levied against mixture models, principal of which is that they tend to promote the selection of multiple latent classes in the presence of non-normally distributed data, even if the population distribution is homogenous (i.e., not composed of subgroups with their own distributions; Bauer & Curran, 2003). Thus, the four latent classes we selected may be statistical artifacts rather than distinct subgroups.

In summary, the present results yield the following conclusions and future directions. For researchers who wish to use mixture modeling approaches to examine different symptom trajectories following 9/11 or other mass

traumas, more parsimonious models may be generated using LGMM versus GBTM. Given longstanding critiques of how mixture modeling has been applied, however, researchers may wish to use either GCMs (e.g., Schwarzer et al., 2016) or indirect applications of mixture models in which latent classes are aggregated to create overall trajectories (Bauer, 2007). Such applications may include modeling latent patterns of missingness in post-9/11 data. Regardless of which quantitative approaches are used to examine heterogeneity in symptom trajectories in future work, researchers may wish to enrich their findings by collecting qualitative data. Such data may be instrumental in understanding what factors contributed to certain trajectories in the wake of 9/11 or other traumatic events.

OPEN PRACTICES STATEMENT

This study was preregistered with the Open Science Framework: osf.io/p74hd. Code and output can be found on the Open Science Framework: osf.io/p5zg4. Materials used in this study (e.g., measures) are publicly available at https://www1.nyc.gov/site/911health/researchers/health-data-tools.page. Requests for data can be sent to the World Trade Center Health Registry (wtchr@health.nyc.gov).

OPEN RESEARCH BADGES

This article has earned Open Materials and Preregistered Research Design badges. Materials and the preregistered design and analysis plan are available at https://osf.io/p5zg4/.

ORCID

Kayla A. Huber https://orcid.org/0000-0002-5228-7977

REFERENCES

Adams, S. W., Allwood, M. A., & Bowler, R. M. (2019). Posttraumatic stress trajectories in World Trade Center tower survivors: Hyperarousal and emotional numbing predict symptom change. *Journal of Traumatic Stress*, *32*(1), 67–77. https://doi.org/10.1002/jts.22357

Asparouhov, T., & Muthén, B. (2013). *Auxiliary variables in mixture modeling: A 3-step approach using Mplus*. https://www.statmodel.com/examples/webnotes/AuxMixture_submitted_corrected_webnote.pdf

Bauer, D. J. (2007). Observations on the use of growth mixture models in psychological research. *Multivariate Behavioral Research*, *42*(4), 757–786. https://doi.org/10.1080/00273170701710338

Bauer, D. J., & Curran, P. J. (2003). Distributional assumptions of growth mixture models: Implications for overextraction of latent trajectory classes. *Psychological Methods*, *8*(3), 338–363. https://doi.org/10.1037/1082-989X.8.3.338

Brackbill, R. M., Hadler, J. L., DiGrande, L., Ekenga, C. C., Farfel, M. R., Friedman, S., Perlman, S. E., Stellman, S. D., Walker, D. J., Wu, D., Yu, S., & Thorpe, L. E. (2009). Asthma and posttraumatic stress symptoms 5 to 6 years following exposure to the World Trade Center terrorist attack. *Jama*, *302*(5), 502–516. https://doi.org/10.1001/jama.2009.1121

Buhi, E., Goodson, P., & Neilands, T. B. (2008). Out of sight, not out of mind: Strategies for handling missing data. *American Journal of Health Behavior*, *32*(1), 83–92. https://doi.org/10.5993/AJHB.32.1.8

Diallo, T. M. O., Morin, A. J. S., & Lu, H. (2016). Impact of misspecifications of the latent variance–covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling: A Multidisciplinary Journal*, *23*(4), 507–531. https://doi.org/10.1080/10705511.2016.1169188

Enders, C. K. (2011). Analyzing longitudinal data with missing values. *Rehabilitation Psychology*, *56*(4), 267–288. https://doi.org/10.1037/a0025579

