

VA-STARRS RESIDENCY

Emily Edwards, PhD

SUMMARY

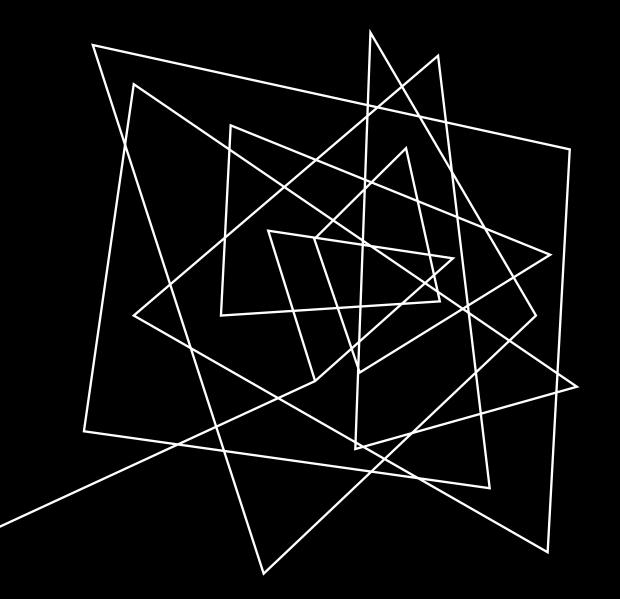
From FY24-25, the VA-STARRS Residency program provides opportunity to conduct research with the Army STARRS research team for 20h per week. Research focuses broadly on suicide prevention among active duty and recently discharged military personnel.

SUMMARY OF VA-STARRS RESIDENCY

- 1. Orientation to the STARRS Datasets
- Collaboration with researchers at Harvard
 & USUHS
- Leading research projects using STARRS data

STARRS DATASETS

- Self-report datasets
 - New Soldier Survey (N=50,765)
 - All Army Survey (N=39,666)
 - Pre-Post Deployment Survey (N=9,415)
 - Longitudinal Follow-up Surveys (1-4) (N=14,508)
 - <u>Publicly available through ICPSR</u>
- Historical Administrative Datasets
 - All administrative data collected from the US Army from 2004-present
 - Only available to STARRS researchers



INITIAL PROJECT

Situational Stress in At Risk Transitioning Veterans

Psychological Medicine

cambridge.org/psm

Original Article

Cite this article: Kearns JC et al (2023). A practical risk calculator for suicidal behavior among transitioning U.S. Army soldiers: results from the Study to Assess Risk and Resilience in Servicemembers-Longitudinal Study (STARRS-LS). *Psychological Medicine* 1–10. https:// doi.org/10.1017/S0033291723000491

Received: 16 December 2022 Revised: 3 February 2023 Accepted: 9 February 2023

Keywords:

Machine learning; suicide attempt; suicide prevention; veterans

Author for correspondence:

Ronald C. Kessler, E-mail: kessler@hcp.med.harvard.edu A practical risk calculator for suicidal behavior among transitioning U.S. Army soldiers: results from the Study to Assess Risk and Resilience in Servicemembers-Longitudinal Study (STARRS-LS)

Jaclyn C. Kearns^{1,2}, Emily R. Edwards^{3,4}, Erin P. Finley^{5,6}, Joseph C. Geraci^{3,4,5,7}, Sarah M. Gildea⁸, Marianne Goodman^{3,5}, Irving Hwang⁸, Chris J. Kennedy⁹, Andrew J. King⁸, Alex Luedtke^{10,11}, Brian P. Marx^{1,2}, Maria V. Petukhova⁸, Nancy A. Sampson⁸, Richard W. Seim⁵, Ian H. Stanley^{12,13}, Murray B. Stein^{14,15,16}, Robert J. Ursano¹⁷ and Ronald C. Kessler⁸

