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# Pre-deployment predictors of suicide attempt during and after combat deployment: Results from the Army Study to Assess Risk and Resilience in Servicemembers

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## ABSTRACT

*Background:* Deployment-related experiences might be risk factors for soldier suicides, in which case identification of vulnerable soldiers before deployment could inform preventive efforts. We investigated this possibility by using pre-deployment survey and administrative data in a sample of US Army soldiers to develop a risk model for suicide attempt (SA) during and shortly after deployment.

*Methods:* Data came from the Army Study to Assess Risk and Resilience in Servicemembers Pre-Post Deployment Survey (PPDS). Soldiers completed a baseline survey shortly before deploying to Afghanistan in 2011–2012. Survey measures were used to predict SAs, defined using administrative and subsequent survey data, through 30 months after deployment. Models were built using penalized regression and ensemble machine learning methods.

*Results:* Significant pre-deployment risk factors were history of traumatic brain injury, 9 + mental health treatment visits in the 12 months before deployment, young age, female, previously married, and low relationship quality. Cross-validated AUC of the best penalized and ensemble models were .75–.77. 21.3–40.4% of

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SAs occurred among the 5–10% of soldiers with highest predicted risk and positive predictive value (PPV) among these high-risk soldiers was 4.4–5.7%.
*Conclusions:* SA can be predicted significantly from pre-deployment data, but intervention planning needs to take PPV into consideration.

## 1. Introduction

Suicide prevention is a high priority of the US Department of Defense (Office of the Under Secretary of Defense for Personnel and Readiness, 2017). Given that an increase in fatal and non-fatal suicide attempts (SAs) has occurred during sustained operations in Iraq and Afghanistan, there has been particular focus on the effects of deployment on suicide (Reger et al., 2018). Evidence for an association between deployment and suicide has been mixed, with some studies finding a substantially elevated suicide rate among ever-deployed soldiers compared to never-deployed soldiers (Schoenbaum et al., 2014) and others finding a weak association (see Bryan et al., 2015 for meta-analytic review) or no association (e.g., LeardMann et al., 2013; Reger et al., 2015). It has been suggested that this inconsistency might be due to heterogeneity in the experiences associated with deployment and in vulnerability to these experiences (Reger et al., 2018). If so, it would be ideal to identify the most vulnerable soldiers *prior* to deployment to inform Army decisions.

Up to now, research on deployment-related predictors of suicidality has focused mostly on deployment-related experiences (e.g., combat experiences such as killing or exposure to death; Bryan et al., 2015) or on other well-known risk factors (e.g., psychiatric disorders) that may or may not have been present pre-deployment. Only limited research exists on other potentially important pre-deployment predictors of deployment-related suicidal-behaviors (Ursano et al., 2016; Shen et al., 2016). The significant predictors in the latter studies include Army occupation (Kessler et al., 2015a; Ursano et al., 2017), length of time in service prior to first deployment (Ursano et al., 2018), and socio-demographics (Gilman et al., 2014; Street et al., 2015), but other potentially important predictors exist that have not been examined. One way to do this would be to combine data collected in self-report surveys obtained shortly before deployment with administrative records to develop a prediction model. This approach has been used to predict other negative outcomes during deployment, including mental disorders and interpersonal violence (Rosellini et al., 2018). We present the results of this approach in the current report. The analysis used baseline data from the Army Study to Assess Risk and Resilience in Servicemembers (STARRS) Pre-Post Deployment Survey (PPDS) and administrative data available for those soldiers at the time of survey to predict subsequent suicide attempts during and after deployment to Afghanistan.

