THE APPLICATION OF LATENT CLASS ANALYSIS AND LATENT TRANSITION ANALYSIS TO LARGE SCALE DISASTER DATA: MODELING PTSD IN A POPULATION OF DISASTER WORKERS

By

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Abstract

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Sophisticated statistical methodologies are needed in order to analyze large, population-based datasets, such as screening projects, following disasters. Currently, the most common methodology applied to disaster research uses marginal or population-averaged models. However, mixture models with latent variables have versatile applications that may provide additional insight into the psychiatric outcomes following disasters and capture population heterogeneity that is usually overlooked. Thus, this dissertation conducts a novel application of these methodologies to a longitudinal database following a disaster.

In the wake of the terrorist attacks on September 11th, the Weill Cornell Screening Project conducted annual psychological screenings with over 3,000 non-rescue, World Trade Center (WTC) disaster workers from 2002-2008. This dissertation applies two types of categorical mixture models to this dataset: latent class analysis (LCA) and its longitudinal extension, latent transition analysis (LTA). Both models are particularly well suited for the analysis of psychiatric screening data, because they allow individuals to be grouped into classes based on their symptomatology. Furthermore, these methods permit the course of symptoms to be examined over time by modeling individuals' developmental trajectories.

The goal of this dissertation was to assess the utility and feasibility of applying LCA and LTA in large scale disaster research, specifically within a study of the longitudinal course of posttraumatic stress symptoms in WTC disaster workers. The LCA model successfully captured the heterogeneity of posttraumatic stress symptoms in this population. Additionally, the LTA model yielded unique information regarding patterns of symptom changes over time. The multiple-group analysis provided information about racial and ethnic differences in PTSD presentation and longitudinal course.

The application of LCA and LTA methodologies in this dissertation yielded practical findings in the field of psychiatric and disaster research. These findings have the potential to inform criteria selection for diagnostic manuals and offer insight into the mechanisms involved in the maintenance and remission of posttraumatic stress symptoms. Challenges associated with the analysis of complex longitudinal data from large screening databases and future directions are discussed.

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INTRODUCTION

Methodology for analyzing longitudinal data is an essential research tool. As more studies are utilizing complex longitudinal designs, it is imperative to apply new methodologies for these types of data. Though multiple methods targeting longitudinal data analysis have been proposed and used for decades, methodological innovation in this domain is the topic of much ongoing research.

Methodologists and practitioners alike agree that the quality of longitudinal research can be improved by using innovative data analytic strategies, which allow for a more efficient use of data and answering research questions that were previously too difficult to tackle (Muthén & Muthén, 2000, Norris et al., 2006, Collins and Lanza, 2010). These advanced methodologies encompass 1) random-effect, subject specific or growth models, and 2) conditional or transitional models (Diggle et al., 1994). In addition to these new data analytic strategies, technological advances in the twenty-first century provide researchers with access to an increasing number of these methodological options for their analyses (Collins, 2006).

The choice of methodology used for analysis of longitudinal data is largely guided by the type of outcome variable observed (e.g., continuous or categorical), its distributional characteristics (e.g., normal or Poisson distribution), and specific research objectives. Latent variables can be integrated into models for various purposes, such as accommodating outcomes that are considered to be measured with error, capturing individual differences, accounting for clustering, and modeling unobserved heterogeneity in the population (Vermunt, 2010). Methodologies with latent variables are collectively called “latent variable models” and include a variety of models with applications to cross-sectional and longitudinal data. Models with continuous latent variables include factor analysis (FA), structural equation models (SEM), and growth models (GM). Latent class models, also referred to as “mixture models,” cover applications with categorical latent variables. The best known latent class models are latent class analysis (LCA), latent class growth models (LCGM), mixture Markov, and latent transition models (LTA). The added value of methodologies with latent variables lies in their wider range of applicability, including in the study of validity of medical and psychiatric diagnoses (Young, 1983, Rindskopf & Rindskopf, 1986).

The use of advanced methodologies in longitudinal research tends to vary by discipline (e.g., psychology, education, or health sciences). Methodological choices may be influenced by the theoretical approach to the study of change, availability of appropriate datasets, and dominant training in each particular field (Collins, 2006). In particular, disaster research is one field that can greatly benefit from applications of advanced methodology for longitudinal research in order to better capture the complexities of response to disaster and its aftermath (e.g., Norris, 2006, Norris, 2009, Houston et al., 2011, Green et al., 2012). This task requires the availability of large datasets, which cover the full range of reactions to trauma, multiple waves of data, and appropriate statistical models. Furthermore, as disasters are associated with significant mental health consequences (e.g., PTSD, depression), the methodology must be suitable for psychiatric outcomes as well. The importance of this assertion lies partly in the fact that disaster research naturally informs psychiatric research, which in turn has an effect on how we perceive and measure the effects of disasters. A dominant example of this connection is the use of psychiatric classification systems to estimate the prevalence and the distribution of psychiatric disorders post disaster. Thus, this relationship potentially has an impact on access to healthcare, and must be considered with care (e.g., Greenberg et al., 1999).

Goals of the dissertation

This dissertation applies advanced state-of-the-art data analytic techniques from the latent class models, namely latent class analysis (LCA) and latent transition analysis (LTA), to the study of posttraumatic stress disorder (PTSD) in a population of non-rescue disaster workers deployed to the World Trade Center (WTC) site following the terrorist attacks on September 11, 2001. The overarching goals of this dissertation are to assess both the utility and feasibility of LCA and LTA to elucidate the longitudinal course of posttraumatic symptoms in this population. This choice of methodology was dictated by a set of specific research objectives relevant to disaster research:

- 1a. Describe latent structure of PTSD in the population of WTC non-rescue disaster workers and compare the results based on the statistical model to the diagnostic model (Diagnostic and Statistical Manual for Mental Disorders, DSM).
- 1b. Evaluate which personal and psychiatric characteristics are related to the model-based classification and assess measurement invariance for different race/ethnic groups.
- 2a. Assess stability of PTSD in this population with respect to change patterns between annual assessments.

2b. Evaluate the effect of concurrent comorbid depression as well as group differences in transitions between PTSD latent status over time.

The remainder of the introduction outlines the rationale for the current study and provides an overview of the sample. The methods section describes the LCA and LTA methodology utilized in the study, including model selection process and assessment of model fit. The results section presents findings corresponding to each research objective summarized both numerically and graphically. Finally, the discussion section addresses study utility and feasibility as well as limitations and implications for future research.

BACKGROUND

Posttraumatic Stress Disorder (PTSD)

Disaster research has shown that posttraumatic stress disorder (PTSD) is the most prevalent mental disorder associated with mass disasters (Norris et al., 2002). PTSD is conceptualized as an anxiety disorder that can develop following exposure to a traumatic event and currently includes three clusters of symptoms: 1) re-experiencing the trauma (i.e., nightmares and flashbacks, intrusive thoughts and images, distress and physiological reactivity to reminders); 2) avoidance/numbing symptoms (i.e., avoidance of trauma-related thoughts, emotions, conversations, places, situations, people; loss of enjoyment in activities, restricted range of affect, social estrangement, and feelings of a foreshortened future); and 3) physical hyperarousal (i.e., insomnia, irritability, poor concentration, hypervigilance, and exaggerated startle response).

PTSD has been extensively studied since its introduction to the third edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM - III) in 1980, and the diagnostic criteria as well as the symptom sets have undergone a number of revisions (Brett, Spitzer, & Williams, 1988, Friedman et al., 2011). The current diagnostic criteria have been in place since the release of the DSM-IV in 1994, and include exposure to a traumatic event accompanied by a response of fear, horror, or helplessness (criterion A) followed by at least one-month duration of at least one symptom from re-experiencing criterion (criterion B), at least three symptoms from avoidance/numbing criterion (criterion C), and at least two symptoms from hyperarousal criterion (criterion D). In addition, clinically significant distress or impairment in social, occupational, or other important areas of functioning is presumed (criterion F). These criteria apply to all types of traumatic events (e.g., wars, human made or technological disasters, personal injury, etc.).

Subthreshold PTSD, a less severe form of posttraumatic stress, is a topic of active research, as individuals with subthreshold PTSD often exhibit substantial symptomatology, comorbid conditions, and impaired functioning (e.g., Cukor et al., 2010, Grubaugh et al., 2005). Although not an officially recognized diagnostic category, three definitions of subthreshold PTSD have been proposed in the literature, with varying criteria at both symptom and cluster levels: 1) meeting criteria in cluster B and D and two symptoms in cluster C (Kilpatrick & Resnick, 1993); 2) meeting criteria in cluster B and either C or D (Blanchard et al., 1996); and 3) a minimum of 1 symptom in each cluster (Stein et al., 1997).

Challenges in defining psychiatric disorders

From the psychometrics perspective, there is an ongoing debate about the validity of the PTSD diagnosis, as incoming evidence challenges its conceptualization and diagnostic criteria. Historically, the diagnostic criteria used for psychiatric disorders, such as PTSD, were chosen with little guidance from measurement theory or modern psychometric methods and were instead based exclusively on conceptual models (Aggen et al., 2005, King et al., 2006). A slow process of gathering empirical data, lack of awareness of the importance of an evidence-based approach, and inadequate statistical methodologies likely contributed to this issue.

As empirical findings related to PTSD have accumulated, the latent structure of the disorder has been scrutinized to ensure its empirical validity. In the past twenty years, factor analytic studies have provided insight into the interrelationships and clustering of posttraumatic symptoms. The majority of these studies did not support the DSM-IV three factor model, instead yielding support for a four factor model, with distinct re-experiencing, avoidance, and hyperarousal clusters, and either a numbing or dysphoria cluster. Regardless of their differences, these studies suggest that the avoidance and numbing symptoms constitute two distinct clusters (For a review of these studies, see Friedman et al., 2011).

Currently, a new edition of the DSM is being prepared for release in May 2013 (DSM-V). Revisions to definitions of psychiatric disorders, including PTSD, have been proposed based on past research and expert recommendations. The preliminary proposals for revising the PTSD diagnosis underwent field trials, and draft revisions were made available for public review. One of the proposed changes is an expansion of the core symptom set from 17 to 20 symptoms, organized in four rather than three clusters, while retaining the basic PTSD template (Friedman et al., 2011). Some of the three additional symptoms are among associated features in the DSM-IV and are proposed to expand the numbing and hyperarousal clusters. However, the avoidance cluster is proposed to be identified by two symptoms only, which could lead to issues associated with construct underrepresentation. Even though the majority of the symptoms will remain unchanged, Rosen et al. (2010) points out that that addition of three symptoms and creation of a new cluster will allow for over 10,000 ways to meet PTSD criteria, as compared to the current 1,750 combinations. This will greatly increase the heterogeneity of PTSD clinical presentation, yet likely result in fewer diagnosed PTSD cases (Forbes et al., 2011).

Currently, neither PTSD subtypes nor subthreshold PTSD are included in the proposed revisions.

The validity study of PTSD also investigates the applicability of diagnostic criteria to diverse trauma populations and diverse cultural groups. The factor structure of PTSD has been studied in a number of discrete trauma samples (e.g., veterans, survivors of natural disasters, disaster workers and cancer patients), and across cultures (for a comprehensive review, see Hinton et al., 2011). However, only a few studies have comparatively tested PTSD structural and measurement invariance across groups with different demographic characteristics (e.g., age, gender, and race/ethnicity) and/or trauma history and type (King et al., 2006, Mansfiled et al., 2010). Among these, factorial invariance among veterans and active duty military personnel was studied in respect to deployment history (Simms et al., 2002, Engdahl et al., 2011, Mansfiled et al., 2010), as well as era of military service and treatment seeking status (McDonald et al., 2008). Race/ethnicity studies compared factorial invariance between American and Mexican survivors of hurricanes Paulina and Andrew (Norris et al., 2001), English and Spanish speaking survivors of community violence (Marshall, 2004), and Hispanic and White college students with unspecified trauma events (Hoyt & Yeater, 2010). Ullman & Long (2008) tested measurement invariance across race (African-American and White) and levels of education among female sexual assault victims.

Collectively, results of factor analytic studies helped inform PTSD criteria revisions (Hinton et al., 2011). However, our understanding of PTSD would benefit from additional research on group differences in regards to PTSD symptom configurations, their prevalence, and developmental trajectories. To date, no such literature has been reported in the field of disaster research.

Challenges of large scale disaster data analysis

PTSD presents a significant burden for individuals, their families, and society at large and can become a chronic condition (Greenberg et al., 1999, Kessler et al., 2000, Norris et al., 2002). It is also associated with substantial comorbidity, including Major Depressive Disorder (MDD) (Kessler et al., 1995, Cukor et al., 2011). Considering the frequency of mass disasters – about 500 annual incidents, including acts of mass violence – it is estimated that 8-9% of the population worldwide is at risk for at least one episode of PTSD in their lifetime (Breslau et al., 2001).

Among occupations at risk, this estimate is considerably higher, ranging from 6 to 35% (Cukor et al., 2011). Occupations at risk are comprised of professionals, such as police and firefighters, as well as non-professionals, including non-rescue disaster workers. Both groups are typically immediately and directly involved in rescue and recovery operations that may last for a prolonged period of time. The intensity and duration of the disaster work, coupled with varying levels of training, are thought to contribute to the elevated rates of PTSD in this population (Norris et al., 2002). Consequently, there is considerable effort in the research community to investigate prevalence and predictors of PTSD among occupations at risk.

In order to fully understand the nature of a disorder such as PTSD and its wider impact, long-term longitudinal research is essential. For most individuals, PTSD symptoms remit within the first 12 months post-trauma, followed by a more gradual decline and stabilization (Kessler et al., 2000). However, PTSD fails to remit in over a third of those affected in both general population and disaster worker samples, regardless of whether they received treatment (Difede & Cukor, 2009). On the other hand, a remarkably large segment of exposed populations, including disaster workers, show resistance to adverse mental health outcomes (Norris et al., 2009, Cukor et al., 2011).

To fully assess varying responses to trauma and diverse trajectories of posttraumatic stress symptoms, large population-based studies, such as screening projects or well-designed epidemiological studies, with long-term follow up are essential. Ideally, such studies should provide reliable data based on clinical interviews, as opposed to self-reports, in order to increase diagnostic accuracy (e.g., by differentiating between pre- and post-trauma symptoms and assessing symptom duration and associated functional impairment).

However, such designs produce psychiatric data that is highly skewed, as only a small percentage of those exposed to a traumatic event will develop PTSD or other psychiatric disorders (Norris et al., 2009). Characteristically, symptom data have only positive outcomes and exhibits a preponderance of zeros, regardless of whether symptom severity or number of symptoms is the topic of interest. These data features make the most commonly used statistical methods based on normal theory (e.g., regression analysis, factor analysis) not well suited for the analysis, not only in the context of evaluating predictors of onset, remission, or persistence of PTSD, but also when studying the latent structure of the disorder (Fox, 2009, Reise & Waller, 2009).

Several modeling alternatives and nonnormality corrections have been proposed in the literature, both for cross-sectional and longitudinal data with the aforementioned characteristics, including censored normal models and zero-inflated Poisson (ZIP) models. The limitations of these methods for use in disaster research stem partly from the fact that: 1) the outcome is required to be either a one number summary for the severity of the disorder or a symptom count, and 2) grouping is typically based on the observed outcomes (e.g., symptom severity of 0 or greater than 0). The nonnormality corrections may have limited utility in the presence of extreme skew in the data.

Latent variables framework as an analytic approach

Latent variable models are a family of flexible models well suited for disaster research for several reasons. These models acknowledge the difficulty in measuring psychiatric disorders by assuming a latent nature of psychiatric constructs. Additionally, they accommodate measured symptom indicators, both in continuous and categorical formats.

Of equal importance, a subset of latent variable models – mixture models – allows for modeling data coming from heterogeneous populations without making any distributional assumptions. Homogeneous groups (i.e., classes) with similar symptom profiles are defined empirically based on symptom patterns, and processes of interest in each class are modeled simultaneously.

The cross-sectional model with categorical latent variable and categorical indicators – latent class analysis – is particularly useful for examining criteria used to assign diagnoses as well as the disorder's presence/absence and subtypes (Clark & Muthén, 2009). Investigation of dimensional and configural differences in symptom profiles can provide insight into the latent structure of the disorder with respect to severity as well as disorder typology (Breslau et al., 2005, Wolf et al., 2012). Disorder prevalence can be estimated and evaluated using LCA. Furthermore, categorical indicators can correspond to clinically significant symptoms, thus facilitating more meaningful comparisons between model-based classifications and existing diagnostic criteria (Young, 1983). Collectively, these strengths make LCA analysis particularly relevant to practitioners and health care providers, due to the predominantly categorical nature of current diagnostic systems, such as the DSM.

LCA has been applied to many psychiatric conditions, including depression, schizophrenia, psychosis, agoraphobia, obsessive-compulsive disorder, conduct disorder, substance abuse and others. The first study applying LCA to PTSD was published by Boulanger and colleagues in 1986. Recent years saw a proliferation of publications in PTSD research using LCA, including studies of PTSD latent structure in two community samples (Breslau et al., 2005, Chung & Breslau, 2008) and PTSD presentation in Iraq and Afghanistan veterans (Maguen et al., 2012). LCA and its variation, latent trait analysis, were used in a study of dissociative subtypes of PTSD (Lanius et al., 2012, Wolf et al., 2012).

The longitudinal mixture models are appropriate for studying heterogeneous populations over time and for assessing both time-invariant and time-varying covariates (Muthén & Muthén, 2000). Depending on the purpose of latent classes in the model, variants of mixture models can be used (Vermunt, 2010). Latent class mixture models (LCMM) allow for modeling multiple trajectories using growth parameters. In contrast, transition models (mixture Markov and latent transition analysis (LTA)) focus on examining transition patterns between consecutive time points. Latent transition analysis is a type of Markov model, in which categorical latent variables are dynamic (i.e., individuals may switch across classes over time) (Vermunt, 2010).

While both approaches offer a rich analysis of change, latent transition analysis allows for the examination of how and why individuals transition between latent classes over time (Collins & Lanza, 2010). This aspect of change may be very important in evaluating the stability of psychiatric disorders, not only in terms of symptom profiles and pathways to remission, but also for planning for post-disaster mental health services. LTA is a natural extension of LCA, and thus it may offer longitudinal evidence for the validity of the psychiatric disorder under consideration (Lamers et al., 2012).

LTA models have been used more widely in educational research (e.g., peer victimization during middle school; Nyland et al., 2007) and substance use research (e.g., drug use among women; Lanza & Bray, 2010). In psychiatry, LTA has been applied to studies of depression (e.g., Lameras et al., 2012) and eating disorders (Peterson et al., 2011, Castellini et al., 2012).

