Complex Posttraumatic Stress Disorder: An Investigation Using Factor Mixture Modeling

by

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Abstract

It has long been established that the experience of traumatic events can result in pathological distress. Some of these reactions, such as hyperarousal or the avoidance of trauma-related cues, are recognized as prototypical stress-response symptoms and have been incorporated into the diagnostic criteria for posttraumatic stress disorder (PTSD). However, the classic symptoms of PTSD are argued to be too limiting in certain cases, as trauma survivors also exhibit symptoms such as emotion dysregulation, negative self-concept, and interpersonal problems. Thus, researchers have suggested that these additional symptoms, which remain absent from the PTSD criteria, represent a distinct diagnosis referred to as complex posttraumatic stress disorder (CPTSD). To date, the relationship between PTSD and CPTSD remains unclear and remains the subject of considerable debate, owing primarily to ambiguity surrounding the definition of CPTSD and methodological limitations of research in this area. In the present study, PTSD and CPTSD were examined using factor mixture modeling, in a trauma-exposed sample of 347 Amazon Mechanical Turk workers. Items from the PTSD Checklist for DSM-5, Patient Health Questionnaire – 4, Rosenberg Self-esteem Scale, and Interpersonal Needs Questionnaire – Revised served as indicators for the symptoms of CPTSD. Results supported a two-factor/three-class solution, including Low Symptoms, Moderate Symptoms, and High Symptoms classes, characterized by differences in symptom severity across the PTSD and additional CPTSD symptoms and not by distinct psychopathological profiles. The implications of these findings for the classification of trauma-related disorders are discussed.

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Introduction

Despite decades of investigation, the consequences of trauma exposure have only recently led to the development of a distinct diagnostic category within accepted mental health taxonomies. This initial codification, first described as posttraumatic stress disorder (PTSD) in the third edition of the Diagnostic and Statistical Manual of Mental Disorders (*DSM–III*; American Psychiatric Association, 1980), has significantly contributed to the developing understanding of trauma (Friedman, Resick, & Keane, 2014). However, since its incorporation PTSD has been found to consistently overlap, or be frequently comorbid, with many other mental health constructs and disorders (e.g., Kessler et al., 2005; Kessler, Sonnega, Bromet, Hughes, & Nelson, 1995; Pagura et al., 2010; Post, Zoellner, Youngstrom, & Feeny, 2011). Furthermore, it has also been argued that PTSD does not provide sufficient or proper construct coverage for all of the victims who suffer from pathological responses to traumatic events, thus necessitating a revision to trauma-related nosology (Herman, 1992a; van der Kolk, Pelcovitz, Roth, & Mandel, 1996). To this end, several PTSD critics have argued in favor of developing a new, more comprehensive trauma diagnosis. This proposed construct, most commonly referred to as "complex posttraumatic stress disorder" (CPTSD; Herman, 1992a, 1992b), has engendered significant debate over the past two decades and remains a contentious issue; today, much of this debate centers on the overlap and structural distinction between CPTSD and the current conceptualization of PTSD (Herman, 2012; Resick et al., 2012).

CPTSD Development

During the mid- to late-1800s, the medical field began to scientifically describe the deleterious effects wrought by trauma exposure. Prominent figures—such as Freud conducting work on hysteria, or Janet studying dissociation—noted that a person's previous life experiences

had the potential to negatively impact the present state of their mental health (van der Kolk, McFarlane, & Weisaeth, 1996). Decades later, the implications of this foundational trauma work would be officially recognized with the *DSM-III* incorporation of PTSD—a disorder characterized by intrusive trauma re-experiencing, disordered arousal, and the avoidance of trauma-related stimuli, following traumatic event exposure (van der Kolk et al., 1996). This pivotal development helped stimulate a burgeoning field of animal and human research, catalyzed the creation of assessments and interventions aimed at identifying and reducing trauma symptoms, and consolidated empirical focus across trauma types (Friedman et al., 2014). While establishing PTSD as an official codified diagnosis has granted validation and therapeutic relief for many, it has also been criticized for its inability to comprehensively describe the full spectrum of pathological responses to traumatic events.

With the intent of one day broadening the diagnostic nomenclature, Herman (1992a) first proposed CPTSD following an extensive literature review on PTSD etiology and comorbidity. In this seminal work, it was argued that the posttraumatic response may be more accurately described dimensionally, on a spectrum of conditions including simple stress reactions, PTSD, and CPTSD—with CPTSD providing diagnostic coverage for the most severe clinical presentations (Herman, 1992a, 1992b). Unlike PTSD, which was originally characterized by three symptom clusters, Herman suggested that people suffering from CPTSD experienced six distinct clusters of symptoms: negative alterations in affect regulation, consciousness (e.g., dissociation), self-perception (e.g., shame), perception of perpetrator, relations with others, and systems of meaning (e.g., loss of faith; Herman, 1992a). It was posited that these severe, more complex stress reactions were a function of specific kinds of traumatic experiences, particularly traumas of an early-onset, interpersonal nature (e.g., childhood abuse; Herman, 1992a; van der

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Kolk et al., 1996)—and such traumas have been well-documented to negatively impact mental health far into adulthood (e.g., Browne & Finkelhor, 1986; Tuscic, Flander, & Mateskovic, 2012). Herman (1992b) claimed that CPTSD might be a function of the coercion and captivity often accompanying interpersonal traumatic experiences, given that such events are commonly characterized by victims being unable to flee or escape perpetrator control. This captivity (e.g., the physical duress during an assault, the psychological coercion imposed by an authority figure, etc.) is believed to cause a gradual deformation of character that eventually manifests as CPTSD, in adulthood (Herman, 1992a). In addition to the potential for more accurate and comprehensive diagnostics, proponents of CPTSD have argued that incorporating a new, complex trauma diagnosis may also improve diagnostic parsimony, reduce clinical complications (e.g., polypharmacy), increase the frequency of appropriate psychotherapy implementation (Herman, 2012), protect trauma survivors from the possibility of judgment resulting from misdiagnosed, stigmatized disorders (e.g., a personality disorder; Herman, 1992a), and stimulate the research necessary to further develop the field's understanding of the pathophysiology of CPTSD (Bryant, 2012, Herman, 2012).

CPTSD Criticisms

However, as evidenced by the ongoing absence of CPTSD from accepted mental health taxonomies, there is a current lack of consensus in the field regarding the necessity for incorporating this proposed disorder. The criticisms most frequently lobbied against CPTSD were recently summarized in a series of review articles arguing for the continued exclusion of the construct (Landy et al., 2015; Resick et al., 2012). First, critics disagreed with the suggestion that CPTSD might increase diagnostic parsimony, suggesting instead that an additional trauma diagnosis may decrease parsimony and increase the complexity of treatment planning; this may

prove to be especially true if future intervention research should fail to identify a clear, best-treatment approach for clients diagnosed with the new disorder (Landy et al., 2015). Second, it was noted that the construct validity of CPTSD is compromised, in part, because a widely accepted symptom set has yet to be established for the proposed disorder (Resick et al., 2012). Since its conception, the proponents of CPTSD have vacillated over which symptoms should be included in the construct, with iterations consisting of six (Herman, 1992a; Maercker et al., 2013), seven (Pelcovitz et al., 1997), and eight symptom clusters (Cloitre et al., 2011). Critics have also highlighted that PTSD symptoms were only recently added to CPTSD, resulting in CPTSD being described as both a distinct diagnosis (Ford, 1999) and as a complex variant of PTSD (Cloitre et al., 2011; Landy et al., 2015). Third, CPTSD has also been criticized for its ambiguous etiology (Resick et al., 2012). Herman (1992a) first described CPTSD as being the consequence of prolonged, early-onset, interpersonal trauma. Yet since then, recent iterations of the construct are argued to also be able to develop from traumatic events experienced during adulthood (e.g., domestic violence) and from single traumas of an especially catastrophic nature (e.g., gang rape; Courtois, 2004). Fourth, critics noted that the construct of CPTSD overlaps with many other disorders, namely PTSD and borderline personality disorder (BPD; Landy et al., 2015). This criticism became especially poignant following the publication of the fifth edition of *DSM* (*DSM–5*; American Psychiatric Association, 2013), after which the PTSD criteria became more inclusive of the proposed CPTSD symptoms. Specifically, the PTSD symptom clusters D (negative alterations in cognition and mood) and E (marked alterations in arousal and reactivity) now cover many of the characteristics otherwise encapsulated by CPTSD's disturbances in emotion regulation and sense of self symptom clusters (see Cloitre et al., 2011). Similarly, the dissociative symptoms that have long been considered a hallmark of CPTSD (and other severe

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trauma reactions) are now encapsulated by the new dissociative subtype of *DSM*-5 PTSD (Blevins, Weathers, & Witte, 2014; Landy et al., 2015; Wolf et al., 2012). Fifth, Resick and colleagues (2012) noted that CPTSD and BPD also share considerable construct overlap, given that the two disorders are theoretically similar in regards to affective instability, intense anger, unstable interpersonal relationships, dissociation, and unstable self-image/sense of self—with trauma history serving as a commonly shared etiology for both BPD and CPTSD (e.g., Herman, 1992a; Gunderson & Sabo, 1993; Vermetten & Spiegel, 2014). Finally, it is also worth mentioning that while new diagnostic categories possess the potential for improved diagnostic coverage and reduced false-negatives (e.g., misdiagnosing a client with BPD), they also carry an increased risk for false-positives—the likelihood of which may be exacerbated by the reality that most diagnoses are rendered by clinicians of varying experience, who may not uniformly apply new diagnostic criteria in the way originally intended by the disseminating researchers (Pincus, Frances, Davis, First, & Widiger, 1992).