¹National Center for PTSD, VA Boston Healthcare System, Boston, MA, USA; ²Department of Psychiatry, Boston University School of Medicine, Boston, MA, USA; ³Transitioning Servicemember/Veteran And Suicide Prevention Center (TASC), VISN 2 Mental Illness Research, Education and Clinical Center, James J. Peters VA Medical Center, Bronx, New York, NY, USA; ⁴Department of Psychiatry, Icahn School of Medicine at Mount Sinai, New York, NY, USA; ⁵Center of Excellence for Research on Returning War Veterans, VISN 17, Doris Miller VA Medical Center, Waco, TX, USA; ⁶Center for the Study of Healthcare Innovation, Implementation, and Policy (CSHIP), VA Greater Los Angeles Healthcare System, Los Angeles, CA, USA; 7Resilience Center for Veterans & Families, Teachers College, Columbia University, New York, NY, USA; ⁸Department of Health Care Policy, Harvard Medical School, Boston, MA, USA; ⁹Department of Psychiatry, Massachusetts General Hospital, Boston, MA, USA; ¹⁰Department of Statistics, University of Washington, Seattle, WA, USA; ¹¹Vaccine and Infectious Disease Division, Fred Hutchinson Cancer Research Center, Seattle, WA, USA; 12 Department of Emergency Medicine, University of Colorado School of Medicine, Aurora, CO, USA; ¹³Department of Emergency Medicine, Center for COMBAT Research, University of Colorado School of Medicine, Aurora, CO, USA; 14 Department of Psychiatry, University of California San Diego, La Jolla, CA, USA; ¹⁵School of Public Health, University of California San Diego, La Jolla, CA, USA; ¹⁶VA San Diego Healthcare System, La Jolla, CA, USA and ¹⁷Department of Psychiatry, Center for the Study of Traumatic Stress, Uniformed Services University of the Health Sciences, Bethesda, MD, USA

Abstract

Background. Risk of suicide-related behaviors is elevated among military personnel transitioning to civilian life. An earlier report showed that high-risk U.S. Army soldiers could be identified shortly before this transition with a machine learning model that included predictors from administrative systems, self-report surveys, and geospatial data. Based on this result, a Veterans Affairs and Army initiative was launched to evaluate a suicide-prevention intervention for high-risk transitioning soldiers. To make targeting practical, though, a streamlined model and risk calculator were needed that used only a short series of self-report survey questions.

Table 3. Predictor importance in the final lasso model^{a,b}

	Multivariable	Univariable
	RR (95% CI)	RR (95% CI)
I. Self-injurious thoughts and behaviors		
Lifetime active suicidal ideation	1.58 (0.97-2.57)	2.85 (1.94-4.19)
Lifetime passive suicidal ideation	1.43 (0.94-2.19)	2.81 (1.99-3.97)
Lifetime suicide attempt	1.24 (1.06-1.45)	1.60 (1.31-1.96)
Suicidal ideation (active or passive) 2 years before leaving active service	1.21 (0.98-1.49)	1.59 (1.32-1.93)
Lifetime suicide plan	1.02 (0.75-1.39)	2.22 (1.62-3.03)
II. Externalizing disorders		
Frequency of substance use-related interpersonal problems (worst lifetime)	1.34 (1.12-1.61)	1.45 (1.19-1.77)
Frequency of school truancy in childhood	1.26 (0.98-1.61)	1.95 (1.43-2.66)
Frequency of running away from home in childhood	1.25 (1.03-1.52)	1.56 (1.29-1.89)
Antisocial personality traits: Physically assault others	1.11 (0.93-1.33)	1.32 (1.09-1.60)
Childhood conduct: How often bullied or threatened kids	1.11 (0.89-1.38)	1.48 (1.22-1.79)
II. Stressor exposure		
Victim of any criminal offense 4 years before leaving active service	1.36 (1.15-1.61)	1.60 (1.37-1.87)
Any lifetime life-threatening accident or other risky/near death experience ^c	0.55 (0.39-0.78)	0.66 (0.45-0.95)
V. Socio-demographic and Army career predictors		
1+ dependent age 6-13 years old	1.63 (1.33-1.99)	1.45 (1.24-1.70)
Discharged Honorably or Under Honorable Conditions	1.46 (1.15-1.86)	1.38 (1.05-1.80)
Identify as gay, lesbian, or bisexual	1.20 (1.02-1.42)	1.36 (1.15-1.61)
34+ years old at the time of leaving active service	0.64 (0.42-0.97)	0.57 (0.39-0.83)
2+ Global War on Terror deployments	0.54 (0.36-0.83)	0.56 (0.34-0.95)

Abbreviations: RR, relative-risk; CI, confidence interval.

