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Evaluating the Dimensionality of PTSD in a Sample of OIF/OEF Veterans

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Both categorical and dimensional models of mental disorders, including posttraumatic stress disorder (PTSD), are useful for diagnostic and heuristic purposes; however, few empirical studies have compared categorical and dimensional models of PTSD side-by-side or compared these models to a hybrid (dimensional and categorical) model. In the present study, the dimensionality of PTSD was examined by fitting latent profile analytic, confirmatory factor analytic, and factor mixture models in 271 Operation Iraqi Freedom/Operation Enduring Freedom veterans 6 months after return from deployment. Latent profile analysis was used to identify subgroups of individuals with similar PTSD symptom profiles and predictors of subgroup membership, confirmatory factor analysis was used to identify the underlying continuous structure of PTSD in this sample, and factor mixture modeling was used to test whether a hybrid categorical and continuous model of PTSD best fit our sample. A factor mixture model consisting of a 4-factor dysphoria model of PTSD with 2 classes characterized by low and moderate symptom severity was the best-fitting model. Dissociation and deployment concerns emerged as significant predictors of membership in the moderate symptoms class. Implications for PTSD diagnostic conceptualization and treatment planning are discussed.

Keywords: PTSD, veterans, latent profile analysis, confirmatory factor analysis, factor mixture model

Both categorical and dimensional models of mental disorders, including posttraumatic stress disorder (PTSD), are useful for diagnostic and heuristic purposes; however, few empirical studies have compared categorical and dimensional models of PTSD side-by-side or compared these models to a hybrid (dimensional and categorical) model. A categorical model of PTSD posits that distinct *categories* of people with and without PTSD can be identified, whereas a continuous model posits that PTSD symptoms are experienced on a severity gradient or continuum. The current model of PTSD in the *Diagnostic and Statistical Manual of Mental Disorders* (*DSM*)-5 is a categorical model (APA, 2013), although quantitative empirical approaches point to the robustness of dimensional models of PTSD (e.g., Armour & Shevlin, 2010). Though empirical evidence supports continuous models of PTSD, researchers and clinicians still need to make categorical decisions: for instance, identifying cut-points for clinically significant PTSD. Thus, a hybrid model may optimally reflect the true nature of PTSD while also permitting categorization.

Prior to the use of hybrid modeling methods, both dimensional and categorical models of PTSD have been tested. A number of researchers have utilized confirmatory factor analysis (CFA) to evaluate dimensionality of PTSD symptoms and to compare fit relative to the three-factor model of PTSD included in the *DSM–IV–TR* (APA, 2000). Although varying numbers of factors have been identified, two four-factor models have garnered the most empirical support and generally provide a better fit to the data than the three-factor model employed in *DSM–IV–TR* (Elhai & Palmieri, 2011). Briefly, the emotional numbing model (King, Leskin, King, & Weathers, 1998) distinguishes avoidance from emotional numbing symptoms; the remaining PTSD symptom clusters are consistent with *DSM–IV* (i.e., reexperiencing: B1-B5, effortful avoidance: C1-C2, emotional numbing: C3-C7, and hyperarousal: D1-D5). The dysphoria model (Simms, Watson, & Doebbelling, 2002) goes a step further by also refiguring emotional numbing and three of the *DSM–IV–TR* hyperarousal symptoms as a dysphoria factor (i.e., intrusions: B1-B5, avoidance: C1-C2, dysphoria: C3-C7, D1-D3, and hyperarousal: D4-D5). Although neither four-factor model has emerged as clearly superior, the dysphoria

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model has slightly more support than the numbing model (Elhai & Palmieri, 2011; Yufik & Simms, 2010).