Present Directions and Support for CPTSD

Given the criticisms of CPTSD, it is clear that further investigation is required before the construct can be confidently included into mental health taxonomies. This is especially noteworthy since CPTSD is currently proposed for inclusion into the upcoming 11th edition of the International Statistical Classification of Diseases and Related Health Problems (*ICD*) classification system (*ICD-11*). This new disorder, identified by the *ICD-11* Workgroup as "complex PTSD," will reportedly describe the pathological response to severe or prolonged traumatic events, and will be in addition to *ICD-11* PTSD (see Maercker et al., 2013). According to Maercker and colleagues (2013), this CPTSD diagnosis will be a combination of the proposed *ICD-11* PTSD symptoms (i.e., two avoidance symptoms, two hypervigilance symptoms, and two

reexperiencing symptoms) plus "enduring disturbances" in the categories of emotion regulation, sense of self, and interpersonal relationships. This new CPTSD proposal is currently being supported by a series of recent mixture modeling studies, conducted by several CPTSD proponents (Cloitre, Garvert, Brewin, Bryant, & Maercker, 2013; Cloitre, Garvert, Weiss, Carlson, & Bryant, 2014; Elklit, Hyland, & Shevlin, 2014; Knefel, Garvert, Cloitre, & Lueger-Schuster, 2015; Perkonigg et al., 2015).

The first of these studies utilized a latent profile analysis (LPA) to discern whether distinct *ICD-11* PTSD and CPTSD classes existed within a sample of 302 treatment-seeking individuals (Cloitre et al., 2013). Using select questionnaire items that provided construct coverage for *ICD-11* PTSD and CPTSD, a three-class solution was found to be the best-fitting model, identifying a low symptom class (32.1% of the sample) with minimal PTSD and CPTSD symptoms, a PTSD class (31.8%) consisting of significant PTSD symptoms only, and a CPTSD class (36.1%) consisting of significant PTSD symptoms and elevated interpersonal problems, affect dysregulation, and negative self-concept (Cloitre et al., 2013). In a similar study, Cloitre and colleagues (2014) then conducted a latent class analysis (LCA) to study not only *ICD-11* CPTSD, but to also investigate the allegations that CPTSD is an indistinguishable repackaging of BPD. Using similar PTSD and CPTSD items as before (with the notable addition of select BPD items) a sample of 280 adult childhood abuse victims yielded a four-class, best-fitting solution to the LCA. Similar to Cloitre et al. (2013), this identified model consisted of a low symptom class (20.4% of the sample), a PTSD class (25.7%), and a CPTSD class (27.5%)—with an additional BPD class (26.4%), characterized by marked elevations on the added BPD items. In addition to these class findings, the researchers concluded that CPTSD was further discriminable from BPD given that only 7.8% of the CPTSD class met criteria for *DSM-IV* BPD, whereas 91.9% of the

BPD class met criteria. Moreover, members of the CPTSD class endorsed significantly lower rates of self-harm/suicidal behaviors compared to members of the BPD class (14.3% for CPTSD and 16.7% for PTSD vs. 48.7% for BPD; Cloitre et al., 2014).

Utilizing a similar methodology to investigate *ICD-11* CPTSD, Elklit et al. (2014) conducted a series of LCAs with a sample 1,251 victims of sexual assault, physical assault, and bereavement. Consistent with previous findings (e.g., Cloitre et al., 2013), three-class solutions were identified for each of the three trauma types, with each solution consisting of a low symptom, a PTSD, and a CPTSD class. In line with Herman's (1992a) original conceptualization, it was also found that the participants who had been sexually assaulted (i.e., those who were victims of interpersonal trauma), were more likely to be members of the CPTSD class (20.7% of the sample) compared to the participants subjected to bereavement (10.4%) or to physical assault (13%; Elklit et al., 2014).

Contrary to most of the initial mixture modeling findings, more recent LPA/LCAs investigating *ICD-11* CPTSD have been consistently identifying four-class, as opposed to three-class, best-fitting models. For example, using a community sample of 3,021 individuals drawn from a 10-year epidemiological study, Perkonigg and colleagues (2015) conducted an LCA and identified a four-class solution: a low symptom class (65.2% of the sample) possessing minimal PTSD and CPTSD symptoms; a PTSD class (18.4%) consisting of elevated PTSD symptoms only; a CPTSD class (8.2%) consisting of elevated PTSD and CPTSD symptoms; and then an untitled class (8.2%), consisting of only the associated CPTSD features (i.e., affect dysregulation, negative self-concept, and interpersonal problems). However, this study was still argued to be a successful replication of the previous LPA/LCA work (e.g., Cloitre et al., 2013), and it was suggested that sample differences (i.e., larger sample size and community/non-

treatment seeking) were the reasons for the unique, four-class solution (Perkonigg et al., 2015).

Yet in another recent LPA study (Knefel et al., 2015), another fourth class was found, and this

time with a much smaller sample (n = 229), consisting of adult childhood abuse victims. The

four-class solution identified in this study consisted of a low symptom class (43.2% of the

sample), a PTSD class (17.5%), a CPTSD class (20.1%), and a fourth class (19.2%) that the

researchers entitled "disturbances in self-organization" (DSO). It was suggested that the DSO

class (characterized by affective disturbances, interpersonal and self-concept problems,

disturbing dreams, and excessive startle) was representative of a group more consistent with

other Axis I and/or Axis II disorders, and that the overall results of this study still provided

empirical support for CPTSD given the CPTSD-looking class that was found (Knefel et al.,

2015).

Opposition to the Inclusion of CPTSD into *ICD-11*

In rejoinder to the conclusions drawn from these finite mixture modeling studies, Wolf

and colleagues (2015) have suggested that, given the current state of the CPTSD literature,

several important research questions must first be answered before the construct can be

established for *ICD-11*. In particular, the researchers noted that the studies supporting CPTSD's

inclusion into *ICD-11* failed to compare categorical (e.g., LPA) and dimensional (e.g.,

confirmatory factor analysis; CFA) models to one another, and further neglected to investigate

the hybridization of these two models (i.e., a factor mixture model; FMM; see Lubke & Muthén,

2005). These comparisons warrant investigation given that each type of model possesses

different implications for nosology. For example, categorical models indicate whether discrete

groups of participants with distinct symptom sets exist within a dataset, and they assume that

membership in one group (e.g., CPTSD) does not predict the likelihood of membership in

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another (e.g., PTSD). This means that, in theory, each group would manifest a unique set of characteristics, including etiology, prognosis, etc., and therefore warrant the incorporation of a distinct diagnosis into the diagnostic nomenclature (Wolf et al., 2015). Alternatively, dimensional models assume that the likelihood of symptom co-occurrence is influenced by a shared, common factor. Thus, characteristics such as etiology or prognosis are viewed as being shared among the symptoms accounted for by the dimensional factor, and do not warrant separate diagnoses (Wolf et al., 2015). Finally, hybrid models combine these elements from both categorical and dimensional models; participants are organized into discrete groups based on symptom presentation, while simultaneously allowing each participant to dimensionally differ from one another, based on their locations along a latent trait (e.g., symptom severity; Masyn, Henderson, & Greenbaum, 2010; Wolf et al., 2015). Therefore, hybrid models enable researchers to better investigate the within-class, individual differences frequently characteristic of heterogeneous disorders like PTSD or CPTSD (Clark et al., 2013).

In a pioneering study utilizing hybrid model methodology to evaluate the validity of *ICD-11* CPTSD, Wolf and colleagues (2015) conducted an FMM with a community sample of 2,695 individuals and a trauma-exposed sample of 323 veterans. In accordance with the recommended analytic strategy for using FMM to examine the underlying structure of psychological disorders (see Clark et al., 2013), the researchers first conducted a series of CFAs and LPAs for the purposes of comparing best-fitting models across model type (i.e., dimensional vs. categorical vs. hybrid). These initial analyses yielded a two-factor best-fitting CFA model and a four-class best-fitting LPA model, for both the community and veteran samples. However, after completing the subsequent FMM analysis, a four-class model with two latent variables (i.e., dimensionality of PTSD items and dimensionality of CPTSD items) was found to be the ultimate, best-fitting

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model for both samples. It was concluded that individuals were best differentiated by their level of symptom severity rather than the proposed *ICD-11* CPTSD and PTSD symptom sets (Wolf et al., 2015). Given these findings, Wolf and colleagues (2015) cautioned against the inclusion of CPTSD into *ICD-11*, and suggested that additional FMM studies should be conducted prior to the incorporation of this proposed trauma diagnosis into accepted nosology.

Present Study

The present study sought to replicate previous FMM findings and investigate the utility of describing CPTSD using such hybrid models. To date, only one study (i.e., Wolf et al., 2015) has utilized FMM for researching CPTSD, and its results were inconsistent with the recent LPA/LCA findings supporting the construct's upcoming inclusion into *ICD-11*. These disparate findings warrant additional investigation, so that the field can better ascertain whether it is presently premature to establish CPTSD as a codified diagnosis. Therefore, the primary aim of the present study is to investigate the replicability of the findings from Wolf et al. (2015) by conducting an FMM analysis with a unique trauma-exposed sample, and a distinct set of items representing the *ICD-11* PTSD and CPTSD constructs.

Based on available theoretical and empirical evidence, the following hypotheses were posited:

Hypothesis 1: Similar to recent LPA/LCA findings (e.g., Knefel et al., 2015), the LPA in this study will also provide evidence supporting a four-class solution (i.e., low symptoms, PTSD, CPTSD, and associated features), yet it will demonstrate poorer model fit compared to the FMM.

Hypothesis 2: Consistent with Wolfe and colleagues (2015), an FMM consisting of four classes (i.e., low symptoms, low moderate symptoms, high moderate symptoms, and high symptoms) and two latent variables (i.e., PTSD item dimensionality and CPTSD item

dimensionality) will be revealed as the best-fitting model for the data, when compared to the dimensional (i.e., CFA) and categorical (i.e., LPA) models alone.