"The coefficients and CI were estimated in multivariable and univariable Poisson regression models with a stable regularization method used to estimate standard errors. However, as a prior lasso model was used to select the predictors included in the models, the confidence intervals should be used only heuristically, as they are not exact when predictor selection is done using lasso. It is noteworthy that some predictors would not be considered statistically significant using conventional criteria but were selected by lasso because they best represent joint effects of all survey predictors. Each predictor was standardized to have a mean of 0 and variance of 1 prior to estimation, resulting in the RR estimates describing the proportional differences in risk of the outcome associated with 1 s.o. changes in each predictor.

^bSee online Supplementary Table S1 for a description of the predictor variables. All variables were defined as of the time period prior to the respondent leaving or being released from active service.

^cOther than physical or sexual assault, illness or injury, or a natural disaster.

Those in the top 10% of predicted risk made 45% of all post-discharge suicide attempts

Those in the top 30% of predicted risk made 93% of all post-discharge suicide attempts

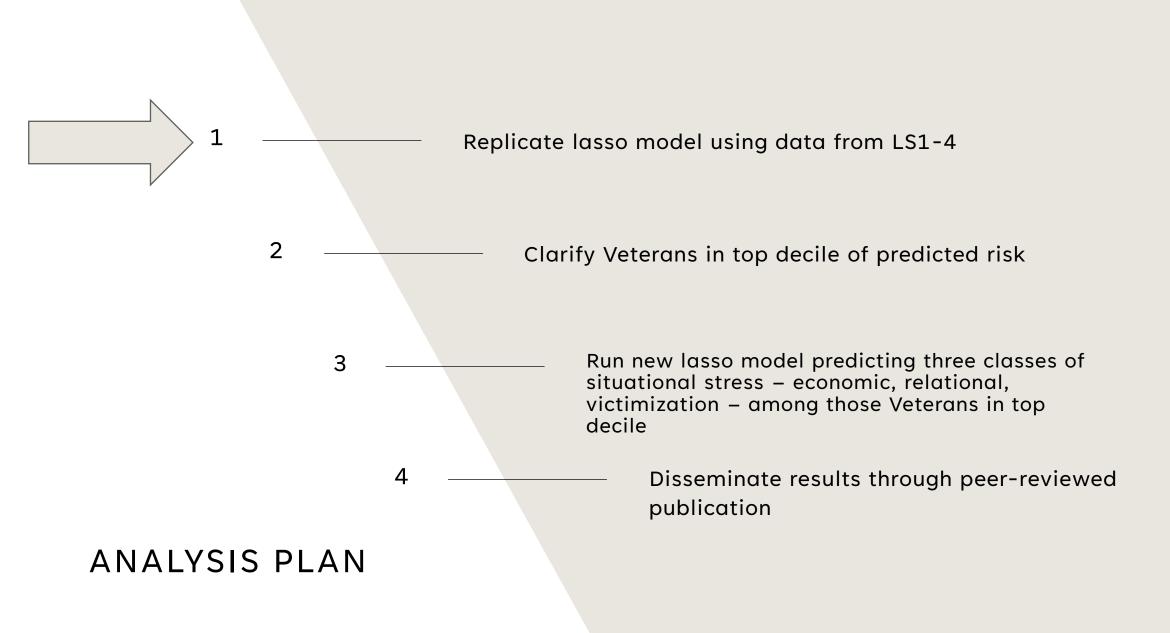
Based on self-report data administered during NSS, AAS, and PPDS and follow-up self-report data administered through LS1 and LS2

Total sample size = 8,335

Suicide attempt sample = 110

AMONG THOSE IDENTIFIED AS AT-RISK, WHO IS MOST LIKELY TO EXPERIENCE SITUATIONAL STRESS DURING THE TRANSITION BACK TO CIVILIAN LIFE?

Even among individuals at high chronic risk for suicide, acute stressors are typically responsible for triggering suicide-related behaviors.



Those in the top 15% of predicted risk made 65% of all post-discharge suicide attempts

Total sample size = ~5200-5800/year

Suicide attempt sample = 217

Year 1 Suicide Attempts

- Pretty good ability to predict suicide attempts occurring within the first 12 months post-discharge
- AUC = 0.85, SE = 0.02