Categorical models of PTSD have been explored using latent class analysis and latent profile analysis. Latent class analysis and latent profile analysis (LPA) are statistical approaches that identify homogenous and distinctive subgroups of similar individuals within a sample (Collins & Lanza, 2010). The application of these techniques to PTSD is still relatively new, and the number of classes found varies by study and sample. Four studies have examined latent classes of PTSD cross-sectionally in a variety of samples, and findings generally converge on a large resilient/low-symptomatic class, a small chronic/high-symptomatic class, and one or more moderately symptomatic classes (e.g., Breslau, Reboussin, Anthony, & Storr, 2005; Maguen et al., 2013; Nugent, Koenen, & Bradley, 2012; Steenkamp et al., 2012). Partially because of methodological differences, there is little consensus about the specific number of PTSD classes. Furthermore, these models are based on the premise that individuals can be classified into (some number of) distinct groups on the basis of PTSD symptomatology; yet, as previously noted, there is also robust evidence supporting the dimensional nature of PTSD (Broman-Fulks et al., 2006; Forbes, Haslam, Williams, & Creamer, 2005; Ruscio, Ruscio, & Keane, 2002).

Categorical questions about a dimensional phenomenon such as PTSD can be addressed by using a hybrid analytic approach, called *factor mixture modeling* (FMM; Lubke & Muthén, 2005; Muthén, 2006). Factor mixture modeling combines categorical latent variables—*classes*, such as those computed in latent class/profile analysis in order to explore groups of individuals—with continuous latent variables—*factors,* such as in CFA in order to explore variation around mean factor scores. Using these combined methods, the dimensionality of PTSD symptoms can be explored within factors and between individuals. Using this approach to study PTSD symptoms in a sample of Canadian treatment seeking veterans, Naifeh and colleagues (2010) found a four-factor model of PTSD with two classes of more and less symptomatic veterans provided the best fit. In addition, the dysphoria model provided marginally better fit for this sample; although the numbing model also adequately fit. Factor mixture modeling was also used in a convenience sample of trauma-exposed medical patients (Elhai, Naifeh, Forbes, Ractliffe, & Tamburrino, 2011). A four-factor model of PTSD with three classes provided the best fit; the factor model was analogous to the dysphoria model, whereas the three classes corresponded to significantly different groups of PTSD symptom severity. Additional research in other samples is warranted to further evaluate the nature of PTSD symptoms.

Researchers have also investigated variables that predict membership in classes of PTSD symptom patterns. For instance, high symptom classes have been associated with increased peritraumatic dissociation (Steenkamp et al., 2012). Also, in military personnel, predeployment emotional problems and traumas, particularly those in childhood, have been shown to predict nonresilient trajectories (Dickstein et al., 2010) as have high levels of combat (e.g., Bonanno et al., 2012; Dickstein et al., 2010). Other factors, such as deployment concerns (i.e., fear for one's safety and well-being in the war zone; King, King, Gudanowski, & Vreven, 1995), and (lack of) postdeployment social support, have not been examined as predictors of class membership despite their associations with PTSD (Iversen et al., 2008; King et al., 1995; King, King, Vogt, Knight, & Samper, 2006).

Although previous investigations of dimensional and categorical PTSD symptom patterns have been illuminating, this body of research has notable limitations. First, few studies have directly compared dimensional and categorical models of PTSD. Second, studies of dimensional models of PTSD have not evaluated relevant covariates which would aide in discrimination of PTSD symptom patterns. Finally, previous studies of categorical models of PTSD (e.g., Breslau et al., 2005) often use *yes/no* indicators of PTSD symptoms, restricting the range of symptom severity and limiting interpretation of findings to probability of symptom endorsement.

In the present study, we examine the dimensionality of PTSD using categorical, dimensional, and hybrid latent variable models (Muthén, 2006). Specifically, we apply latent profile analysis, factor analysis, and factor mixture models to a sample of Operation Iraqi Freedom/Operation Enduring Freedom (OIF/OEF) veterans. Factor mixture model research has been called for in order to explore the categorical and dimensional structure of PTSD (Elhai & Palmieri, 2011). Given research demonstrating that subthreshold PTSD symptoms are associated with high levels of impairment (Breslau, Lucia, & Davis, 2004), we included veterans with varying severity of PTSD symptoms. We were interested in how the rates of probable PTSD in the sample would change with different methods of identifying symptomatic individuals (e.g., LPA, FMM). Finally, we examined whether common predictors of PTSD predict membership in latent classes.