## 2. Materials and methods

### 2.1. Participants

The PPDS was a four-wave panel survey of soldiers from three Brigade Combat Teams (BCTs). Baseline assessments (T0) were conducted 1–2 months prior to unit deployment to Afghanistan (October 2011–February 2012). Upon return from deployment, follow-up surveys were collected within one month of return (T1; September 2012–February 2013), two months after return (T2; October 2012–March 2013), and 9–12 months after return (T3; June 2013–May 2014). Self-administered questionnaires were administered at each wave to assess socio-demographic characteristics, lifetime and current mental disorders, history of suicidal behavior, and a multitude of other risk and resilience factors. We focus in the current report only on survey data from T0 as predictors of subsequent SAs. We used data from later surveys to identify self-reported SAs (see *The Outcome* below) that occurred either during or after deployment. All participants provided written informed consent prior to participation. All study procedures were approved by the human subjects boards of all involved organizations.

Baseline PPDS participants were drawn from the soldiers present for duty in three BCTs about to deploy to Afghanistan. Of the 9949 soldiers in these BCTs at baseline, 9488 (95.3%) consented to participate in the survey. Most (n = 8558; 86.0%) provided complete T0 survey responses and consented to linking their responses to administrative records. Only T0 soldiers who subsequently deployed to Afghanistan (n = 7742; 90.5%) were included in T1-T3. However, 65 of the latter were excluded from analysis either because they had no administrative record (n = 1), were currently deployed at T0 (n = 1), were in the National Guard or Army Reserve (n = 2), or had more than one deployment between T0 and T3 (n = 65), leaving n = 7677 in the analysis. The remaining n = 4645 (60.0%) provided complete data at all post-deployment assessments. Analyses were weighted to adjust for baseline differences between soldiers who completed the T0 survey versus non-completers, agreed versus did not agree to have their administrative data linked to their survey data, and completed versus did not complete the full set of T1-T3 post-deployment surveys. Additional details on the PPDS design and sampling procedures are reported elsewhere (Kessler et al., 2013a, 2013b).

### 2.2. The outcome

**Suicide attempts (SAs).** SAs following T0 were determined using data from both self-report PPDS data and Army administrative data up to 30 months after baseline. Self-reported SAs were assessed in the T2-T3 surveys with a question adapted from the Columbia-Suicide Severity Rating Scale (*Did you ever make a suicide attempt; that is, purposefully hurt yourself with at least some intention to die?* Posner et al., 2011). At T2, soldiers were asked separately to report any SAs that occurred during their recent deployment and since returning from deployment. At T3, soldiers who completed T2 were asked to report additional SAs that had occurred since T2, whereas soldiers who did not participate in T2 were asked to report SAs occurring during or following their most recent deployment.

Administrative records of SAs came from the Army STARRS Historical Administrative Data Study (HADS; Kessler et al., 2013a). The HADS includes records from 38 Army/DoD administrative data systems. Records on SAs were obtained from four of these data systems: the Department of Defense Suicide Event Report (DoDSER), the Military Health System Data Repository (MDR), the Theater Medical Data Store (TMDS), and the TRANSCOM (Transportation Command) Regulating and Command and Control Evacuating System (TRAC$^2$ES). These data systems together provide healthcare encounter information from military and civilian treatment facilities, combat operations, and aeromedical evacuations. One of these systems, DoDSER, is a DoD-wide surveillance system that aggregates information on suicidal behaviors (ideation, attempts, deaths) via a standardized form completed by medical providers at DoD treatment facilities. Our definition of SA included either DoDSER records or an ICD-9-CM diagnostic code (E950-E958) in one or more of the other healthcare encounter systems listed above. The decision to combine these was based on prior work showing that these outcomes have very similar correlates (Ursano et al., 2015). Self-reported and administratively-reported SAs were combined into a single person-level outcome measure for whether each soldier made one or more suicide attempts subsequent to deployment.

### 2.3. Pre-deployment predictors

**Pre-deployment survey variables.** T0 variables were grouped broadly into 11 categories: lifetime mental disorders, lifetime self-injurious thoughts and behaviors, personality, childhood adversities, lifetime traumatic events, recent and chronic stress, social support, recent health problems, traumatic brain injury, recent mental health treatment, and sociodemographic and Army career characteristics. Detailed information about items used to assess constructs within these categories can be found in Supplemental Materials.