Method

Participants and Procedure

Participants were 347 individuals drawn from an archival dataset ($N = 589$), consisting of questionnaire responses taken from English-speaking, U.S. residents who were at least 18 years old or older. The present study was approved by the Auburn University's institutional review board (IRB) as a modification of the original project for which this dataset was collected. All participant data were collected via Amazon Mechanical Turk (MTurk), an online crowdsourcing marketplace that provides researchers with an opportunity to quickly and efficiently gather inexpensive, valid, and reliable data, from participants located around the world (for a review, see Chandler & Shapiro, 2016). However, consistent with current recommendations for studies without a cultural focus, sampling for this dataset was restricted to U.S. residents only, to reduce error from the administration of surveys validated with only English-speaking populations (Feitosa, Joseph, & Newman, 2015). To collect these data, 1,940 potential participants initially completed a screener questionnaire on MTurk, inquiring about lifetime suicide behavior (i.e., ideation, plan, or attempt). Additional distracter questions (e.g., Patient Health Questionnaire-4 items; Löwe et al., 2010) were added to this questionnaire to obstruct participants from determining the study's objectives. Respondents who reported a history of suicide behavior ($N = 1,029$; i.e., those who answered *yes* to any of the following questions: *Have you ever had thoughts of killing yourself?, Have you ever made a plan to kill yourself?, or Have you ever made an actual attempt to kill yourself in which you had at least some intent to die?*) were invited to participate in the study and complete an online battery of questionnaires. After the

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dissemination of these invitations, 589 participants (57.24% of those invited) responded and took part in the study.

While the original dataset consisted of six waves of data collection (occurring over a 15-day period), only the data collected at the first timepoint (i.e., Wave 1) was used for the purposes of the present study. Following an initial demographics form, Wave 1 consisted of a randomized battery of questionnaires assessing for suicidality symptoms, trauma history, PTSD symptoms, and other associated features (e.g., depressive symptoms). Participants completed the measures on Qualtrics, after following a link to the study posted on MTurk. In addition to the $.10 that was earned by completing the initial screening questionnaire, participants were also paid $2.50 worth of monetary compensation for completing Wave 1 (which took approximately 30 minutes). In accordance with previous FMM analyses on *ICD-11* CPTSD (Wolf et al., 2015), exposure to at least one traumatic event (as defined by *DSM-5* PTSD Criterion A) served as an inclusion criterion for the final dataset and analyses. Two graduate clinicians independently reviewed self-reported, worst event narratives for each Wave 1 participant, and determined whether those events met criteria; disagreements were resolved through discussion and consensus. Of the 589 participants who took part in Wave 1, 349 participants (59.3%) were found to have been exposed to at least one Criterion A event. Additionally, two participants were omitted from analyses because they only completed the demographics and trauma history surveys, and none of the other measures in the study.

Participants retained for the final analysis (n = 347) were predominantly female (73.5%) and White (86.5%) or Black (8.9%), and ranged in age from 18 to 77 years old ($M = 33.04$, $SD = 10.59$). Participants reported experiencing a wide range of serious or traumatic events, including getting in a transportation accident (67.1%), being the victim of sexual assault or other

unwanted/uncomfortable sexual experience (41.5% and 56.5%, respectively), being the victim of physical assault (53.3%), surviving a natural disaster (46.1%), witnessing a life-threatening illness or injury (42.1%), witnessing a transportation accident (41.2%), and witnessing a physical assault (37.2%).

Measures

The following measures from Wave 1 described below were used in the analysis for the present study.

The *Life Events Checklist for DSM-5* (LEC-5; Weathers, Blake, Schnurr, Kaloupek, Marx, & Keane, 2013) was utilized for assessing trauma exposure within the sample. The LEC-5 is a 17-item self-report measure that screens for a history of exposure to 16 different events known to be associated with the development of PTSD (e.g., sexual assault). It also includes an item for inquiring about "any other very stressful event" not otherwise covered in the first 16 items, as well as a short-answer item that allows respondents to describe their worst traumatic event (Weathers et al., 2013). While the psychometric properties for the LEC-5 are currently unavailable, the original version of the LEC has been found to have adequate psychometric properties (see Gray, Litz, Hsu, & Lombardo, 2004) and thus it is anticipated that, given the minimal discrepancies between the LEC and the LEC-5, the LEC-5 will also demonstrate adequate psychometric properties (Weathers et al., 2013).

The *PTSD Checklist for DSM-5* (PCL-5; Weathers, Litz, Keane, Palmieri, Marx, & Schnurr, 2013) was used in this study to measure PTSD symptom severity. The PCL-5 is a 20-item self-report measure that assesses for each of the 20 *DSM-5* symptoms of PTSD. On the PCL-5, respondents first identify a worst traumatic event and are then asked to refer to this event as they complete each item. Items require them to indicate how much they were bothered by a

specific PTSD symptom in the past month, using a five-point scale (1 = *not at all* to 5 = *extremely*). The PCL for *DSM-IV* has been widely used for PTSD assessment across many trauma populations and its scores have been consistently shown to have excellent psychometric properties (for a review, see Wilkins, Lang, & Norman, 2011). Likewise, initial psychometric investigations of the PCL-5 have also found it to be an internally consistent measure, with good convergent and discriminant validity (Blevins, Weathers, Davis, Witte, & Domino, 2015). In this study, PTSD symptom severity was defined by the proposed PTSD construct for *ICD-11* (i.e., consisting of only the reexperiencing, avoidance, and hypervigilance symptom clusters). Specifically, two reexperiencing items (i.e., *Repeated, disturbing dreams of the stressful experience?*; *Suddenly feeling or acting as if the stressful experience were happening again (as if you were actually back there reliving it)?*), two avoidance items (i.e., *Avoiding memories, thoughts, or feelings related to the stressful experience?*; *Avoiding external reminders of the stressful experience (for example, people, places, conversations, activities, objects, or situations)?*), and two hypervigilance items (i.e., *Being "superalert" or watchful or on guard?*; *Feeling jumpy or easily startled?*) provided construct coverage for PTSD. Internal consistencies for these two-item scale scores in the present study were high (Cronbach's α = .79, .87, and .82, respectively). Additionally, the PCL-5 anger item (i.e., *Irritable behavior, angry outbursts, or acting aggressively?)* was used to partially cover the construct of emotion dysregulation, discussed in more detail below.

The *Patient Health Questionnaire - 4* (PHQ-4; Löwe et al., 2010) provided partial construct coverage for emotion dysregulation in this study. The PHQ-4 is a short, four-item, depression screening instrument on which respondents indicate how much they were bothered by depressive symptoms over the past two weeks, using a four-point scale (1 = *not at all* to 4 =

nearly every day). The PHQ-4 has been found to be internally consistent and to possess good convergent and discriminant validity when used with the U.S. general population (Löwe et al., 2010). In particular, the PHQ-4 item assessing for anxious distress (i.e., *Not being able to stop or control worrying*) was used in conjunction with the PCL-5 anger item, to represent emotion dysregulation in this study. Internal consistency for this two-item scale score was low ($\alpha = .59$), however, such a finding is not surprising given that Cronbach's α is artificially reduced as the number of items in a scale decreases (Cortina, 1993).

The *Rosenberg Self-esteem Scale* (RSE; Rosenberg, 1965, 1979) was used in this study to measure negative self-concept. The RSE is a 10-item, global self-esteem instrument consisting of a four-point scale (1 = *Strongly Disagree* to 4 = *Strongly Agree*) that respondents use to identify the degree to which they agree or disagree with a list of statements regarding their feelings about themselves. As one of the most widely used measures of self-esteem, the RSE has demonstrated excellent psychometric properties across a range of populations, including both residents of the U.S. and abroad (Schmitt & Allik, 2005; Sinclair, Blais, Gansler, Sandberg, Bistis, & LoCicero, 2010). Specifically, the RSE items assessing satisfaction with self (i.e., *On the whole, I am satisfied with myself*) and feelings of self-worth (i.e., *I feel that I am a person of worth*) provided construct coverage for negative self-concept in this analysis. Internal consistency for this two-item scale score in the present study was acceptable ($\alpha = .79$).

The *Interpersonal Needs Questionnaire – Revised* (INQ-R; Van Orden, Cukrowicz, Witte, & Joiner, 2012; Van Orden, Witte, Gordon, Bender, & Joiner, 2008) was used to represent the interpersonal problems construct, in the present study. The INQ-R is a 15-item self-report measure that assesses the constructs of perceived burdensomeness and thwarted belongingness. Respondents on the INQ-R are asked to think about themselves and others and then rate, on a 7-

point scale (1 = *Not at all true for me* to 7 = *Very true for me*), the veracity of a series of interpersonal statements about themselves. Both the perceived burdensomeness and thwarted belongingness subscales of the INQ-R have displayed acceptable psychometric properties (Van Orden et al., 2012). The INQ-R items which inquire about disconnection from others (i.e., *These days, I feel disconnected from other people*) and a lack of social closeness (i.e., *These days I am close to other people*) were used to measure interpersonal problems. In the present study, internal consistency was acceptable (α = .77) for this two-item scale score.

Analytic Strategy

To maintain consistency with the existing CPTSD literature (Wolf et al., 2015), as well as to follow the best-practice approach for FMM (e.g., Clark et al., 2013), data from the present study were first analyzed by modeling item relationships dimensionally (i.e., CFA) and categorically (i.e., LPA), prior to engaging in hybrid modeling. Once CFA and LPA models were fit to the data, these solutions served as cutoff points for determining when to stop adding factors and classes into the iterative, FMM model-building process. CFAs and LPAs are useful for this purpose because, as model comparisons, they act as "special cases" of FMMs; mathematically, a CFA is an FMM with a single latent class that every participant is a member of, and an LPA is an FMM with a factor covariance matrix of zero (Clark et al., 2013, p. 690).

Initially, prior to modeling, all reverse-scored items were recoded and item scores were translated into z-scores, to address dissimilar scaling issues. Mean z-scores were then calculated for each of the item pairs, and used to represent the three PTSD indicators (i.e., reexperiencing, avoidance, and hypervigilance) and the three CPTSD indicators (i.e., emotion dysregulation, negative self-concept, and interpersonal problems). Consistent with Wolf and colleagues (2015), modeling was done in this way so that PTSD and CPTSD symptom clusters could be represented

more equally, the possibility of under-identified factors could be avoided, and model fit across analyses could be compared with greater accuracy.

