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Key patterns and predictors of response to treatment for military veterans with post-traumatic stress disorder: a growth mixture modelling approach

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Background. To determine the patterns and predictors of treatment response trajectories for veterans with post-traumatic stress disorder (PTSD).

Methods. Conditional latent growth mixture modelling was used to identify classes and predictors of class membership. In total, 2686 veterans treated for PTSD between 2002 and 2015 across 14 hospitals in Australia completed the PTSD Checklist at intake, discharge, and 3 and 9 months follow-up. Predictor variables included co-morbid mental health problems, relationship functioning, employment and compensation status.

Results. Five distinct classes were found: those with the most severe PTSD at intake separated into a relatively large class (32.5%) with small change, and a small class (3%) with a large change. Those with slightly less severe PTSD separated into one class comprising 49.9% of the total sample with large change effects, and a second class comprising 7.9% with extremely large treatment effects. The final class (6.7%) with least severe PTSD at intake also showed a large treatment effect. Of the multiple predictor variables, depression and guilt were the only two found to predict differences in response trajectories.

Conclusions. These findings highlight the importance of assessing guilt and depression prior to treatment for PTSD, and for severe cases with co-morbid guilt and depression, considering an approach to trauma-focused therapy that specifically targets guilt and depression-related cognitions.

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Post-traumatic stress disorder (PTSD) can be a severe, debilitating condition, associated with significant co-morbidity and reduced quality of life (Bryant *et al.* 2010). While effective treatments are available, treatment outcomes for military veterans with PTSD have been found to be more modest than outcomes for other populations, with 30–50% of veterans not deriving clinically meaningful benefit (Steenkamp *et al.* 2015). Studies examining the efficacy of interventions for PTSD typically report mean change with little focus on potential variability in treatment responses (Steenkamp *et al.* 2015). The identification of subclasses of veterans and the variables that predict membership of those classes would contribute to our understanding of why veterans with PTSD remain difficult to treat, provide valuable information to clinicians about those most and least likely to respond to standard treatment (Steenkamp *et al.* 2012), and pave the way for future treatment modifications based on the factors associated with poor treatment response (Elliott *et al.* 2005; Yehuda & Hoge, 2016).

Growth mixture modelling (GMM) is used to investigate classes of individuals within a group with different treatment response trajectories (Ram & Grimm, 2009). Three studies into veterans with PTSD have found significantly different treatment trajectories: two studies found sub-groups of non-responders (Elliott *et al.* 2005; Currier *et al.* 2014), while a third study found three groups of responders with dramatically varying levels of improvement (Schumm *et al.* 2013). All three studies included a limited range of predictor variables (e.g. type of trauma exposure, age, and mental and physical health) and how they

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subsequently impacted trajectory outcomes significantly varied across studies. Two of the previous studies were based on audits of routinely collected data (Schumm *et al.* 2013; Currier *et al.* 2014), so that potential covariates for determining class membership could only be drawn from the clinical variables used for diagnostic/treatment purposes. In contrast, variables such as guilt (Stapleton *et al.* 2006), pain (Otis *et al.* 2009), dissociation, and social factors such as compensation seeking (Fontana & Rosenheck, 1998) and relationship quality (Evans *et al.* 2009) have been found to predict PTSD treatment outcomes, and as such, warrant investigation.

This study aims to investigate the patterns and predictors of response trajectory for Australian veterans who participated in hospital-based treatment for PTSD. It builds on previous studies by including a broader range of predictor variables: age, alcohol use, depression, anger, guilt, dissociation, pain, relationship functioning, and compensation seeking status.