Only a handful of studies to date have used longitudinal growth mixture modeling (GMM) for longitudinal research in PTSD. For example, Dickstein et al. (2010) studied heterogeneity in the course of PTSD in NATO veterans from Kosovo; Armour et al., (2012) and Steencamp et al. (2012) evaluated trajectories of PTSD in rape victims; and Stein et al. (2012) used this methodology to assess predictors of CBT treatment for PTSD. However, to our knowledge, no studies have applied LTA to PTSD or disaster research.

Overall, LCA and LTA methodologies provide a unique perspective to the study of PTSD following a disaster. They are person-centered, model-based approaches that do not rely on external criterion or cut points and can be used to model processes in heterogeneous populations (Nyland, 2007). Modeling extensions of LCA and LTA include multiple-group analyses well suited to examining group differences in PTSD presentation and course. Moreover, longitudinal analysis is efficient in its treatment of missing data (Hyatt & Collins, 1998, Vermunt & Magidson, 2008). Lastly, the proliferation of statistical software to fit LCA , and LTA in particular, make the choice of methodologies more feasible to researchers.

THE CURRENT STUDY OF PTSD

The data used in this dissertation is part of an archival dataset collected through the Weill Cornell 9/11 Mental Health Screening Program (see Difede et al., 2006, Cukor et al., 2011 for program details). Participants were WTC non-rescue disaster workers who were deployed to work at the WTC as part of their occupational duties. All workers were assessed annually for WTC-related PTSD and other psychopathology. The interviews were piggybacked onto their fitness-for-duty evaluations and were conducted by independent doctoral level psychologists from Weill Cornell Medical College. The daily assessment data was incorporated into a master database and assessed for data entry errors on a weekly basis. The confidentiality of all individuals was preserved by utilizing identification numbers, rather than worker names. The employer received only overall statistics on the prevalence of PTSD symptoms and related psychopathology. The Weill Cornell Medical College and the City University of New York Institutional Review Boards approved use of this data for research purposes.

Participants

The sample for this project includes 2,960 workers with complete PTSD data at Round 1 assessments, which took place between July 2002 and April 2004. (In total, 3,550 workers were evaluated; excluded individuals did not differ on any variables from those included in the analyses, and about 2% of the workers refused to participate in the study.) These workers assisted in clean-up and utility service restoration during several months following the WTC disaster. Notably, they did not volunteer to work at the site, but rather were deployed by their employer.

Participants were mostly white (65.7%), male (96.9%), and married/cohabitating (75.4%), and many had completed at least some college (52.6%). The mean age was 45.2 years (SD = 9.6). The race/ethnicity of the remaining participants was as follows: Black (17.9%), Hispanic (12.8%), and Other (3.0%) (Table 1). Three percent were at the WTC site at the time of the attack, and another 9.6% arrived at the site on 9/11/01, some while the attacks were occurring. The mean number of days worked at the site was 23.3 (SD 38.3), and 29% of workers reported believing that their life was in danger while they were working at the site (Cukor et al., 2011). The extent of exposure to the disaster varied considerably, as some of the workers endured personal loss (e.g., knew someone who was killed in the attacks) and/or occupational exposure (e.g., saw bodies, body bags, or body parts in the course of their work).

The project ended in 2008, yielding 6 waves of annual data. In 2005, the study procedure was changed for cost-effectiveness reasons so that only workers who were deemed at risk for PTSD and related psychopathology (1114/2960, 37%), as well as a random sample of those not at risk (control group, 419/2960, 14.2%), continued to be assessed using clinician administered interviews and self-report measures. The remaining workers completed self-report measures only and were referred for clinical interviews on an as-needed basis (Cukor et al., 2011). For the purpose of this dissertation, data from the first 3 rounds was analyzed.

Figure 1 depicts the flow of participants during the course of the first 3 rounds of the screening project. Notably, the composition of the sample at Round 2 in terms of percentage of individuals at risk and not at risk controls resembled that of the original sample at Round 1 (38.4% and 13.8%, respectively). At Round 3, the sample consisted of slightly more individuals at risk and not at risk controls (48.8% and 16.7%, respectively) and a smaller percentage of those who were deemed not at risk (34.5%).

Figure 1. Flow of participants during the first three rounds of the screening project.

Round 1	→	Round 2	→	Round 3
n=2960*		**n=2613***		**n=1555***
clinical interviews & self-reports:		clinical interviews & self-reports:		clinical interviews & self-reports
• at risk: 37.6%		• at risk: 38.4%		• at risk: 48.8%
• not at risk control: 14.2%		• not at risk control: 13.8%		• not at risk control: 16.7%
• not at risk: 48.2%		• not at risk: 47.8%		• not at risk: 34.5%
				n=951

Note: Asterisk denotes the samples used in the analysis.

Individuals who underwent assessments were compared to those unavailable at Round 2 and Round 3 in terms of demographic characteristics and baseline posttraumatic stress symptomatology. Workers unavailable for assessments at Round 2 and Round 3 assessments were older (Round 2: M=45.92, SD=10.58 vs. M=43.21, SD=9.38, t(1, 2935) = 4.85, p<.001; Round 3: M=44.91, SD=9.83 vs. M=42.38, SD=9.22, t(1, 2935) = 7.19, p<.001); and more likely to be white (Round 2: 15.0% vs. 11.3%, χ^2 (1, 2936) = 7.01; p=0.006; Round 3: 49.2% vs. 44.7%, χ^2 (1, 2936) = 5.50; p=0.019).

At Round 2, those unavailable for the interview did not differ from workers with complete data in baseline levels of PTSD symptomatology (baseline CAPS total severity: M=12.76, SD=15.91 vs. M=13.10, SD=16.10, t(1, 2958) = -3.54, p=.723). However, those with missing data at Round 3 had lower PTSD levels at Round 1 (M=9.92, SD=13.60 vs. M=15.98, SD=17.58, t(1, 2867) = -10.43, p<.001), and at Round 2:

($M=9.34$, $SD=12.94$ vs. $M=15.97$, $SD=17.62$, $t(1, 2644) = -10.73$, $p<.001$), as compared with individuals who underwent these assessments. The same pattern of missingness was observed for PTSD diagnosis status (i.e., meet full PTSD diagnosis, does not meet no PTSD diagnosis). These differences are predominantly due to the change in study design at Round 3, where a lower percentage of individuals not at risk for PTSD were scheduled for assessments via clinical interviews. This missing data mechanism can be considered as missing at random (MAR), as missingness is largely conditional on observed baseline PTSD symptomatology, and is therefore ignorable (Schafer & Graham, 2002).

Measures

Study measures were comprised of standard assessments of PTSD and related psychopathology (Major Depressive Disorder (MDD), Panic Disorder, Generalized Anxiety Disorder (GAD)). In addition, lifetime trauma history and exposure to the WTC disaster were included as literature suggests that these variables are highly correlated with and predictive of PTSD (Cukor et al., 2011). Lastly, self-reported demographic information was utilized.

PTSD symptoms were assessed using the Clinician-Administered PTSD Scale (CAPS) (Blake et al., 1990), the standard measure in the assessment of PTSD. The CAPS is a clinical interview that assesses the frequency (rated on a scale of 0-4) and intensity (rated on a scale 0-4) of 17 PTSD symptoms. The symptoms are defined using the frequency-1/intensity-2 scoring rule (F1/I2) , in which a symptom counts toward the diagnosis if it is present at a minimum frequency of one and a minimum intensity of two (Weathers, Ruscio, & Keane, 1999). A PTSD diagnosis requires at least one reexperiencing symptom (criterion B), at least three avoidance and numbing symptoms (criterion C), and at least two hyperarousal symptoms (criterion D). Symptom scores can also be summed to create a score for each of three symptom criteria and for the total severity score. The definition of subthreshold PTSD for this study was adapted from Blanchard et al. (1996), which requires meeting criteria for cluster B and for either cluster C or D.

Past and current psychiatric diagnosis (MDD, Panic Disorder, and GAD) were assessed at each time point using the Structured Clinical Interview for the DSM-IV (SCID-I; First et al., 1995). The original variables were also combined to form dichotomized indicators of past psychiatric history (presence vs. absence) and current psychiatric diagnosis (presence vs. absence).

Lifetime trauma history was assessed at each time point with the Traumatic History Questionnaire (Green, 1993), which probes for potentially traumatic events including disasters, accidents/injuries, life-threatening illness, combat/war zone service, traumatic deaths, physical and sexual assaults, and childhood abuse. The lifetime trauma history dichotomous variable was derived from this questionnaire (presence vs. absence).

Exposure to the events of September 11th at the WTC was assessed using an instrument developed at Weill Cornell Medical College by a panel of trauma experts. This instrument specifically assesses an individual's location during the attacks; direct witnessing of the attack from other locations; presence of loved ones in the WTC or vicinity; injury or death to a family member, friend, or colleague; attendance at funerals/memorials; displacement from one's home; duration of work on the site; nature of work at the site (e.g., bucket brigade, areas of operation); exposure to bodies, body parts, body bags, people jumping; disturbance by the smell at the site; perceived danger while working at the site; and having to be evacuated to avoid building collapse during restoration work. The exposure variable was derived from data available from all annual data, and the total exposure score was determined by summing all endorsed exposure items.

Demographic variables include self-reported age, race/ethnicity, education, and marital status. The demographic information was pooled from all available annual data where appropriate. The education and marital status variables were dichotomized as follows: education level (high school diploma or less vs. more than high school diploma) and marital status (married or cohabiting vs. other). The race/ethnicity variable was used as either a dichotomous variable (white vs. other), or categorical variable (white, black, Hispanic) as indicated in a particular analysis.

Basic descriptive statistics

PTSD diagnosis (full or subthreshold) was based on the F1/I2 rules described in the methods section. At Round 1, 8% of participants had symptoms consistent with full PTSD and another 9.3% had symptoms consistent with subthreshold PTSD. The estimates of PTSD prevalence at Round 2 and 3 were 5.5% and 5.4% for full PTSD and 5.8% and 6.1% for subthreshold PTSD (Table 1). Almost half of participants (45%) reported exposure to the WTC disaster, defined as endorsement of at least one exposure item from the Weill Cornell Exposure Questionnaire. The most frequent comorbid diagnosis was MDD (6.2%), followed by GAD (3.4%) and Panic Disorder (2.4%). Thirty-nine percent reported a history of trauma, and 14.5% had a prior psychiatric history. Descriptive statistics show that there was a decrease in comorbid psychopathology over time (Table 1). The slight increase in rates at Round 3 may reflect the compositional change in the sample at this round, as a slightly greater percentage of individuals deemed at risk for PTSD and related psychopathology were included.

Table 1

Basic sample descriptive statistics

	Round 1 (%Yes)	n (% Missing)	Round 2 (%Yes)	n (% Missing)	Round 3 (%Yes)	n (% Missing)
PTSD	8	2960(0)	5.5	2532(14.0)	5.4	1534(48.0)
Subsyndromal PTSD	9.3	2960(0)	5.8	2532(14.0)	6.1	1534(48.0)
WTC Exposure (M(SD))	2.02(2.49)	2960(0)	*	*	*	*
Trauma history	39.2	2927(1.1)	*	*	*	*
MDD	6.2	2959 (0)	3.7	2632 (11.1)	3.9	1555 (47.5)
Panic Attack	2.4	2959(0)	1.7	2632 (11.1)	2.2	1555 (47.5)
GAD	3.4	2959 (0)	2.5	2632 (11.1)	3.8	1555 (47.5)
Current Psychiatric Dx[a]	10.6	2959 (0)	6.6	2632 (11.1)	7.3	1554 (47.5)
Past Psychiatric Hx[b]	14	2959 (0)	15	2632 (11.1)	18.7	1554 (47.5)
Demographics						
Age (M(SD))	43.59(9.62)	2936(0.8)	*	*	*	*
Gender (Male)	96.8	2948(0.4)	*	*	*	*
Education (HS or more)	52.6	2718(8.2)	*	*	*	*
Marital Status (Married or cohabitating)	75.4	2851(3.7)	*	*	*	*
Race/Ethnicity (White)	65.7	^	*	*	*	*
Race/Ethnicity (Black)	17.8	^	*	*	*	*
Race/Ethnicity (Hispanic)	12.7	^	*	*	*	*
Race/Ethnicity (Other)	3.0	^	*	*	*	*

[a] Current Psychiatric Diagnosis includes MDD and/or Panic and/or GAD; [b]Past psychiatric History includes history of MDD and/or Panic and/or GAD; [c]Past Trauma History only includes past trauma history and no past psychiatric history; [d] Past Psychiatric History only includes past psychiatric history and no past trauma history; ^ Overall Race/Ethnicity missing % - 0.8; * is not applicable.

METHODS OVERVIEW

Latent Variable Models

The conceptual foundation of latent variables framework rests on the idea that many concepts and theories that are conceptually defined and thought to account for regularities in behavior are not directly observable (called "latent") and are measured with errors (Rindskopf, 1984). The observed indicators of underlying latent variable(s), such as disease symptoms or physical measurements, are considered to be caused by the latent variable(s), and consequently should be correlated with each other. The study of plausibility of latent variable(s) is based on the theory that if such variable(s) exist, thus explaining the relationship between observed indicators, then controlling for them should result in independence of the observed indicators (i.e., the correlations between the indicators will be attributed to chance variation alone) (McCutcheon, 1987).

Both the latent variables and observed indicators can be continuous or categorical. Moreover, because of their conceptual flexibility, latent variables can be used in diverse modeling contexts, such as in psychometrics and longitudinal data analysis (Rindskopf, 1984, Ruscio & Ruscio, 2002, Collins, 2006, Vermunt, 2010). Regardless of the context and type of latent variable, the model is expressed by a series of equations. In the continuous case, these equations are specified within ordinary regression framework and imply a particular pattern of correlations among the observed indicators. In the categorical case, associations in multidimensional contingency table are studied using logistic regression tools and cell proportions under the model are compared to the observed values. The latter case is particularly of interest in person-centered research applications, such as when classifying individuals into homogeneous groups, or representing heterogeneity in developmental trajectories (Muthén & Muthén, 2000), which is the focus of this dissertation. Both methodologies for cross-sectional models and longitudinal models will be described using notation from Collins & Lanza (2010).

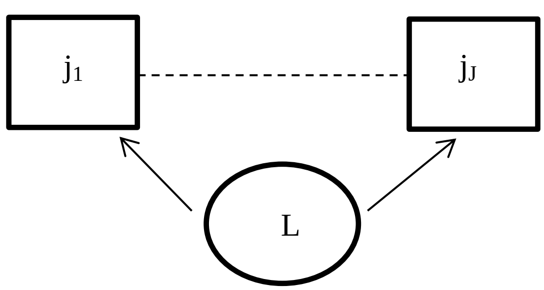
Latent Class Analysis (LCA)

Latent class analysis (LCA) is a latent variable model with categorical latent class and categorical observed indicators. It was introduced by Lazarsfeld and Henry in the 1950s and was subsequently developed by Goodman in the 1970s, setting the stage for statistical software implementation as well as further development and diverse applications.

Fundamental expressions

The conceptual model for LCA is presented in Figure 2, where circles represent latent variables and rectangles indicate the observed indicators.

Figure 2. Latent class analysis model diagram.



Formally, the LCA model postulates that there exists an unordered latent variable L with c=1,…, C classes and that the association among observed indicators j (interchangeably called items) is due to an underlying class structure. Each of the j items,

$j=1,\ldots, J$, has $r_j=1,\ldots, R_j$ response categories. The model assumes local independence, which implies that there is no residual correlation between the indicators.

The class membership is based on the observed pattern of indicators. The indicators form a contingency table with W= $\prod_{j=1}^{J} Rj$ cells. Each of these cells is associated with a complete response pattern $\mathbf{y} = (r_1,\ldots, r_J)$ and each cell provides the frequency (or proportion) of individuals responding with this particular pattern. The response patterns form the array of response patterns **Y** and each response pattern is associated with probability $P(\mathbf{Y}= \mathbf{y})$, such that $\Sigma\, P(\mathbf{Y}= \mathbf{y}) = 1$. The probability of observing a particular vector of responses is a function of two kinds of parameters: 1) the probabilities of membership in each latent class (γ parameters), and 2) the probabilities of observing each response, conditional on latent class membership (ρ parameters). Practically, the γ parameters estimate the relative size of each class/proportion of population in that class, also referred to as class prevalence, and ρ parameters estimate the probability that an individual in a particular class will endorse an item. The latter parameters are used to interpret the meaning of obtained classes and are typically presented in profile plots.

The LCA model, assuming conditional independence, can be expressed as:

$$P(\mathbf{Y}=\mathbf{y}) = \sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{rj=1}^{Rj} \rho_{j,r_j/c}^{I(y_j=r_j)},$$

where

- γ_c is the probability of membership in latent class c P(L = c) and $\sum_{c=1}^{C} \gamma_c = 1$
- $\rho_{j,r_j/c}$ is the probability of response r_j to observed variable j, conditional on membership in latent class c and $\sum_{r_j=1}^{Rj} \rho_{j,r_j/c} = 1$ for all j

- y_j is the element j of a response pattern **y** and $I(y_j = r_j)$ is the indicator variable such that it equals 1 when $j = r_j$ and 0 otherwise.

The model can equivalently be written in terms of the joint and conditional probabilities, illustrating it from a more conceptual perspective:

$$P(\mathbf{Y}=\mathbf{y}) = \sum_{c=1}^{C} P(Y = y, L = c) = \sum_{c=1}^{C} P(L = c)P(Y = y / L = c),$$

The parameter estimates in the final model are used to determine final class assignment for each individual. Posterior probabilities, also called classification probabilities, depict the probability of membership in latent class c conditional on response pattern **y**, P (L=c / **Y**= **y**). Typically, for each response pattern, there is a non-zero probability of membership in each latent class, and ultimately the highest posterior probability determines the final class membership (modal assignment).

LCA model selection

LCA is predominantly used in an exploratory fashion, though a confirmatory approach is possible and utilized to test specific research hypotheses. Even though the exploratory approach does not require having an explicit theory, the theoretical considerations as well as prior research on the structure of the latent variable are useful in model selection process (McCutcheon, 1987).

The initial analytic step is to identify the appropriate number of classes that adequately account for the observed indicators. The candidate models are tested in a sequential manner, starting with the most parsimonious model and gradually increasing the number of classes. Finding the optimal number of classes is challenging in mixture models (the so-called “class enumeration problem”). The current guidelines propose that the decision when to stop the search process is based on a combination of statistical indicators, substantive interpretation, and model parsimony (Muthén, 2003, Collins & Lanza, 2010). From the statistical perspective, the best fitting model is the one with the largest log-likelihood (best absolute fit) and smallest information criteria indices, such as BIC (best relative fit). In addition, two chi-square difference-like tests are sometimes considered: 1) LMR-LRT test (also called the Vuong-Lo-Mendell-Rubin test), and 2) BLRT (the parametric bootstrap LRT). Both of these tests allow comparing non-nested models with c and (c +1) classes, where a non-significant p-value suggests rejecting a (c+1)-class model in favor of a c-class model. Given the complexity of the class enumeration problem and computation demands of some of the tests, Nylund et al. (2007) recommended to initially consider BIC index, followed by the LMR-LRT, and finally BLRT tests.