We hypothesized that at least three classes of PTSD symptoms will be identified using LPA: subgroups of PTSD symptom patterns reflecting low, intermediate, and high PTSD symptoms. We also predicted that a four-factor dysphoria model of PTSD would best fit our sample. Given the paucity of studies examining the dimensionality of PTSD using FMM, we considered these analyses exploratory. We hypothesized that covariates (i.e., dissociation, total number of life traumas, deployment concerns, total number of combat experiences, and total number of adverse childhood events) would predict membership in more severe PTSD symptom classes and social support would predict membership in the resilient class.

Method

Participants

The sample included 271 OIF/OEF veterans who registered for VA health care subsequent to return from deployment. Fewer than half had used any VA services at the time of recruitment into the study and, as requested by the local Institutional Review Board, veterans receiving VA mental health services at the study's inception were excluded from recruitment. Thus, this was a nonclinical sample. The evaluation took place approximately 6 months following their return. In adherence to the Declaration of Helsinki, all participants provided written informed consent prior to participating. The study protocol was approved by local Institutional Review Boards.

Of the sample, nine had data missing on all variables and were excluded from subsequent analyses, thus $N = 262$. The remaining veteran participants were largely male (84.9%) and ranged in age from 19 to 58 years ($M = 31.03$, $SD = 9.29$). Some participants (28.4%) did not provide data on their race/ethnicity; the remainder was primarily White (67.5% of total). Approximately half (48.1%) of participants described themselves as single/never married, 43.5% were married, and 8% were divorced. Almost all participants (96.57%) had a high school diploma or equivalent. Regarding the most recent deployment, 33.6% reported mainly combat duties, 47.7% reported mainly combat support, and 18.7% reported noncombat-related duty. The majority of participants (54.4%) were in the National Guard on the most recent deployment, 23.4% were reservists, and 22.2% were full-time active-duty status. Forty-four percent served in the Army. The Navy, Air Force, and Marines each accounted for about 5% of participants.

Measures

Deployment risk and resilience. The *Deployment Risk and Resilience Inventory* (King et al., 2006) consists of a series of self-report scales assessing predeployment, deployment, and postdeployment factors that have been linked to veteran physical and mental health outcomes. The present study used three of the scales. The Predeployment Life Events Scale consists of 15 *yes/no* items evaluating predeployment exposure to highly stressful or traumatic events (e.g., sexual abuse). The Combat Experiences Scale is a *yes/no* scale that assesses exposure to a variety of combat experiences, such as firing a weapon at the enemy or participating in missions. The Deployment Concerns Scale assesses perceived threat and concern about safety, with items such as "I thought I would never survive," answered on a 5-point Likert-type scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Finally, using the same Likert-type scale, the Postdeployment Social Support Scale evaluates the extent to which the respondent feels understood and able to rely on others for support when needed. Internal consistency reliability in the present study was as follows: Predeployment Life Events (Cronbach's α = .70), Combat Experiences (Cronbach's α = .86), Deployment Concerns (Cronbach's α = .74), and Postdeployment Social Support (Cronbach's α = .81).