Farfel, M., DiGrande, L., Brackbill, R., Prann, A., Cone, J., Friedman, S., Walker, D. J., Pezeshki, G., Thomas, P., Galea, S., Williamson, D., Frieden, T. R., & Thorpe, L. (2008). An overview of 9/11 experiences and respiratory and mental health conditions among World Trade Center Health Registry enrollees. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, *85*(6), 880–909. https://doi.org/10.1007/s11524-008-9317-4

Feder, A., Mota, N., Salim, R., Rodriguez, J., Singh, R., Schaffer, J., Schechter, C. B., Cancelmo, L. M., Bromet, E. J., Katz, C. L., Reissman, D. B., Ozbay, F., Kotov, R., Crane, M., Harrison, D. J., Herbert, R., Levin, S. M., Luft, B. J., Moline, J. M., …, & Pietrzak, R. H. (2016). Risk, coping and PTSD symptom trajectories in World Trade Center responders. *Journal of Psychiatric Research*, *82*, 68–79. https://doi.org/10.1016/j.jpsychires.2016.07.003

Galatzer-Levy, I. R., Huang, S. H., & Bonanno, G. A. (2018). Trajectories of resilience and dysfunction following potential trauma: A review and statistical evaluation. *Clinical Psychology Review*, *63*, 41–55. https://doi.org/10.1016/j.cpr.2018.05.008

Grimm, K. J., Mazza, G. L., & Davoudzadeh, P. (2017). Model selection in finite mixture models: A k-fold cross-validation approach. *Structural Equation Modeling: A Multidisciplinary Journal*, *24*(2), 246–256. https://doi.org/10.1080/10705511.2016.1250638

Hamwey, M. K., Gargano, L. M., Friedman, L. G., Leon, L. F., Petrsoric, L. J., & Brackbill, R. M. (2020). Post-traumatic stress disorder among survivors of the September 11, 2001, World Trade Center attacks: A review of the literature. *International Journal of Environmental Research and Public Health*, *17*(12), 4344. https://doi.org/10.3390/ijerph17124344

Helms, J. E., Jernigan, M., & Mascher, J. (2005). The meaning of race in psychology and how to change it: A methodological perspective. *American Psychologist*, *60*(1), 27–36. https://doi.org/10.1037/0003-066X.60.1.27

Infurna, F. J., & Grimm, K. J. (2018). The use of growth mixture modeling for studying resilience to major life stressors in adulthood and old age: Lessons for class size and identification and model selection. *The Journals of Gerontology: Series B*, *73*(1), 148–159. https://doi.org/10.1093/geronb/gbx019

Infurna, F. J., & Luthar, S. S. (2017). The multidimensional nature of resilience to spousal loss. *Journal of Personality and Social Psychology*, *112*(6), 926–947. https://doi.org/10.1037/pspp0000095

Ko, T. M., Alper, H. E., Brackbill, R. H., & Jacobson, M. H. (2021). Trajectories of psychological distress among individuals exposed to the 9/11 World Trade Center disaster. *Psychological Medicine*, Advance online publication. https://doi.org/10.1017/S0033291720004912

Lubke, G., & Muthén, B. O. (2007). Performance of factor mixture models as a function of model size, covariate effects, and class-specific parameters. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(1), 26–47. https://doi.org/10.1080/10705510709336735

Maslow, C. B., Caramanica, K., Welch, A. E., Stellman, S. D., Brackbill, R. M., & Farfel, M. R. (2015). Trajectories of scores on a screening instrument for PTSD among World Trade Center rescue, recovery, and clean-up workers. *Journal of Traumatic Stress*, *28*(3), 198–205. https://doi.org/10.1002/jts.22011

Murphy, J., Brackbill, R. M., Thalji, L., Dolan, M., Pulliam, P., & Walker, D. J. (2007). Measuring and maximizing coverage in the World Trade Center Health Registry. *Statistics in Medicine*, *26*(8), 1688–1701. https://doi.org/10.1002/sim.2806