LCA is a complex model in which the maximum-likelihood parameter estimates are obtained using a version of an iterative estimation algorithm that utilizes some pre-specified convergence criteria (e.g., maximum absolute deviation, MAD, less than a specified number). A well-known problem with mixture models is that they may converge on local rather than global maxima. It is recommended that multiple sets of starting values (automatic or user-provided) are used to monitor the consistency of model convergence to the same solution. Another general approach to help identify the model is to apply parameter restrictions, thus simplifying the model by reducing the number of parameters estimated (Collins & Lanza, 2010).

Model checks include examination of class profiles, class sizes, mean posterior probabilities for each class along with their variation within each latent class, entropy measures (one-number summary of the degree of uncertainty, commonly computed based on posterior probabilities), pattern response tables, and model residuals.

Covariates and grouping variables in LCA models

Useful extensions of traditional LCA models are inclusion of covariates and/or grouping variables. Incorporating covariates generally serve two purposes: 1) to predict latent class membership and help validate classes obtained in the LCA model without covariates, and 2) test hypotheses about group differences.

The prediction approach is focused on testing hypotheses about significant associations between covariates and class membership. The validation process is concerned with checking whether emergent classes have expected relationships with covariates, both in terms of direction as well as magnitude. The covariates (numeric and/or categorical) are incorporated into the model using multinomial logistic regression (Collins & Lanza, 2010). A model with one covariate can be written as follows:

$$\mathrm{P}(\mathbf{Y}=\mathbf{y}/\mathbf{X}=\mathbf{x}) = \sum_{c=1}^{C} \gamma_c(x) \prod_{j=1}^{J} \prod_{rj=1}^{Rj} \rho_{j,rj/c}^{I(yj=rj)},$$

where

- $\gamma_c\ (x)$ is the standard baseline-category C multinomial logistic model $\gamma_c\ (x) =$

  $\mathrm{P}(\mathrm{L=c/X=x}) = \frac{e^{\beta_{0c}+\beta_{1c}\, x}}{1+\sum_{c'=1}^{C-1} e^{\beta_{0c}+\beta_{1c}\, x}}$, where c'= 1,…, C - 1.

This equation can be expressed in terms of the logit, where logit = log $(\frac{\gamma_c}{\gamma_C}) = \beta_{0c} + \beta_{1c}$ and $e^{\beta_{0c}}$ represents the odds of membership in latent class c in relation to the reference latent category C when X = 0, and $e^{\beta_{1c}}$ represents the change in odds of membership in latent lass c in relation to the reference latent category C that is associated with an observed one-unit difference in X.

The parameter estimates are used to investigate the covariates' effect for each latent class in relation to an arbitrary reference latent class category. Therefore, there are C-1 intercepts and C-1 regression coefficients for each covariate. The hypothesis testing and coefficient interpretation is essentially identical to logistic regression procedure (i.e., using likelihood ratio χ^2 tests with appropriate degrees of freedom and odds ratios). Measurement invariance of item-response probabilities across all values of any covariates is assumed.

More than one covariate and their interactions can be incorporated into the model in the same manner as in a standard logistic regression. However, multiple covariates may be related to a substantial increase in computation time and estimation issues, often due to sparseness in the data. A Bayesian approach to LCA is typically used, where data-driven stabilizing prior is imposed on β parameters (Collins & Lanza, 2010, Lanza et al., 2011). This approach allows solving a majority of sparseness-related estimation issues by adding a small amount of prior information ("pseudo-data") to the data, therefore preventing beta parameters from diverging to infinity in the presence of sparse cells. The strength of the prior is controlled by a researcher and, typically, the prior either has no impact or only slightly diminishes the effects of covariates considered in the model (i.e., flattening prior).

Multiple-group LCA allows testing hypotheses about measurement invariance in groups of interest, both in item-response probabilities (ρ parameters) and/or latent classes prevalence (γ parameters). Model comparison typically involves comparisons of a series of nested models specified using parameter restrictions. Hypotheses about varying degree of measurement invariance can be tested (full or partial invariance, or noninvariance). Model fit is assessed using the likelihood ratio test (LRT) and information criteria indices (e.g., BIC). Examination of the between-group differences in parameters of interest is essential, as the LRT and information criteria often disagree (Collins & Lanza, 2010).

The model multiple- group LCA model is specified as follows:

$$\mathrm{P}(\mathbf{Y{=}y/V{=}q}) = \sum_{c=1}^{C} \gamma_{c/q} \prod_{j=1}^{J} \prod_{rj=1}^{Rj} \rho_{j,\frac{rj}{c},q}^{I(y_j=r_j)},$$

where

- V is a grouping variable with q=1,…, Q groups. The contingency table has W= Q $\prod_{j=1}^{J} Rj$ cells.

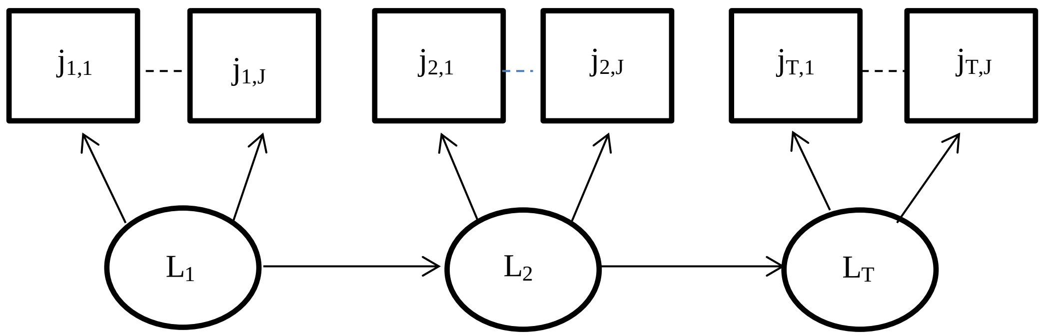
Latent Transition Analysis (LTA)

Latent Transition Analysis (LTA) can be seen as an extension of LCA in that it permits a dynamic change between classes over time (Collins, 2006). LTA consists of a measurement model, typically specified as LCA at each time point, and transitional model, describing change between consecutive time points. Categorical latent classes at each time point are related to each other using an autoregressive relationship, so that the probability of class membership at time t is conditioned on latent class membership at time t-1. This possible temporal class membership is reflected in the fact that latent classes in LTA are sometimes referred to as latent statuses (Collins & Lanza, 2010). Many LTA features, including parameters, their interpretations and modeling extensions, are similar to their counterparts in LCA models.

Fundamental expressions

Now L_t represents the categorical latent variable at Time t with S latent classes (or statuses), where s_1= 1,…, S at Time 1, s_2=1,…, S at Time 2, and finally s_T=1,…, S at Time T. The conceptual diagram of the model is presented in Figure 3.

Figure 3. Latent transition analysis model diagram.



In the unrestricted model, there are j items * s classes * t time points parameters for the contingency table with W = $\prod_{t=1}^{T}\prod_{j=1}^{J} R_j$ cells. Each cell is associated with a response pattern represented by **y**= ($r_{1,1}$,…, $r_{J,T}$). The model can be specified using the following equation (for simplicity, it is assumed that the same j indicator variables are measured at each occasion, the number of classes is the same at each time point, and there is no missing data on indicators):

$$P(Y = y) = \sum_{s_1=1}^{S} \dots \sum_{s_T=1}^{S} \delta_{s_1} \tau_{s_2|s_1} \dots \tau_{s_T|s_{T-1}} \prod_{t=1}^{T} \prod_{j=1}^{J} \prod_{r_{j,t}=1}^{R_j} \rho_{j,r_{j,t}|s_t}^{I(y_{j,t}=r_{j,t})},$$

where

- P(Y=y) is the probability of observing a particular vector of responses, and $\sum P(\boldsymbol{Y} = \boldsymbol{y}) = 1$
- j=1,…, J are indicator variables measured at t=1,…, T times

- δ_{s_1} is the probability of membership in each latent class at Time 1. In general, δ_{s_t} is the probability of membership in latent class s at Time t, and $\sum_{s_t=1}^{S} \delta_{s_t} = 1$
- $\tau's$ are the probabilities of transitioning to a latent status at a particular time, conditional on latent status membership at the immediately previous time. Specifically, $\tau_{s_{t+1}|s_t}$ is the probability of a transition to latent status s at Time t+1 conditional on membership in latent status s at Time t, and $\sum_{s_{t+1}=1}^{S} \tau_{s_{t+1}|s_t} = 1$. These probabilities form the following transition probability matrix:

$$\begin{bmatrix} \tau_{1_{t+1}|1_t} & \tau_{2_{t+1}|1_t} & \cdots & \tau_{S_{t+1}|1_t} \\ \tau_{1_{t+1}|2_t} & \tau_{2_{t+1}|2_t} & \cdots & \tau_{S_{t+1}|2_t} \\ \cdots & \cdots & \cdots & \cdots \\ \tau_{1_{t+1}|S_t} & \tau_{2_{t+1}|S_t} & \cdots & \tau_{S_{t+1}|S_t} \end{bmatrix}$$

- $\rho's$ are the probabilities of observing each response at each time, conditional on latent status membership. Specifically, $\rho_{j,r_{j,t}|s_t}$ is the probability or response $r_{j,t}$ to observed variable j, conditional on membership in latent status s_t at Time t, and $\sum_{r_{j,t}=1}^{R_j} \rho_{j,r_{j,t}|s_t} = 1$
- $I(y_{j,t} = r_{j,t})$ is an indicator variable such that it equals1 when the response to variable j= r_j at Time t and 0 otherwise.

In summary, the τ parameters are of primary interest in LTA because they describe change in the latent statuses over time. The interpretation of the item-response parameters and class membership probabilities are similar to that in LCA models, except now parameters at a subsequent time (t+1) are conditional on parameters from previous time point (t). The number of parameter estimates in LTA model is usually very large. Likewise, the degrees of freedom, computed as df = W - # of δ parameters - # of ρ parameters - # of τ parameters -1, where W is the number of cells in the contingency table, are also large.

LTA model selection

Two model selection procedures have been proposed in the literature. In the first approach, a series of LCA models are explored at each time point and used in the longitudinal model (bottom-up approach) (e.g., Nyland, 2007, Lanza & Bray, 2010). Alternatively, a series of longitudinal models with varying number of classes are fit and compared. Subsequently, the latent structure at each time point is verified (top-down approach) (Collins & Lanza, 2010).

Each of these model selection methods has their own advantages and disadvantages. Specifically, the top-down approach involves a “one-step” comparison of complex models, with assumed equal number of classes at each time point, and measurement invariance in item-response probabilities over time (ρ parameters). Otherwise, the specification and interpretation of the latent transition model could be very challenging. However, the advantage of this approach stems from the concern that cross-sectional LCA models may fail to detect all existing classes, due to an increased lack of power associated with attrition, and/or changes in class prevalences over time (Collins & Lanza, 2010).

The bottom-up approach is conceptually more appealing, particularly for complex models with many time points and indicators. It is a multifaceted process involving 1) preliminary examination of the measurement model by fitting the LCA models at each time point and comparing them using relative fit indices (e.g., BIC) and other tests for non-nested models; 2) fitting LTA model sequentially, first using two time points and then all available data, in the effort to ensure that model is identified and latent statuses are interpretable; and 3) exploring measurement invariance in all three types of LTA parameters.

Testing hypotheses about measurement invariance over time, particularly in terms of item-response probabilities (equity restriction in ρ parameters over time), is essential, as the interpretation of the transition model is greatly simplified when this assumption holds (Collins & Lanza, 2010). As in LCA, model comparison involves comparing nested models using LRT and/or information criteria indices (e.g., BIC).

Overall, model identification concerns present in LCA models are applicable here as well. Parameter restrictions may help resolve possible problems, such as those related to sparseness cells in the contingency table.

Covariates and grouping variables in LTA model

Covariates (categorical and/or continuous, time-invariant, and time-varying) and/or grouping variables can be incorporated into the model. They can be used to: 1) predict membership in latent classes at Time 1, and/or transitions between latent classes over time, and 2) test hypotheses about group differences over time.

As in LCA, covariates are included in the model via multinomial logistic regression. Again, as the focus is on assessing the effect of covariate(s) on select LTA model parameters, only regression coefficients β are directly estimated, whereas model parameters δ and τ are derived from other estimated coefficients and observed covariate values. The model implies measurement invariance across all values of all covariates, and can be specified as follows (for simplicity, only one covariate is considered):

$$P(\boldsymbol{Y}=\boldsymbol{y}|X=x)=\sum_{s_1=1}^{S}\dots\sum_{s_T=1}^{S}\delta_{s_1}(x)\tau_{s_2|s_1}(x)\dots\tau_{s_T|s_{T-1}(x)}\prod_{t=1}^{T}\prod_{j=1}^{J}\prod_{r_{j,t}=1}^{R_j}\rho_{j,r_{j,t}|s_t}^{I(y_{j,t}=r_{j,t})},$$

where $\delta_{s_1}(x)\ and\ \tau_{s_T|s_{T-1}(x)}$ are standard baseline-category multinomial logistic models with reference category set to S_1 (i.e., δ_{s_1}):

- $\delta_{s_1}(x)=P(L_1=s_1)|X=x)=\frac{e^{\beta_{0s1}+\beta_{1s1}x}}{1+\sum_{s"\prime 1=1}^{S-1}e^{\beta_{0s1}+\beta_{1s1}x}}$, s_1'= 1, …, S-1
- $\tau_{s_t|s_{t-1}(x)}=P(L_t=s_t)\big|\,L_{t-1=s-1,}X=x\big)=\frac{e^{\beta_{0st|s_{t-1}}+\beta_{1s_t|s_{t-1}}x}}{1+\sum_{s"\prime 1=1}^{S-1}e^{\beta_{0st|s_{t-1}}+\beta_{1s_t|s_{t-1}}x}}$

The interpretation of the effect of covariates on latent class prevalences at Time 1 (δ parameters) is relatively straightforward. However, the prediction of transition probabilities is more complicated as it is now conditioned on the previous time point and the values of covariates, requiring separate multinomial logistic regression equation for each row of the transition probability matrix. As a result, predictions for subsets of individuals are obtained and odds ratios are interpreted accordingly (Collins & Lanza, 2010).

Multiple-group LTA typically involves comparing groups of interest in terms of differences in transition probabilities (τ parameters). Parameter restrictions can be specified to test particular hypotheses of interest (e.g., full measurement invariance vs. partial measurement invariance). The usual LRT tests and information criteria indices are used. The model is specified as follows:

$$P(\boldsymbol{Y} = \boldsymbol{y}|V = q) = \sum_{s_1=1}^{S} \dots \sum_{s_T=1}^{S} \delta_{s_{1/q}} \tau_{s_2|s_{1,q}} \dots \tau_{s_T|s_{T-1,q}} \prod_{t=1}^{T} \prod_{j=1}^{J} \prod_{r_{j,t}=1}^{R_j} \rho_{j,r_{j,t}|s_{t,q}}^{I(y_{j,t}=r_{j,t})} ,$$

where

- V is a grouping variable with q = 1, … ,Q groups. The contingency table now has W = Q $\prod_{t=1}^{T} \prod_{j=1}^{J} R_j$ cells.

Missing data in LCA and LTA models

Both the LCA and LTA models assume that missing data is missing at random (MAR). The full-information maximum likelihood estimation method (FIML) is typically employed, allowing all available information to be utilized in the estimation process. This estimation approach in LCA and LTA allows missing data on the model indicators, but not on any covariates or grouping variables. All such cases are then deleted from the analysis (Collins & Lanza, 2010).

RESULTS

In order to address research objectives outlined in the introduction, the LCA and LTA models were applied and results are organized as follows:

First, results from the cross-sectional model of PTSD are presented (LCA; Round 1). Model selection process is outlined and competing models are compared. The final model is compared and contrasted with the diagnostic model (DSM-IV and proposed DSM-V).

Subsequently, a longitudinal model for PTSD was fitted to the data using measurement models selected at 3 assessment occasions (LTA; Round 1, 2 and 3). Transitions between consecutive assessments are described in detail and the effect of concurrent Major Depressive Disorder (MDD) on these transitions is assessed using logistic regression model.

Hypotheses regarding measurement invariance by race/ethnicity and time are tested using multiple-group LCA and multiple- group LTA models.

All analyses were carried out using SAS procLCA and procLTA, Version 1.2.7. SAS procedures were used to fit all latent class and latent transition models using a full-information maximum likelihood estimation method (FIML); sub-analyses not available in SAS were supplemented with M-PLUS, Version 4.1 procedures (e.g., residual analyses).

Latent Class Analysis (LCA)

The latent structure of PTSD at Round 1

The first step in LCA modeling is to examine all class indicators in terms of their marginal distributions. In this study, seventeen PTSD symptoms were considered at

Round 1. All symptom descriptions and endorsement rates are presented in Table 2. In order to help with the interpretation of subsequent analyses, all symptoms were coded according to their position and cluster membership. This coding is used throughout the entire results section.

Symptom endorsement differed considerably, ranging from about 3% (acting or feeling as if events were recurring - 2.8%; and inability to recall important aspects of trauma - 3.1%), to over 20% (psychological distress at exposure to cues - 22.4% and hypervigilance - 34.2%). At the cluster level, hyperarousal symptoms (cluster D) were endorsed at the highest rate (range 10.8% - 34.2%), followed by several symptoms from the avoidance/numbing cluster (cluster C). These symptoms included both avoidance symptoms (avoidance of thoughts and feelings - 14.6%; avoidance of activities, places, or people - 13.8%) and one numbing symptom (diminished interest in activities - 11.2%). Re-experiencing symptoms from cluster B generally had the lowest endorsement rates, with the exception of psychological distress at exposure to cues (22.4%).

Information contained in marginal distributions of individual symptoms provides information about overall posttraumatic stress symptomatology in the sample, but reveals little regarding symptom patterns present in the data. The marginal distributions suggest that 1) a large number of individuals in the dataset did not endorse any symptoms, and 2) the contingency table may include a large number of cells that are either sparse or have small counts.