**Pre-deployment administrative variables.** STARRS analyses reported elsewhere extracted a set of 1399 administrative variables that we conceptualized as potential predictors of suicidal behaviors and other negative outcomes (Kessler et al., 2015b). Previous reports used these variables to predict other outcomes in the entire Army, such as sexual assault (Rosellini et al., 2017; Street et al., 2016) and violent crime (Rosellini et al., 2016; Bernecker et al., 2018). We used similar procedures to predict suicide in the total Army with a 12-month time horizon. The final model included 27 administrative variables (see Supplemental Materials for descriptions of all administrative predictors). These significant predictors were in three broad categories: recent mental health treatment (e.g., inpatient and outpatient treatment use, psychotropic medication use), criminal history (i.e., perpetrator of any crime in past 24 months), and socio-demographics/Army career characteristics (e.g., gender, age, time in service). Given the large number of administrative predictors in this model in relation to the number of SAs in our PPDS sample, we created a composite predicted risk score based on the model and assigned this as a single variable to each PPDS respondent as of T0 rather than include the 27 administrative predictors as separate predictors in the PPDS model. Scores on this composite risk score were standardized to a mean of 0 and a standard deviation of 1 in the total PPDS sample.

### 2.4. Analysis methods

We used a three-step process to build a model for survey predictors. In the first step, we focused separately on the potential predictors within each of the 11 categories listed above and examined bivariate associations. In the second step, we used penalized regression to estimate within-category multivariate models that included all significant bivariate predictors. Detailed results of these first two model-building steps are presented in Supplemental Tables 1–12. In the third step, we estimated an overall multivariate model that included all significant predictors in all within-category multivariate models, using elastic net penalized regression to select the optimal final subset of these predictors (Friedman et al., 2010). This final model was then re-estimated with conventional weighted logistic regression to obtain odds-ratios and design-based 95% confidence intervals based on the Taylor series linearization method (Wolter, 2007) to adjust for the weighting of the PPDS data.

After this three-step process was complete and the final multivariate model obtained, we estimated a model that included these same survey predictors along with the HADS administrative composite risk score to determine whether the survey variables remained significant after controlling for administrative predictors. Finally, in order to make a head-to-head comparison of prediction strength of survey and administrative variables, we created a survey composite risk score that, like the administrative composite risk score, was standardized to have a mean of 0 and variance of 1 and estimated a model that contained only the two composite risk scores as predictors.

The above model-building approach did not allow for the possibility of interactions either within or between administrative and survey predictors. This is a limitation, as some theories of suicide hypothesize the existence of interactions among predictors (O'Connor and Nock, 2014). To address this limitation partially we used the Super Learner ensemble machine learning algorithm (van der Laan et al., 2007) to investigate whether stable interactions existed either among the survey predictors or between the survey predictors and the composite HADS risk score. Four classifiers that capture interactions were included in the ensemble: multivariate adaptive regression splines (Friedman, 1991), random forest (Breiman, 2001), gradient boosting (Chen and Guestrin, 2016), and Bayesian additive regression trees (Chipman et al., 2010). Rather than require us to choose among these different classifiers, Super Learner allowed us to combine results across all four in addition to conventional additive models by developing an optimal weighted average across the individual-level predicted probabilities based on each classifier that is guaranteed to perform at least as well as the best individual model (i.e., when the weight for that model is 1.0 and the weights for the other models are all 0) and generally performs considerably better than the best individual model.

We used a number of different hyper-parameter tunings for each component classifier in our Super Learner library (Supplemental Table 12). For both the final logistic model and the final Super Learner model, we adjusted for over-fitting in estimating out-of-sample performance by using 5-fold cross-validation (5F-CV; James et al., 2013) to generate a pooled receiver operating characteristic (ROC) curve (Smith et al., 2014). Area under the ROC curve (AUC) was calculated to evaluate cross-validated model fit. Sensitivity (SN; the proportion of observed true cases found among soldiers above a given threshold on the predicted outcome scale) and positive predictive value (PPV; the prevalence of SAs among soldiers above a given threshold on the same outcome scale) were computed from cross-validated outcome scores. Statistical significance was evaluated using 2-sided 0.05-level tests. Missing data were imputed using multiple imputation (MI) (Little and Rubin, 2002) with SAS *proc MI* (SAS Institute Inc, 2010).