The structural models were evaluated next, beginning first with the dimensional, CFA models. Consistent with substantive theory (Wolf et al., 2015), a one-factor CFA (with all six indicators loaded onto the same trauma factor) and a two-factor CFA (with the three PTSD indicators loaded onto one factor and the three CPTSD indicators loaded onto a second, correlated factor) were fit to the data. The fit for each of these models was evaluated by following accepted interpretation guidelines for standard fit statistics, including the chi-square test of model fit, the root mean square error of approximation (RMSEA), the comparative fit index (CFI), the Tucker-Lewis index (TLI), and the standardized root mean square residual (SRMR). Established CFA recommendations for good model fit suggest a non-significant chi-square value, an RMSEA near or below .06 (with a 90% confidence interval that has a lower bound ≤ .05 and an upper bound ≤ .10), a CFI and TLI ≥ .95, and an SRMR ≤ .08 (e.g., Hu & Bentler, 1999; Kline, 2011).

Second, using the same six PTSD and CPTSD indicators, the categorical, LPA models were evaluated to determine a best-class solution. Following established practice for LPA (e.g., Masyn, 2013; Nylund, Asparouhov, & Muthén, 2007), the process of searching for a best-class solution proceeded sequentially and no a priori assumptions were made while enumerating the classes. Initially, a one-class model was specified, followed by an increasingly greater number of specified classes until a best-fitting class solution could be established using several different fit statistics. These fit statistics included the Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-A; Lo, Mendell & Rubin, 2001), the bootstrapped likelihood ratio test (BLRT; Nylund et al., 2007), and the Bayesian information criterion (BIC; McLachlan & Peel, 2000). Generally, a

smaller BIC indicates a better-fitting model, while significant LMR-A and BLRT values suggest that a model provides better fit than the previous model with one fewer class (Nylund et al., 2007). Classification quality was also measured using class entropy values, as greater classification uniqueness is often associated with values that are closest to 1.0 (Muthén, 2004).

Third, a series of hybrid, FMMs were fit to the data. The upper limit of factors and classes added to the iterative FMM modeling process was determined by the initial CFAs and LPAs run previously, resulting in models ranging from one factor with two classes, to two factors with four classes. In accordance with the FMM guidelines described by Clark and colleagues (2013), four FMM model variants were tested, with each subsequent variant relaxing additional model constraints. Thus, six FMMs (i.e., one-factor/two-classes, one-factor/three-classes, one-factor/four-classes, two-factors/two-classes, two-factors/three-classes, and two-factors/four-classes) were run for each of the four FMM variants, resulting in a total of 24 distinct FMM models.

In the first (most restrictive) FMM variant (FMM-1), factor means were allowed to change across classes, while factor loadings and item means were held invariant across classes, and the factor covariance matrix was fixed at zero. When modeling psychological disorders, an FMM-1 model suggests that disorders are consistently measured across all classes and are absent all with-in class heterogeneity (Clark et al., 2013). In the second FMM variant (FMM-2), factor means were still allowed to change across classes and factor loadings and item means remained invariant. However, with FMM-2, the factor covariance matrix was no longer fixed at zero and was freely estimated across classes. This allows for with-in class heterogeneity and suggests that an individual can have many possible amounts of a disorder (Clark et al., 2013). According to Clark and colleagues (2013) though, the FMM-1 and FMM-2 variants are often found to be

overly restrictive models and rarely fit real data due to the invariant factor loadings and item means.

In the third FMM variant (FMM-3), factor means were fixed at zero, factor loadings were held invariant, and the factor covariance matrix varied across classes. Also in FMM-3, item means were freely estimated. This enabled classes to be based on item responses, as opposed to factor means and variances, and suggests that varying amounts of symptom heterogeneity exist within each class (Clark et al., 2013). Additionally, for the two-factor FMM-3 models in the present study, factor covariances remained freely estimated, while factor variances were fixed at one. This model adjustment assisted with identification and was determined to not have undermined the fidelity of the results (L. Muthén, personal communication, March 6, 2017). Last, for the final and least restrictive FMM variant (FMM-4), factor loadings were no longer held invariant and varied across classes. Factor means remained fixed at zero, item means were freely estimated, and the factor covariance matrix varied across classes (with variances fixed at one and covariances freely estimated). Due to the number of freely estimated parameters in this variant, factors in an FMM-4 model can be thought of as being measured differently across classes, resulting in the potential for each class to possess a different factor (e.g., the distinct subpopulations of attention-deficit/hyperactivity disorder; Clark et al., 2013). Consistent with the approach for determining a best-fitting LPA solution (Nylund et al., 2007), a range of fit statistics, including the BIC, LMR-A, and BLRT, were reviewed for identifying a best-fitting FMM. Finally, the best-fitting CFA, LPA, and FMM models were compared using substantive interpretation and the BIC fit statistic, with the lowest BIC value denoting the overall best-fitting solution for the data.

All structural analyses were conducted with Mplus Version 7.4 (Muthén & Muthén, 1998-2015) with Mixture Add-on, using the robust maximum likelihood estimator (MLR) to help account for non-normality in the data. Full information maximum likelihood (FIML) was used to handle missing data, with excellent covariance coverage found in the present study (99.1% to 99.7%). It has been demonstrated in simulation studies that FIML, compared to other methods, is a superior method for handling missing data (Enders, 2010). All mixture models were rerun with at least double the random starts, to rule out the possibility of local maxima in cases where the best log-likelihood value was replicated. Additionally, self-report diagnoses for ICD-11 PTSD, ICD-11 CPTSD, and DSM-5 PTSD were calculated by class, using the most likely class membership, from the best-fitting model identified during the structural analyses. Consistent with the CPTSD literature (e.g., Perkonigg et al., 2015) and proposed diagnostic guidelines (Maercker et al., 2013), a diagnosis of ICD-11 PTSD required a "*moderate*" or greater endorsement for at least one item from each of the three PCL-5 symptom pairs used in the present study. Likewise, a diagnosis of ICD-11 CPTSD required a similar pattern of endorsement, but for all six symptom pairs, covering both the PTSD and associated CPTSD features. Given that some of the items used for CPTSD construct coverage in the present study did not all possess explicitly "*moderate*" answer options, cut points were established using the same midpoint-or-greater severity approach found in the literature. Thus, cut-points of "*More than half the days*," "*Somewhat true for me*," and "*Agree*," were used on the PHQ-4, INQ-R, and RSE, respectively. A self-report diagnosis of DSM-5 PTSD was established using the recommended PCL-5 total score cut-point of 33 (Weathers et al., 2013).

Dimensional and Categorical Models

Initial results revealed poor model fit for both the one-factor [$\chi^2(9) = 231.28$, $p < .001$; RMSEA = .27, 90% confidence interval (CI) = [.24, .30]; CFI = .69; TLI =.48; SRMR = .12] and two-factor CFA models [$\chi^2(8) = 163.77$, $p < .001$; RMSEA = .24, 90% CI [.21, .27]; CFI = .78; TLI =.59; SRMR = .10]. However, after modifying the two-factor model by allowing emotion dysregulation to serve as a complex indicator loading onto both the PTSD and CPTSD factors, model fit was improved and found to be acceptable [$\chi^2(7) = 16.79$, $p = .019$; RMSEA = .06, 90% CI [.02, .10]; CFI = .99; TLI =.97; SRMR = .03]. The PTSD and CPTSD factors were determined to be significantly correlated with one another ($r = .26$, $p < .001$) and all indicators significantly loaded on their respective factors (standardized β ranged from .33 to .91, $p < .001$). Given that *ICD* is a taxonomy possessing intentionally constrained constructs designed for clinical utility (Reed, 2010), and that the *DSM-5*'s definition for PTSD incorporates "negative alterations in cognition and mood" (APA, 2013), this modification is well substantiated within the literature. Emotion dysregulation served as a complex indicator for all subsequent FMM analyses in the present study, to facilitate final model comparison across analyses.

To conduct the latent profile analyses, 1- to 5-class models were fit to the data and evaluated to establish a best-fitting LPA model (see Table 1). The 3- to 5-class models were all found to have significant BLRT values and lower BIC values than the 2-class model. This suggested that the best-fitting LPA solution contained more than two classes. Next, it was determined that the best-fitting solution was either a 3- or 4-class model, given that it is recommended additional class enumeration cease once the first non-significant LMR-A value has been identified (Nylund et al., 2007). Furthermore, an inspection of the 5-class model yielded

a class that was difficult to interpret as it contained only 4.32% of the sample (n = 15). Finally, in comparing the 3- and 4-class models, the 4-class model was selected as the better-fitting model, given the 4-class model's lower BIC and significant BLRT. The four-class model was also found to have high entropy (suggesting good classification uniqueness) and to be partially congruent with recent LPA findings on CPTSD (e.g., Cloitre et al., 2013). Thus, the four-class solution was identified as the best-fitting categorical model in the present study.

Findings from the four-class solution are plotted in Figure 1, with mean standardized scores depicting the degree to which class members endorsed each symptom, by class. Classes 1- –3 were labeled based on similarities between their respective symptom profiles and those found previously in the existing CPTSD literature (e.g., Cloitre et al., 2013; Wolf et al., 2015). Comprising 48% of the sample, Class 1 was characterized by low symptom elevations across all PTSD and CPTSD constructs. This class was labeled "Low Symptoms," given its minimal symptom profile. Comprising 24% of the sample, Class 2 consisted of low to moderate PTSD scores, coupled with high scores for the CPTSD constructs of interpersonal problems, emotion dysregulation, and negative self-concept. Class 2 was labeled "CPTSD," as this class closely approximates CPTSD classes found previously. Comprising 15% of the sample, Class 3 was characterized by moderate PTSD scores and low CPTSD scores. Given this profile, Class 3 was identified as the "PTSD" class. Finally, comprising 13% of the sample, Class 4 consisted of very high PTSD and emotion dysregulation scores, coupled with low scores for interpersonal problems and negative self-concept. Class 4 was labeled the "High Symptoms" class.