Table 2

Symptom descriptions and endorsement frequency at Round 1

Symptom	Symptom code		Symptom description	% Yes
CLUSTER B Reexperiencing symptoms				
1	1B	Rx	intrusive recollections	8.1
2	2B	Rx	distressing dreams	5.8
3	3B	Rx	acting or feeling as if event were recurring	2.8
4	4B	Rx	psychological distress at exposure to cues	24.3
5	5B	Rx	physiological reactivity on exposure to cues	5.5
CLUSTER C Avoidance and numbing symptoms				
6	6C	Av	avoidance of thoughts and feelings	14.6
7	7C	Av	avoidance of activities, places, or people	13.8
8	8C	Num	inability to recall important aspects of trauma	3.1
9	9C	Num	diminished interest in activities	11.2
10	10C	Num	detachment or estrangement	7.9
11	11C	Num	restricted range of affect	7.5
12	12C	Num	sense of a foreshortened future	9.5
CLUSTER D Hyperarousal symptoms				
13	13D	Hx	difficulty falling or staying asleep	19.8
14	14D	Hx	irritability and outbursts of anger	17.6
15	15D	Hx	difficulty concentrating	10.9
16	16D	Hx	hypervigilance	34.2
17	17D	Hx	exaggerated startle response	10.8

Notes: Rx-re-experiencing; Av-avoidance; Num- numbing; Hx-hyperarousal.

Results of the sequential LCA model fitting procedure are summarized in Table 3. One through six classes were considered[1]. The BIC criterion suggested that the four class model was preferred over the three and five-class models. On the other hand, the first time that LMR-LRT and BLRT tests p-values were non-significant ($p>.05$) was for the six-class model, suggesting that the five-class model had the best fit. The assessment of

[1] A series of confirmatory LCA were also considered, where the probabilities of endorsing symptoms in clusters B, A, N, and D were pre-specified and varied (McCutcheon, 1987). These analyses yielded results comparable with exploratory LCA; therefore, only the latter results are presented.

absolute model fit based on the likelihood – ratio G^2 statistic was not feasible because of a large number of degrees of freedom associated with considered models (Collins & Lanza, 2010).

Table 3

LCA Models Fit at Round 1

# of classes	Log-likelihood	G^2	# of parameters	BIC	AIC	LMR-LRT p-value	BLRT p-value
2	-13742	5604.50	35	5883	5674	.0000	.000
3	-13403	4926.54	53	5350	5032	.0000	.000
4	-13305	4729.68	71	5297	4871	.0099	.000
5	-13234	4588.78	89	5300	4766	.0133	.000
6	-13202	4524.04	107	5379	4738	.2026	.000

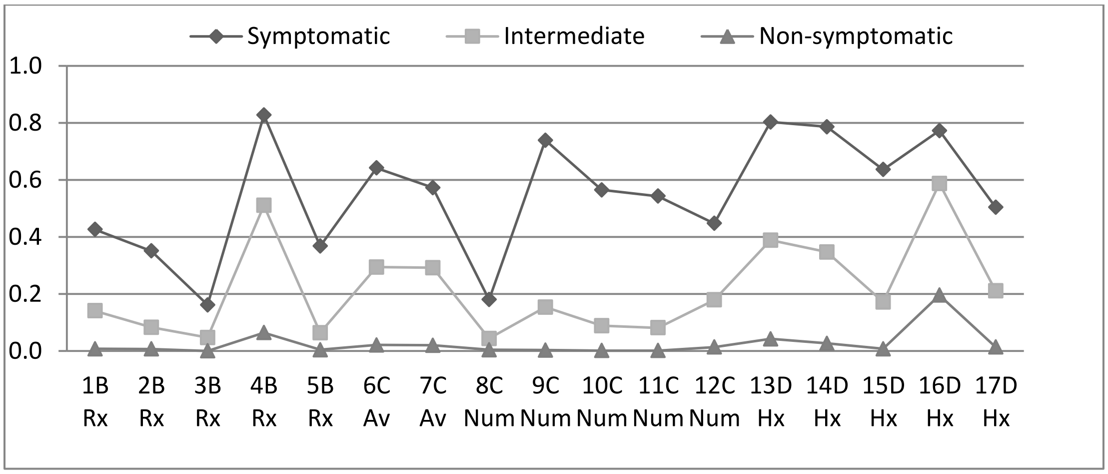
Taking into consideration prior PTSD research and the interpretability of the classes from all considered models, the three and four class solutions emerged as the final competing models. Figure 4 shows item profile plots and Table 4 presents the conditional item-response probabilities for both models (ρ parameters).

The classes that emerged from the three class model were labeled based on the items-response probabilities (ρ parameters) as Symptomatic (10.0%), Intermediate (21.5%), and Non-symptomatic (68.4%). The Symptomatic class was characterized by high probabilities of endorsing a majority of symptoms from all clusters (ρ=.50 or greater for 11 out of 17 symptoms). Taking into consideration the constellation of these symptoms, one can conceptualize this class as consisting of individuals who likely received the full

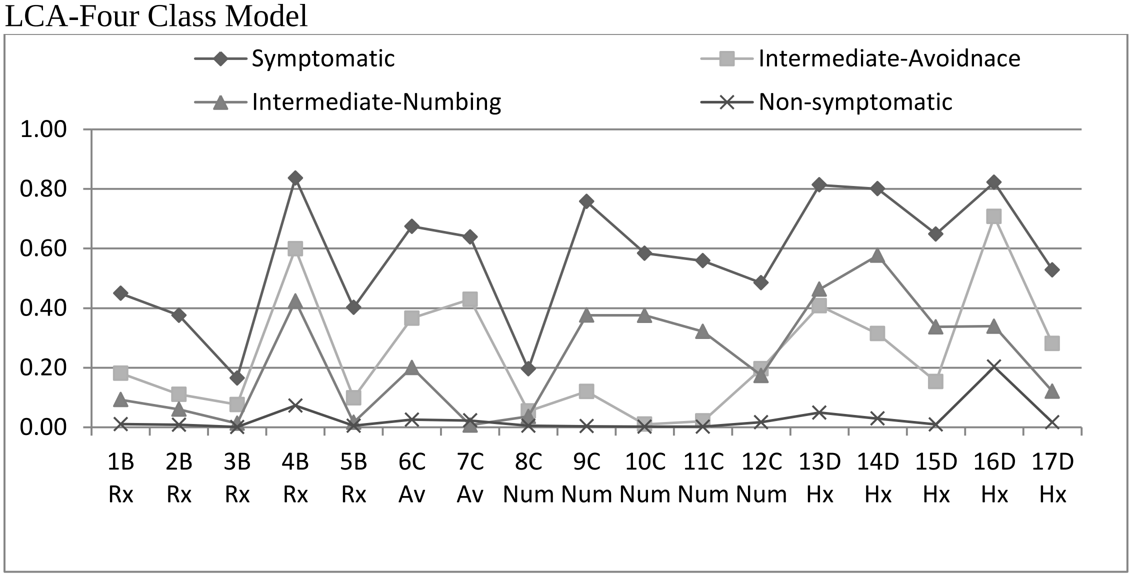
DSM-IV PTSD diagnosis. In addition, this class had the highest average symptom severity (M=50.64, SD= 13.69), typically characterized as moderate PTSD (Table 5).

Figure 4. Items profile plots for LCA-three and LCA-four class models at Round 1.

LCA-Three Class Model



LCA-Four Class Model



Legend:
1B Rx: intrusive recollections, **2B Rx**: distressing dreams, **3B Rx:** acting or feeling as if event were recurring, **4B Rx:** psychological distress at exposure to cues, **5B Rx:** physiological reactivity on exposure to cues, **6C Av**: avoidance of thoughts and feelings, **7C Av**: avoidance of activities, places, or people, **8C Num**: inability to recall important aspects of trauma, **9C Num**: diminished interest in activities, **10C Num**: detachment or estrangement, **11C Num**: restricted range of affect, **12C Num**: sense of a foreshortened future, **13D Hx**: difficulty falling or staying asleep, **14D Hx**: irritability and outbursts of anger, **15D Hx**: difficulty concentrating, **16D Hx**: hypervigilance, **17D Hx**: exaggerated startle response

Table 4

Item-response probabilities for three class and four class LCA models

		Three class LCA			Four class LCA			
		Non-symptomatic Class size=68.4%	Intermediate Class size= 21.5%	Symptomatic Class size=10.0%	Non-symptomatic Class size=69.5%	Intermediate-Avoidance Class size=15.1%	Intermediate-Numbing Class size= 6.9%	Symptomatic Class size=8.9%
1B	Rx	0.01	0.14	**0.43**	0.01	0.18	0.09	**0.45**
2B	Rx	0.01	0.08	**0.35**	0.01	0.11	0.06	**0.38**
3B	Rx	0.00	0.05	0.16	0.00	0.08	0.01	0.17
4B	Rx	0.07	**0.51**	**0.83**	0.07	**0.60**	**0.42**	**0.84**
5B	Rx	0.00	0.06	**0.37**	0.01	0.10	0.02	**0.40**
6C	Av	0.02	**0.29**	**0.64**	0.03	**0.37**	**0.20**	**0.67**
7C	Av	0.02	**0.29**	**0.57**	0.02	**0.43**	0.01	**0.64**
8C	Num	0.00	0.04	0.18	0.00	0.05	0.04	**0.20**
9C	Num	0.00	0.15	**0.74**	0.00	0.12	**0.38**	**0.76**
10C	Num	0.00	0.09	**0.57**	0.00	0.01	**0.38**	**0.58**
11C	Num	0.00	0.08	**0.54**	0.00	0.02	**0.32**	**0.56**
12C	Num	0.01	0.18	**0.45**	0.02	**0.20**	0.17	**0.48**
13D	Hx	0.04	**0.39**	**0.80**	0.05	**0.41**	**0.46**	**0.81**
14D	Hx	0.03	**0.35**	**0.79**	0.03	**0.31**	**0.58**	**0.80**
15D	Hx	0.01	0.17	**0.64**	0.01	0.15	**0.34**	**0.65**
16D	Hx	**0.20**	**0.59**	**0.77**	**0.20**	**0.71**	**0.34**	**0.82**
17D	Hx	0.01	**0.21**	**0.50**	0.02	**0.28**	0.12	**0.53**

Legend:

1B Rx: intrusive recollections, **2B Rx**: distressing dreams, **3B Rx:** acting or feeling as if event were recurring, **4B Rx:** psychological distress at exposure to cues, **5B Rx:** physiological reactivity on exposure to cues, **6C Av**: avoidance of thoughts and feelings, **7C Av**: avoidance of activities, places, or people, **8C Num**: inability to recall important aspects of trauma, **9C Num**: diminished interest in activities, **10C Num**: detachment or estrangement, **11C Num**: restricted range of affect, **12C Num**: sense of a foreshortened future, **13D Hx**: difficulty falling or staying asleep, **14D Hx**: irritability and outbursts of anger, **15D Hx**: difficulty concentrating, **16D Hx**: hypervigilance, **17D Hx**: exaggerated startle response

Note. Item response probability >.20 were bolded to facilitate interpretation.

The average symptom severity of the Intermediate class was at the low end of the mild range (M=21.98, SD=8.65), and this class had much lower probabilities of endorsing PTSD symptoms overall, as compared to the Symptomatic class. This class is characterized by an elevated probability of endorsing one symptom in the re-experiencing cluster (psychological distress at exposure to cues, ρ=.51), both avoidance symptoms (ρ=.29 for both avoidance of thoughts and feelings and avoidance of activities, places, or people), as well as four of the five hyperarousal symptoms (difficulty falling or staying asleep ρ=.39, irritability and outburst of anger ρ=.35, hypervigilance ρ=.59, and exaggerated startle response ρ=.21). Interestingly, the majority of the item-response probabilities for numbing symptoms were in the low range (ρ<.10). This class can be conceptualized as the subclinical PTSD, with the majority of individuals endorsing symptoms consistent with subthreshold PTSD. Last, the most prevalent class (68.4%) is characterized by extremely small item-response probabilities for all symptoms except hypervigilance from the hyperarousal cluster (ρ=.20). Therefore, this class was labeled as the Non-symptomatic class (symptom severity M=4.73, SD=4.95).

The four class solution yielded classes that can be characterized as the Symptomatic class (8.9%, symptom severity M=52.941, SD=13.41), Intermediate-Avoidance class (15.1%, symptom severity M=25.05, SD=8.77), Intermediate- Numbing class (6.9%, symptom severity M=24.86, SD=8.81) and Non-symptomatic class (69.5% symptom severity M=5.19, SD=5.36). The profiles of the Symptomatic class as well as Non-symptomatic class are virtually identical to those obtained in the three class model, with all item-response probabilities in the remarkably matching range. The three and four class models generally differ in the classification of individuals without extreme probabilities of endorsing or not endorsing PTSD symptoms, placing them either in one class (Intermediate class, three class solution) or differentiating them into two separate classes (Intermediate-Avoidance and Intermediate-Numbing class, four class solution). The more prevalent of these classes, the Intermediate-Avoidance class (15.1%), can be described by elevated probability of endorsing both avoidance symptoms (ρ=.37 and ρ=.43 respectively) and one numbing symptom (sense of a foreshortened future, ρ=.20). The Intermediate-Numbing class (6.9%) is characterized by high probabilities of endorsing 3 out of 5 numbing symptoms (diminished interest in activities ρ=.38, detachment or estrangement ρ=.38, restricted range of affect ρ=.32) and one avoidance symptom (avoidance of thoughts and feelings, ρ=.20). Both the Intermediate-Avoidance and Intermediate-Numbing classes had elevated probabilities of endorsing one re-experiencing symptom (psychological distress at exposure to cues, ρ=.60 and ρ=.42, respectively), as well as endorsing the majority of hyperarousal symptoms. In particular, the Intermediate-Avoidance class had much higher probability of endorsing symptoms of hypervigilance (ρ=.71 vs. ρ=.24) and exaggerated startle response (ρ=.28 vs. ρ=.12), whereas the Intermediate-Numbing group had almost double the probability of endorsing symptoms of irritability (ρ=.58 vs. ρ=.31) and difficulty concentrating (ρ=.34 vs. ρ=.15).

Overall, both the three class and four class models suggest that there exists one class that can be characterized by a high probability of symptom endorsement and another class that can be characterized as non-symptomatic. The information criteria indices (BIC) favor the four class solution over the three class solution (BIC= 5297 and BIC= 5350, respectively), suggesting that differentiating between the Intermediate-Avoidance and Intermediate-Numbing classes results in a better model fit.

Table 5

Symptoms severity and number of symptoms by three class and four class LCA models

	Symptoms Severity					Number of symptoms			
	N	Mean	SD	Min	Max	Mean	SD	Min	Max
Three class LCA									
Symptomatic	298	50.65	13.69	21	95	9.49	2.18	5	16
Intermediate	637	21.98	8.65	6	54	3.85	1.52	2	8
Non-symptomatic	2025	4.73	4.95	0	34	.44	.63	0	2
Four class LCA									
Symptomatic	252	52.94	13.41	26	95	9.94	2.05	6	16
Intermediate-Avoidance	400	25.05	8.77	6	51	4.56	1.52	2	8
Intermediate-Numbing	170	24.86	8.81	8	52	4.28	1.57	2	7
Non-symptomatic	2138	5.19	5.36	0	54	.52	.70	0	2

Above and beyond examining global fit measures and the conceptual plausibility of the emergent classes, the final model checks involve inspection of mean posterior probabilities and their variation within each class, odds of correct classification (OCC) for each class (defined as the improvement over chance in a model assignment accuracy), entropy measures, residuals and pattern response tables.

These indicators generally support the choice of the four class model as the model with the best fit. The posterior probabilities were in the same range in terms of class means and standard deviations (Table 6 and Table 7). However, the four class model had slightly better entropy (.86 and .84, respectively) and slightly fewer significant response pattern residuals (34.9% vs. 39.7%).

Table 6

Mean posterior probabilities for three class LCA model

Class		Non-symptomatic		Intermediate		Symptomatic	
	n	M/SD	Min/Max	M/SD	Min/Max	M/SD	Min/Max
Non-symptomatic	2025	**.95/.09**	**.51/1.00**	.01/.49	.05/.09	.00/.00	.00/.00
Intermediate	637	.00/.49	.09/.15	**.86/.15**	**.50/1.00**	.00/.50	.05/.10
Symptomatic	292	.00/.00	.00/.00	.00/.48	.08/.13	**.92/.13**	**.52/1.00**

Table 7

Mean posterior probabilities for four class model

Class		Non-symptomatic		Intermediate-Avoidance		Intermediate-Numbing		Symptomatic	
	n	M/SD	Min/Max	M/SD	Min/Max	M/SD	Min/Max	M/SD	Min/Max
Non-symptomatic	2138	**.95/.11**	**.42/.1.00**	.04/.08	.00/.48	.01/.49	.05/.09	.00/.00	.00/.00
Intermediate-Avoidance	400	.05/.08	.00/.49	**.84/.15**	**.43/1.00**	.06/.11	.00/.50	.05/.01	.00/.47
Intermediate-Numbing	170	.03/.07	.00/.30	.12/.15	.00/.48	**.79/.179**	**.40/1.00**	.06/.11	.00/.49
Symptomatic	252	.00/.00	.00/.00	.04/.10	.00/.46	.03/.13	.00/.43	**.93/.13**	**.43/1.00**

As expected, there was an extremely high level of heterogeneity in symptom presentation in all classes with elevated probabilities of symptoms endorsement (Symptomatic, Intermediate-Avoidance, and Intermediate-Numbing classes). Overall, we observed 768 response patterns across all classes.

In the Symptomatic class, 97.6% (246/252) of individuals had distinct response patterns representing the most heterogeneity, followed by the Intermediate-Numbing class (87.6%, 149/170) and the Intermediate-Avoidance class (77.6%, 308/400). Furthermore, each of these classes had response patterns that did not entirely coincide with conceptually defined features of the class. Specifically, 3.9% (10/252) of individuals in the Symptomatic class did not endorse any of the re-experiencing symptoms, 11.9% (30/252) did not endorse any avoidance symptoms, and 1.9% did not endorse any numbing symptoms. The mean number of symptoms in this group was M=8.88 (SD=1.59). In the Intermediate-Avoidance class, 32.3% (129/400) individuals did not endorse any of the avoidance symptoms, and 10.6% (18/170) of those in the Intermediate-Numbing class did not endorse any numbing symptoms. The mean number of symptoms in these groups were M=4.61 (SD=1.42) and M=3.17 (SD=0.75), respectively.

The Non-symptomatic class was the most homogenous class, with 60% of individuals endorsing no symptoms, 13.8% endorsing one symptom from the hyperarousal cluster (hypervigilance), and 4.1% endorsing one re-experiencing symptom (psychological distress at exposure to cues). Overall, there were 65 distinct response patterns in the Non-symptomatic class.

To help facilitate the analysis of response patterns, the number of symptoms endorsed in each cluster was used as a grouping variable. The most prevalent patterns in each class are presented in Table 8.