## 3. Results

### 3.1. Distribution of prospective SAs among deployed soldiers

A suicide attempt subsequent to T0 was either self-reported in the T2-T3 surveys or recorded in the administrative records for 103 (1.3%, SE = 0.1) of the 7677 soldiers in the analysis sample (Table 1). The plurality of these SAs were reported only in the surveys (n = 48), fewer only in the administrative data (n = 33), and fewest in both the surveys and administrative data (n = 22).

### 3.2. Risk factors associated with SAs among deployed soldiers

Many T0 survey predictors had significant bivariate associations with subsequent SAs (Supplemental Tables 1–12). After trimming within-category multivariate models and using elastic net penalized regression to select the optimal final subset of predictors, a multivariate survey model was developed that had 24 predictors (Table 2). The predictors in this model included indicators of childhood adversities (parental maltreatment; parent impaired due to physical illness/disability), lifetime traumatic events (interpersonal violence; other events), personality traits (negative affect; fearlessness), lifetime mental

**Table 1**
Distribution of self-reported and administratively-recorded suicide attempts during and after deployment among deployed soldiers who completed T0 PPDS (n = 7677).

| | Distribution | | Percentage of all attempts | | (n) |
|---|---|---|---|---|---|
| | % | (SE) | % | (SE) | |
| Suicide attempts | | | | | |
| Survey only | 0.6 | (0.1) | 48.0 | (5.7) | (48) |
| Administrative only | 0.4 | (0.1) | 31.7 | (5.8) | (33) |
| Both | 0.3 | (0.1) | 20.3 | (4.1) | (22) |
| Total | 1.3 | (0.1) | 100.0 | – | (103) |

**Table 2**
Best-fitting logistic regression models for pre-deployment risk factors predicting suicide attempt 30 months following baseline among deployed soldiers who completed T0 PPDS (n = 7677).