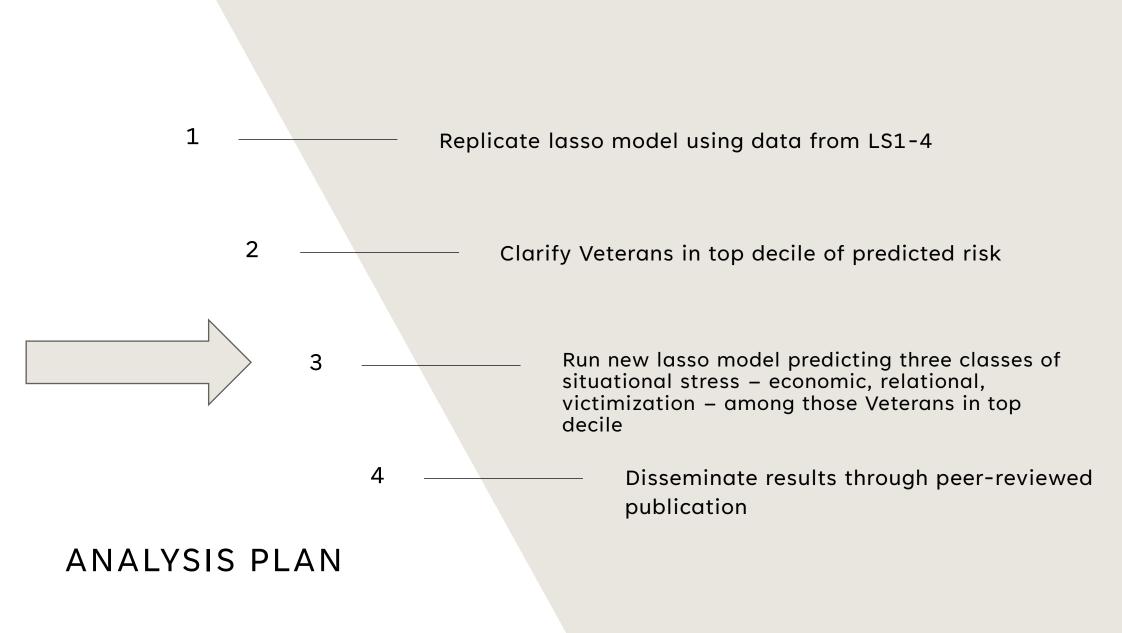
Year 2 Suicide Attempts

RESULTS

- Not as great, but still pretty decent!
- AUC = 0.77, SE = 0.03

Year 3 Suicide Attempts

- Model is still holding!
- AUC = 0.77, SE = 0.04



RESULTS

Economic

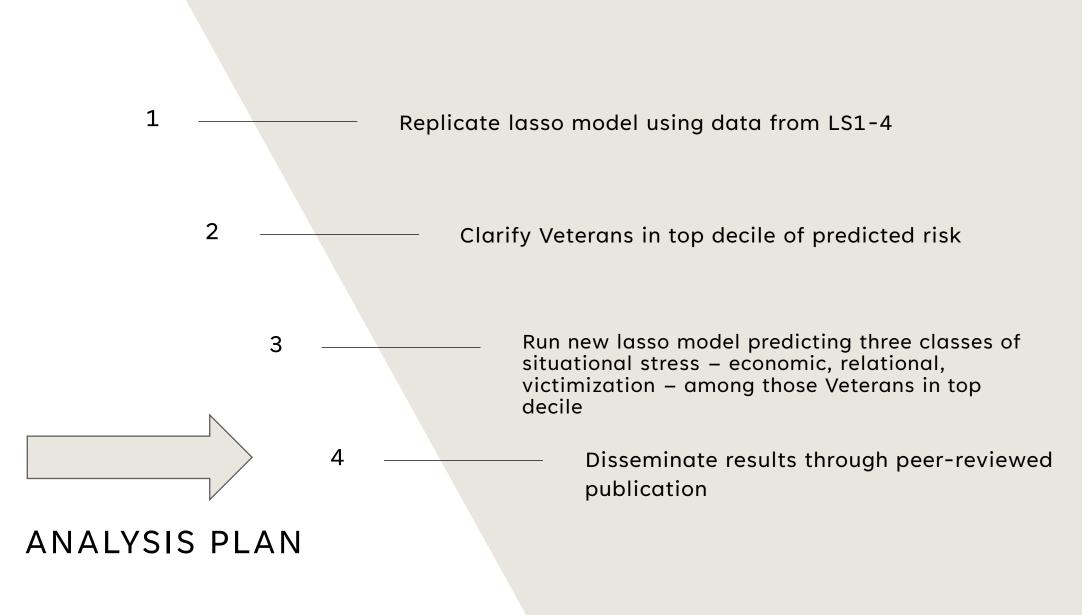
- NOPE...
- AUC = 0.55, SE = 0.02

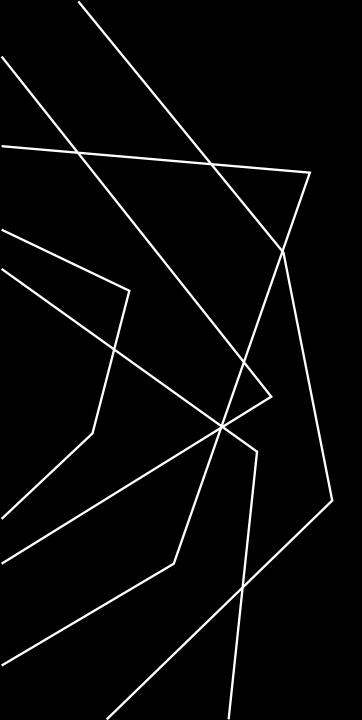
Relational

- NOPE...
- AUC = 0.57, SE = 0.02

Victimization

- ANOTHER NOPE...
- AUC = 0.60, SE = 0.02





THANK YOU

Emily Edwards

Emily.Edwards5@va.gov

A MACHINE LEARNING MODEL TO PREDICT FIREARM SUICIDE

Claire Houtsma, PhD Southeast Louisiana Veterans Health Care System South Central Mental Illness Research, Education and Clinical Center <u>Supervisor</u>: Ronald C. Kessler, PhD McNeil Family Professor of Health Care Policy, Department of Health Care Policy, Harvard Medical School

DISCLOSURE:

THIS WORK WAS SUPPORTED IN PART BY THE UNITED STATES DEPARTMENT OF VETERANS AFFAIRS, CLINICAL SCIENCES RESEARCH AND DEVELOPMENT SERVICE (CSR&D) UNDER CAREER DEVELOPMENT AWARD-1 IK1 