Method

Participants were 2686 veterans and other ex-serving members of the Australian Defence Force, who participated in an accredited PTSD outpatient treatment programme funded by the Australian Department of Veterans' Affairs (DVA) between 2002 and 2015. The majority of participants (98.8%) were male. PTSD diagnosis was established using the Clinician Administered PTSD Scale (CAPS IV). In order to qualify for treatment, the veteran's PTSD had to be military-related. Treatment followed accreditation standards with components of psychoeducation, symptom management (for co-morbid problems including anxiety, anger and depression), trauma-focused therapy, graded *in vivo* exposure, substance use issues, interpersonal skills, physical health and lifestyle issues, and relapse prevention. Programmes incorporated 20–30 treatment days with 6–10 participants receiving a combination of individual and group therapy. Exclusion criteria included being currently psychotic, actively suicidal, current substance abuse or currently involved in a major life crisis. The DVA Human Research Ethics Committee approved the study.

Measures

Participants completed questionnaires at intake, discharge, 3-month and 9-month follow-up as part of the programme evaluation process. Self-reported PTSD severity was assessed using the PTSD Checklist (PCL; Blake *et al.* 1995), a 17-item scale that measures Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV) PTSD symptoms in the past month (scores range 17–85; internal consistency 0.94–0.97; Blanchard *et al.* 1996). Participants were asked to answer the PCL in relation to their most traumatic military experience. Alcohol use was measured using the Alcohol Use Disorders Identification Test (AUDIT; Saunders *et al.* 1993), a 10-item scale that assesses alcohol consumption and alcohol-related problems (scores range 0–40; internal consistency 0.80–0.94; Forbes *et al.* 2004). Depression was assessed using the Hospital Anxiety and Depression Scale (HADS), which comprises two sub-scales that measure symptoms of anxiety and depression over the past week (Zigmond & Snaith, 1983). The sub-scales have seven items each with maximum scores of 21 for each sub-scale. A review of studies found that the two sub-scales had average internal reliability coefficients of 0.83 (anxiety) and 0.82 (depression; Bjelland *et al.* 2002). Anger was measured using the seven-item Dimensions of Anger Reactions (DAR) scale, which measures anger disposition directed towards others with total possible scores of 56 (internal consistency 0.91; Forbes *et al.* 2004). Veterans in a relationship completed the Abbreviated Dyadic Adjustment Scale, a seven-item scale that measures dyadic consensus, cohesion and satisfaction (internal consistency 0.75–0.80; Hunsley *et al.* 2001). Guilt and dissociation were assessed via a two-item (range 0–8) and three-item (range 0–12) scale, respectively, derived from the CAPS IV associated features questions. The internal consistency for the guilt and dissociation scales were high ($\alpha = 0.89$; $\alpha = 0.90$), item-total correlations ranged from 0.84 to 0.86 (guilt) and 0.87–0.89 (dissociation). Pain was measured via a single item from the World Health Organization Quality of Life brief scale (WHOQOL-BREF) on a scale of 1–5 (Creamer *et al.* 2002). Demographic data, including age at intake, pension status, compensation-seeking status, and employment status, were also collected from veterans. Presence of co-morbidity was determined by clinicians.

Statistical analyses

Latent growth mixture modelling (LGMM) identifies classes of individuals with similar response trajectories. LGMM with four time points provides the opportunity to model change in both linear and non-linear (quadratic) trajectories. Intercepts were allowed to vary, as the study focused on change over time (slopes), rather than the start points. Variance of slopes was constrained within each group to 0, which sets the homogeneity of growth trajectories within each class (Feng & McCulloch, 1996). Selection of the preferred model was based on statistical and practical criteria. Statistical criteria included reviewing the Bayesian

Information Criterion (BIC; Schwarz, 1978), the Sample Size Adjusted Bayesian Information Criterion (SS-BIC), and the Akaike's Information Criterion (AIC; Akaike, 1973). Entropy values range between 0 and 1, with 1 indicating perfect differentiation between classes (Ramaswamy *et al.* 1993). Finally, the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT; Lo *et al.* 2001) and the bootstrap likelihood ratio test (BLRT; Feng & McCulloch, 1996) were reviewed. A significant LMR-LRT and BLRT indicates that the current model is better fitting than the *k*-1 class model. Practical criteria for model selection included determining that each trajectory class was of sufficient size, the final solution was interpretable and theoretically coherent. Treatment effect was calculated using Cohen's *d* following a repeated measures *t* test comparing change in scores between pre-treatment and 9-month follow-up. Cohen's *d* scores were calculated applying Morris and DeShon's correction for the correlations between mean scores for these within-subjects repeated measures (Morris & DeShon, 2002).