PTSD. Symptoms of PTSD were assessed with the *PTSD Symptom Checklist—Civilian* version (PCL-C; Weathers, Litz, Huska, & Keane, 1994), a 17-item self-report scale that assesses PTSD symptoms based on *DSM–IV* criteria. Participants are asked to rate how much they have been bothered by each symptom in the last month using a five-point scale, ranging from 1 (*not at all*) to 5 (*extremely*). The total score, which ranges from 17 to 85, provides an index of current PTSD symptom severity. Although a total score of 50 is typically considered the diagnostic cut-off for PTSD in treatment-seeking samples (Weathers, Litz, Herman, Huska, & Keane, 1993), research has demonstrated that a total score 34 or greater is considered the diagnostically efficient cut-off for PTSD in non-treatment-seeking veterans (Bliese et al., 2008). In the present study, 46.9% of participants met or exceeded that threshold (internal consistency: Cronbach's α = .94). Approximately 3%–4% of cases (n = 9–12) were missing on each PCL variable.

Peritraumatic dissociation. The Peritraumatic Dissociative Experiences Questionnaire—Self-Report version (Birmes et al., 2005) is a 10-item scale assessing dissociative experiences during trauma exposure. Items are scored on a 5-point Likert-type scale ranging from 1 (*not at all true*) to (*extremely true*); internal consistency: Cronbach's α = .89.

Data Analysis Plan

LPA was used to identify subgroups of individuals with similar PTSD symptom patterns. LPA is a finite mixture modeling technique, wherein the population is assumed to be composed of "mixtures" of multiple subpopulation distributions (Collins & Lanza, 2010). Similarity between individuals within a population is due to membership in the same latent class, or subpopulation. Latent profile analyses were conducted with a recently developed three-step procedure that incorporates information about classification uncertainty and the impact of covariates on class membership into the assignment of individuals into classes (Asparouhov & Muthén, 2013). The three-step analytic method assessed whether total number of predeployment life experiences, total number of combat experiences, total number of deployment concerns, total number of life events, postdeployment social support, or peritraumatic dissociation significantly predicted class membership.

Factor analysis is well-established method for exploring the dimensionality of a construct. Two different four-factor models of PTSD, the emotional numbing model (King et al., 1998) and the dysphoria model (Simms et al., 2002) are well-studied alternatives to the three-factor model. In both the dysphoria and emotional numbing models, the third factor was scaled using the "loss of interest," rather than the "trauma-related amnesia" item because previous studies have found the amnesia item to a poor indicator of PTSD (e.g., Naifeh et al., 2010). Adequately fitting models were identified by using commonly referenced fit criteria (e.g., Comparative Fit Index [CFI] $\geq$ .95, root mean square error of approximation [RMSEA] $\leq$ .08; Hu & Bentler, 1999).

Factor mixture modeling is a hybrid modeling strategy that uses both categorical and continuous latent variables to model the dimensionality of a construct (Muthén, 2006). The factor mixture model adds a dimensional factor to the classes in the LPA model, thus allowing for the exploration of within-class variability. Conceptually, this within-class variability is considered to be the product of a common source of variance (e.g., severity of PTSD symptom). The FMM has class-varying intercepts and factor variances and class-invariant factor loadings. Muthén (2006) suggested this specification to test how individuals group together (rather than for examining a single dimension for the entire sample). In FMM, each class inhabits a separate dimensional space and measures a unique manifestation of the construct (Muthén, 2006).

The best latent profile model and factor mixture model was identified using theoretical and statistical guidelines. The final models were chosen on the basis of conceptual justification, parsimony, and coherence (Kuhn, 1977; Meehl, 1967). The meaningfulness of these models also depends on whether we can predict who is in each class and whether class membership predicts other important outcomes (Muthén, 2004). We consulted the following statistical indices: Bayesian information criteria (BIC; Henson, Reise, & Kim, 2007), entropy, and bootstrapped likelihood ratio test (BLRT; Nylund et al., 2007). The BIC (Kass & Raftery, 1995) is the fit index most often reported in LPA/FMM studies. The BIC is calculated by the formula: BIC $= -2 \times \text{Log}(L) + p \times \ln(n)$. L is the log likelihood, p is the number of free parameters in the model, and n is the sample size (Nylund et al., 2007). We report the BIC because simulation studies have found it to be the most accurate criterion fit index (Nylund et al., 2007). A difference of 10 or more BIC points between a k–1 and k–class model suggests that the additional class meaningfully improves model fit (Raftery, 1995). Because simulation studies have demonstrated sampling variability in the BIC (Preacher & Merkle, 2012), additional fit indices were consulted to provide converging evidence for the best class solution. The BLRT evaluates whether a *k*– class solution fits significantly better than a *k*–1 class model, and provides a *p* value assessing whether the *k*–class model fits significantly better. Entropy indexes the classification accuracy of the classes, essentially describing the likelihood that an individual was classified into the correct class. Entropy values range from 0 to 1, with higher values indicating more accurate classification of individuals into classes.