| Risk factor | Distribution | | Univariate associations | | Model 1 Best multivariate survey predictors[a] | | Model 2 Best multivariate survey predictors plus administrative composite[a] | | Model 3 Significant predictors from Model 2[a] | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Estimate | SE | OR | 95% CI | OR | 95% CI | OR | 95% CI | OR | 95% CI |
| **Childhood adversities** | | | | | | | | | | |
| Frequent emotional and physical maltreatment (%) | 2.8 | (0.2) | 2.8* | (1.2-6.8) | 1.7 | (0.5-5.9) | 1.7 | (0.5-5.8) | – | – |
| Frequent emotional, physical, and sexual maltreatment (%) | 0.4 | (0.1) | 5.4* | (1.1-25.0) | 3.3 | (0.4-27.5) | 3.3 | (0.4-27.0) | – | – |
| Overall maltreatment frequency (mean of a summary scale coded 0–4) | 0.2 | (0.0) | 1.5* | (1.2-1.9) | 1.0 | (0.6-1.6) | 1.0 | (0.6-1.6) | – | – |
| Parent impaired due to physical illness/disability (%) | 6.8 | (0.3) | 2.4* | (1.3-4.3) | 1.5 | (0.8-3.0) | 1.5 | (0.8-3.0) | – | – |
| $\chi^2_4$ | | | | | 5.7 | p = .22 | 5.7 | p = .23 | | |
| **Lifetime traumatic events** | | | | | | | | | | |
| Exposed to traumatic interpersonal violence (%) | 36.5 | (0.7) | 2.1* | (1.4-3.3) | 1.1 | (0.7-2.0) | 1.1 | (0.7-2.0) | – | – |
| Other[b] (%) | 65.2 | (0.7) | 2.0* | (1.3-3.1) | 1.3 | (0.8-2.1) | 1.3 | (0.8-2.1) | – | – |
| $\chi^2_2$ | | | | | 1.5 | p = .48 | 1.1 | p = .57 | | |
| **Personality** | | | | | | | | | | |
| Negative affectivity (mean of deciles coded 1–10) | 5.6 | (0.1) | 1.1* | (1.0-1.3) | 1.0 | (0.9-1.2) | 1.0 | (0.9-1.2) | – | – |
| Negative affectivity (% in top two deciles) | 20.1 | (0.6) | 2.3* | (1.3-4.1) | 1.3 | (0.6-2.9) | 1.3 | (0.6-2.9) | – | – |
| Fearlessness (mean of standardized 0 [1] scale)[c] | 0.0 | (0.0) | 1.3* | (1.1-1.6) | 1.0 | (0.8-1.3) | 1.0 | (0.8-1.3) | – | – |
| $\chi^2_3$ | | | | | 1.5 | p = .69 | 1.5 | p = .69 | | |
| **Lifetime mental disorders** | | | | | | | | | | |
| Any lifetime mental disorder (%) | 42.8 | (0.8) | 2.9* | (2.0-4.3) | 1.2 | (0.7-2.1) | 1.2 | (0.7-2.1) | – | – |
| PTSD months in the past year (mean number of months coded 0–12) | 0.5 | (0.0) | 1.2* | (1.1-1.2) | 1.1 | (1.0-1.2) | 1.1 | (1.0-1.2) | – | – |
| $\chi^2_2$ | | | | | 3.3 | p = .19 | 3.3 | p = .19 | | |
| **Lifetime suicidality** | | | | | | | | | | |
| Worst week suicide ideation (% more than a few seconds/minutes) | 74.5 | (1.5) | 7.6* | (1.1-51.2) | 1.6 | (0.8-2.9) | 1.6 | (0.9-2.9) | – | – |
| **Social support** | | | | | | | | | | |
| Social burden (mean of standardized 0 [1] scale)[c] | 0.0 | (0.0) | 1.2* | (1.1-1.4) | 1.1 | (0.9-1.3) | 1.1 | (0.9-1.3) | – | – |
| Relationship quality (mean of standardized 0 [1] scale)[c] | 0.0 | (0.0) | 0.7* | (0.5-0.8) | 0.8* | (0.6-0.9) | 0.8* | (0.6-0.9) | 0.7* | (0.5-0.8) |
| $\chi^2_2$ | | | | | 7.1* | p = .03 | 7.1* | p = .03 | | |
| **Recent health problems** | | | | | | | | | | |
| Health interfered with life (mean of standardized 0[1] scale)[c] | 0.0 | (0.0) | 1.5* | (1.2-1.7) | 1.1 | (0.8-1.4) | 1.1 | (0.8-1.4) | – | – |
| **Traumatic brain injury** | | | | | | | | | | |
| Worst severity was very mild (%) | 23.6 | (0.5) | 0.4* | (0.2-0.7) | 0.4* | (0.3-0.7) | 0.4* | (0.3-0.7) | 0.4* | (0.2-0.7) |
| **Risk factor** | | | | | | | | | | |
| Post-concussive symptoms (mean of standardized 0[1] scale)[c] | 0.0 | (1.0) | 1.6* | (1.3-2.0) | 1.1 | (0.8-1.5) | 1.1 | (0.8-1.5) | – | - |
| $\chi^2_2$ | | | | | 10.7 | p = .005 | 10.7 | p = 0.005 | | |
| **Mental health treatment (Past 12 months)** | | | | | | | | | | |
| 1–8 visits for any mental health treatment (%) | 12.2 | (0.5) | 1.9* | (1.1-3.3) | 1.2 | (0.7-2.0) | 1.2 | (0.7-2.0) | – | – |
| 9 + visits for any mental health treatment (%) | 3.8 | (0.2) | 7.3* | (4.7-11.6) | 3.6* | (2.0-6.5) | 3.5* | (2.0-6.3) | 6.1* | (3.9-9.5) |
| $\chi^2_2$ | | | 84.6* | p < .001 | 19.1* | p < .001 | 19.6* | p < .001 | | |
| **Army career characteristics** | | | | | | | | | | |
| Unit cohesion (mean of standardized 0[1] scale)[c] | 0.0 | (0.0) | 0.8* | (0.7-1.0) | 1.2 | (1.0-1.5) | 1.2 | (1.0-1.5) | – | – |
| **Composite Risk Score Variables** | | | | | | | | | | |
| Survey composite risk score | 0.0 | (0.0) | 2.2* | (2.0-2.4) | – | – | – | – | – | – |
| Administrative composite risk score | 0.0 | (0.0) | 1.3* | (1.1-1.6) | – | – | 1.0 | (0.8-1.2) | – | – |
| **Sociodemographics** | | | | | | | | | | |
| Age at T0 (mean in years) | 25.0 | (8.3) | 0.9* | (0.9-1.0) | 0.9* | (0.9-1.0) | 0.9* | (0.9-1.0) | 0.9* | (0.9-1.0) |

