A Machine Learning Approach to Identifying Soldiers in the U.S. Army General Population at Risk for Suicide Attempt or Death

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Introduction

The Leading Cause of Mortality

Suicide has been the primary cause of death for U.S. military service members since 2008, with annual increases necessitating more robust intervention strategies.

Limitations of Self-Disclosure

Military cultural stigma significantly hinders the effectiveness of traditional self-report screenings; only 0.2% of soldiers admit to suicidality during PHAs, making these reports uninformative for risk prediction.

Administrative Data as a Proxy

- Demographic
- Career
- Psychopathological
- Physical Health Records

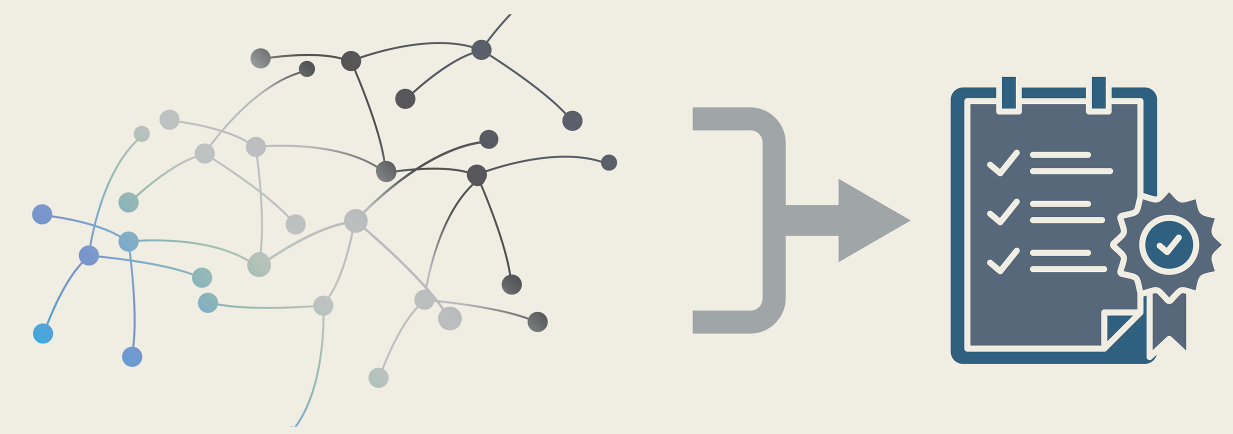
ML risk prediction offers a pathway to bypass self-report biases by using longitudinal administrative variables to identify risk for subsequent fatal and nonfatal behaviors.

Materials and Methods

668,684

Large-Scale Longitudinal Cohort: The study analyzed a population of 668,684 Regular U.S. Army soldiers who completed 1,932,243 PHAs between 2015 and 2019.

Ensemble Modeling Approach



Researchers employed stacked generalization algorithms using the "Super Learner" method, pooling results across diverse algorithms to maximize predictive accuracy.

24-Month Risk Horizon

PHA → 24-month →
- **Suicide Deaths** (verified via National Death Index)
- **Suicide Attempts** (verified via DoW Records)

The models were designed to predict suicide deaths and nonfatal suicide attempts over a 24-month period following a PHA.

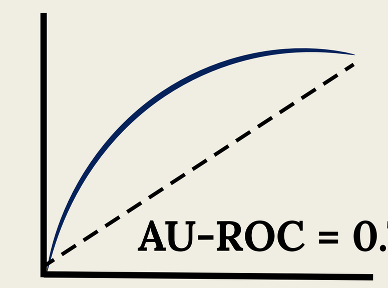
Predictor Classification

- Demographics (age, sex, education)
- Army career characteristics (rank, MOS, deployments)
- Psychopathological history
- Physical health conditions

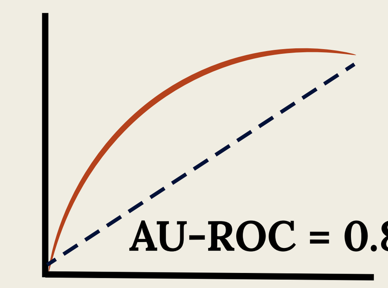
Predictors were categorized into four domains.