The best-fitting overall model among FA, LPA, and FMM was chosen with regard to parsimony, theoretical justification, and statistical fit indices. All analyses were conducted with the statistical software package Mplus (Version 7.11). Models with 1 to 5 classes were run, exhausting the likeliest potential number of classes. The power of the CFA was assessed using Statistica software package (StatSoft, Plano, TX); the power to detect a RMSEA value of .08 with a sample size of 262 and 57 degrees of freedom (α = .05) was .9175. Although power is traditionally defined as the ability to correctly reject a false null hypothesis, latent class models do not have a "null model" per se to reject. Instead, simulation studies of power calculations for latent class models (e.g., Nylund, Asparohouv, Muthén, 2007; Tein, Coxe, & Cham, 2013) focus on the ability to identify the "correct" model and detect significant differences between classes. To date, no guidelines for sample size requirements or power calculations for factor mixture modeling has been widely disseminated. Our sample size is comparable to previously published studies of latent profile analysis (Maguen et al., 2013; Steenkamp et al., 2012) and factor mixture models (Elhai et al., 2011).

Results

Latent Profile Analysis

First, a single-class model without predictors was run to assess the presence of significant variability around the PCL item scores. Significant variability ($p < .01$) was found around the mean and variance for all PCL items in the sample and provided justification for assessing for relevant subgroups. Profiles of PTSD criteria were explored using LPA with increasing numbers of classes. Table 1 shows model fit as evidenced by the maximum log-likelihood, BIC, and the BLRT. The four-class model was chosen as the best-fitting model for the sample because it had theoretical justification, was parsimonious, and explained the sample with conceptual clarity. The four-class model had the lowest BIC value, a significant BLRT *p* value, and the largest log-likelihood. Individuals were well-classified as demonstrated by the high entropy score.

Individuals were classified into a *resilient* class (55%, n = 145), a *dysphoric* class (14%, n = 37), a *reexperiencing/hyperarousal* class (19%, n = 50), and a *PTSD* class (11%, n = 30). The average PCL score of the PTSD class was 65.7 (SD = 6.7), which is above the cut-off for probable PTSD in a sample for nontreatment-seeking veterans (Bliese et al., 2008). These findings converge with prior research and empirically based expectations to find three classes of individuals with varying severity of PTSD symptoms; the additional fourth class likely captures individuals with intermediate levels of PTSD symptoms that are primarily characterized by dysphoric symptoms (e.g., Simms et al., 2002). Only peritraumatic dissociation, deployment concerns, and postdeployment social support emerged as significant predictors of class membership; these were retained for factor mixture modeling analyses.[1]

Table 1
Fit Indices for Latent Profile Analysis (LPA), Confirmatory Factor Analysis (CFA), and Factor Mixture Model (FMM)

Model	Log likelihood	Number of parameters	ssBIC	BLRT *p*
LPA				
2c	−6,053.037	52	12,230.764	0.00
3c	−5,763.538	70	11,694.928	0.00
4c	−5,694.643	88	11,600.301	0.00
5c	Errors in model estimation; Class 5 was empty			
CFA				
4f, dysphoria	−5,593.249	57	11,323.179	
4f, numbing	−5,618.738	57	11,374.156	
FMM, dysphoria				
2c, 4f	−5,496.320	79	11,182.074	0.00
3c, 4f[a]	−5,431.744	101	11,105.675	0.00

Note. ssBIC = sample-size adjusted Bayesian Criteria Index; BLRT = bootstrapped likelihood ratio test; c = number of classes tested: f = number of factors tested.
[a] This model is not interpretable due to correlation greater than one between two latent variables (i.e., class).