Analyses were completed in Mplus version 7.11, which utilises all available data to estimate the model using full information maximum likelihood when completing analyses (Muthén & Muthén, 2004). In the first step, the unconditional model that best fit the data was defined. The most parsimonious (one-class) model was fitted first, followed by models with increasing numbers of classes. Both linear and quadratic growth mixture models were fitted to the PCL data obtained at the four time points. In the second step, we ran conditional LGMMs to identify potential predictors of the different classes.

Predictors investigated were intake measures of: age, applying for a pension, applying for a pension increase, relationship status, psychiatric co-morbidity, employment status, alcohol use, anger, depressive symptoms, guilt symptoms, and dissociation symptoms. The inclusion of predictors into the LGMM can result in minor changes to the class structure. Therefore, if multiple models in the unconditional analyses perform similarly, it is prudent to investigate them both in the conditional analyses (Jung & Wickrama, 2008).

As the data were collected from 14 different Australian sites, we also investigated symptom clustering by site. The intra-class correlation (ICC) using absolute agreement for PCL scores at intake was ICC = 0.021, below the 0.1 of a small effect size for ICC. The effect of the ICC on sample size indicated that we had sufficient participants to run GMM. A multivariate analysis of variance on the conditional probability of being in each class (C1–C5) at each time point with site as the factor and found no evidence of systematic bias across sites.

Table 1. *Sample demographics at intake (unless stated otherwise)*

	Mean (S.D.)
Age (at intake)	55.92 (10.54)
PCL (intake)	61.4 (11.20)
PCL (end treatment)	55.15 (12.92)
PCL (3 months)	54.31 (12.83)
PCL (9 months)	53.17 (12.95)
AUDIT	14.38 (9.73)
HADS – depression	11.50 (3.69)
Pain (WHO item 3)	3.45 (1.03)
Guilt	7.30 (4.29)
Dissociation	9.24 (5.29)
Co-morbid psych – number	1.04 (0.97), range 0–8
Co-morbid psych (yes)	64.6%
Applying DVA pension (yes)	42.7%
Applying DVA pension increase (yes)	47.3%
Employment (yes)	13.2%
Relationship status	
Single (never married)	3.9%
Married	70.1%
De facto	6.7%
Separated/divorced	17.0%
Widowed	2.2%
Employment status	
Full-time	10.2%
Part-time	3.0%
Retired	21.7%
Unemployed	5.8%
Unable to work	57.3%

PCL, post-traumatic stress disorder checklist; AUDIT, alcohol use disorders identification test; HADS, hospital anxiety and depression scale; DVA, Australian Department of Veterans' Affairs.

Results

Table 1 provides participant demographics. The *t* tests and χ^2 analyses were completed on demographic variables to analyse lost to follow-up (LTFU), which were $n = 345$ by end of treatment, $n = 379$ between end of treatment and 3-month follow-up, and $n = 400$ between 3-month and 9-month follow-up. Importantly, these figures represent non-compliance with data collection rather than treatment drop out, which is very low at around 2%. Those LTFU at the end of treatment had fewer co-morbidities ($M = 0.89$) than those who remained in the study ($M = 1.10$), and were more likely to be single at intake. Those LTFU between end of treatment and 3-month follow-up were higher on dissociation at intake ($M = 10.00$) than those who remained in the study ($M = 9.06$), and again were more likely to be single at intake. Those LTFU between 3 and 9-month follow-up were higher on AUDIT

Table 2. *Fit indices for the unconditional latent growth mixture model analyses*