Table 8

Most prevalent item-response patterns by class for four class LCA model

Symptomatic class n= 252						
B Rx	A Av	N Num	D Hx	# of symptoms	Frequency	Percent
2	1	3	3	9	9	3.6
1	1	2	4	8	7	2.8
3	2	3	5	13	7	2.8
3	2	3	4	12	6	2.4
1	2	2	3	8	5	2.0
2	1	3	4	10	5	2.0
1	2	1	5	9	4	1.6
2	0	2	4	8	4	1.6
2	1	2	5	10	4	1.6
2	1	4	3	10	4	1.6
2	2	3	3	10	4	1.6
3	1	2	4	10	4	1.6
				Total	**63**	**25**

Intermediate-Avoidance class n= 400						
B Rx	A Av	N Num	D Hx	# of symptoms	Frequency	Percent
1	1	0	1	3	29	7.3
1	1	0	2	4	21	5.3
0	1	0	2	3	19	4.8
1	0	0	2	3	19	4.8
0	0	0	3	3	16	4.0
2	0	0	1	3	12	3.0
1	1	1	2	5	11	2.8
1	1	0	3	5	10	2.5
1	1	1	3	6	10	2.5
1	0	1	2	4	8	2.0
2	0	1	2	5	8	2.0
0	1	0	3	4	7	1.8
0	2	0	1	3	7	1.8
2	1	0	1	4	7	1.8
0	2	0	2	4	6	1.5
1	1	1	1	4	6	1.5
1	2	0	3	6	6	1.5
				Total	**202**	**50.1**

Table 8 continues

Intermediate-Numbing class n= 170

B Rx	A Av	N Num	D Hx	# of symptoms	Frequency	Percent
0	0	1	2	3	15	8.8
0	0	1	1	2	9	5.3
1	0	1	2	4	7	4.1
0	0	1	3	4	6	3.5
0	0	2	1	3	6	3.5
0	0	2	2	4	6	3.5
0	0	2	0	2	5	2.9
1	0	0	2	3	5	2.9
1	0	1	3	5	5	2.9
1	0	2	1	4	5	2.9
1	0	2	2	5	5	2.9
0	0	0	2	2	4	2.4
0	0	0	4	4	4	2.4
1	0	2	3	6	4	2.4
1	1	1	3	6	4	2.4
			Total		**90**	**52.9**

Non-symptomatic class n= 2138

B Rx	A Av	N Num	D Hx	# of symptoms	Frequency	Percent
0	0	0	0	0	1291	60.4
0	0	0	1	1	401	18.8
1	0	0	0	1	109	5.1
1	0	0	1	2	74	3.5
0	0	0	2	2	72	3.4
0	1	0	1	2	51	2.4
0	1	0	0	1	42	2.0
0	0	1	0	1	31	1.4
0	0	1	1	2	24	1.1
1	1	0	0	2	21	1.0
2	0	0	0	2	11	0.5
1	0	1	0	2	9	0.4
0	1	1	0	2	2	0.1
			Total		**2138**	**100**

Comparing results from the LCA model and the diagnostic model (DSM)

Results of the LCA and diagnostic model (DSM) comparisons are presented in Table 9. The LCA class assignment for each individual was based on the highest posterior probability (modal assignment). The classification derived from the diagnostic model included the current DSM-IV PTSD criteria and subsyndromal PTSD criteria (Blanchard et al., 1996), as well as a variation of hypothetical scoring rules based on the upcoming DSM-V.

The highest level of agreement was found for groups characterized by either a very low or very high level of symptoms. The distribution of DSM-IV diagnoses by LCA classes was as follows: 82% of individuals in the Symptomatic class met criteria for full PTSD, and 100% of individuals in the Non-symptomatic class did not meet any diagnostic criteria (no PTSD group). Among those in the Intermediate-Avoidance class, the split between the subthreshold PTSD and no PTSD groups was about 50%. In contrast, the majority of individuals in the Intermediate-Numbing class (62%) were in the no PTSD group.

In order to make similar comparisons based on the proposed DSM-V, we used the existing DSM-IV symptoms and applied a variety of hypothesized scoring rules inspired by the proposed DSM-V criteria as well as by the nature of the classes that emerged in the LCA model. After taking into consideration the significant overlap between the DSM-IV and DSM-V symptoms, both in terms of the quantity as well as meaning, and the nature of cluster reorganization (splitting of the avoidance/numbing cluster into two separate clusters, avoidance and numbing), crude comparisons were deemed reasonable. The three new additional symptoms proposed for inclusion in the DSM-V were not considered.

The following new scoring rules were used: 1) full PTSD required meeting criteria for all clusters (i.e., at least 1 re-experiencing symptom, at least 1 avoidance symptom, at least 2 numbing symptom and at least 2 hyperarousal symptoms); 2) full PTSD-Avoidance subtype was defined by meeting criteria for re-experiencing, avoidance and hyperarousal clusters, whereas the full PTSD-Numbing subtype was defined as meeting criteria for the numbing instead of avoidance cluster in the aforementioned configuration; 3) subthreshold PTSD-Avoidance subtype required at least one symptom in the re-experiencing, avoidance, and hyperarousal clusters, and fewer than two symptoms in the numbing cluster; subthreshold PTSD-Numbing subtype required at least one symptom in the re-experiencing, numbing, and hyperarousal clusters, and no symptoms in the avoidance cluster.

In this scoring scheme, only 67% of individuals in the Symptomatic class met full PTSD criteria. This represents a 25% (n=59) decrease in the diagnosable PTSD cases, as compared to the DSM-IV criteria. This rate is identical to the findings from Forbes et al. (2011) in a sample of traumatic injury survivors, who argued that this revision will help refine the PTSD diagnosis mostly by improving specificity and reducing spurious diagnoses of PTSD and depression. For exploratory purposes, we examined the distribution of cases that missed the DSM-V PTSD criteria with respect to their rates of MDD as well as full PTSD subtype. The cases were evenly classified as either full PTSD-Avoidance subtype (54%) or full PTSD-Numbing subtype (46%), with the latter group having slightly higher symptom severity (M=47.15, SD=13.61 vs. M=41.91, SD=9.38), as well as higher rate of MDD (37% vs. 15.6%).

It should be noted that the LCA model did not suggest distinct subtypes among individuals with high level of PTSD symptoms. However, in light of the proposed DSM-V criteria, this distinction was explored to better understand symptom presentation in individuals falling into those categories. Among individuals in the full PTSD-Avoidance subtype (n=165), 46.7% (n=77) did not have any numbing symptoms and 53.3% reported one numbing symptom (n=88), with nearly half reporting diminished interest in activities and another 34% reporting sense of foreshortened future. In the full PTSD-Numbing subtype (n=50), by design, every individual was one symptom short of meeting full PTSD criteria. Forty-six percent of this subtype reported two numbing symptoms (n= 23), 34% reported three, and 20% reported four or five numbing symptoms. Interestingly, only 22% of this subtype did not include diminished interest in activities as one of the symptoms. Overall, individuals in these two subtypes did not differ much in terms of number of symptoms met (M=6.48, SD=1.73 vs. M=7.80, SD= 1.97), while the difference in the symptom severity fell short of the clinically significant difference of 10 points (M=33.96, SD=10.17 vs. M=41.86, SD= 13.09).

Lastly, the hypothesized subthreshold categories (subthreshold PTSD-Avoidance subtype and Numbing subtype) showed a similar distribution of diagnostic criteria to the current subthreshold PTSD definition of Blanchard and colleagues (1996). Overall, a substantial percentage of cases from both the Intermediate-Avoidance and Intermediate-Numbing classes were classified into no PTSD group, regardless of the subthreshold scoring rule used. Closer examination of disagreement cases reveals that the majority of these individuals failed to meet symptom criteria in all clusters (Table 9). These findings suggest that results from LCA should be taken into consideration for future selections of the subthreshold PTSD criteria.

Table 9

Cross-classification of four class LCA solution (modal assignment) and diagnostic model criteria

		DSM-IV			DSM-V-based				DSM-V-based			
Latent Class		Full PTSD n=238	Subthreshold PTSD[a] n=276	No PTSD n=2446	Full PTSD[b] n=179	Full PTSD Subtype Avoidance[c] n=165	Full PTSD Subtype Numbing[d] n=50	No PTSD n=2566	Full PTSD[b] n=179	Subthreshold Avoidance[e] n=229	Subthreshold Numbing[f] n=122	No PTSD n=2430
Symptomatic	n=252	206	36	10[11]	168	37	26	21[12]	168	38	29	17[13]
Intermed.-Avoidance	n=400	18	190	192[21]	6	120	1	273[22]	6	182	40	172[23]
Intermed.-Numbing	n=170	14	50	106[31]	5	8	23	134[32]	5	9	53	103[33]
Non-symptomatic	n=2138	0	0	2138	0	0	0	2138	0	0	0	2138

Note. All classifications are based on the DSM-IV symptoms; Intermed.-Avoidance is Intermediate-Avoidance; Intermed.-Numbing is Intermediate-Numbing.

[a] Based on the subthreshold PTSD definition by Blanchard et al. (1996) (meeting criteria in cluster B and cluster C or D)

[b] **Full PTSD** is defined as meeting criteria for cluster B (at least one re-experiencing symptom), cluster A (at least one avoidance symptom), cluster N (at least two numbing symptoms) and cluster D (at least 2 hyperarousal symptoms)

[c] **Full PTSD - Subtype Avoidance** is defined as meeting criteria for cluster B (at least one re-experiencing symptom), cluster A (at least one avoidance symptom) and cluster D (at least 2 hyperarousal symptoms)

[d] **Full PTSD - Subtype Numbing** is defined as meeting criteria for cluster B (at least one re-experiencing symptom), cluster N (at least two numbing symptoms) and cluster D (at least 2 hyperarousal symptoms)

[e] **Subtreshold PTSD - Subtype Avoidance** is defined as having at least one re-experiencing , at least one avoidance, at least 1 hyperarousal symptoms and fewer than 2 numbing symptoms

[f] **Subtreshold PTSD - Subtype Numbing** is defined as having at least one re-experiencing , at least one numbing and at least 1 hyperarousal symptoms and no avoidance symptoms

% cases not meeting criterion B: [11] 0%, [12] 47.6%, [13]47.6%, [21] 50.5%, [22]35.5%, [23]66.4%, [31] 84.0%, [32] 66.4%, [33] 53.9%
% cases not meeting criterion A: [11] 50%, [12] 14.3%, [13]0%, [21] 30.2%, [22]46.9%, [23]51.7%, [31] 82.1%, [32] 84.3%, [33] 80.6%
% cases not meeting criterion N: [11] 0%, [12]14.3%, [13]0%, [21] 97.4%, [22]96.7%, [23]95.3%, [31] 57.5%, [32] 61.9%, [33] 60.2%
% cases not meeting criterion D: [11] 0%, [12] 42.9% [13]58.8%, [21] 59.9%, [22] 46.2%, [23]56.4%, [31] 45.5%, [32] 40.3%, [33] 86.4%

Predicting PTSD latent classes - covariates in LCA at Round 1

Demographics and psychiatric variables were incorporated into the four class LCA model at Round 1. Demographic variables included age (centered at the mean of 43.59), education level, race/ethnicity, and marital status. Trauma history, past psychiatric history, and current psychiatric diagnoses were also included in the model. Lastly, the extent of the WTC exposure was considered. All variables except age and exposure level were dichotomous variables. The Non-symptomatic class was set as the reference category.

Based on the extensive literature on PTSD and comorbid conditions, it was hypothesized that trauma history, psychiatric variables and greater WTC exposure will be associated with classes with higher probabilities of PTSD symptom endorsements. However, the nature of these relationships was difficult to hypothesize in terms of the differentiating effects of these variables on the Intermediate-Avoidance and Intermediate-Numbing classes, mainly because published findings are limited to reporting some overlap between numbing symptoms and features of depression (e.g., Forbes et al., 2011). The expected effect of demographic variables on class memberships was also unclear.

The class membership estimates changed only slightly when compared with the model without covariates, attesting to the stability of the LCA model. Marital status, trauma history, past psychiatric history, and current psychiatric diagnosis emerged as significant predictors of class membership (Table 10). The direction and magnitude of the psychiatric variables effects were in line with expectations. Results of all pairwise class comparisons are presented in Figure 5.

Specifically, individuals with past psychiatric history and trauma history were significantly more likely to belong to the Symptomatic class as compared to the Non-symptomatic class

(OR=1.75, CI (1.32, 2.31) and OR=1.73, CI (1.37, 2.19) respectively), followed by the Intermediate-Avoidance class (OR=1.53, CI (1.19, 1.96) and OR=1.77, CI (1.46, 2.13). The Intermediate-Avoidance and Intermediate-Numbing classes did not differ significantly with respect to either variable (OR=1.19, CI (0.79, 1.79) and OR=1.37, CI (0.99, 1.89)).

Table 10

Predictors of membership in latent classes (four class LCA)

	Symptomatic Class		Intermediate - Avoidance Class		Intermediate- Numbing Class		Non-symptomatic Class
	OR	CI	OR	CI	OR	CI	
Intercept	0.04	(0.03,0.06)	0.11	(0.08,0.14)	0.10	(0.07,0.14)	ref
Age	1.02	(1.00,1.03)	1.00	(0.99,1.01)	1.01	(0.99,1.02)	ref
Education	1.03	(0.82,1.31)	1.08	(0.89,1.30)	0.88	(0.67,1.16)	ref
Race/Ethnicity	1.07	(0.83,1.38)	0.94	(0.77,1.14)	1.02	(0.77,1.36)	ref
Marital Status	1.11	(0.84,1.46)	1.59*	(1.26,2.00)	0.72	(0.54,1.00)	ref
Trauma History	1.73*	(1.37,2.19)	1.77*	(1.46,2.13)	1.29	(0.98,1.70)	ref
Past Psychiatric Hx	1.75*	(1.32,2.31)	1.53*	(1.19,1.96)	1.28	(0.90,1.83)	ref
Current Psychiatric Dx	17.41*	(13.16,23.04)	2.87*	(2.09,3.92)	6.93*	(4.85,9.90)	ref
Exposure	1.05	(1.01,1.09)	0.98	(0.95,1.01)	0.97	(0.93,1.02)	ref

n=2681, *l* = -11611, beta prior=1, odds ratios (OR) with significant p-values (<.05) are denoted with *
Age was centered at its mean of 43.59; Education (HS or more vs. Less than HS); Race/Ethnicity (White vs. Other); Marital Status (Married/cohabiting vs. Other); Trauma Hx, Past Psychiatric Hx and Current Psychiatric Dx (Yes vs. No), Exposure (Total)

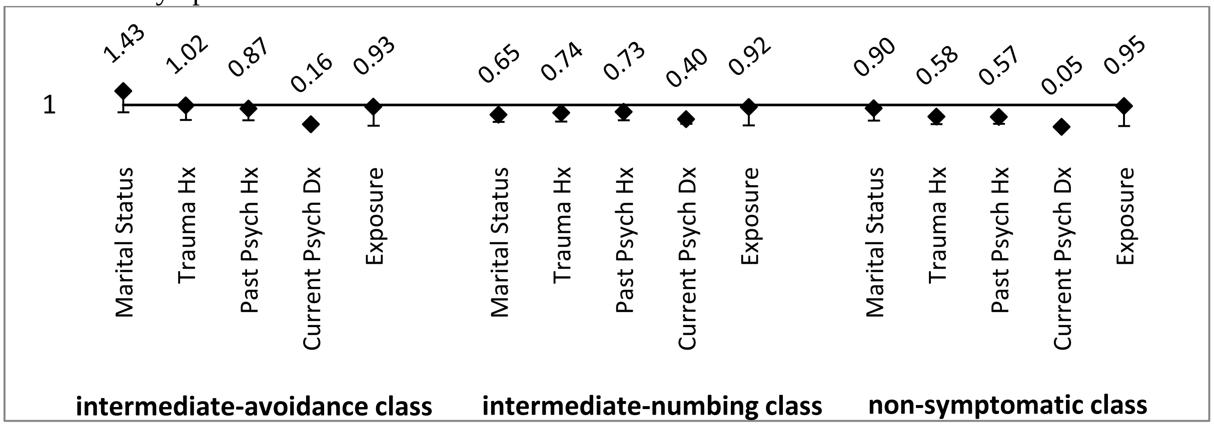
Current psychiatric diagnosis emerged as a significant predictor for all classes. As compared to the Non-symptomatic class, individuals with current psychiatric diagnoses were most likely to belong to the Symptomatic class, followed by the Intermediate-Numbing class and Intermediate-Avoidance class (OR=17.41, CI (13.16, 23.04), OR=6.93, CI (4.85, 9.90) and OR=2.87, CI (2.09, 3.92), respectively). Furthermore, in the presence of any current psychiatric diagnosis, the odds of membership in the Intermediate-Numbing were significantly higher as compared to the Intermediate-Avoidance class (OR=2.42, CI (1.60, 3.65)).

Individuals who were married or cohabiting were almost twice as likely to belong to the Intermediate-Avoidance class as compared to the Intermediate-Numbing class (OR=2.19, CI (1.53, 3.14)). No other demographic characteristics were found to be associated with any class membership. Finally, the extent of WTC exposure did not reach statistical significance.

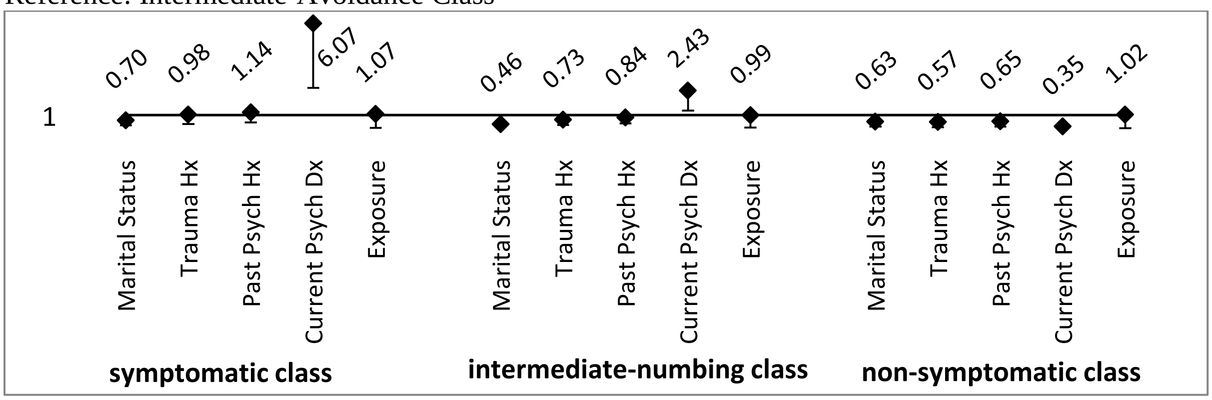
These results further support the conclusion that the four classes that emerged from the LCA model are qualitatively different from each other. Current psychiatric diagnosis was found to be the most differentiating predictor of latent classes. Membership in the Symptomatic class was associated with the highest level of psychiatric comorbidity. This covariate further differentiated between the Intermediate-Avoidance and Intermediate-Numbing classes as well. However, the finding of the difference in marital status distribution between the Intermediate-Avoidance and Intermediate-Numbing classes is interesting.