Confirmatory Factor Analysis

CFAs were run to explore the best–fitting PTSD model to test in our sample (see Table 1 for fit statistics). Two four-factor PTSD models were tested in our sample—the dysphoria (Simms et al., 2002) and emotional numbing (King et al., 1998) models. Both the dysphoria and emotional numbing models provided adequate fit to our sample and had CFI and TLI values of >.9 and RMSEA values of ≤.08. The dysphoria model was chosen as the best-fitting model given its larger log-likelihood and sample-size adjusted Bayesian Criteria Index (ssBIC) value of 10+ points fewer than that of the emotional numbing model. The loadings are generally similar to one another between the two models, with the exception of PCL Item 14 (irritable/angry), Item 15 (difficulty concentrating), and Item 16 (overly alert). Because the four-factor dysphoria model was determined to best fit our data, this model was used in subsequent factor mixture model analyses.

Factor Mixture Model

The three-step method was used to compute the impact of covariates on model specification and class membership. The three predictors, which were significant in the LPA (e.g., deployment concerns, dissociation, and social support) were used in FMMs. Given the four profiles found in the latent profile analysis and the four-factor model identified in the factor analysis, follow-up factor mixture modeling was performed. Model fit statistics are displayed in Table 1.

A two-class, four-factor dysphoria model of PTSD was identified as the best-fitting FMM (see Figure 1). Models with more than two classes had factor correlations of greater than one in at least one of the classes and thus were not interpreted or reported. The first class (81%, n = 212) had low levels of symptom endorsement, as indicated by factor intercepts of <2 for all PTSD indi-

[1] Interested readers can contact Sheila Frankfurt for these results.

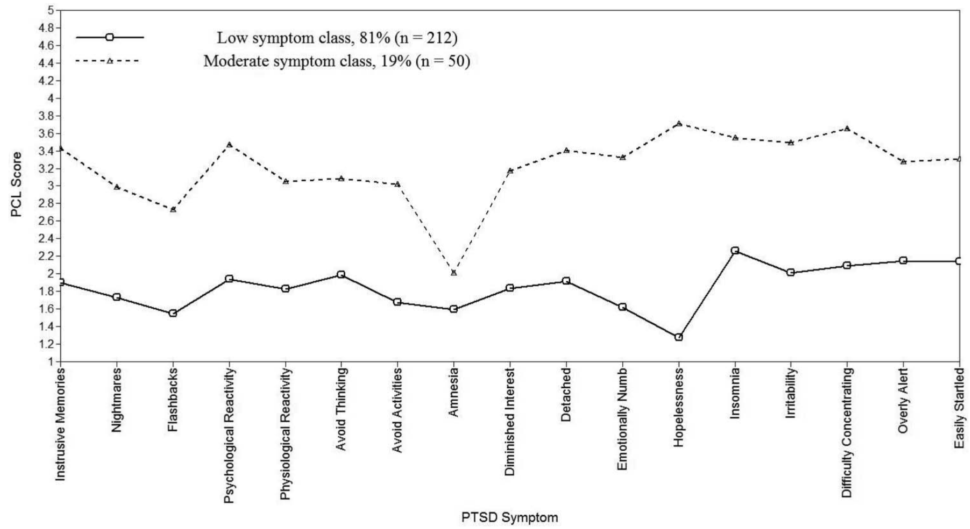

Figure 1. Best-fitting factor mixture model with two classes and four factors.