Model tested	Log likelihood	AIC	BIC	Adjusted BIC	Entropy	LMR-LRT	BLRT
Linear							
1 Class	−32 953.478	65 920.955	65 962.226	65 939.985	**	**	**
2 Class	−32 875.931	65 771.861	65 830.819	65 799.046	0.419	<0.0001	<0.0001
3 Class	−32 858.087	65 742.174	65 818.819	65 777.514	0.522	0.1391	<0.0001
4 Class	−32 847.794	65 727.589	65 821.922	65 771.085	0.610	0.2843	<0.0001
5 Class	−32 838.806	65 715.612	65 827.632	65 767.263	0.547	0.2832	<0.0001
6 Class	−32 831.737	65 707.475	65 837.183	65 767.282	0.557	0.0783	<0.0001
Quadratic and linear							
1 Class	−32 761.428	65 538.855	65 586.022	65 560.603	n/a		
2 Class	−32 613.609	65 251.219	65 321.969	65 283.841	0.606	0.0002	<0.0001
3 Class	−32 571.899	65 175.798	65 270.131	65 219.294	0.551	0.5595	<0.0001
4 Class	−32 543.494	65 126.988	65 244.904	65 181.358	0.647	0.0004	<0.0001
5 Class	−32 515.419	65 078.838	65 220.338	65 144.082	0.639	<0.0001	<0.0001
6 Class	−32 500.613	65 057.226	65 222.308	65 133.344	0.653	0.0360	<0.0001
7 Class	−32 488.466	65 040.932	65 229.598	65 127.924	0.662	0.2145	<0.0001

AIC, Akaike's Information Criterion; BIC, Bayesian Information Criterion; LMR-LRT, Lo-Mendell-Rubin likelihood ratio test; BLRT, bootstrap likelihood ratio test.

Table 3. *Mean scores on predictor variables by class*

Variable	Class 1 very high symptom/ small change	Class 2 very high symptom/ large change	Class 3 high symptom/ large change	Class 4 high symptom/ extra-large change	Class 5 low symptom/large change
N (%)	803 (32.5%)	73 (3%)	1233 (49.9%)	196 (7.9%)	166 (6.7%)
PCL Pre-tx	66.86	67.28	59.93	63.13	43.91
PCL Post-tx	65.00	62.62	53.24	43.48	37.84
PCL 3 month	66.19	60.73	51.77	36.68	36.78
PCL 9 month	63.62	58.27	51.36	38.35	35.70
Guilt	8.62[a,b]	0.01[c,d,e,b]	7.26[a,b]	7.73[a,b]	4.05[c,a,d,e]
Depression	13.17[d,e,b]	11.91[d,e,b]	10.91[c,a,b]	11.22[c,a,b]	8.18[c,a,d,e]

PCL, post-traumatic stress disorder checklist; Pre-tx, pre-treatment; Post-tx, post-treatment.
[a] $p < 0.05$ for reference class in table column v class 1.
[b] $p < 0.05$ for reference class in table column v class 2.
[c] $p < 0.05$ for reference class in table column v class 3.
[d] $p < 0.05$ for reference class in table column v class 4.
[e] $p < 0.05$ for reference class in table column v class 5.

scores at intake ($M = 16.04$) than those who remained ($M = 14.13$).

Tables 2 and 4 contain the full results of the unconditional LGMM analyses. Quadratic models demonstrated improved fit over linear models. As the 5 and 6 class models performed similarly in the quadratic analyses, we ran the conditional analyses with both these models before selecting the preferred model. The conditional analyses were run in two stages. Firstly, each predictor (age, applying for a pension, applying for a pension increase, relationship status, psychiatric co-morbidity, employment status, alcohol use, anger, depressive symptoms, guilt symptoms, and dissociation symptoms) was entered into the model individually. Predictor variables were included in stage 2 if there were significant results for 50% of comparisons between classes. Following this approach, guilt, depression, dissociation, and anger were included as simultaneous predictors in stage 2.