CX002370-01A1 AND PROJECT SPR-002-24F. THE VIEWS EXPRESSED IN THIS PRESENTATION ARE THOSE OF THE AUTHORS AND DO NOT NECESSARILY REFLECT THE POSITION OR POLICY OF THE DEPARTMENT OF VETERANS AFFAIRS, DEPARTMENT OF DEFENSE, OR UNITED STATES GOVERNMENT.



AGENDA

- Background of the Problem
- Machine Learning Models
- Current Study
- Preliminary Results and Interpretations
- Questions



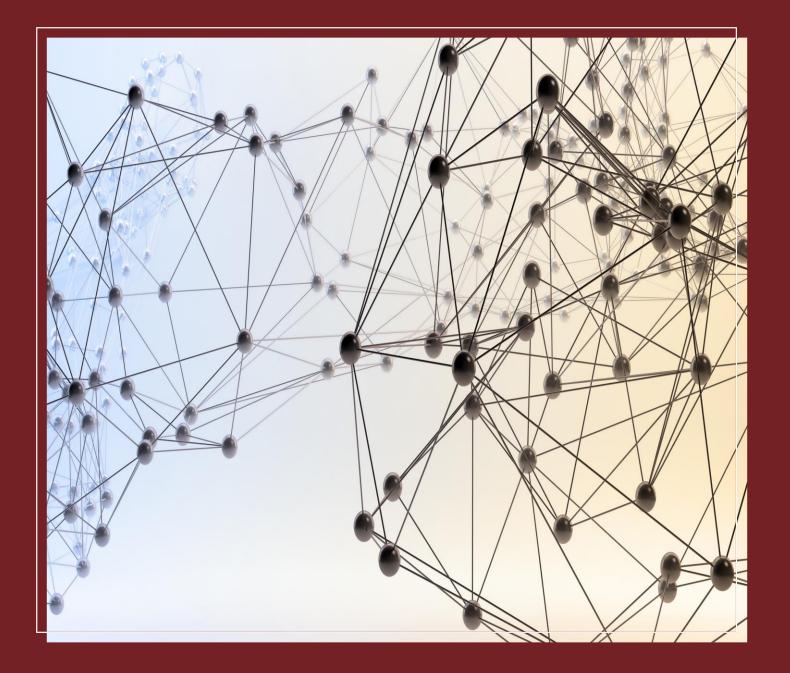
BACKGROUND OF THE <u>PROBLE</u>M





- Suicide is a significant concern among military service members and Veterans, with most deaths involving firearm-related injury
- Risk of suicide nearly triples during the first year post-separation, and remains elevated for up to six years post-separation
- There are many barriers to identifying those at risk before it is too late (e.g., service members and Veterans are unlikely to disclose suicidal thoughts)
- Our ability to predict suicidal ideation and behavior has not improved in the last 50 years, indicating a need for novel approaches to risk identification