Hybrid Modeling

Next, using the best-fitting dimensional and categorical models as upper bounds, a series of FMMs were run ranging from a one-factor/two-class model to a two-factor/four-class model,

for each of the four FMM variants described previously (see Table 2). As anticipated, due to their overly restrictive nature, all models from the FMM-1 and FMM-2 variants demonstrated poor fit to the data (Clark et al., 2013). While the models from these variants converged, each was found to have information matrix singularity concerns due to either model identification issues or the presence of empty cells in the joint distributions for the categorical variables. Additionally, except for the one-factor/two-class model, all other FMM-4 models run in the present study failed to converge and subsequently, did not provide model estimates that could be trusted. Of the converged models, fit statistics and symptom profiles were reviewed and compared, to establish a best-fitting FMM.

From the FMMs run, the two-factor/three-class and two-factor/four-class FMM-3 models produced the lowest BIC values. Of these two models, the two-factor/four-class model had a slightly lower BIC and a significant BLRT value, suggesting better fit compared to the two-factor/three-class model. However, the two-factor/four-class model was also found to have a non-significant LMR-A value and lower entropy, compared to the two-factor/three-class model. Moreover, after considering profile interpretability, the two-factor/three class model displayed better class separation compared to the two-factor/four-class model (with average latent class probabilities for most likely class membership ranging from .91–.96 and .88–.95, respectively). Lastly, whereas the two-factor/four-class model produced a symptom profile with two interwoven/indistinguishable classes (reflecting the model's poorer class separation), the two-factor/three-class model produced a symptom profile of distinguishable classes, partially congruent with recent findings from the FMM literature on CPTSD (Wolf et al., 2015). Thus, while fit indices were partially ambiguous, the two-factor/three-class FMM-3 model was identified as the FMM model most strongly supported by the pattern of results. Finally,

following a comparison of the BIC values from the best-fitting dimensional (i.e., 2-factor CFA), categorical (i.e., 4-class LPA), and hybrid models (2-factor/3-class FMM), the 2-factor/3-class FMM was determined to be the overall best-fitting model for the data.

Results from the two-factor/three-class solution are plotted in Figure 2, with mean standardized scores representing the degree of symptom severity endorsed for each symptom, by class. Consistent with Wolf and colleagues (2015), an examination of the symptom profiles depicted classes primarily differentiated by symptom severity, ranging from low to high, along the factors of PTSD item and CPTSD item dimensionality. However, in the present study, this differentiation occurred across three classes instead of four, as was found by Wolf et al. (2015). Class 1, accounting for 67% of the sample, was distinguished by its minimal elevations across all symptoms. Diagnostic prevalences of DSM-5 PTSD, ICD-11 PTSD, and ICD-11 CPTSD in this class were 16.2%, 3.4%, and 2.6%, respectively. Given this profile, Class 1 was labeled the "Low Symptoms" class. Class 2, accounting for 22% of the sample, was found to have a largely parallel profile to Class 1, with moderate elevations across all symptoms. Diagnostic prevalences of DSM-5 PTSD, ICD-11 PTSD, and ICD-11 CPTSD in this class were 71.1%, 76.3%, and 44.7%, respectively. Thus, Class 2 was labeled the "Moderate Symptoms" class. And finally, Class 3, accounting for 11% of the sample, consisted of low interpersonal problems and negative self-concept scores, but high reexperiencing, avoidance, hyperarousal, and emotion dysregulation scores. Diagnostic prevalences of DSM-5 PTSD, ICD-11 PTSD, and ICD-11 CPTSD in this class were 94.6%, 91.9%, and 51.4%, respectively. Given the predominantly elevated symptom profile, this class was labeled the "High Symptoms" class.

Discussion

The present study aimed to replicate results from the existing FMM literature on CPTSD, and in doing so, contribute to the ongoing debate surrounding the construct's existence and its upcoming controversial inclusion into *ICD-11*. Using a unique trauma-exposed sample, results highlighted the importance of utilizing FMM to investigate hybrid models of the underlying structure of CPTSD. First, as hypothesized, a four-class solution was identified as the best-fitting LPA model in the present study. It was also found that this model demonstrated poorer fit to the data when compared to the overall best-fitting, two-factor/three-class FMM model. This four-class LPA solution included Low Symptoms, PTSD, CPTSD, and High Symptoms classes. Second, contrary to the hypothesized two-factor/four-class solution, the present FMM identified a two-factor/three-class best-fitting solution, including Low Symptoms, Moderate Symptoms, and High Symptoms classes, across the factors of PTSD and CPTSD item dimensionality. Consistent with Wolf et al. (2015), these classes were found to be primarily discriminated by symptom severity across indicators, as opposed to being organized around distinct psychopathological symptom profiles, such as CPTSD.

Ultimately, these findings were found to be partially congruent with the only previous FMM study on CPTSD (Wolf et al., 2015) and, consequently, incongruent with much of the supportive LPA/LCA CPTSD literature (e.g., Cloitre et al., 2013; Knefel et al., 2015; Perkonigg et al., 2015). To date, the majority of the LPA/LCA CPTSD literature has identified three- or four-class solutions consisting of at least one class consistent with the proposed CPTSD construct; these findings have been used to justify the inclusion of CPTSD into the upcoming ICD-11. Contrary to these findings, two studies (including the current one) have now failed to identify distinct ICD-11 CPTSD classes with FMM modeling, as opposed to with the traditional

LPA/LCA approach. This failure to identify a CPTSD class with hybrid modeling is significant, given that FMM is arguably a superior methodology for modeling psychological disorders, since it relaxes the assumption of conditional independence for each latent class (see Clark et al., 2013). Moreover, the present study confirmed Wolf et al.'s finding that if analyses had ceased after only conducting the LPA, a CPTSD group would have emerged from the best-fitting LPA solution, and results would have aligned with the supportive CPTSD literature.

While the findings were largely consistent with Wolf et al., results from the present study were also distinct in that a two-factor/three-class solution, instead of a two-factor/four-class solution, was identified as the best-fitting model. The two-factor/four-class solution was considered for best-fitting model, given the lower BIC and significant BLRT value. However, in addition to its non-significant LMR-A value, this model possessed poor class separation. As noted by Masyn (2013), class separation is an integral part of interpretation and as such, a lack of separation between two or more classes is likely an indication that too many classes are attempting to be extracted from the data. A review of the symptom profiles for the two-factor/four-class solution depicted exactly that—the High Symptoms and Low Symptoms classes remained unchanged while the Moderate Symptoms class was split into two interwoven, indistinguishable classes. While the BIC and BLRT are at times purported to be more reliable tools than the LMR-A, it is worth noting that the model identification accuracies of these fit statistics are comparable. Currently, there is an unfortunate lack of Monte Carlo research on fit statistic accuracy for FMM models with continuous indicators. However, as a reference, Nylund and colleagues (2007) investigated FMMs with categorical indicators; using a sample of 200, it was found that both the LMR-A and BLRT performed well, accurately identifying the best-fitting model 80% and 87% of the time, respectively. As noted by the researchers, more work is

needed in this area to develop a better understanding of the robustness of these fit statistics across different combinations of analyses, sample sizes, and indicator types (Nylund et al., 2007).

In addition to the disparate number of classes compared to Wolf et al. (2015), the High Symptoms class from the present study also displayed some unique characteristics. Whereas Wolf and colleagues found a High Symptoms class possessing a continuously parallel symptom profile to the Moderate and Low Symptoms classes, this study found a High Symptoms class with distinctly elevated reexperiencing symptoms, coupled with low interpersonal problems and negative self-concept. Considering that this study is the first to use MTurk to investigate CPTSD, this unexpected profile could be the result of some unanticipated subject-selection bias associated with MTurk sampling. However, it is worth noting that initial methodological evaluations of the use of MTurk for clinical research have found that MTurk samples produce largely valid and reliable results, when compared to other forms of convenience sampling (Chandler & Shapiro, 2016). The unique High Symptoms class could also be related to the fact that the present study was the first CPTSD investigation to utilize a sample consisting of participants all reporting some degree of past suicide behavior (e.g., suicidal ideation). Given that reexperiencing symptoms have been previously identified as the PTSD symptom cluster most strongly associated with suicidal ideation (e.g., Bell & Nye, 2007), elevated reexperiencing symptoms in the High Symptoms class may be indicative of significant suicidality among those class members. However, if this were the case, it is surprising that the High Symptoms class does not also display elevated interpersonal problems, considering the negative association between suicidality and social support that is well-documented in the literature (e.g., Panagioti, Gooding,

Taylor, & Tarrier, 2014). Future FMM CPTSD research is needed to determine the replicability of this unique High Symptoms profile from the present study.

Given the identified symptom profiles of the best-fitting solution in the present study, one might argue that the High Symptoms class would be better conceptualized as a PTSD class, while the Moderate Symptoms class—with its elevations across all six symptom clusters—may represent a CPTSD class. However, in rejoinder to this notion, it should be noted that the literature does not support a CPTSD class of individuals with less severe presentations than the PTSD class. In fact, CPTSD has always been conceptualized as the most severe trauma disorder along a spectrum of posttraumatic reactions (Herman, 1992a, 1992b). This conceptualization reverberates within the construct's proposal for ICD-11, as it is argued that CPTSD arises from exposure to a stressor of an "extreme" or "severe" nature (Maercker et al., 2013). Moreover, a review of the supportive LPA/LCA CPTSD literature finds that the CPTSD classes identified possess either commensurate or greater PTSD symptom severity, when compared to the identified PTSD classes (e.g., Cloitre et al., 2013; Cloitre et al., 2014; Knefel et al., 2015; Perkonigg et al., 2015). Last, the High Symptoms and Moderate Symptoms classes identified in the present study did not differ in terms of self-reported PTSD or CPTSD diagnostic prevalence. In fact, the High Symptoms class was even found to have a slightly higher CPTSD prevalence than the Moderate Symptoms class (51.4% vs. 44.7%, respectively), further undermining the notion that the Moderate Symptoms class is representative of a distinct ICD-11 CPTSD diagnosis.