Results

Model Discrimination Performance



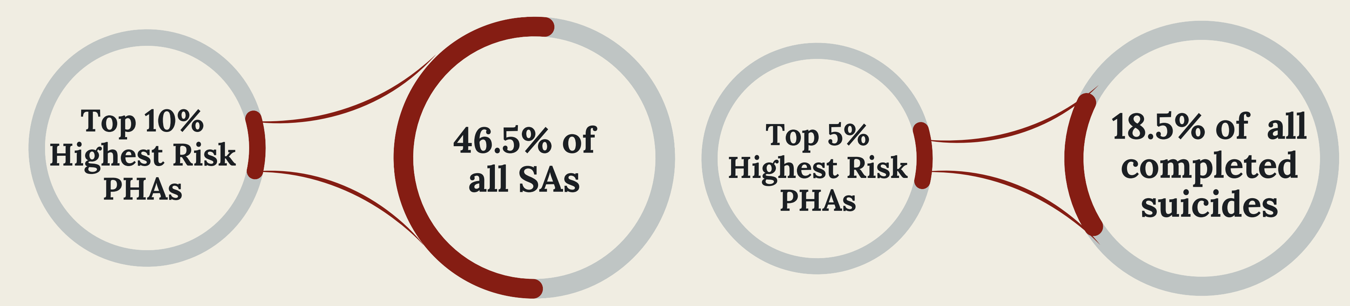
Suicide Deaths
("Fair" Discrimination)



Nonfatal Suicide Attempts
("Good" Discrimination)

Validation in the test sample demonstrated "fair" discrimination for suicide deaths and "good" discrimination for nonfatal suicide attempts.

Concentration of Risk



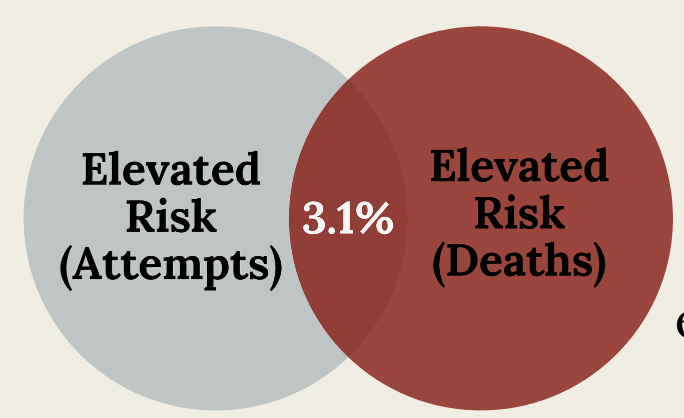
Risk is highly concentrated: the top 5% of PHAs by predicted risk captured 18.6% of all suicides, while the top 10% captured 46.5% of all nonfatal suicide attempts.

Differentiating Attempt vs. Death Profiles

Suicide Deaths	Suicide Attempts
Male Sex	Female Sex
Non-Hispanic White Race	Younger Age

Predictor importance analysis (SHAP values) revealed distrinct risk profiles.

Modest Outcome Overlap



The correlation between predicted probabilities for suicide and SA was modest (r=0.29). 11.9% were at elevated risk for at least one.

Driver Dominance

Psychopathological 70.6% - 95.4%	Demographics	Career	Health

Psychopathological risk factors were the most important class of predictors across all models.

Conclusions

Structural Risk Identification

Subjective self-reporting → Structural computational process

Shifting from subjective self-reporting to a structural computational process allows for the objective identification of high-risk soldiers without relying on disclosure.

Nuanced Resource Allocation

Risk Identification →
- **Tailored for Suicide Deaths**
- **Tailored for Suicide Attempts**

Because suicide deaths and attempts have distinct predictors and only partially overlapping risk groups, intervention strategies must be tailored to specific outcomes to optimize net benefits.

Implementation of Operation Life Force

RCT → **Fort Hood, Texas**

This ML-based approach is currently being applied in a real-world Randomized Clinical Trial (RCT) to recruit high-risk soldiers for the Operation Life Force intervention.