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Supplementary Material

Article Title: Latent Trajectories of Trauma Symptoms and Resilience: The 3-Year Longitudinal Prospective USPER Study of Danish Veterans Deployed in Afghanistan

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List of Supplementary Material for the article

1. **eAnalysis** Data Analytic Approach

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Supplementary eAnalysis. Data Analytic Approach

The main analysis was conducted in Mplus version 7[1].

We included all soldiers who participated at the first assessment in the trajectory analysis to aid model estimation and avoid listwise deletion. Missing data were handled using the method of Full Information Maximum Likelihood (FIML;[2]). To check for potential bias of including all participants, we also conducted the analysis including only participants who provided data in at least four assessments (N=416). The model resulting from this procedure was very similar to the model including all participants. Hence, to maintain larger sample size and power for the subsequent analysis, we included all participants in the model.

We used Latent Growth Mixture Modeling (LGMM) to empirically identify heterogeneous trajectories of PTSD-symptoms over time. LGMM combines the methods of Latent Class Analysis (LCA) and Growth Modeling, and as such, it expects different subpopulations with unique growth trajectories within the sample [3]. LGMM allows intragroup variance of growth parameters. To accommodate expected fluctuations over time, we estimated linear as well as quadratic terms.

Initially, we estimated a series of LGMM-models with number of classes ranging from 1-8. We evaluated these models based on available fit indices, namely the Bayesian Information Criteria (BIC), the Akaike Information Criteria (AIC;[4]), and the Sample-Size adjusted BIC (SSBIC). For all three fit indices, lower values imply better fit of the model. Furthermore, we assessed the entropy of the model, which assesses the ability of the model to distinguish between classes (ranges from 0-1, where values closer to 1 represents better distinction by the model). Finally, we tested the improvement in fit with the addition of each extra class by implementing the Lo-Mendell-Rubin likelihood ratio test (LMR;[5]) and the Bootstrap Likelihood Ratio Test (BLRT). However, even with the evaluation of the mentioned fit indices, model selection also relies on subjective evaluation of the models parsimony and theoretical meaningfulness [6]. Hence, the final selection of the appropriated model relied on the combined information from fit indices and meaningfulness and parsimony of the model.

Due to a very small sample size in one of the resulting classes, and a theoretical wish of investigating several possible predictors, it was not possible to conduct multinomial logistic regression analysis nested within the LGMM analysis. Hence, the class membership variable was exported to the full dataset, and analysis of the relevant covariates was conducted post hoc outside of the model. For models with high entropy (>.80), this is viable alternative to including predictors in the model[7]. As our model had high entropy (.93), the risk of bias using the procedure is considered low. In the post hoc analyses, stepwise multivariable hierarchical logistic regression analyses were used to examine potential predictors of class membership. We selected variables for the multivariate hierarchical logistic regressions based on their significance in a series of univariate analyses. Potential predictors entered into these analyses were entered into the full model in the order of collection; namely background, demographic, and personality variables collected at Time 1, deployment stressors collected at Time 3, and post deployment support and life events after deployment collected at Time 6. Only results from the final model will be described.

Results

LGMM

Models with number of classes ranging from 1-8 can be seen in Table 1. Fit increased with the addition of every class, including the 7- and 8-class models. Whereas the BLRT suggest that each extra class added significantly to the model, the LMR suggested that no additional information was added beyond the fourth class. Of these two, BLRT is assumed to be the best class indicator[3], hence suggesting superiority of models with more classes. The entropy was identical for models with 3 through 6 classes (.93) increasing marginally with the addition of the 7th (.94) class and then returning to the 6-class entropy level for the 8-class model (.93).

Since the fit indices of these models did not unequivocally suggest on model over the others, we evaluated meaningfulness and parsimony of each model carefully. With addition of each new class through the six class model, all identified trajectories were unique, theoretically meaningful, and the model seemed parsimonious. However, the addition of a 7th class, this seemed to split an existing class into two very similar classes, hence providing a less parsimonious solution. Further, one class in the 7-class model contained only 1.5% of the participants. The addition of the 7th class therefore resulted in a clearly unparsimonious model, whereas the six class model revealed six unique trajectories that all seemed theoretically relevant. Two classes in this model were small (2.0 and 2.7% of the participants, respectively), but were nonetheless clearly different from the other trajectories. Hence, we settled on the six class model as the best fit of our data.

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