Results from the present study should be considered in light of several caveats. First, given the lack of an established CPTSD assessment measure, the items chosen to represent CPTSD in the present study were selected based on the existing CPTSD literature and the

relevance of each item to the proposed construct. Thus, despite all indicators possessing face validity, additional measurement error may have been incidentally introduced due to the unstandardized nature of these items. While a gold-standard CPTSD instrument does not yet exist, progress is being made in that direction, as the ICD-11 workgroup is actively developing a new ICD-11 trauma questionnaire intended for both PTSD and CPTSD assessment (see Karatzias et al., 2016). Future CPTSD research will benefit from being able to utilize a standardized conceptualization of the construct. Second, as described previously, the emotion dysregulation scale from the present study was found to have low internal consistency. This finding could be the result of items that ended up being poorly representative of emotion dysregulation, or it could simply be a mathematical artifact resulting from the small number of items used for the scale. Given the lack of additional emotion dysregulation items in the dataset, this question cannot be definitively answered. Future research will need to continue investigating what items best constitute emotion dysregulation in regards to CPTSD. Given weak emotion dysregulation factor loadings from the initial psychometric work on the ICD-11 Trauma Questionnaire, Karatzias and colleagues (2016) noted that, going forward, it will be a challenge for the ICD-11 workgroup to establish an emotion dysregulation item set of ICD-11 CPTSD. Third, because of the internet-based administration of the measures used in this study, the testing situation for each participant was highly variable, thus reducing environmental control and potentially increasing measurement error. Last, due to the narrow range of demographics found in this non-clinical, mixed civilian trauma sample (i.e., participants were predominantly White and female), the generalizability of the study's findings may have been reduced. Future CPTSD research should incorporate more demographically diverse, multinational samples, especially

given the World Health Organization's goal of developing the ICD into a multilingual taxonomy suited for clinical utility around the world (Reed, 2010).

Despite these limitations, findings from the present study support the position that it is currently premature to incorporate a new, complex PTSD diagnosis into the upcoming ICD-11. Proponents of CPTSD inclusion will certainly disagree with this position, citing both the existence of empirical support and the clinical need for a new diagnosis as license to incorporate the proposed disorder into accepted mental health taxonomy. It is believed that the establishment of CPTSD will improve assessment accuracy and psychotherapy implementation, reduce the side effects of poor diagnostics (e.g., polypharmacy, stigma), catalyze new programs of research (e.g., CPTSD interventions), and ultimately usher in greater clarity within the field of traumatic stress (e.g., Bryant, 2012; Cloitre et al., 2015; Herman, 1992a; Herman 2012). However, there is now a growing body of literature undermining the fidelity of the empirical foundation for CPTSD. While additional research is needed to know with confidence whether CPTSD is a distinct diagnosis or not, enough current discrepant findings exist that the field should suspend the incorporation of CPTSD into ICD-11.

While PTSD is far from a perfectly defined construct, the prevailing strategy since its conception in 1980 has been to systematically update the construct with each subsequent diagnostic manual edition published. Reversing this approach, by creating a new disorder in response to diagnostic concerns, is a drastic step that could lead to major consequences. As noted, the premature incorporation of a more severe PTSD variant might negatively impact classification parsimony and diagnostic reliability (Resick et al., 2012). Moreover, given the current lack of consensus on how to best treat CPTSD, expanding the nomenclature may obfuscate the dissemination and implementation of currently available, evidence-based PTSD

interventions (Landy et al., 2015; cf. Cloitre, 2015). Additionally, many of the practical implications of incorporating CPTSD have largely been ignored in the literature to date, and still require thorough planning and forethought. For example, given that U.S. Veterans are currently entitled to financial compensation for military-related PTSD, the codification of a more complex version of this disorder may subsequently incur additional benefits—this funding would be drawn from an already severely taxed healthcare system. In fact, a recent simulation study projected that by 2025, the direct costs of treating PTSD alone for the Department of Veterans Affairs will approximate $3 billion annually, assuming no change in current combat deployment frequency (Ghaffarzadegan, Ebrahimvandi, & Jalali, 2016). Finally, while it has been suggested that CPTSD will provide diagnostic shelter for individuals misdiagnosed with commonly stigmatized disorders (e.g., BPD; Herman, 1992a, 1992b), it has also been argued that CPTSD could present its own stigma-related concerns. As noted by Landy and colleagues (2015), an individual diagnosed with CPTSD may believe that their condition is more challenging to treat, or that CPTSD possesses a poorer treatment prognosis compared to PTSD.

Considering these implications, the gravity of incorporating CPTSD into *ICD-11* cannot be overstated. Following the recent federal mandate to use *ICD* for all health service coding, *ICD* is potentially positioned to become the dominant classification system in the U.S. (Wolf et al., 2015). Thus, the field of traumatic stress finds itself at a critical juncture.

References

American Psychiatric Association (1980). *Diagnostic and statistical manual of mental disorders* (3rd ed). Washington DC: Author.

American Psychiatric Association. (1994). *Diagnostic and statistical manual of mental disorders* (4th ed). Arlington, VA: Author.

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed). Washington, DC: Author.

Bell, J. B., & Nye, E. C. (2007). Specific symptoms predict suicidal ideation in Vietnam combat veterans with chronic post-traumatic stress disorder. *Military Medicine, 172*(11), 1144-1147.

Blevins, C. A., Weathers, F. W., Davis, M. T., Witte, T. K., & Domino, J. L. (2015). The Posttraumatic Stress Disorder Checklist for DSM-5 (PCL-5): Development and Initial Psychometric Evaluation. *Journal of Traumatic Stress, 28*, 489-498.

Blevins, C. A., Weathers, F. W., & Witte, T. K. (2014). Dissociation and posttraumatic stress disorder: A latent profile analysis. *Journal of Traumatic Stress, 27*, 388-396.

Browne, A., & Finkelhor, D. (1986). Impact of child sexual abuse: A review of the research. *Psychological Bulletin, 99*(1), 66-77.

Bryant, R. A. (2012). Simplifying complex PTSD: Comment on Resick et al. (2012). *Journal of Traumatic Stress, 25*(3), 252-253.

Chandler, J., & Shapiro, D. (2016). Conducting clinical research using crowdsourced convenience samples. *Clinical Psychology, 12*(1), 53-81.

Clark, S. L., Muthén, B., Kaprio, J., D'Onofrio, B. M., Viken, R., & Rose, R. J. (2013). Models and strategies for factor mixture analysis: An example concerning the structure

underlying psychological disorders. *Structural Equation Modeling: A Multidisciplinary Journal, 20*, 681-703.

Cloitre, M. (2015). The "one size fits all" approach to trauma treatment: should we be satisfied?. *European Journal of Psychotraumatology, 6,* 1-8.

Cloitre, M., Courtois, C. A., Charuvastra, A., Carapezza, R., Stolbach, B. C., & Green, B. L. (2011). Treatment of complex PTSD: Results of the ISTSS expert clinician survey on best practices. *Journal of Traumatic Stress*, *24*, 615-627.

Cloitre, M., Garvert, D. W., Brewin, C. R., Bryant, R. A., & Maercker, A. (2013). Evidence for proposed ICD-11 PTSD and complex PTSD: A latent profile analysis. *European Journal of Psychotraumatology, 4*.

Cloitre, M., Garvert, D. W., Weiss, B., Carlson, E. B., & Bryant, R. A. (2014). Distinguishing PTSD, Complex PTSD, and Borderline Personality Disorder: A latent class analysis. *European Journal of Psychotraumatology, 5*.

Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology*, *78*, 98-104.

Courtois, C. A. (2004). Complex trauma, complex reactions: Assessment and treatment. *Psychotherapy: Theory, Research, Practice, Training*, *41*, 412-425.

Elklit, A., Hyland, P., & Shevlin, M. (2014). Evidence of symptom profiles consistent with posttraumatic stress disorder and complex posttraumatic stress disorder in different trauma samples. *European Journal of Psychotraumatology, 5*.

Enders, C. K. (2010). *Applied missing data analysis*. New York: Guilford Press.

Feitosa, J., Joseph, D. L., & Newman, D. A. (2015). Crowdsourcing and personality measurement equivalence: A warning about countries whose primary language is not English. *Personality and Individual Differences, 75*, 47-52.

Ford, J. D. (1999). Disorders of extreme stress following war-zone military trauma: Associated features of posttraumatic stress disorder or comorbid but distinct syndromes? *Journal of Consulting and Clinical Psychology*, *67*(1), 3-12.

Friedman, M. J., Resick, P. A., & Keane, T. M. (2014). PTSD from DSM-III to DSM-5: Progress and challenges. In M. J. Friedman, T. M. Keane, P. A. Resick, M. J. Friedman, T. M. Keane, P. A. Resick (Eds.), *Handbook of PTSD: Science and practice* (*2nd ed.*) (pp. 3-20). New York: Guilford Press.

Ghaffarzadegan, N., Ebrahimvandi, A., & Jalali, M. S. (2016). A Dynamic Model of Post-Traumatic Stress Disorder for Military Personnel and Veterans. *PloS One, 11*(10), e0161405.

Gray, M. J., Litz, B. T., Hsu, J. L., & Lombardo, T. W. (2004). Psychometric properties of the life events checklist. *Assessment, 11*(4), 330-341.

Gunderson, J. G., & Sabo, A. N. (1993). The phenomenological and conceptual interface between borderline personality disorder and PTSD. *The American Journal of Psychiatry, 150*(1), 19-27.

Herman, J. L. (1992a). *Trauma and Recovery*. New York: Basic Books.