In stage 2, the conditional LGMM was subject to model reduction and any non-significant predictors adjusting for other predictors were removed to derive

Table 4. *Guilt and depression as predictors of class membership in the 5 class latent growth mixture model*

	Guilt		Depression	
	Unstd β	p	Unstd β	p
Reference class : high symptom/large change				
Low/large	−0.181	<0.001	−0.187	0.002
Very high/large	−2.602	0.019	0.190	0.001
Very high/small	0.037	0.161	0.181	<0.001
High/extra-large	0.025	0.507	0.018	0.628
Reference class: low symptom/large change				
High/large	0.181	<0.001	0.187	0.002
Very high/large	−2.422	0.029	0.377	<0.001
Very high/small	0.218	<0.001	0.368	<0.001
High/extra-large	0.206	<0.001	0.206	0.006
Reference class: very high symptom/large change				
High/large	2.602	0.019	−0.190	0.001
Low/large	2.422	0.029	−0.377	<0.001
Very high/small	2.639	0.017	−0.009	0.883
High/extra-large	2.627	0.018	−0.171	0.010
Reference class: very high symptom/small change				
High/large	−0.037	0.161	−0.181	<0.001
Low/large	−0.218	<0.001	−0.368	<0.001
Very high/large	−2.639	0.017	0.009	0.883
High/extra-large	0.012	0.767	−0.163	0.001
Reference class: high symptom/extra-large change				
High/large	−0.025	0.507	−0.018	0.628
Low/large	−0.206	<0.001	−0.206	0.006
Very high/large	−2.627	0.018	0.171	0.010
Very high/small	0.012	0.767	0.163	0.001

the most parsimonious explanation for the selected model. This process sequentially removed dissociation and anger as predictors. In the model with guilt and depression as predictors, the LMR-LRT found the 6 class model was not significantly different to the 5 class model ($p = 0.2230$) and entropy was acceptable (0.639). The BLRT was significant for both the 5 class and 6 class models ($p < 0.001$). However, the 6 class solution included one excessively small class ($N \approx 1.0\%$). The 5 class model was therefore selected as the preferred model. See Table 3 for the mean PCL, guilt and depression scores for each class.

Figure 1 shows the trajectory of PCL scores for the selected LGMM conditional model with guilt and depression predicting class membership. We identified two very high-symptom classes (PCL > 67), two high-symptom classes (PCL 60–64), and one low-symptom class (PCL = 44). The two very high-symptom classes separated into a relatively large class (32.5%) with a small treatment effect size between intake and 9-month follow-up ($d = 0.3$; very high-symptom/small change class) and a very small class (3%) with a large treatment effect size ($d = 1.0$; very high-symptom/large change class). There were two high-symptom classes, one comprising the largest number of participants (49.9%) showed a large treatment effect size ($d = 1.6$; high-symptom/large change class) and another, comprising 7.9% of participants, showed an extremely large change ($d = 2.6$; high-symptom/extra-large change class). The final class (6.7%), which started with relatively low PCL scores, showed a large treatment effect size between intake and 9-month follow-up ($d = 0.9$; low-symptom/large change class).

Table 3 shows the results for guilt and depression as predictors of class membership with each class placed iteratively as the reference class. Guilt was an important predictor of outcome for participants with the most severe PTSD at intake. Amongst those with very high PTSD at intake, those with more severe guilt showed smaller treatment effects (very high-symptom/small change class), while those with lower guilt scores showed a large effect size change (very high-symptom/large change class). Depression scores, on the other hand, did not predict the small *v.* the large change trajectory profile of participants with very high PTSD at intake.