Figure 5. Latent class model with covariates-odds ratios from four class solution.

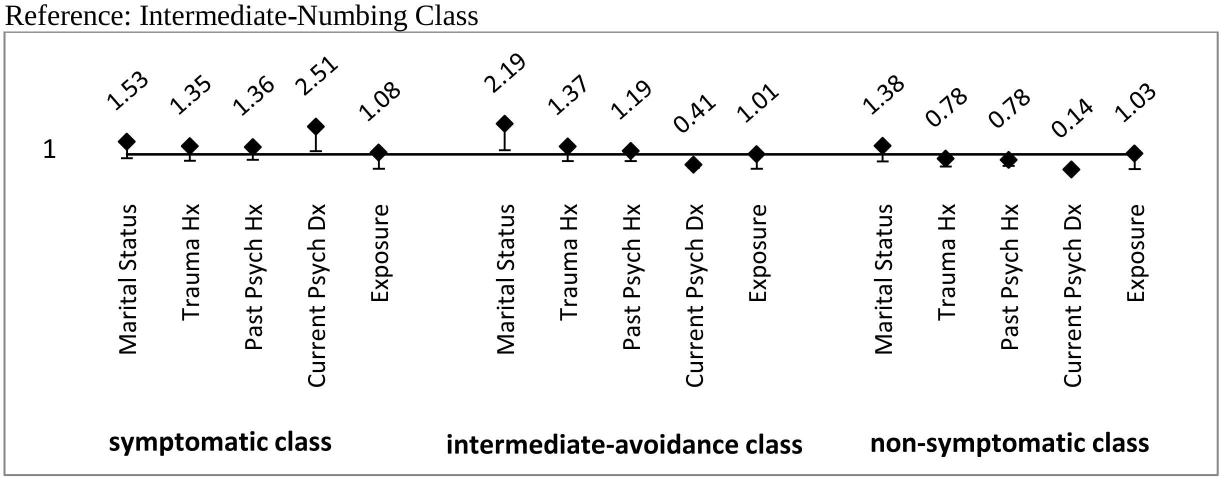
Reference: Symptomatic Class



Reference: Intermediate-Avoidance Class



Reference: Intermediate-Numbing Class



Assessing measurement invariance by race/ethnicity

The four class LCA model was assessed for measurement invariance by race/ethnicity (White-65.7%, Black-17.8%, and Hispanic-12.7%). Measurement invariance was tested sequentially by examining whether the latent model is the same in groups of interest in terms of two model parameters: 1) the item-response probabilities ρ, and 2) the latent class membership probabilities γ. Model 1, with all parameters freely estimated (full measurement noninvariance), was compared to Model 2, with ρ parameters set equal between the groups (measurement invariance in item-response parameters). Subsequently, the equivalence of latent class prevalences across groups was examined by comparing the fit of a model with select restrictions in γ parameters (partial measurement invariance in class prevalences) with a model with no such restrictions (Model 1 or Model 2).

The models were compared in the multiple-group LCA setting using a combination of statistical indicators (BIC and likelihood-ratio difference test G^2) and relative size of the observed differences (Collins & Lanza, 2010).

The G^2 difference test comparing Model 1 and Model 2 was significant ($p<.001$) (Table 11), pointing to unequal item-response probabilities in at least a subset of groups and/or symptoms. In contrast, both information criteria supported the model with measurement invariance (Model 2).

Table 11

Fit statistics for measurement invariance tests by race/ethnicity

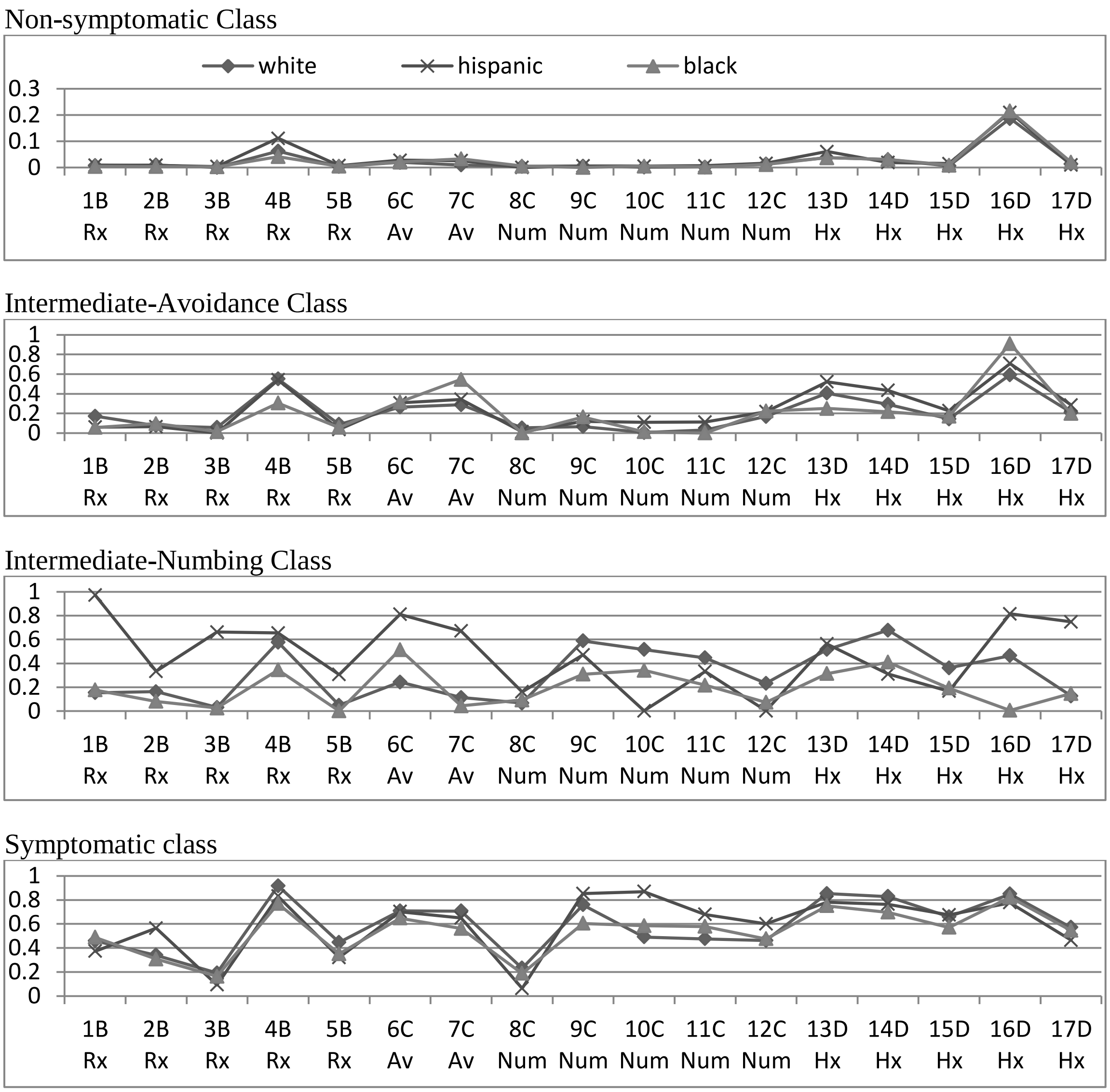
	Race/ethnicity[a]			
	G^2	df	BIC	AIC
Model 1: Measurement noninvariance[1] (ρ)	5719.1	393002	7413	6145
Model 2: Measurement invariance[2] (ρ)	5910.7	393138	6523	6064
Model 3: Measurement noninvariance (ρ) and partial measurement invariance[3] (γ)	5720.8	393007	7375	6136
	Model 1 vs. Model 2: G^2_{Δ} =232.7, df= 136, p<.001			
	Model 1 vs. Model 3: G^2_{Δ} =1.7, df= 5, p=.889			

[a] race/ethnicity: White - 65.7%, Black-17.8% and Hispanic -12.7%
[1] Model 1: both item-response probabilities and class prevalences were freely estimated
[2] Model 2: item-response probabilities were set equal between groups, class prevalences were freely estimated
[3] Model 2: item-response probabilities were freely estimated, select class prevalences were restricted

The size of differences in the item-response probabilities were useful indicators of race/ethnicity group dissimilarities. Whereas they were relatively small in the Symptomatic, Intermediate-Avoidance, and Non-symptomatic classes, they were the largest and most prevalent in the Intermediate-Numbing class (Figure 7). Specifically, individuals who identified themselves as Hispanic were more likely to endorse any of the re-experiencing, avoidance and two hyperarousal symptoms (hypervigilance and exaggerated startle response), as compared to both Whites and Blacks. The pattern of endorsing numbing symptoms differentiated them further in that they were extremely unlikely to endorse symptoms of detachment or estrangement, and sense of foreshortened future. This trend was reversed when comparisons were made in the Symptomatic as well as the Intermediate-Avoidance classes. Lastly, examination of the differences between Whites and Blacks suggested that the latter group reported somewhat lower symptom endorsement for the majority symptoms.

Overall, the shape of the symptom profiles suggested that while the meaning of the classes remained the same for all race/ethnic groups, the magnitude of the group differences in item-response probabilities did not support full measurement invariance across these groups.

Figure 6. Symptom profiles by race/ethnicity.

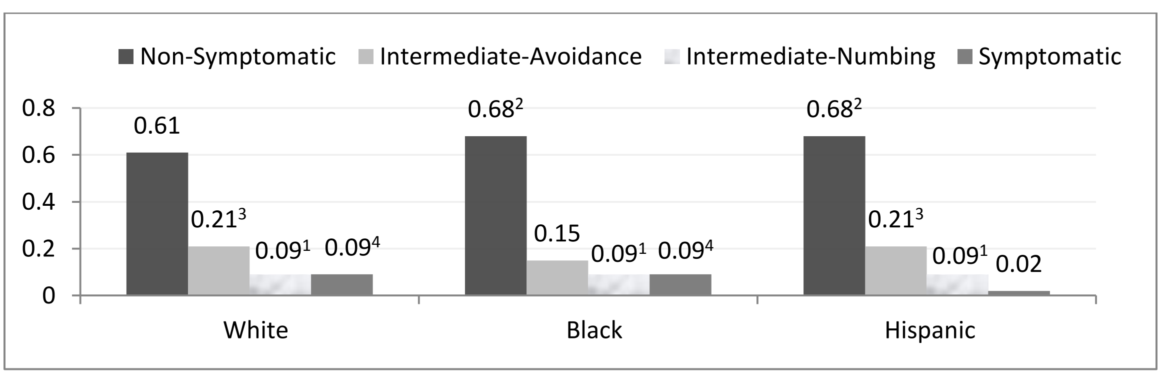


Legend:
1B Rx: intrusive recollections, **2B Rx**: distressing dreams, **3B Rx:** acting or feeling as if event were recurring, **4B Rx:** psychological distress at exposure to cues, **5B Rx:** physiological reactivity on exposure to cues, **6C Av**: avoidance of thoughts and feelings, **7C Av**: avoidance of activities, places, or people, **8C Num**: inability to recall important aspects of trauma, **9C Num**: diminished interest in activities, **10C Num**: detachment or estrangement, **11C Num**: restricted range of affect, **12C Num**: sense of a foreshortened future, **13D Hx**: difficulty falling or staying asleep, **14D Hx**: irritability and outbursts of anger, **15D Hx**: difficulty concentrating, **16D Hx**: hypervigilance, **17D Hx**: exaggerated startle response

The examination of class prevalences from Model 1 revealed relatively small between-groups differences. In an effort to simplify the model the following equality restrictions were used: 1) all group prevalences were set equal in the Intermediate-Numbing class; 2) prevalences for Black and Hispanic groups were set equal in the Non-symptomatic class; 3) prevalences for White and Hispanic groups were set equal in the Intermediate-Avoidance class; and 4) prevalences for White and Black groups were set equal in the Symptomatic class. The resultant model (Model 3) was more parsimonious and fit the data equally well (G^2_{Δ} =1.7, df= 5, p=.889, BIC=7375).

All race/ethnic groups were most likely to belong to the Non-symptomatic class, followed by the Intermediate-Avoidance class (Figure 8). The group differences were manifested in lower probabilities of membership in the Non-symptomatic class for Whites and in the Intermediate-Avoidance class for Blacks. About 10 % of individuals from all three groups were in the Intermediate-Numbing and Symptomatic classes, with the exception that only 2% of Hispanics were members of the Symptomatic class. This last result is surprising, as it has been reported that the rates of PTSD among Hispanics are generally higher as compared to other race/ethnic groups (Hinton et al., 2011).

Figure 7. Class prevalences by race/ethnicity.



Note: Classes with same number indicators were set equal (γ parameters).

Latent Transition Analysis

The examination of symptom endorsement over time showed a general decrease in the proportion of individuals reporting clinical level of PTSD symptoms (Table 12). This trend was expected as posttraumatic stress symptoms tend to diminish as the time from the traumatic event increases (Norris et al., 2009). It is of note however that that majority of symptoms across all clusters appear to have similar levels at both Round 2 and Round 3. The largest decease was reported for experiencing psychological distress at exposure to cues (about 40% decrease at Round 2 and Round 3), as well as hypervigilance (decrease of 34% at Round 2 and 44% at Round 3) and exaggerated startle response (decrease of 24% at Round 2 and 44% at Round 3). However, two of the numbing symptoms (feeling of detachment or estrangement and restricted range of affect) and one hyperarousal symptom (difficulty falling or staying asleep) were reported as frequently in Round 1 as in Round 3.

These marginal proportions coincide with cross-sectional estimates of PTSD rates (based on DSM-IV) at each Round (8% at Round 1, 5.5% at Round 2 and 5.4% at Round 3). As noted earlier, only 52.9% of the original sample underwent clinical assessments at Round 3. Even though the composition of the sample in terms of individuals at risk for PTSD (at risk, not at risk control, and not at risk) was similar at each round, the Round 3 sample had a somewhat greater percentage of individuals in the former two groups and lower percentage of individuals in the latter group. Thus, caution should be used when interpreting the estimates based on the observed data from Round 3.

Table 12

Symptom descriptions and endorsement frequency over time

Symptom code		Symptom description	Round 1 n=2960	Round 2 n= 2613	Round 3 n=1553
CLUSTER B: Re-experiencing symptoms			% Yes	% Yes	% Yes
1B	Rx	intrusive recollections	8.1	7	6.2
2B	Rx	distressing dreams	5.8	4.2	4.5
3B	Rx	acting or feeling as if event were recurring	2.8	1.9	1.4
4B	Rx	psychological distress at exposure to cues	24.3	15.2	14.7
5B	Rx	physiological reactivity on exposure to cues	5.5	4	4.6
CLUSTER C: Avoidance and numbing symptoms					
6C	Av	avoidance of thoughts and feelings	14.6	9.1	9.8
7C	Av	avoidance of activities, places, or people	13.8	8.8	9.1
8C	Num	inability to recall important aspects of trauma	3.1	2.5	1.8
9C	Num	diminished interest in activities	11.2	8.8	9.8
10C	Num	detachment or estrangement	7.9	6.8	8
11C	Num	restricted range of affect	7.5	5.9	8.1
12C	Num	sense of a foreshortened future	9.5	5.7	6.3
CLUSTER D Hyperarousal symptoms					
13D	Hx	difficulty falling or staying asleep	19.8	17.6	20.9
14D	Hx	irritability and outbursts of anger	17.6	12	14.1
15D	Hx	difficulty concentrating	10.9	7.1	7.9
16D	Hx	hypervigilance	34.2	22.5	19.3
17D	Hx	exaggerated startle response	10.8	8.2	6

Note. Marginal proportions from Round 1 are repeated here to facilitate comparisons.

Measurement models at Round 2 and Round 3

At both Round 2 and Round 3, a set of possible latent class models was fitted to the data to examine the class structure using estimated item-response probabilities and class prevalences. This exploratory stage is considered to be a preliminary step aiming to inform model selection for the latent transition analysis (Nyland, 2007).

At both rounds, the four class model had the best fit, as measured by the BIC index (Table 13). This result made the study of transition probabilities more straightforward, as the interpretation of model parameters in latent transition analysis is much easier when the measurement models at each time point are equivalent (Collins & Lanza, 2010). The LRT and BLRT tests were not informative in the model selection process as their p-values did not discriminate between competing models.

Table 13

Measurement model selection at Round 2 and Round 3

	# of classes	Log-likelihood	BIC	AIC	LRT p-value	BLRT p-value	Entropy
Round 2	2	-9357	4504	4298	.000	.000	.95
n=2532	3	-8969	3869	3558	.000	.000	.89
	4	-8865	**3803**	3386	.000	.000	.84
	5	-8807	3830	**3307**	.000	.000	.83
Round 3	2	-5852	3162	2975	.000	.000	.93
n=1539	3	-5654	2898	2615	.000	.000	.88
	4	-5573	**2869**	2489	.000	.000	.89
	5	-5535	2925	**2448**	.000	.000	.87

The interpretations of the classes, based on the patterns in item-response probabilities, were in line with the Round 1 solution (Figure 9). At each time point, the four classes were clearly distinct: the Symptomatic class was characterized by the highest probabilities of endorsing the majority of symptoms (generally greater than 0.5); the

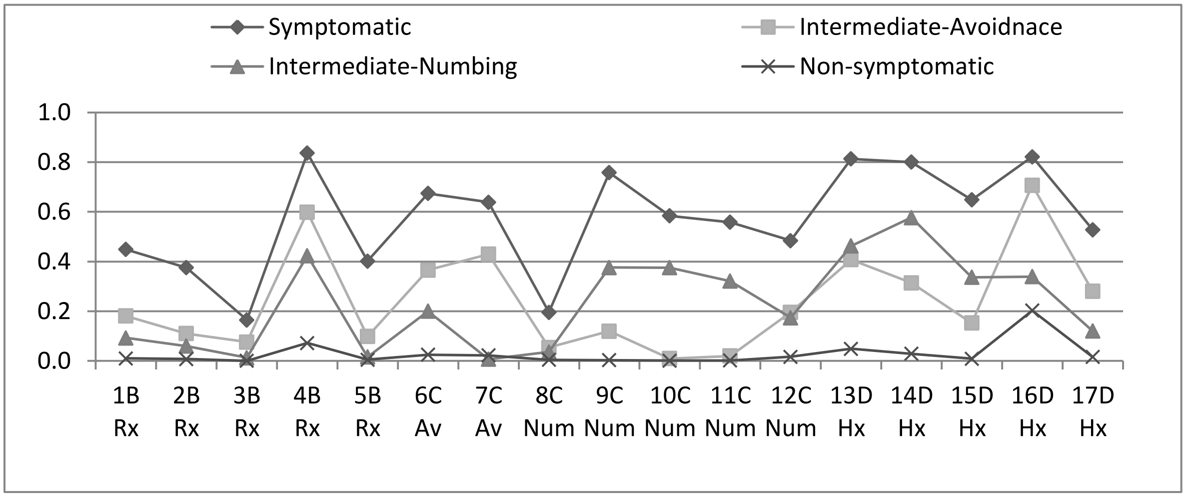
Non-symptomatic class had these probabilities close to zero for almost all symptoms (generally less than 0.05); and the Intermediate-Avoidance and Intermediate-Numbing classes were differentiated mainly by probabilities of endorsing the avoidance and numbing symptoms, respectively.