Herman, J. L. (1992b). Complex PTSD: A syndrome in survivors of prolonged and repeated trauma. *Journal of Traumatic Stress, 5*, 377-391.

Herman, J. (2012). CPTSD is a distinct entity: Comment on Resick et al. (2012). *Journal of Traumatic Stress*, 25, 256-257.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55.

Karatzias, T., Shevlin, M., Fyvie, C., Hyland, P., Efthymiadou, E., Wilson, D., ... & Cloitre, M. (2016). An initial psychometric assessment of an ICD-11 based measure of PTSD and complex PTSD (ICD-TQ): Evidence of construct validity. *Journal of Anxiety Disorders, 44*, 73-79.

Kessler, R. C., Berglund, P., Demler, O., Jin, R., Merikangas, K. R., & Walters, E. E. (2005). Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. *Archives of General Psychiatry, 62*, 593-602.

Kessler, R. C., Sonnega, A., Bromet, E., Hughes, M., & Nelson, C. B. (1995). Posttraumatic stress disorder in the National Comorbidity Survey. *Archives of General Psychiatry, 52*, 1048-1060.

Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling*., 3rd ed. New York, NY, US: Guilford Press.

Knefel, M., Garvert, D. W., Cloitre, M., & Lueger-Schuster, B. (2015). Update to an evaluation of *ICD-11* PTSD and complex PTSD criteria in a sample of adult survivors of childhood institutional abuse by Knefel & Lueger-Schuster (2013): A latent profile analysis. *European Journal of Psychotraumatology, 6*.

Landy, M. H., Wagner, A. C., Brown-Bowers, A., & Monson, C. M. (2015). Examining the evidence for complex posttraumatic stress disorder as a clinical diagnosis. *Journal of Aggression, Maltreatment & Trauma, 24*(3), 215-236. doi:10.1080/10926771.2015.1002649

Lo, Y., Mendell, N., & Rubin, D. (2001). Testing the number of components in a normal

    mixture. *Biometrika, 88*, 767-778.

Löwe, B., Wahl, I., Rose, M., Spitzer, C., Glaesmer, H., Wingenfeld, K., … Brähler, E. (2010).

    A 4-item measure of depression and anxiety: Validation and standardization of the

    Patient Health Questionnaire-4 (PHQ-4) in the general population. *Journal of Affective*

    Disorders, 122(1), 86–95.

Lubke, G. H., & Muthén, B. (2005). Investigating population heterogeneity with factor mixture

    models. *Psychological Methods, 10*(1), 21-39.

McLachlan, G., & Peel, D. (2000). *Finite Mixture Models* (1st ed.). New York: Wiley.

Maercker, A., Brewin, C. R., Bryant, R. A., Cloitre, M., Reed, G. M., van Ommeren, M., & ...

    Saxena, S. (2013). Proposals for mental disorders specifically associated with stress in

    the International Classification of Diseases-11. *The Lancet*, *381*, 1683-1685.

Masyn, K. (2013). Latent class analysis and finite mixture modeling. *The Oxford Handbook of*

    Quantitative Methods in Psychology, *2*, 551-611.

Masyn, K. E., Henderson, C. E., & Greenbaum, P. E. (2010). Exploring the latent structures of

    psychological constructs in social development using the dimensional–categorical

    spectrum. *Social Development, 19*, 470-493.

Muthén, L. K., & Muthén, B. O. (1998-2015). *Mplus User's Guide*. Seventh Edition.

    Los Angeles, CA: Muthén & Muthén.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in

    latent class analysis and growth mixture modeling: A Monte Carlo simulation

    study. *Structural Equation Modeling*, *14*, 535-569.

Pagura, J., Stein, M. B., Bolton, J. M., Cox, B. J., Grant, B., & Sareen, J. (2010). Comorbidity of borderline personality disorder and posttraumatic stress disorder in the US population. *Journal of Psychiatric Research, 44*(16), 1190-1198.

Panagioti, M., Gooding, P. A., Taylor, P. J., & Tarrier, N. (2014). Perceived social support buffers the impact of PTSD symptoms on suicidal behavior: Implications into suicide resilience research. *Comprehensive Psychiatry, 55*(1), 104-112.

Pelcovitz, D., van der Kolk, B., Roth, S., Mandel, F., Kaplan, S., & Resick, P. (1997). Development of a criteria set and a structured interview for disorders of extreme stress (SIDES). *Journal of Traumatic Stress*, *10*(1), 3-16.

Perkonigg, A., Höfler, M., Cloitre, M., Wittchen, H.-U., Trautmann, S., & Maercker, A. (2015). Evidence for two different ICD-11 posttraumatic stress disorders in a community sample of adolescents and young adults. *European Archives of Psychiatry and Clinical Neuroscience*, 1-12. http://dx.doi.org/10.1007/s00406-01500639-4

Pincus, H. A., Frances, A., Davis, W. W., First, M. B., & Widiger, T. A. (1992). DSM-IV and new diagnostic categories: holding the line on proliferation. *American Journal of Psychiatry, 149*(1), 112-117.

Post, L. M., Zoellner, L. A., Youngstrom, E., & Feeny, N. C. (2011). Understanding the relationship between co-occurring PTSD and MDD: Symptom severity and affect. *Journal of Anxiety Disorders*, *25*, 1123-1130.

Reed, G. M. (2010). Toward *ICD-11*: Improving the clinical utility of WHO's International Classification of mental disorders. *Professional Psychology: Research and Practice, 41*, 457.

Resick, P. A., Bovin, M. J., Calloway, A. L., Dick, A. M., King, M. W., Mitchell, K. S., et al.

(2012). A critical evaluation of the complex PTSD literature: Implications for DSM-5. *Journal of Traumatic Stress, 25*, 241-251.

Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton, NJ: Princeton University Press.

Rosenberg, M. (1979). *Conceiving the self*. New York: Basic Books.

Schmitt, D. P., & Allik, J. (2005). Simultaneous administration of the Rosenberg Self-Esteem Scale in 53 nations: exploring the universal and culture-specific features of global self-esteem. Journal of Personality and Social Psychology, 89(4), 623-642.

Sinclair, S. J., Blais, M. A., Gansler, D. A., Sandberg, E., Bistis, K., & LoCicero, A. (2010). Psychometric properties of the Rosenberg Self-Esteem Scale: Overall and across demographic groups living within the United States. *Evaluation & the Health Professions, 33*(1), 56-80.

Tuscic, S. J., Flander, G. B., & Mateskovic, D. (2012). The Consequences of childhood abuse. *Paediatrics Today, 9*(1), 24-35.

Van der Kolk, B. A., McFarlane, A. C., & Weisaeth, L. (1996). *Traumatic stress*. New York: Guilford.

van der Kolk, B. A., Pelcovitz, D., Roth, S., & Mandel, F. S. (1996). Dissociation, somatization, and affect dysregulation: The complexity of adaption to trauma. *The American Journal of Psychiatry*, *153*(Suppl), 83-93.

Van Orden, K. A., Cukrowicz, K. C., Witte, T. K., & Joiner Jr, T. E. (2012). Thwarted belongingness and perceived burdensomeness: construct validity and psychometric properties of the Interpersonal Needs Questionnaire. *Psychological Assessment, 24*(1), 197-215.

Vermetten, E., & Spiegel, D. (2014). Trauma and dissociation: implications for borderline personality disorder. *Current Psychiatry Reports, 16*(2), 1-10.

Weathers, F.W., Blake, D.D., Schnurr, P.P., Kaloupek, D.G., Marx, B.P., & Keane, T.M. (2013). *The Life Events Checklist for DSM-5 (LEC-5).* Instrument available from the National Center for PTSD at www.ptsd.va.gov

Weathers, F. W., Litz, B. T., Keane, T. M., Palmieri, P. A., Marx, B. P., & Schnurr, P.P. (2013). *The PTSD Checklist for DSM-5 (PCL-5).* Instrument available from the National Center for PTSD at www.ptsd.va.gov

Wolf, E. J., Lunney, C. A., Miller, M. W., Resick, P. A., Friedman, M. J., & Schnurr, P. P. (2012). The dissociative subtype of PTSD: A replication and extension. *Depression and Anxiety, 29*(8), 679-688. doi:10.1002/da.21946

Wolf, E. J., Miller, M. W., Kilpatrick, D., Resnick, H. S., Badour, C. L., Marx, B. P., ... & Friedman, M. J. (2015). *ICD–11* complex PTSD in US national and veteran samples prevalence and structural associations with PTSD. *Clinical Psychological Science, 3*, 215-229.