Neither guilt nor depression predicted class membership for those who had slightly less severe but

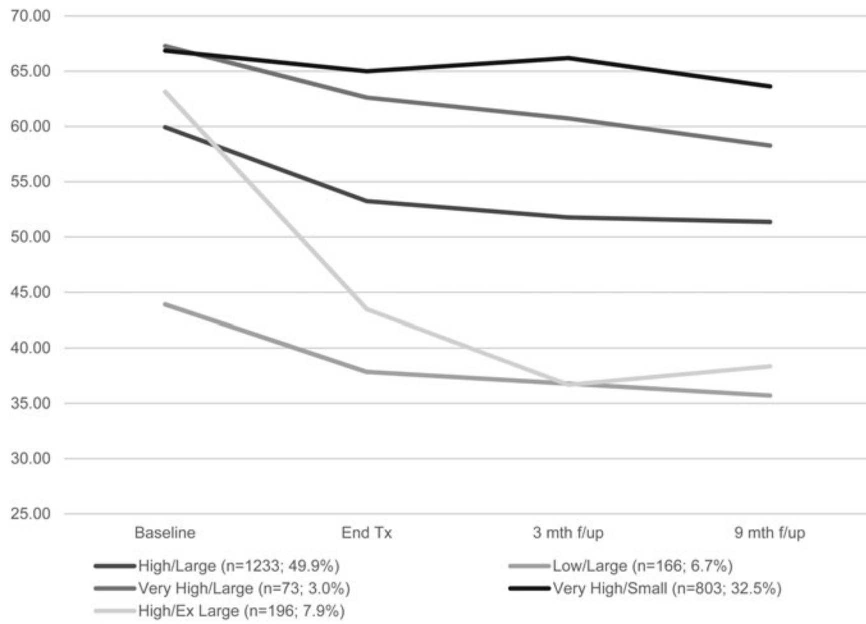

Fig. 1. Mean PCL scores for conditional 5 class latent growth mixture model with depression and guilt as predictors. PCL, post-traumatic stress disorder checklist.

still high PTSD scores at intake; as shown in Table 4, neither guilt nor depression predicted membership in the high-symptom/large change class *v.* the high-symptom/extra-large change class. The low-symptom/large change class was associated with low scores on both depression and guilt, while higher depression scores predicted being in either of the very high start classes, compared with the high-symptom/extra-large change class. Lower scores on guilt predicted being in both the low-symptom/large change and the very high-symptom/large change classes compared with the high-symptom/extra-large change class.

Post hoc analyses were run to investigate the differences in trajectories between the two very high-symptom start classes. Logistic regression analyses were run initially on each individual predictor included in the conditional LGMM procedure. Then the significant predictors were included in a backwards elimination model. The results were that alcohol use ($p = 0.018$) was found to be an additional predictor, along with depression and guilt, of class membership. Higher scores predicted being in the small change class ($M = 15.89$, S.D. $= 10.36$), rather than the large change class ($M = 12.24$, S.D. $= 9.96$).

Discussion

The current study adds to growing evidence that treatment outcome studies should investigate potential heterogeneity in response trajectories. The key finding was that veterans with the most severe PTSD, depression and guilt had the poorest treatment response. It should be noted that anger and dissociation were also important variables in differentiating between classes but were not retained in the parsimonious model due to shared variance with other variables. Our findings indicate that it is the combination of PTSD, depression and guilt that is critical; the second small class with very high PTSD at intake, which showed large effect size changes, had comparable depression scores, but very low guilt scores. It may be that in cases of severe PTSD, the two co-morbidities in combination are more likely to interfere with symptom improvement than either alone. When we investigated whether other co-morbidities further predicted the differences between these two very severe classes, alcohol use was found to be an additional predictor. The combination of severe PTSD, depression and guilt, combined with alcohol use, distinguishes this low treatment response group from the other more responsive groups. Interestingly, for those with slightly less severe PTSD, depression and guilt (that is, the high-symptom/large change and high-symptom/extra-large change groups) the combination of PTSD, depression and guilt was not a barrier to symptom improvement.