Moreover, the latter two classes had item-response probabilities in a lower range, as compared to the Symptomatic class (generally less than 0.5). This pattern was consistent over time. However, the shapes of the profiles for the Intermediate-Avoidance and Intermediate-Numbing classes at Round 2 suggest a slight departure from Round 1 and Round 3 profiles, as the classes had comparable probabilities for endorsing both avoidance symptoms and one re-experiencing symptom (psychological distress at exposure to cues). In addition, at Round 3, the item-response probabilities for two of the hyperarousal symptoms (hypervigilance and exaggerated startle response) were lower as compared to the previous rounds. These cross-sectional results suggest that measurement invariance over time should be considered with care.

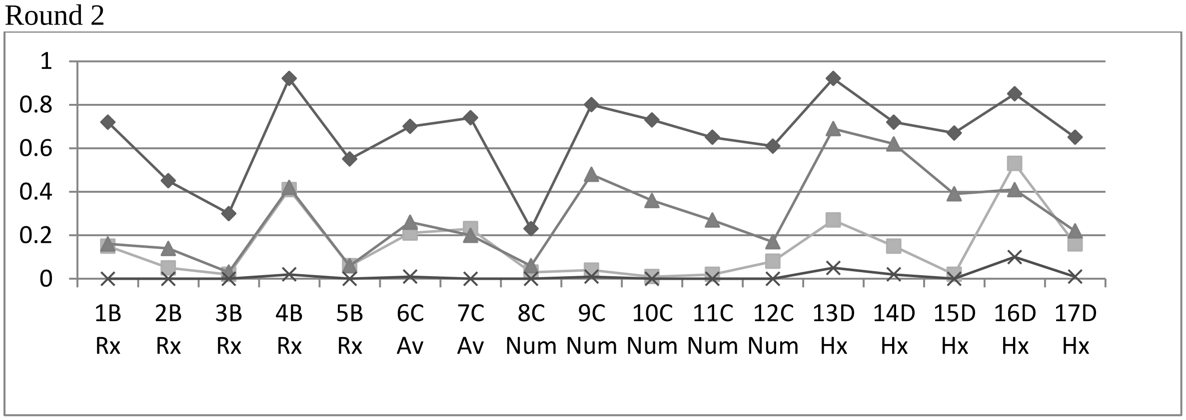
The emergent classes were also validated using the LCA with covariates approach used in the analysis of Round 1. The odds ratios obtained at Round 2 and Round 3 coincide with those obtained in Round 1, yielding further support for the 4 class measurement models over time.

Figure 8. Item profile plots at Rounds 1, 2 and 3.

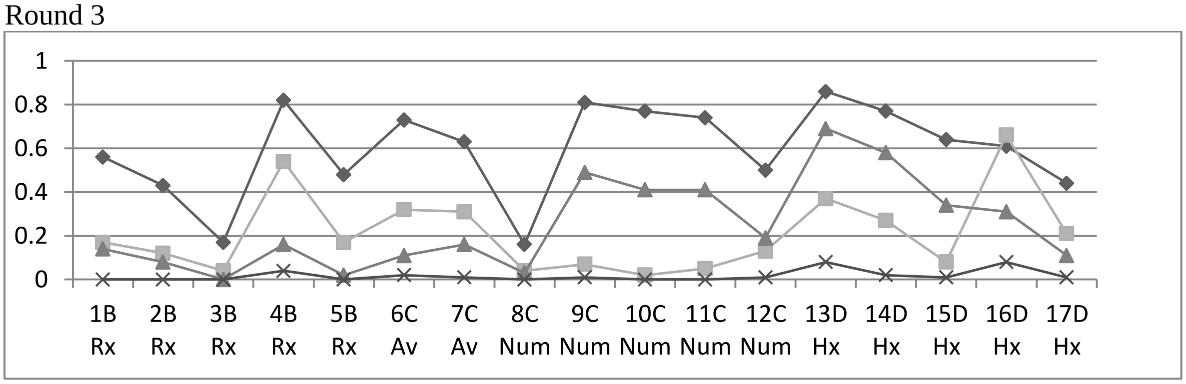
Round 1



Round 2



Round 3



Legend:
1B Rx: intrusive recollections, **2B Rx**: distressing dreams, **3B Rx:** acting or feeling as if event were recurring, **4B Rx:** psychological distress at exposure to cues, **5B Rx:** physiological reactivity on exposure to cues, **6C Av**: avoidance of thoughts and feelings, **7C Av**: avoidance of activities, places, or people, **8C Num**: inability to recall important aspects of trauma, **9C Num**: diminished interest in activities, **10C Num**: detachment or estrangement, **11C Num**: restricted range of affect, **12C Num**: sense of a foreshortened future, **13D Hx**: difficulty falling or staying asleep, **14D Hx**: irritability and outbursts of anger, **15D Hx**: difficulty concentrating, **16D Hx**: hypervigilance, **17D Hx**: exaggerated startle response.

Finally, the relative ordering of the class sizes over time remained unchanged (Table 14). The size of the Symptomatic class decreased from 8.9% at Round 1 to about 4.9% at Round 2 and 5.4% at Round 3. The Intermediate-Avoidance class also decreased in relative size while the Non-symptomatic class size, as expected, increased over time. There was, however, a slight increase in the Intermediate-Numbing group's relative size. At Rounds 2 and 3, the Numbing class was larger than the Symptomatic class (7.4% vs. 4.9% at Round 2 and 8.8% vs. 5.4 at Round 3).

Table 14

Cross-sectional class prevalences over time

Round	n	Symptomatic class	Intermediate-Avoidance class	Intermediate-Numbing class	Non-symptomatic class
1	2960	8.9	15.1	6.9	69.4
2	2532	4.9	14.8	7.4	71.9
3	1539	5.4	11.4	8.8	74.4

Latent transition model

Table 15 summarizes results of latent transition model with four classes at each round and measurement invariance over time (ρ parameters over time). The transition probabilities estimated in the model (τ parameters) offer insight into the stability of PTSD over time.

The trends observed at the diagonals of the transition matrix suggest that the Non-symptomatic class was the most stable class over time, since the probability of staying in this class were the highest ($\tau = 0.92$ and $\tau = 0.91$ at Round 2 and Round 3 transition points, respectively). Among classes with elevated probabilities of endorsing symptoms, individuals in the Symptomatic class had the highest probability of remaining in the same class ($\tau = 0.51$ at both Round 1 and Round 2), followed by the Intermediate-Avoidance class ($\tau = 0.42$ and $\tau = 0.53$, respectively) and Intermediate-Numbing class ($\tau = 0.20$ and $\tau = 0.43$, respectively). Notably, the probabilities of staying in the same class were larger at Round 3 than at Round 2 for the Intermediate-Avoidance and Intermediate-Numbing classes.

When examining the transition probabilities on the off diagonals describing movements between classes, several conclusions emerge. First, for the individuals in the Symptomatic class, the most likely path was transitioning to the Intermediate-Avoidance class ($\tau = 0.30$ and $\tau = 0.32$ at Round 2 and Round 3, respectively), followed by transitioning to the Intermediate-Numbing class ($\tau = 0.11$ and $\tau = 0.08$, respectively).

There were, however, different types of likely transitions for the Intermediate-Avoidance and Intermediate-Numbing classes. Individuals in the former class were most likely to transition to the Non-symptomatic class ($\tau = 0.51$ and $\tau = 0.32$ at Round 2 and Round 3), and very unlikely to transition to either the Symptomatic or the Intermediate-Numbing class at both rounds (τs < 0.10 at both rounds). In contrast, the transition path for the Intermediate-Numbing class was most likely to the Intermediate-Avoidance class (0.39 and 0.38 at Round 2 and Round 3). In addition, at each transition point, 12% of individuals in the Intermediate-Numbing class transitioned to a class with a higher PTSD severity (Symptomatic class).

Also of note are changes in the latent class prevalences estimated in the latent transition model, as compared with the cross-sectional estimates (γ parameters). Whereas the relative ordering of the class sizes remained the same, the prevalence estimates for the

Intermediate-Avoidance class were higher in the transition model over time (26% vs. 15.1% at Round 1, 20% vs. 14.8% at Round 2, and 20% vs. 11.4% at Round 3). In contrast, for the Symptomatic and the Intermediate-Numbing classes, the prevalences were higher in the cross-sectional models, with the exception of the latter group at Round 1 (6.9% vs. 10%).

Table 15

LTA model over time

	Latent Status			
	Symptomatic	Intermediate-Avoidance	Intermediate-Numbing	Non-symptomatic
Latent Status prevalences				
Round 1	0.07	0.26	0.10	0.56
Round 2	0.06	0.20	0.04	0.69
Round 3	0.05	0.20	0.04	0.71
Probability of transitioning to….	Round 2 latent status			
Conditioned on Round 1				
Symptomatic	**.51**	.30	.11	.08
Intermediate-Avoidance	.03	**.42**	.03	.51
Intermediate-Numbing	.12	.39	**.20**	.29
Non-symptomatic	.00	.05	.01	**.93**
Probability of transitioning to…	Round 3 latent status			
Conditioned on Round 2				
Symptomatic	**.51**	.32	.08	.09
Intermediate-Avoidance	.07	**.53**	.08	.32
Intermediate-Numbing	.12	.38	**.43**	.06
Non-symptomatic	.00	.08	.00	**.91**

Assessing measurement invariance over time

In the previous section, the transition model with equality restrictions on all item-response probabilities over time was used (full measurement invariance in ρ). This assumption was subsequently tested by comparatively assessing the fit of several partial invariance models. As a large number of such models exist, candidate model selection relied on the visual inspection of the item-response probabilities from the LCA measurement models at each round (Figure 9).

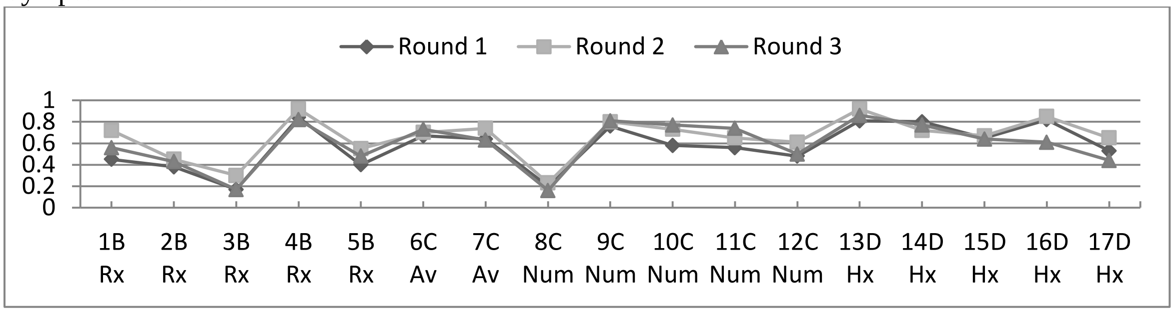
The examination of changes in the item-response probabilities between rounds suggested that while the majority of the ρ parameters were quite stable over time in all classes, some symptoms exhibited potentially differential item functioning over time. The largest differences were observed in the avoidance and hyperarousal cluster as well as in the re-experiencing symptom of psychological distress at exposure to cues.

Three partial invariance models were compared against the full measurement invariance model. The equality restriction was relaxed for the following item-response probabilities: 1) two avoidance symptoms (6C Av and 7C AV); 2) two avoidance (6C Av and 7C AV) and two hyperarousal symptoms (16D Hx and 17D Hx) symptoms; and 3) two avoidance (6C Av and 7C AV), two hyperarousal (16D Hx and 17D Hx), and one re-experiencing symptom (4B Rx). In lieu of G^2 statistic, BIC index was used for model fit comparison.

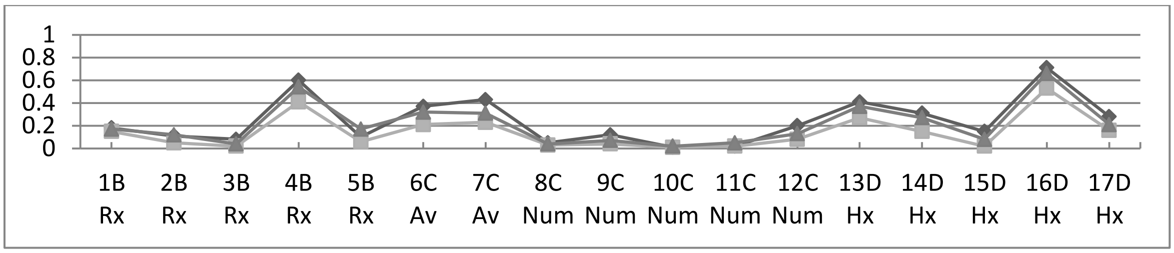
The BIC criteria supported full measurement invariance over time in all comparisons, thus facilitating the LTA model interpretation. In fact, relaxing the select item-response probabilities resulted in only minimal differences between ρ parameters estimates from full measurement model and all partial measurements model.

Figure 9. Item profile plots over time by latent class.

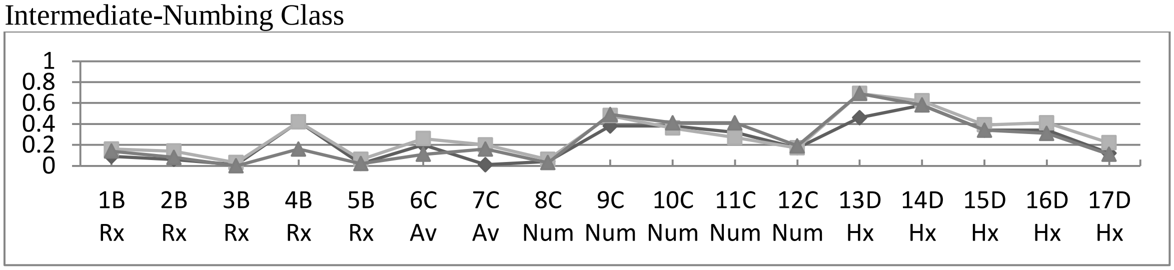
Symptomatic Class



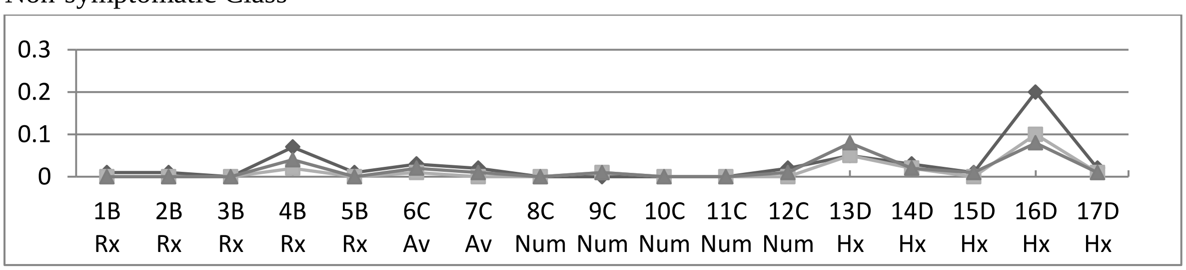
Intermediate-Avoidance Class



Intermediate-Numbing Class



Non-symptomatic Class



Legend:

1B Rx: intrusive recollections, **2B Rx**: distressing dreams, **3B Rx:** acting or feeling as if event were recurring, **4B Rx:** psychological distress at exposure to cues, **5B Rx:** physiological reactivity on exposure to cues, **6C Av**: avoidance of thoughts and feelings, **7C Av**: avoidance of activities, places, or people, **8C Num**: inability to recall important aspects of trauma, **9C Num**: diminished interest in activities, **10C Num**: detachment or estrangement, **11C Num**: restricted range of affect, **12C Num**: sense of a foreshortened future, **13D Hx**: difficulty falling or staying asleep, **14D Hx**: irritability and outbursts of anger, **15D Hx**: difficulty concentrating, **16D Hx**: hypervigilance, **17D Hx**: exaggerated startle response.

Latent transition model by race/ethnicity

Results of the multiple-group LTA with race/ethnicity as a grouping variable are presented in Table 16. In this model the measurement invariance over time was assumed, but, in accordance with the findings from the cross-sectional LCA, the item-response probabilities were allowed to vary by group.

Overall, the group transition matrices were in line with those estimated in the entire sample. A number of racial/ethnic differences emerged. At Round 2, the probability of staying in the Symptomatic class for Whites was $\tau = .43$, with the most likely transition out being into the Intermediate-Numbing Class ($\tau = 0.41$). In contrast, while the probabilities of staying in the Symptomatic class were higher for Blacks and Hispanics ($\tau = .59$ and $\tau = .49$, respectively), the most likely transition out was into the Intermediate-Avoidance class ($\tau = 0.31$ and $\tau = 0.27$, respectively). Notably, 20% of Hispanics transitioned directly into the Non-symptomatic class ($\tau = 0.20$). On the other hand, the Intermediate-Avoidance class was less stable among Blacks and Hispanics, as compared to Whites ($\tau = 0.27$, $\tau = 0.36$ and $\tau = 0.49$, respectively), with approximately 60% of Non-symptomatic class transitions in the former two groups, compared to only 45% among Whites.

The Intermediate-Numbing class was the least stable for all three racial/ethnic groups, particularly among Hispanics ($\tau = 0.00$; White: $\tau = 0.28$, Black: $\tau = 0.35$). Transition patterns out of this class showed different paths for Hispanics and Blacks (Intermediate-Avoidance class ($\tau = 0.66$)) vs. the Non-symptomatic group ($\tau = 0.51$)), while these probabilities were more evenly split for Whites ($\tau = 0.35$ for Intermediate-Avoidance, and $\tau = 0.25$ for Intermediate-Numbing).