Table 1

Fit indices for the LPA and CFA models

Model	log likelihood	BIC	LMR-A *p*-value	BLRT *p*-value	Entropy	$\chi^2(df)$	RMSEA [90% CI]	CFI	TLI	SRMR
CFA: 1-factor	-2399	4903				231.28** (9)	.27 [.24, .30]	.69	.48	.12
CFA: 2-factor	**-2298**	**4712**				**16.79* (7)**	**.06 [.02, .10]**	**.99**	**.97**	**.03**
LPA: 1-class	-2727	5524								
LPA: 2-class	-2414	4939	<.001	<.001	.88					
LPA: 3-class	-2322	4796	.01	<.001	.89					
LPA: 4-class	**-2284**	**4761**	**.17**	**<.001**	**.86**					
LPA: 5-class	-2244	4722	.38	<.001	.88					

Note. Bolded text indicates the best-fitting dimensional or categorical model used for establishing the upper limits for FMM model building, and for overall best-fitting model comparisons. BIC = Bayesian information criterion; BLRT = bootstrapped likelihood ratio test; CFA = confirmatory factor analysis; CFI = comparative fit index; CI = confidence interval; FMM = factor mixture modeling; LMR-A = Lo-Mendell-Rubin adjusted likelihood ratio test; LPA = latent profile analysis; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

*p < .05. **p < .001

Table 2

Fit indices for the FMM models, by variant

Model	log likelihood	BIC	LMR-A p-value	BLRT p-value	Entropy
FMM-1: 1-factor/2-class[a]	-2414	4979	0.24	<.001	0.88
FMM-1: 1-factor/3-class[a]	-2322	4843	0.24	<.001[a]	0.89
FMM-1: 1-factor/4-class[a]	-2284	4814	0.18	<.001	0.86
FMM-1: 2-factor/2-class[a]	-2414	4979	<.001	<.001	0.88
FMM-1: 2-factor/3-class[a]	-2322	4849	0.20	<.001[a]	0.89
FMM-1: 2-factor/4-class[a]	-2284	4826	0.18	<.001[a]	0.86
FMM-2: 1-factor/2-class[a]	-2266	4691	0.08	<.001	0.88
FMM-2: 1-factor/3-class[a]	-2224	4658	0.05	<.001	0.89
FMM-2: 1-factor/4-class[a]	-2224	4711	0.24[a]	1[a]	0.91
FMM-2: 2-factor/2-class[a]	-2230	4647	<.01	<.001	0.88
FMM-2: 2-factor/3-class[a]	-2230	4717	0.16[a]	1[a]	0.92
FMM-2: 2-factor/4-class[a]	-2194	4715	0.24	<.001[a]	0.91
FMM-3: 1-factor/2-class	-2313	4772	0.02	<.001	0.72
FMM-3: 1-factor/3-class	-2225	4638	0.07	<.001	0.89
FMM-3: 1-factor/4-class	-2189	4606	0.24	<.001	0.88
FMM-3: 2-factor/2-class	-2230	4624	<.001	<.001	0.88
FMM-3: 2-factor/3-class	**-2196**	**4602**	**0.05**	**<.001**	**0.88**
FMM-3: 2-factor/4-class	-2159	4575	0.06	<.001	0.85
FMM-4: 1-factor/2-class	-2258	4698	<.01	<.001	0.89
FMM-4: 1-factor/3-class	—[c]				
FMM-4: 1-factor/4-class	—[c]				
FMM-4: 2-factor/2-class	—[c]				
FMM-4: 2-factor/3-class	—[c]				
FMM-4: 2-factor/4-class	—[c]				

Note. Bolded text indicates both the best-fitting hybrid model, as well as the overall best-fitting model when compared to the dimensional and categorical models. BIC = Bayesian information criterion; BLRT = bootstrapped likelihood ratio test; FMM = factor mixture modeling; LMR-A = Lo-Mendell-Rubin adjusted likelihood ratio test.

[a] Parameters automatically fixed to avoid a singularity of the information matrix caused by either model nonidentification or the presence of empty cells in the joint distributions for the categorical variables.

[b] The best log likelihood value for the overall model, the LMR-A *p*-value, or the BLRT *p*-value was not replicated, despite adjusting the random starts.
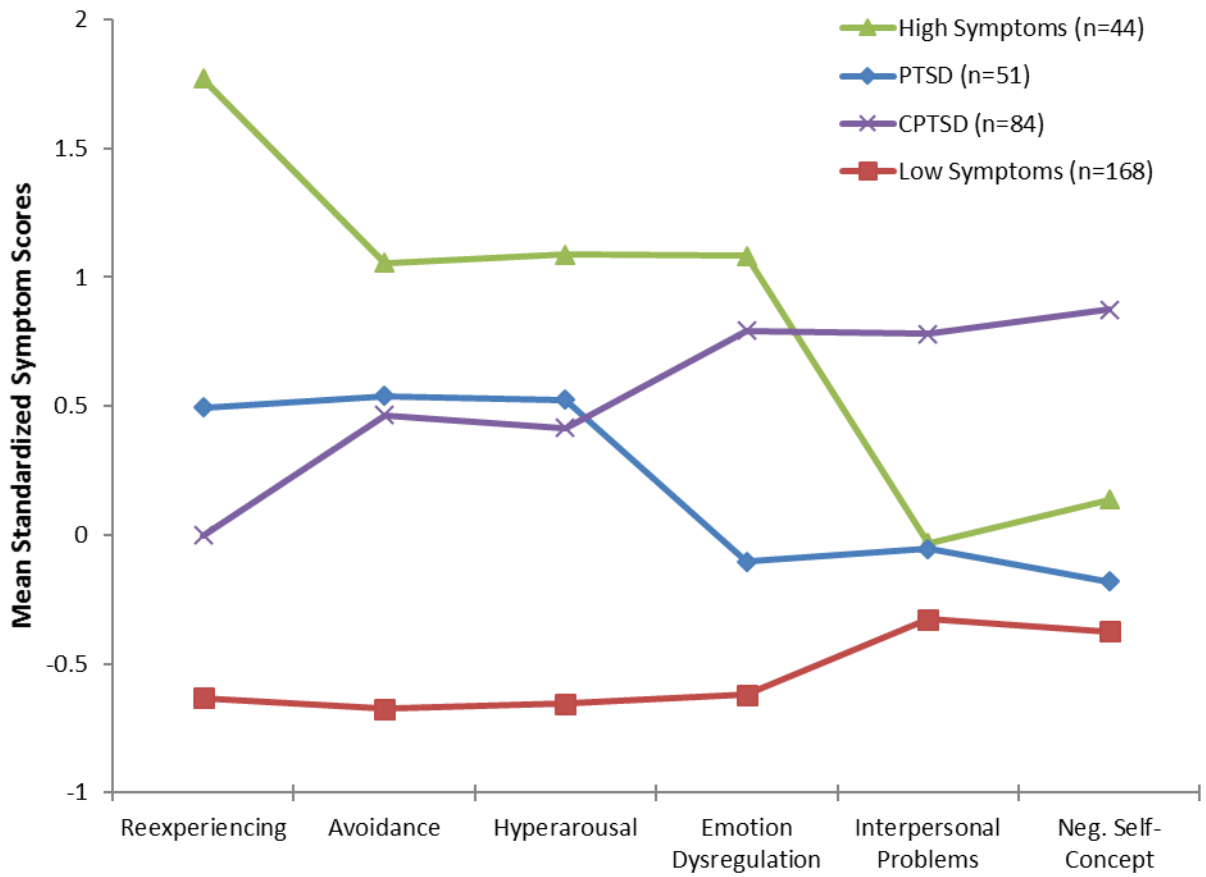
[c] Overall model failed to converge.

Figure 1. Mean standardized symptom scores, organized by class, from the best-fitting, four-class solution for the latent profile analysis.
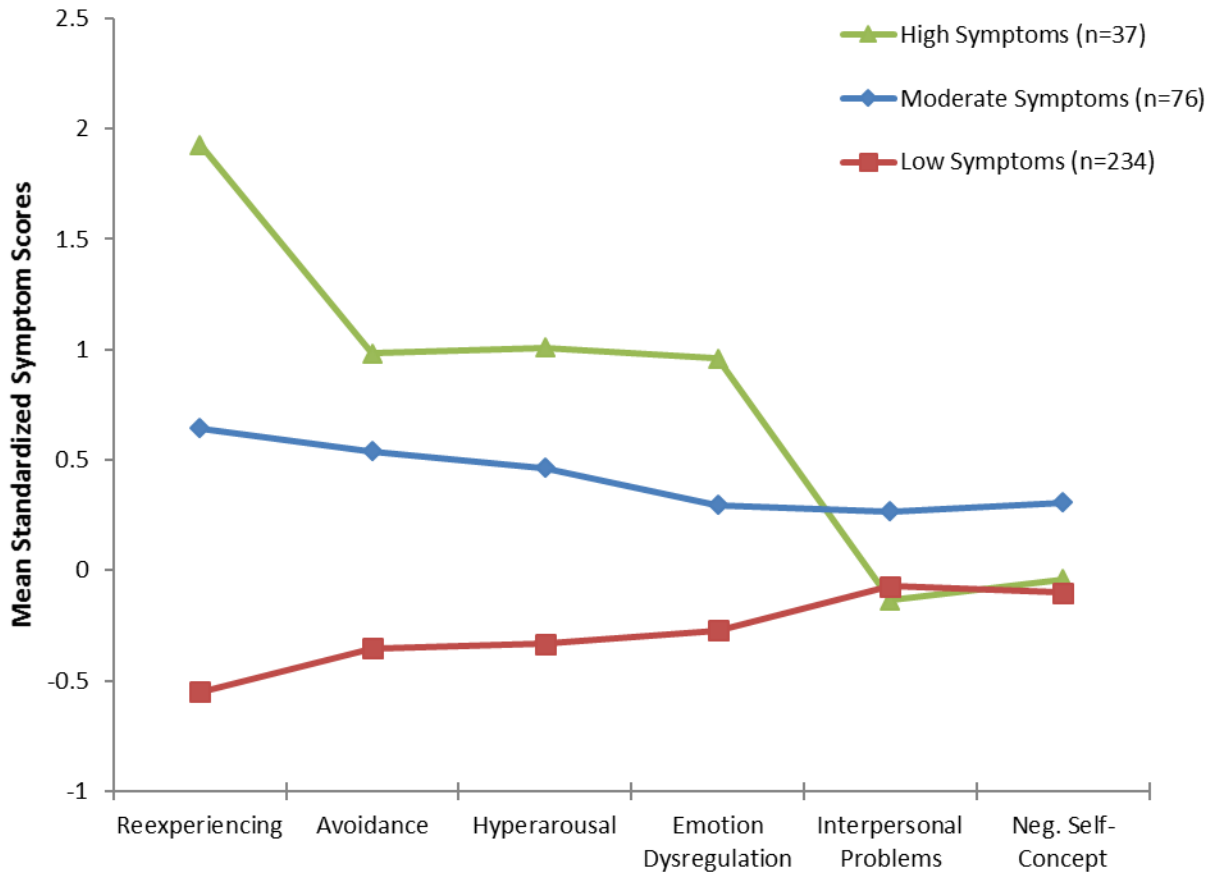
Figure 2. Mean standardized symptom scores, organized by class, from the best-fitting, two-factor/three-class solution for the factor mixture model.