The results of this study are at odds with previous findings of greater improvement in PTSD amongst those with higher pre-treatment guilt and depression compared with those with lower initial guilt and depression (Rizvi *et al.* 2009). The authors of this previous study concluded that evidence-based PTSD treatment is effective for these co-morbid symptoms. Taking into consideration the differential effects of guilt and depression on response trajectories depending upon the severity of PTSD, the results of the current study suggest that the combination of high guilt and depression with severe PTSD does indeed impede symptom improvement more than an elevation in one of these co-morbidities alone, or slightly lower scores on the three variables (PTSD, guilt and depression). The mechanism by which this occurs is a matter of conjecture; however, it seems likely that the combination of severe PTSD, guilt and depression interferes with the individual's capacity to fully engage in trauma-focused treatment or successfully process trauma memories. It may be that the degree of affective and cognitive flexibility required to address high levels of traumatic guilt are not available to the severely depressed individual, relative to the person with less severe depression. Equally, for the person with severe depression and PTSD in the absence of severe guilt, the cognitive and emotional work required to process traumatic memories may be less complex without the presence of guilt interfering with the trauma processing. In brief, it may be that in the absence of severe depression, standard treatments can deal with the guilt and PTSD, and in the absence of severe guilt, depression does not interfere with PTSD trauma processing. What then are the implications for treatment when all three – severe PTSD, severe depression and severe guilt – are present?

Where PTSD is co-morbid with depression, PTSD treatment guidelines recommend that the two conditions are treated concurrently unless the severity of the depression precludes effective engagement in trauma-focused therapy (Australian Centre for Posttraumatic Mental Health, 2007). The complication in applying this same principle to the triad of PTSD, depression and guilt is that guilt, in particular, is likely to be integrally linked to the traumatic event, meaning it may not be possible to effectively address guilt without addressing the trauma. The question of whether guilt can be adequately addressed with standard PTSD treatments, such as prolonged exposure, or requires a different approach is the subject of current debate in the literature (e.g. Smith *et al.* 2013; Steenkamp *et al.* 2013). The finding in the current study that veterans with the combination of PTSD, guilt and depression were not responsive to standard trauma-focused treatment would seem to support the view that a different approach is required. For clients with this triad of symptoms, it may be prudent to use a trauma-focused approach that directly targets the guilt-related cognitions as a primary focus or alternatively to directly target the depression to improve the level of cognitive function required to address the combination of PTSD and guilt in treatment. To the extent that this combination of PTSD, guilt and depression is reflective of the moral injury construct receiving increasing attention in the veteran and military literature, a targeted approach such as Adaptive Disclosure may be indicated (Litz *et al.* 2015).

Unfortunately, despite the breadth of predictors used in this analysis, we were not able to identify the factors that predicted membership of the group with the strongest outcomes (high-symptom/extra-large change). Of particular note, in light of ongoing debate about the role of compensation seeking in poor treatment response (Frueh *et al.* 2007), compensation seeking was not a significant predictor in this study. A range of variables, including personality factors, cognitive variables such as working memory, attention and executive function (Pe *et al.* 2013), and hormonal variables such as brain-derived neurotrophic factor and glucocorticoids (Felmingham *et al.* 2013; Yehuda *et al.* 2013), epigenetics (Yehuda *et al.* 2013), or trauma-type characteristics (Stein *et al.* 2012), that were not available for this study may be at play here. Future studies would benefit from including a range of measures across the psychological, neuropsychological, neurobiological, and epigenetic domains.

Limitations

Limitations in the data used for this study need to be acknowledged. Firstly, the data were collected as part of routine programme participation with no control condition. Secondly, although statistical models made use of all available data, it was not possible to account for missing data from non-completers. Thirdly, while the Australian PTSD programme standards specify the components of treatment, treatment integrity was not independently assessed by fidelity investigations, and so some level of heterogeneity in programme content and delivery must be acknowledged. Importantly however, ICCs revealed no clustering effects for programmes. Fourthly, the findings from this study are based solely on self-report scores (PCL), as opposed to changes in clinician-measured PTSD. Finally, the entropy value of 0.639, though acceptable, was lower than the 0.8, often held as a marker for very good class distinction. This indicates a degree of imprecision within the classes.

Supplementary material

The supplementary material for this article can be found at https://doi.org/10.1017/S0033291717001404.

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