Although similar trends were observed at Round 3, the overall stability of classes was greater among Whites and Blacks (range .50-67) as compared to Hispanics (range .26-.43), and the probabilities of transitioning into the Non-symptomatic class diminished for all race/ethnic groups. Lastly, a greater percentage of individuals transitioned into the Intermediate-Numbing class, particularly out of the Intermediate-Avoidance and Symptomatic classes.

Table 16

Transition probabilities over time by race/ethnicity

Transition Probabilities										
White		Round 2						Round 3		
	Round 1	Ns	Av	Nu	Sx	Round2	Ns	Av	Nu	Sx
	Ns	**0.94**	0.05	0.01	0.00	Ns	**0.91**	0.07	0.01	0.00
	Av	0.45	**0.49**	0.06	0.01	Av	0.32	**0.53**	0.13	0.01
	Nu	0.25	0.35	**0.28**	0.13	Nu	0.05	0.37	**0.56**	0.03
	Sx	0.05	0.12	0.41	**0.43**	Sx	0.00	0.20	0.25	**0.55**
Black		Round 2						Round 3		
	Round 1	Ns	Av	Nu	Sx	Round2	Ns	Av	Nu	Sx
	Ns	**0.93**	0.05	0.02	0.00	Ns	**0.90**	0.03	0.07	0.00
	Av	0.62	**0.27**	0.10	0.01	Av	0.23	**0.67**	0.00	0.10
	Nu	0.51	0.04	**0.35**	0.09	Nu	0.42	0.00	**0.58**	0.00
	Sx	0.05	0.31	0.06	**0.59**	Sx	0.22	0.13	0.16	**0.50**
Hispanic		Round 2						Round 3		
	Round 1	Ns	Av	Nu	Sx	Round2	Ns	Av	Nu	Sx
	Ns	**0.91**	0.08	0.00	0.01	Ns	**0.93**	0.07	0.00	0.00
	Av	0.57	**0.36**	0.07	0.00	Av	0.45	**0.34**	0.18	0.02
	Nu	0.14	0.66	**0.00**	0.20	Nu	0.00	0.74	**0.26**	0.00
	Sx	0.20	0.27	0.04	**0.49**	Sx	0.27	0.21	0.10	**0.43**

Note: Ns-Non-symptomatic class; Av-Intermediate-Avoidance class; Nu-Intermediate- Numbing class; Sx-Symptomatic class

Predicting transition probabilities-covariates in LTA model

A time-varying covariate, concurrent comorbid Major Depressive Disorder (MDD) was incorporated into the model LTA model to predict transitions between PTSD classes over time. The effect of MDD on transitioning out of a class relative to staying in the same class was assessed.

In order to avoid estimation issues in this complex model, the magnitude of transitions in the LTA without covariates were assessed for parameters restrictions. As it has been shown the Non-symptomatic class was the most stable class over time and the probabilities of transitioning out of the Non-symptomatic class were small and not of directly of interest, they were constrained to the value of zero. In consequence, the effect of the covariate on these transitions was not estimated.

During the estimation process the logit model did not converged. This problem is not unlikely in LTA with covariates due to likely sparseness in the data (Dziak et al., 2011). It is recommended to utilize a stabilizing prior distribution on the β parameters, with its strength specified by the user. In the attempt to solve the problem, beta prior of twelve was used, as the LTA model had four classes at each of the three time points. This attempt appeared to significantly stabilize the model.

Table 17 summarizes results of the LTA model with MDD as time-varying covariate. Overall, the direction of the effect was as expected. At Round 2, among individuals in each class, those who had comorbid MDD diagnosis were more likely to transition to the Intermediate-Numbing or Symptomatic class relative to remaining in the same class compared to those without MDD diagnosis. They were also less likely to transition to

Non-symptomatic class. However, at Round 3 the increased odds were observed for the Intermediate-Numbing and Symptomatic class only.

Table 17

Predictors of transitions between latent statuses (LTA model)

Odds ratios associated with transitions relative to staying in the same class									
	Round 2					Round 3			
Round 1					Round 2				
MDD	Ns	Av	Num	Sx	MDD	Ns	Av	Num	Sx
Ns	*	*	*	*	Ns	*	*	*	*
Av	0.62	-	1.36	2.20	Av	0.46	-	0.54	0.71
Num	0.82	0.68	-	1.78	Nu	0.76	0.81	-	6.70
Sx	0.75	0.49	0.28	-	Sx	0.32	0.60	1.40	-

Note: MDD-Major Depressive disorder; * logistic regression not conducted for this row; - denotes reference category.

DISCUSSION

The purpose of this dissertation was to assess the utility and feasibility of two types of mixture models, LCA and LTA, to inform disaster research. In particular, these models were used to explore the nature and course of posttraumatic stress disorder (PTSD) resulting from the WTC disaster using a large longitudinal screening database. The utility of the methodology was considered in the context of its unique contributions to PTSD literature, with a focus on the disorder's structure, course, and the evaluation of PTSD diagnostic criteria. The feasibility was assessed with respect to potential issues generally associated with complex longitudinal methodology (e.g., model identification, model selection, and viability of subgroup analyses). Challenges encountered in this study are discussed; modeling decisions are described; and future directions are proposed.

Unique contributions to PTSD literature

PTSD is a significant public health issue following mass disasters, such as terrorist attacks. In particular, the disorder affects disaster workers at higher rates, yet the psychiatric consequences of disaster work are not well understood (Norris, 2006). The refractory nature of posttraumatic symptoms underscores the need for innovative research that can shed light on their etiology, risk factors, and longitudinal course. Furthermore, periodic reviews of psychiatric disorders' diagnostic criteria are necessary to ensure their improved validity, particularly through a greater utilization of modern statistical methodology, such as mixture models.

Analyses of PTSD data in the current study were largely guided by interest in uncovering unique information about the stability of posttraumatic symptoms in WTC non-rescue disaster workers, particularly with respect to their initial presentation and change patterns between annual psychological assessments. Equally important to the choice of methodology were the unique features of the PTSD dataset available for this dissertation from the Weill Cornell WTC Screening Program (Difede et al., 2006), which was characterized by highly skewed distribution of the response variable (posttraumatic stress symptomatology).

The imminent release of the revised Diagnostic and Statistical Manual for Mental Disorders (DSM-V) provided an opportunity to evaluate the existing and proposed PTSD diagnostic criteria, shedding light on potential issues and public health implications related to the proposed changes, as well as future directions for research related to the selection of diagnostic criteria for psychiatric disorders.

Latent structure of PTSD in WTC disaster workers

LCA methodology successfully captured the heterogeneity of posttraumatic stress symptoms in this population. While the overall prevalence of PTSD was low (full PTSD: 8%-5.4% and subthreshold PTSD: 9.3%-5.8% over time), and symptom endorsement rates were between 2.8% and 34.2%, the model revealed four classes with quantitatively and qualitatively distinct symptom profiles: Symptomatic (8.9%), Intermediate-Avoidance (15.1%), Intermediate-Numbing (6.9%), and Non-symptomatic classes (69.5%). These findings offer a unique insight into shared symptom profiles among WTC non-rescue disaster workers that would otherwise have been unknown. The LCA approach used in this analysis supplemented findings from a PTSD factor analytic study in this population (Palmieri et al., 2007) by providing information about typology of symptom profiles and their predictors.

These findings may have a number of ramifications for how PTSD is conceptualized and assessed. First, the LCA results shown great potential to inform criteria selection for diagnostic manuals, particularly when clinically defined symptoms are used as class indicators (Muthén & Muthén, 2000). In the current study, we found evidence of the existence of a group with severe posttraumatic stress symptoms, but not for full PTSD subtypes. In addition, the model suggested that the existing diagnostic criteria for PTSD, requiring symptoms in all three symptom clusters (i.e., re-experiencing, avoidance/ numbing, and hyperarousal symptoms), may be too restrictive, as only 82% of individuals nominated by the model met DSM-IV PTSD criteria. The proposed DSM-V criteria (i.e., endorsing symptoms in four proposed clusters: re-experiencing, avoidance, numbing, and hyperarousal) are even more restrictive, resulting in a 25% decrease in diagnosable PTSD cases, as compared to the DSM-IV. Thus, the proposed changes may potentially limit access to care for a significant percentage of individuals with elevated PTSD symptomatology. Furthermore, the model discriminated between two subtypes at the intermediate symptom level: Intermediate-Avoidance and Intermediate-Numbing classes. In the wake of the criteria change in the DSM-V, these findings may provide useful information when operationalizing optimal criteria for the revised full and subthreshold PTSD.

Stability of PTSD symptoms in WTC disaster workers

Uncovering the stability of classes with distinct symptom profiles and their remission paths, defined in the sense of categorical change patterns, has important implications for theoretical models of response to disasters as well as post-disaster interventions and treatment of PTSD (Norris et al., 2009, Asmundsen et al., 2004). Information relevant to both aspects of longitudinal PTSD research can be captured via transition probabilities estimated in a LTA model. By utilizing a complex LTA model with three time points, we were able to attest to the constancy of classes with distinct symptom profiles in WTC non-rescue disaster workers over the three year span, while providing information about rates and directions of between-class transitions.

In concordance with hypothesized patterns of response to mass disasters (Norris et al., 2009), LTA parameter estimates provided evidence of great resistance and resilience to posttraumatic stress in this population. In addition, the model identified high rates of chronic dysfunction for all subgroups with elevated posttraumatic stress symptoms as well as the detrimental effect of concurrent co-morbid MDD on lack of remission at any time point.

Finally, transition probabilities were able to explicitly delineate prognostic differences between classes with distinct symptom profiles. Individuals in the Symptomatic and the Intermediate-Numbing class were most likely to transition into the Intermediate-Avoidance class at both time points (Round 2: $\tau = .30$ and $\tau = .32$, respectively; Round 3: $\tau = .39$ and $\tau = .38$, respectively), whereas those in the Intermediate-Avoidance class most often transitioned into the Non-symptomatic class (Round 2: $\tau = .51$ and Round 3: $\tau = .32$). These results provided further evidence of the importance of studying the mechanisms underlying posttraumatic stress symptom maintenance and remission, including the use of compensatory strategies to cope with distress and treatment response at the symptom clusters level (Malta et al., 2009, Taylor et al., 2003).

Measurement invariance by race/ethnicity

Multiple-group LCA and LTA methodologies yielded several findings related to the racial/ethnic differences in posttraumatic stress symptomatology in WTC non-rescue disaster workers. While differences were expected, their nature was assessed in the context of symptom configuration, rather than overall disorder prevalence or marginal symptom endorsement. Overall, the meaning of the classes remained the same for all racial/ethnic groups. However, some differences were observed in probabilities of endorsing individual symptoms (ρ parameters), and most notably in class prevalences (γ parameters) and the stability as well as trends of transitions across time (τ parameters). Specifically, a smaller percentage of Hispanics were in the Symptomatic class at Round 1(2% vs. 9% for Whites and Blacks). Over time, the paths of transitioning out of the Symptomatic class were different for Whites, as compared to Blacks and Hispanics, where the former group more often transitioned into the Intermediate-Numbing class (Round 2: τ=.41, Round 3: τ=.25), and the latter groups into the Intermediate-Avoidance class (Round 2: τ=.41 and τ=.27, respectively), and the Non-Symptomatic class (Round 3: τ=.22 and τ=.27, respectively). These findings offered insight into the location of the racial/ethnic differences not typically investigated.

Feasibility

The potential of latent class methodologies, such as LCA and LTA, to model psychiatric outcomes in disaster research may be impeded by the complexities of these models, and issues related to model identification, model selection, and statistical power, among others (Lanza & Bray, 2008, Collins and Lanza, 2010). This can be especially true for models of disorders characterized by a large number of essential features, low prevalence of symptoms, and multiple longitudinal assessments. All of these features were present in the longitudinal screening data used in this dissertation.

The feasibility of utilizing LCA with a large number of indicators has been demonstrated in the past (e.g., Breslau et al., 2005). However, most studies using LTA were either limited to two time points or utilized few indicators. This study assessed the feasibility of incorporating 17 indicators and three time points, thus testing the viability of this approach for the analysis of complex datasets in disaster and psychiatric research.

Model identification

Complex models require estimation of a large number of parameters via the maximum likelihood (ML) estimation procedure, which is easier when data contains a large amount of information. In general, the more parameters that must be estimated, the greater chance that identification issues will be encountered.

A common technique used to reduce complexity in LCA and LTA models is to impose a variety of parameter restrictions. In addition to these practical purposes, there are conceptual justifications for such restrictions. It is recommended, for example, that measurement invariance over time be assumed to facilitate LTA model interpretation. In addition, fixing select parameter estimates to pre-specified values can help with model identification when their values are close to zero, because such values are being estimated on the boundary of the parameter space (Lanza & Bray, 2007).

While model comparison is typically conducted using likelihood-ratio difference tests (nested models) and/or information criteria indices (e.g., BIC) (nested and non-nested models), it is also recommended that the fitted parameter values are examined (Collins & Lanza, 2010). However, it is unclear how to judge the size of observed differences, particularly in instances when statistical indices do not agree.

In this dissertation, the choice of parameter restrictions was largely guided by the examination of the fitted parameter values. For example, based on minimal differences in item-response probabilities over time, measurement invariance was assumed, resulting in 136 fewer parameters estimated (equality constraint). In contrast, in the multiple-group analyses group measurement invariance was not assumed, raising questions about the conceptual plausibility of group comparisons (measurement noninvariance). Finally, in order to stabilize the estimation of the LTA model with a time-varying covariate, a number of transition probabilities were fixed and a Bayesian approach was used to stabilize logistic regression coefficients.

Overall, the identification of the global ML solution can be quite difficult in mixture models. However, both SAS and MPLUS software allow for the specification of multiple sets of starting values, generated either automatically or provided by the user. Tracking model convergence for these values is currently the preferred method to ensure that the optimal solution has been found. One guideline is that at least 50% of the random sets of starting values converge to the highest log-likelihood value (Dziak & Lanza, 2010). We have utilized identification plots available in SAS Graphic Macro to visually assess potential issues with model identification, both in cross-sectional and longitudinal analyses. The models converged relatively quickly and no major problems were detected. It should be noted, however, that providing user starting values for models with many indicators and multiple measurement times can be quite time consuming and error prone.

Model selection

Finding the most parsimonious model that captures otherwise unobserved population heterogeneity is another challenge in applying LCA and LTA models. The guidelines related to the class enumeration problem are relatively straightforward for LCA models (e.g., Nyland et al., 2007). However, there is little research regarding model selection for LTA models, in particular with respect to the advantages and disadvantages of the “bottom-up” and “top-down” model selection approaches. The literature is informal and inconclusive, often providing opposing recommendations.

Class enumeration issues are also challenging when multi-group analysis is considered. Forcing identical latent structure to each group may result in model misspecification and instability of parameter estimates in classes with low prevalences. On the other hand, it may be difficult to justify model selection decisions based on exploratory LCA fitted to each group separately, because the group sizes may be small relative to the overall sample and little is known about statistical power in LCA and LTA models.

Taking into consideration the complexity of the data in this study and the group sizes in the multiple-group analysis, we utilized a combination of model selection approaches.

The bottom-up approach was used to choose and validate the measurement models at each round, and subsequently build the longitudinal model. Model selection criteria at each round included information criteria index BIC and substantive class interpretation. The prevalences of the smallest classes extracted in the analysis ranged from 10% to 4%. With attrition close to 50%, the estimation of model parameters in these classes in the longitudinal model was based on sample sizes ranging from 252 and 170 individuals at Round 1, to 78 and 62 individuals at Round 3 (Symptomatic and Intermediate-Numbing Classes).

In light of these findings, it was unclear whether all four classes would be extracted in the multiple-group LCA and LTA analysis by race/ethnicity. Therefore, we chose to impose the four class structure in both analyses. A non-informative prior for item-response estimates was used to help stabilize the estimation (Dziak et al., 2011). We observed the largest differences in the estimated parameters (i.e., item- response probabilities and transition probabilities) in classes with the smallest prevalences (Symptomatic and Intermediate-Numbing Classes). However, this pattern was not consistent across classes, as about twice as many large differences occurred in the Intermediate-Numbing class, as compared to the Symptomatic class. It is, therefore, unclear whether observed differences and their magnitudes reflect true between group differences or lack of information.

Limitations and implications for future research

Although this dissertation represents an important contribution to the PTSD literature resulting from the application of a novel methodology to the analysis of psychiatric data, this study has several important limitations.

First, the sample is comprised mostly of white, middle-aged men who performed non-rescue disaster relief and recovery work at the WTC site, thus limiting the generalizability of the findings to different populations. In addition, the assessment of PTSD symptomatology took place between 9 and 45 months post exposure to the WTC disaster and, while the symptoms were assessed via clinical interviews explicitly in relation to disaster work, it is unclear whether they reflect only the effect of exposure to the WTC trauma or are confounded with reactions to lifetime traumatic events. Furthermore, the assessment timeframe suggests that observed PTSD symptoms are expressions of the unremitted, chronic indicators of WTC trauma exposure consequences. Future research should involve samples assessed for PTSD and related psychopathology closer to the index trauma of interest and include more diverse populations (e.g., women).

Next, the evaluation of the latent structure of PTSD was based on symptoms listed in the DSM-IV. Despite the fact that the results obtained in this study were validated using concurrent measures of related psychopathology, it would be desirable to assess the robustness of the findings with independent indicators of PTSD, such as extended measures of posttraumatic symptomatology, biological responses, or health service utilization. Furthermore, to fully assess the validity and reliability of the PTSD diagnosis, a comprehensive analysis of PTSD diagnostic criteria and symptoms must take into account modern statistical methodology, such as latent class analysis (LCA) and/or item response analysis (IRT). The consequences of using the non-compensatory rules (i.e., scoring rules that require meeting criteria in multiple symptom clusters) should be critically evaluated and alternatives proposed, if needed.

In addition, study findings may be sensitive to the type of indicators used in the analysis. We have chosen to utilize categorical symptom indicators derived from the DSM-IV F1/I2 scoring rule, partly because we were interested in comparing empirically derived categories to the official DSM-IV diagnostic criteria. Such indicators provide only partial information about the severity of PTSD symptoms. Future studies should investigate the sensitivity of the findings to an alternative indicator choice, thus testing whether the F1/I2 scoring rule is optimal in defining clinically relevant PTSD symptoms.

Throughout the analyses conducted in this dissertation, we have presumed that the fundamental assumption of latent class methodology (i.e., the local independence assumption) has been met. It is plausible that a model with more adequate model fit could be obtained, while allowing for residual interdependence between indicators from the same and from varying symptom clusters.

Finally, methodological research is needed to help guide researchers interested in applying latent class modeling techniques to problems in disaster research and psychiatry. As new methodologies emerge, it is important to relate them to existing statistical models so as to fully understand their advantages and limitations.

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