(*continued on next page*)

**Table 2** (*continued*)

| Risk factor | Distribution | | Univariate associations | | Model 1 Best multivariate survey predictors[a] | | Model 2 Best multivariate survey predictors plus administrative composite[a] | | Model 3 Significant predictors from Model 2[a] | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Estimate | SE | OR | 95% CI | OR | 95% CI | OR | 95% CI | OR | 95% CI |
| Male (%) | 94.9 | (0.5) | 0.4* | (0.2-0.8) | 0.5* | (0.3-1.0) | 0.5* | (0.3-1.0) | 0.5* | (0.3-1.0) |
| High school education or less (%) | 80.6 | (1.1) | 4.1* | (1.2-13.8) | 2.0 | (0.7-5.6) | 2.0 | (0.7-5.5) | – | – |
| Previously married (%) | 5.6 | (0.4) | 3.2* | (1.6-6.6) | 2.7* | (1.3-5.6) | 2.7* | (1.3-5.6) | 3.2* | (1.6-6.5) |
| $\chi^2_4$ | | | | | 31.5* | $p < .001$ | 31.8* | $p < .001$ | | |
| $\chi^2_{24/25/6}$ | | | | | 638.0* | $p < .001$ | 659.7* | $p < .001$ | 117.1* | $p < .001$ |
| Cross-validated AUC | | | | | 0.75 | | 0.75 | | 0.73 | |

*Significant at the .05 level, two-sided test.

[a] Controlling for months in administrative data and dummy variables for completing T2-only, T3-only, and both. The omitted category is made up of respondents who completed neither follow-up survey. Information about SA for the latter respondents came exclusively from administrative data.

[b] Other lifetime traumatic events include: Murder of close friend/relative; suicide of close friend/relative; suicide attempt of close friend/relative; discovered dead body; assault of close friend/relative; and any other event that created risk of death for a close friend/relative.

[c] The variable was standardized to have a mean of 0 and a variance of 1.0 in this sample.

disorders (any lifetime mental disorder; PTSD months in the past year), lifetime suicidality (duration of suicidal ideation during worst week), social support (feelings of being a burden; relationship quality), recent health problems (health interfered with life), traumatic brain injury (lifetime experience; worst severity; post-concussive symptoms), recent (past year) treatment of mental health problems (number of visits, 1–8 vs. 9+; no treatment but needed it vs. didn't need it), and several socio-demographic and Army career characteristics (age at baseline; gender; education; marital status; any prior deployment; unit cohesion).

All survey variables had significant univariate associations with the outcome. However, only 6 of these 24 remained significant in the best-fitting multivariate model: relationship quality (OR = 0.77), worst TBI was very mild (OR = 0.44), having 9 + mental health treatment visits (OR = 3.58), age (OR = 0.91), male gender (OR = 0.51), and previously married (either dating or not dating currently) (OR = 2.72) (Model 1; Table 2). After adding in the administrative composite variable (Model 2; Table 2), these 6 predictors all remained significant and their ORs were largely unchanged, whereas the administrative composite variable was not a significant predictor of SA. Consistent with the fact that all 24 variables in Model 1 were selected as important in the penalized regression analysis, though, the cross-validated AUC of the Model containing all 24 predictors (Model 1; AUC = 0.75) was higher than that of the model containing only the 6 individually significant predictors (Model 3; AUC = 0.73).

