PRE-DEPLOYMENT HEALTH ASSESSMENTS: USING MACHINE LEARNING TO ASSIST MILITARY HEALTH CARE PROVIDERS IN PREDICTING NON-DEPLOYABILITY

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Background

- The Pre-Deployment Health Assessment (PreDHA) is one of five health assessments administered by the U.S. military to monitor service members' health throughout their deployment cycle
- The PreDHA determines the medical needs for a service member prior to deployment, and if they are deployable
- Service members are required to take the PreDHA within 120 days prior to the start of deployment
- There is a lack of research using machine learning capabilities to determine what medically limiting factors are attributed to a non-deployable status on the PreDHA

Objectives

1. Describe the performance of a machine learning model predicting PreDHA deployment outcome
2. Describe the impact of different military data in predicting PreDHA deployment status
3. Discuss specific variables that have the highest impact on model classification status

Methods

Study Population

- This retrospective cohort study included a randomized sample of active duty U.S. service members in the Army, Marine Corps, and Navy who completed a PreDHA between 1 January 2012 and 31 December 2022

Data

- Data for the PreDHA were sourced from the Defense Health Agency and included only the most recently completed PreDHA for each service member during the study period
- Key variables from the PreDHA were selected for inclusion in machine learning modeling
- Medical and demographic variables within 1 year prior to the date of each PreDHA were sourced from the Military Health System Data Repository
- The outcome variable was dichotomized as "Deployable" and "Not Deployable based on PreDHA disposition field 14

Analysis

- Service members were stratified by the outcome variable then randomly divided into training and testing sets
- Scaling hyperparameters were used to adjust class balances during model training
- Three binary classifiers were trained and tested, including logistic regression, random forest, and boosted trees

Results

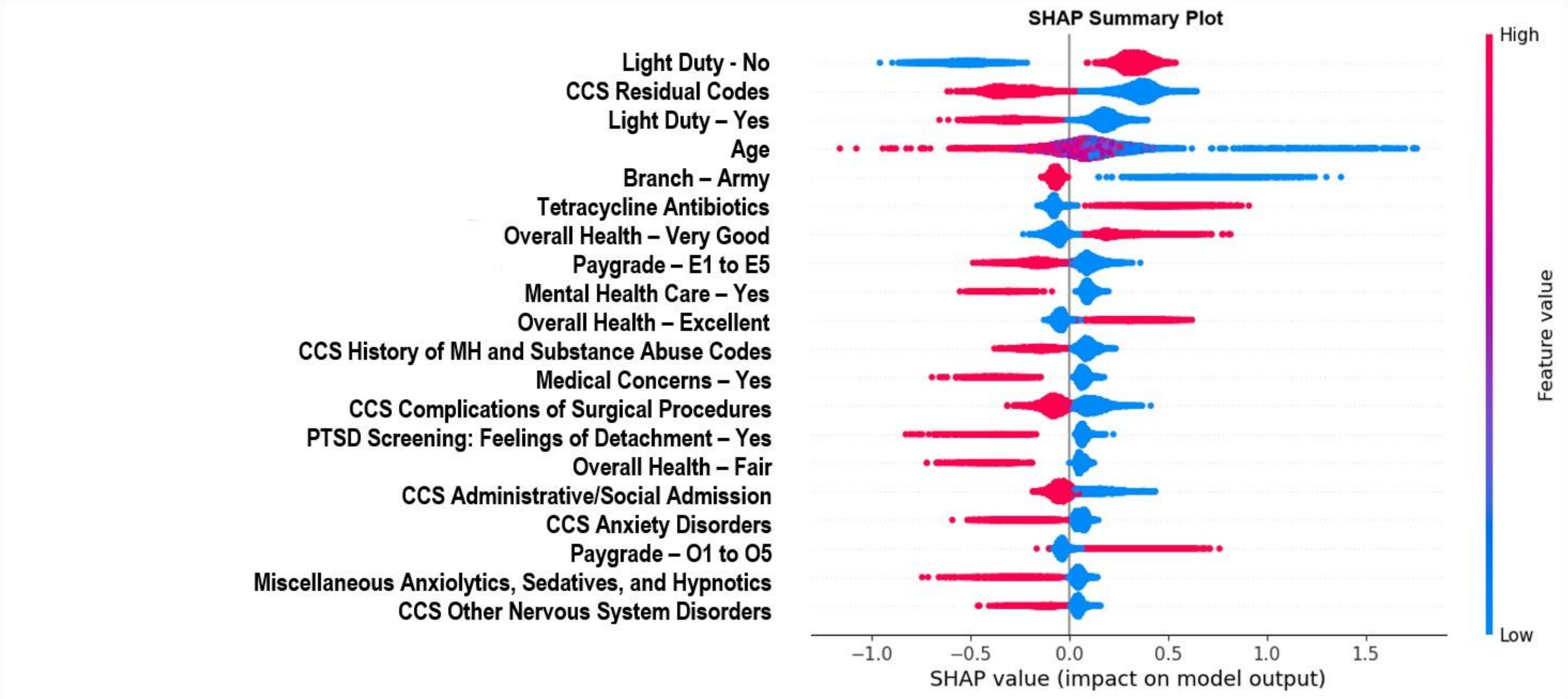
Table. Frequencies of PreDHA Final Disposition Dichotomized by the Outcome Variable