cators, excepting PCL13–17. These four items had intercepts between 2 and 3 and indicate marginally more impairment. These items correspond to a general malaise condition and two hyperarousal items. The second class (19%, $n = 50$) had moderate levels of symptom endorsement, as indicated by factor intercepts ≥ 3 for all items except for two. (These items, PCL3 and PCL8, had factor loadings of <3). The highest factor loadings (~ 3.5) included items that corresponded to a general malaise syndrome with prominent intrusive thoughts and emotional reliving. The average total PCL score in the second class was 54.7 ($SD = 13.7$), which is above the cut-off for probable PTSD in a nontreatment-seeking sample of veterans (Bliese et al., 2008). The largest difference in PCL scores between the two classes, and the only difference that was greater than two points, was on PCL12 (e.g., hopelessness or sense of foreshortened future), $t(57) = -21.77$, $p < .001$. To maximize power for the logistic regression, the low symptom class was used as the reference group because it is the largest. Deployment concerns ($B = .049$, $SE = .018$, $p < .01$) and dissociation ($B = .076$, $SE = .025$, $p < .01$) significantly predicted membership in the moderate versus low symptoms class, although they had a marginal effect. The average score on the measure of deployment concerns, $t(64) = -4.53$, $p < .001$, and on the measure of dissociation, $t(56) = -3.50$, $p < .001$, differed significantly between the two classes.

Comparing across the LPA, factor analytic, and FMM models, the four-factor, two-class dysphoria model of PTSD appeared to fit best (see Table 1). The FMM had the largest log-likelihood and the smallest BIC among the three models tested, indicating statistically preferential fit. In addition, this model was more parsimonious than is the LPA and thus had increased power for detecting the effect of covariates.

Discussion

We used LPA, CFA, and FMM to examine the dimensionality of PTSD symptoms in a group of OIF/OEF veterans postdeployment. Among all of the models tested, a factor mixture model consisting of two classes and four factors emerged as the best-fitting model. The four-factor model conformed to the dysphoria model of PTSD (intrusions, avoidance, dysphoria, hyperarousal; Simms et al., 2002), and the two classes were a low symptom class and a moderate symptom class. Our results are consistent with previous studies that used factor mixture modeling in veteran samples that also identified a two-class, four-factor model as the best fit (i.e., Naifeh, 2010). Our findings suggest that resilience is the norm response to trauma, and nonclinical veteran populations might display predominantly dysphoric presentation with few prominent reexperiencing symptoms. Findings that the dysphoria model of PTSD best fits our data is congruent with accumulating evidence that dysphoria might be a nonspecific factor of distress in PTSD (Armour & Shevlin, 2010). On average, our sample was characterized by low levels of PTSD severity, although a significant minority of participants had PCL scores at or above a diagnostic threshold. The difficulty that these veterans may experience postdeployment is picked up by the nonspecific components of this PTSD model.

Although the FMM fit our sample the best, pointing to a dimensional understanding of PTSD, both the LPA and total sample analyses provided interesting and potentially useful information. In our sample, the different methods of identifying individuals with probable PTSD (i.e., PCL cut-off score, LPA, FMM) resulted in different rates of probable PTSD prevalence. Using a PCL cut-off score of 34, which is recommended in nontreatment-seeking samples (Bliese et al., 2008), 44.6% of the sample would have been referred for additional mental health screening. Using a cut-off of 50 to identify probable PTSD (the cut-off used in mental health settings), about 15% of the sample would have been identified as "probable PTSD," which is in line with the findings from the latent class models. In our FMM analyses, most participants belonged to the resilient class (81%), consistent with the large body of research that shows that most veterans do not have significant posttraumatic stress difficulties following deployment (e.g., Hoge et al., 2004). Few veterans were classified into the moderate severity group (19%), which is consistent with previous findings in Vietnam veterans (25.6% of their sample;

Steenkamp et al., 2012) but in contrast to findings with a previous study of OIF/OEF veterans that found larger classes of moderately distressed individuals (51% of their sample; Maguen et al., 2013). The PTSD group (11%) in the LPA analysis had an average total PCL score of 65.7 ($SD = 6.7$), which suggests this group is highly symptomatic. The moderate severity group (19%) in the factor mixture model had an average total PCL score of 54.7($SD = 13.7$), which is above the cut-off for probable PTSD in a treatment-seeking sample. These results indicate that these models provide different vantage points from which to examine the rates of PTSD in a sample and are sensitive to identifying individuals with probable PTSD.