### 3.3. *Development and performance of machine learning models*

All the dozens of significant variables from the bivariate models within each risk factor category (Supplemental Tables 1–12) were included in a Super Learner ensemble model. The cross-validated AUC of that model was 0.77 (Fig. 1), which is not much higher than the 0.75 AUC of Model 1. We also estimated several elastic net models on this larger set of risk factors. Cross-validated AUCs from these models were 0.75–0.76 depending on the value specified for the mixing parameter (Fig. 1). As shown in Fig. 1 and Table 3, 21.3–22.7% of all subsequent SAs occurred among the 5% of soldiers at highest predicted SA risk and that 34.4–40.4% of all subsequent suicide attempts occurred among the 10% of soldiers at highest predicted risk in the various models. PPV was in the range 5.3–5.7% in these models among the 5% and 4.4–5.1% among the 10% of soldiers at highest predicted risk.

## 4. Discussion

We sought to determine if risk models using pre-deployment survey data would have sufficient strength for practical use predicting SAs during and after deployment. Three key findings emerged. First, we identified an optimal subset of 24 predictors from a much larger number of survey variables originally considered, and only 6 of these 24 remained significant in our final multivariate logistic model. A composite administrative predictor was non-significant. Second, an ensemble machine learning model allowing for interactions had only a marginally higher AUC than the final logistic model. Third, PPV was quite low despite the relatively good model AUC due to the rarity of SAs. We expand on each of these findings below.

The final significant predictors were largely consistent with prior military and general population research (e.g., Franklin et al., 2017; Nock et al., 2013; Ursano et al., 2016): history of minor TBI, frequent recent mental health treatment visits, young age, female, and indicators of relationship difficulties (low relationship quality, previously married, not dating). We also considered several distal risk factors that have received less attention in military populations (e.g., childhood adversities), but none entered the final model.

Although overall model accuracy, as indicated by AUC, was good, some other studies predicting SAs had higher AUCs (see the recent review by Belsher et al., 2019). However, the latter studies all predicted over considerably shorter follow-up periods than the 30-month time

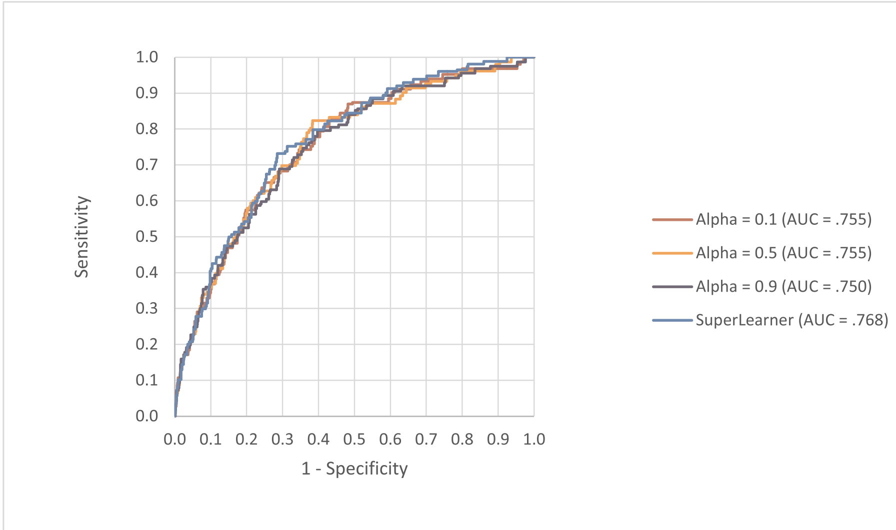


**Fig. 1.** Cross-validated ROC curves for elastic nets vs Super Learner in predicting prospective suicide attempts among deployed soldiers who completed the T0 PPDS (n = 7,677).