Nandi, A., Tracy, M., Beard, J. R., Vlahov, D., & Galea, S. (2009). Patterns and predictors of trajectories of depression after an urban disaster. *Annals of Epidemiology*, *19*(11), 761–770. https://doi.org/10.1016/j.annepidem.2009.06.005

Neria, Y., DiGrande, L., & Adams, B. G. (2011). Posttraumatic stress disorder following the September 11, 2001, terrorist attacks: A review of the literature among highly exposed populations. *The American Psychologist*, *66*(6), 429–446. https://doi.org/10.1037/a0024791

Norris, F. H., Tracy, M., & Galea, S. (2009). Looking for resilience: Understanding the longitudinal trajectories of responses to stress. *Social Science & Medicine*, *68*(12), 2190–2198. https://doi.org/10.1016/j.socscimed.2009.03.043

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Paul, K. I., & Moser, K. (2009). Unemployment impairs mental health: Meta-analyses. *Journal of Vocational Behavior*, *74*(3), 264–282. https://doi.org/10.1016/j.jvb.2009.01.001

Pietrzak, R. H., Feder, A., Singh, R., Schechter, C. B., Bromet, E. J., Katz, C. L., Reissman, D. B., Ozbay, F., Sharma, V., Crane, M., Harrison, D., Herbert, R., Levin, S. M., Luft, B. J., Moline, J. M., Stellman, J. M., Udasin, I. G., Landrigan, P. J., & Southwick, S. M. (2014). Trajectories of PTSD risk and resilience in World Trade Center responders: An 8-year prospective cohort study. *Psychological Medicine*, *44*(1), 205–219. https://doi.org/10.1017/S0033291713000597

Sareen, J., Afifi, T. O., McMillan, K. A., & Asmundson, G. J. G. (2011). Relationship between household income and mental disorders: Findings from a population-based longitudinal study. *Archives of General Psychiatry*, *68*(4), 419–427. https://doi.org/10.1001/archgenpsychiatry.2011.15

Schwarzer, R., Cone, J. E., Li, J., & Bowler, R. M. (2016). A PTSD symptoms trajectory mediates between exposure levels and emotional support in police responders to 9/11: A growth curve analysis. *Bmc Psychiatry [Electronic Resource]*, *16*. https://doi.org/10.1186/s12888-016-0907-5

van de Schoot, R., Sijbrandij, M., Winter, S. D., Depaoli, S., & Vermunt, J. K. (2017). The GRoLTS-checklist: Guidelines for reporting on latent trajectory studies. *Structural Equation Modeling: A Multidisciplinary Journal*, *24*(3), 451–467. https://doi.org/10.1080/10705511.2016.1247646

Weathers, F. W., Litz, B. T., Herman, D. S., Huska, J. A. & Keane, T. M. (1993, October). The PTSD Checklist (PCL): Reliability, validity, and diagnostic utility [Conference presentation]. 9th Annual Conference of the ISTSS, San Antonio, TX, USA.

Welch, A. E., Caramanica, K., Maslow, C. B., Brackbill, R. M., Stellman, S. D., & Farfel, M. R. (2016). Trajectories of PTSD among lower Manhattan residents and area workers following the 2001 World Trade Center Disaster, 2003–2012. *Journal of Traumatic Stress*, *29*(2), 158–166. https://doi.org/10.1002/jts.22090

Wilkins, K. C., Lang, A. J., & Norman, S. B. (2011). Synthesis of the psychometric properties of the PTSD checklist (PCL) military, civilian, and specific versions. *Depression and Anxiety*, *28*(7), 596–606. https://doi.org/10.1002/da.20837

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Huber, K. A., Frazier, P. A., Alper, H. E., & Brackbill, R. R. (2022). Trajectories of posttraumatic stress symptoms following the September 11, 2001, terrorist attacks: A comparison of two modeling approaches. *Journal of Traumatic Stress*, 1-13. https://doi.org/10.1002/jts.22763