Of the predictors evaluated, only peritraumatic dissociation and deployment concerns were significant predictors of class membership in the factor mixture model. These findings are consistent with previous findings that peritraumatic dissociation (e.g., Steenkamp et al., 2012) and deployment concerns (e.g., King et al., 1995) are robustly associated with post–deployment outcomes. Notably, deployment concerns significantly predicted classification to all of the nonresilient classes in our LPA, highlighting the effects of deployment-related concerns about safety and survival. Although postdeployment social support was not a significant predictor of severity in the FMM, previous studies have identified social support as an important predictor of postdeployment well-being (e.g., Iversen et al., 2008). In our LPAs, postdeployment social support significantly predicted membership in the resilient class versus all of the symptomatic classes. It is interesting to note that precombat life experiences, which are similar to predictors of PTSD identified in meta-analyses (e.g., prior trauma or life stress; Ozer, Best, Lipsey, & Weiss, 2003) did not significantly predict membership to the nonresilient classes. These predictor results support the notion that peritraumatic psychological processes (e.g., dissociation) and conditions (e.g., deployment concerns) are stronger predictors of postdeployment health than are prior characteristics or experiences (e.g., precombat life experiences; Ozer et al., 2003).

Overall, the findings suggested that the PTSD construct is a dimensional phenomenon in OIF/OEF veterans and is associated with specific deployment experiences, including peritraumatic dissociation and concerns about safety and survival. These findings, however, must be considered in the context of study limitations. Although we identified a four-factor, two-class model of PTSD symptoms and important class predictors, we did not have adequate sample sizes at follow-up data collection time points to assess stability of our model. Our FMM might be underpowered to detect small effects, given our relatively small sample size; however, no published guidelines for calculating FMM sample sizes are readily available and our sample size is comparable to other published studies using FMM and LPA analyses. Furthermore, we used self-report measures instead of clinical interviews, and predeployment variables were assessed retrospectively. Future research incorporating clinical interviews at multiple time points would provide further support for the present findings.

Despite these limitations, this work adds to our understanding of postdeployment adjustment for OIF/OEF veterans, the nature of PTSD for this group, as well as important predictors of PTSD presentation. Because this research is in its infancy, future studies are warranted prior to drawing firm conclusions about PTSD symptom presentation in OIF/OEF veterans. Studies that have used LPA to examine the structure of PTSD have proliferated in the literature, and our findings suggest that, although interesting, PTSD phenomena is not well-characterized with categorical models. Instead, the structure and dimensionality of PTSD, and other mental disorders, ought to be examined with dimensional and hybrid models. In addition, a new set of PTSD criteria were published after the present data collection occurred (i.e., *DSM–5*) that includes a greater emphasis on negative trauma-related cognitions and peri- and posttraumatic dissociation as symptoms of PTSD. It is interesting to note that the diagnostic criteria on which the two FMM classes differed the greatest (i.e., foreshortened future) was removed from the *DSM–5*. Although the conclusions would not be likely to change dramatically with the new PTSD criteria, this remains an open question that bears further investigation. Nonetheless, our results indicate that a significant minority of OIF/OEF veterans experience some degree of PTSD symptoms, particularly given certain deployment-related experiences. The conceptualization of psychopathology has profound implications for the assessment and treatment of mental disorders. Consequently, it is critical that researchers and clinicians recognize various patterns of postdeployment mental health adjustment to appropriately understand and serve the needs of newer veterans.

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