**Table 3**
Associations of risk strata with subsequent suicide attempts.

| Model | Sensitivity | | Positive Predictive Value | |
|---|---|---|---|---|
| | % | (SE) | % | (SE) |
| **I. Five percent of soldiers with highest predicted risk** | | | | |
| Elastic net (.1 mixing parameter) | 22.7 | (4.5) | 5.7 | (1.3) |
| Elastic net (.5 mixing parameter) | 21.7 | (4.4) | 5.4 | (1.2) |
| Elastic net (.9 mixing parameter) | 22.7 | (4.6) | 5.7 | (1.3) |
| Super Learner | 21.4 | (4.4) | 5.3 | (1.2) |
| **II. Ten percent of soldiers with highest predicted risk** | | | | |
| Elastic net (.1 mixing parameter) | 34.4 | (5.1) | 4.4 | (0.8) |
| Elastic net (.5 mixing parameter) | 35.9 | (5.1) | 4.5 | (0.8) |
| Elastic net (.9 mixing parameter) | 37.4 | (5.1) | 4.7 | (0.8) |
| Super Learner | 40.4 | (5.2) | 5.1 | (0.8) |

horizon in our study. AUC would be expected to increase as the time horizon decreases to the extent that predictors change.

Despite relatively good AUC, especially given the long time horizon, PPV was low due to the rarity of SAs. Moreover, PPV would be expected to decrease if the time horizon was shortened. Recent commentators have argued that low PPV undercuts the value of prediction models for suicidal behaviors (Belsher et al., 2019). However, this is not necessarily the case so long as intervention costs are low enough relative to anticipated benefits (Kessler, 2019; Simon et al., 2019). For example, soldiers with comparatively high predicted SA risk might cost-effectively be assigned to inexpensive low-risk interventions (Greden et al., 2010; Torous and Walker, 2019) or model results might be used to target a subset of soldiers for additional assessments to determine next steps (Matarazzo et al., 2019; Zuromski et al., 2019).

One noteworthy limitation of our study is that classification accuracy might have been affected by our small sample size, as we had to use a composite administrative risk score rather than consider the many individual administrative variables available for each soldier for inclusion in the model. A larger sample in future replications would allow more nuanced analyses of administrative predictors. A larger sample would also make it possible to develop models over shorter time horizons, which might have greater practical value to decision-makers. It would also be of interest to expand the variety of predictors considered in future expansions of our work. For example, suggestions exist that experiences from prior deployments (e.g., combat) and time-related variables related to time since prior deployment might be significant predictors of suicidal behaviors during subsequent deployments. (Bryan et al., 2015; Ursano et al., 2018). Information obtained from various biomarkers (Niculescu et al., 2017; Stein et al., 2017) and other data sources (e.g., social media posts; Bryan et al., 2018) might also be of value.

Another potentially important limitation is that we combined information about self-reported and administratively-recorded SAs. Although the prevalence of SAs in our sample was higher than estimated for the general US population (Olfson et al., 2017), the relative rarity of SAs made it impossible to carry out separate analyses of self-reported and administratively-recorded SAs. Furthermore, we excluded the small number of PPDS respondents who died by suicide because of the extreme rarity of this outcome. It might well be that predictors are different for self-reported SA, administratively-recorded SA, and suicide death. A final important limitation is that PPDS respondents were given assurances that their survey responses would be confidential, which may have encouraged more open responding than if a similar survey without this guarantee of confidentiality was carried out in the future for the purpose of targeting soldiers for preventive interventions.

The latter limitation means that any attempt to use the current results to build a SA risk model would need to replicate our study using a survey in which respondents were aware that their responses are identified, possibly supplementing the questions we found to be significant predictors with other measures designed to be less subject to response bias in identified surveys (Nock et al., 2010; Bryan et al., 2014). Iterative refinement would doubtlessly be needed prior to such a model being used for practical decision-making (Fusar-Poli et al., 2018).

## Declaration of competing interest

None.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jpsychires.2019.12.003.

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