PreDHA Outcome	No.	Percent
Deployable	**25,252**	**92.0%**
Deployable	24,318	88.6%
Deployable but requires medical readiness updates	934	3.4%
Not Deployable	**2,199**	**8.0%**
Not Deployable – other	1,257	4.6%
Not Deployable – potentially disqualifying condition	942	3.4%
Total	**27,451**	**100.0%**

Figure 1. Classification Performance of Best Performing Boosted Tree Model

Class	Precision	Recall	F1-Score	Support
Deployable	0.96	0.90	0.93	5,051
Not Deployable	0.34	0.56	0.42	440
Accuracy			0.88	5,491
Macro Average	0.65	0.73	0.68	5,491
Weighted Average	0.91	0.88	0.89	5,491

Figure 2. Highest 20 SHAP Values for Features in Best Performing Model



Results

- The study sample included N = 27,451 U.S. service members, of whom 92.0% received a deployable outcome and 8.0% received a not deployable outcome
- The boosted tree model had the best performance in both accuracy (87.7%) and area under the curve (AUC; .8454)
- The best performing model trained exclusively on variables from the PreDHA performed similarly to the best performing model trained on medical and demographic variables (AUC .8082 vs. .7945) while requiring significantly less features (9 vs. 524)
- Model performance was higher for the deployable group than the non-deployable group according to F1 score (.92 vs. .41)
- Tree-based SHapley Additive exPlanations (SHAP) analysis showed PreDHA Question 2 ("Currently on profile, limited duty, MMRB decision, MEB or PEB") had the highest average impact on model performance

Conclusions

- Features from the PreDHA demonstrated a high degree of importance to model decision, comprising 8 of the 20 highest SHAP values
- While the best performing model demonstrated a high overall AUC, the per-class F1 scores indicated a significantly weaker classification performance for the non-deployable group compared with the deployable group
- Future studies are warranted to develop a model with a more balanced performance for deployment determinations
- Results suggest including a more robust set of longitudinal health and PreDHA data may improve model performance in the future

References

U.S. Department of War. *Pre-Deployment Health Assessment* (DD Form 2795). U.S. Dept. of War; October 2015. Accessed June 23, 2026. https://api.army.mil/e2/c/downloads/2025/12/11/f93e02b4/pre-deployment-health-assessment-dd-form-2795.pdf

U.S. Department of the Navy. *Deployment Health Assessment Process* (OPNAVINST 6100.3A CH-1). U.S. Dept of the Navy; February 1, 2016. Accessed June 23, 2026. https://www.secnav.navy.mil/doni/Directives/06000%20Medical%20and%20Dental%20Services/06-100%20General%20Physical%20Fitness/6100.3A%20CH-1.pdf

Navy and Marine Corps Force Health Protection Command. *Deployment Health Assessments*. Accessed June 23, 2026. https://www.med.navy.mil/Navy-and-Marine-Corps-Force-Health-Protection-Command/Population-Health/Epi-Data-Center/Deployment-Health-Assessments/

 This work was supported by the U.S. Navy Bureau of Medicine and Surgery under work unit no. 60808.