Department of Defense, 2022; U.S. Department of Veterans Affairs, 2023; Ravindran et al., 2020; Horwitz et al., 2019; Franklin et al., 2017



MACHINE LEARNING MODELS

THE BASICS

- Machine learning is a subfield of artificial intelligence, with the goal of using computers to perform complex tasks, similar to how humans solve problems
- This process starts with a subset of data on which to "train" the computer program. From there, you let the model find patterns or make predictions
- The remaining data is held out from this process to be used as the "evaluation" data, which tests the accuracy of the model is when it is shown new data

MACHINE LEARNING AND SUICIDE

- Systematic review of 87 machine learning studies examining prediction of suicide risk found:
 - Classification studies were the most common
 - Excellent accuracy and area under the curve (AUC) values primary indicators of a good model (AUCs ranged from 0.61 to 0.99)
 - Many pre-identified risk factors emerged as important within these models (e.g., mood/substance use disorders, male gender) but newly identified risk factors emerged as well (e.g., neural substrates)
 - Methods varied widely, limited examples within military/Veteran samples

MACHINE LEARNING AND SUICIDE

- Kessler et al (in progress):
 - Supervised machine learning model using administrative data of Army soldiers from 2010-2019
 - Predicting suicide by any method
 - Good accuracy and AUC
- However:
 - The majority of Army suicides involve firearms
 - Given the high lethality rate of firearms, there is less opportunity to intervene on suicide risk than with other suicide methods
 - I wondered if a model based on firearm suicide would improve upon the "suicide by any method" model in this population, giving us a chance to intervene with firearm-specific suicide prevention interventions for those at risk

CURRENT STUDY





CURRENT STUDY

- Supervised machine learning model trained on the same Army administrative data from 2010 to 2019
 - Specifically, firearm suicide decedents and matched controls (20 controls: 1 case)
- Evaluated the resulting model's ability to predict firearm suicide
 - We also compared this model's accuracy to the "any suicide method" model developed by Kessler et al.

\square	

PRELIMINARY RESULTS

Model	AUC	95% Confidence Interval
"Any suicide method" model (Kessler et al)	0.710	0.699, 0.721
Firearm suicide model (Houtsma et al)	0.710	0.699, 0.721

PRELIMINARY INTERPRETATIONS

- No difference between the two models in terms of accuracy
- Could mean that using the "any suicide method" model is best
- Another possible interpretation:
 - Given:
 - 1. The preponderance of firearm suicide among service members and Veterans
 - 2. The lethality of firearms as a suicide method
 - 3. Realistic limitations for rolling out interventions in this large population

It may be preferable to identify those who are at risk of firearm suicide specifically, so that firearm-specific suicide prevention interventions can be used with these individuals

NEXT STEPS

- Currently running a "net-benefit analysis" to determine whether there is a statistical advantage to using the firearm model over the "any suicide method" model when trying to predict firearm suicide among Army soldiers
- If the firearm model is advantageous, we could use this to identify soldiers at elevated risk prior to discharge and connect them with relevant primary prevention (e.g., lethal means counseling, firearm locking devices)
- Another possibility is to look at Shapley Additive Explanations (SHAP values) as a metric of variable importance within the model – our team is still determining whether this is an appropriate/important step to take

THANK YOU



Claire Houtsma

<u>Claire.Houtsma@va.gov</u>

REFERENCES

- Bernert, R. A., Hilberg, A. M., Melia, R., Kim, J. P., Shah, N. H., & Abnousi, F. (2020). Artificial intelligence and suicide prevention: A systematic review of machine learning investigations. *International Journal of Environmental Research and Public Health*, 17(16), 5929.
- Brown, S. (2021, April 21). Machine learning, explained. MIT. https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-explained
- Department of Defense. (2022). *Annual Report on Suicide in the Military: Calendar Year 2022*. Under Secretary of Defense for Personnel and Readiness. https://www.dspo.mil/Portals/113/Documents/ARSM_CY22.pdf?ver=StAk_q6lJgNRUsOlptzVVA%3d%3d
- Franklin, J. C., Ribeiro, J. D., Fox, K. R., Bentley, K. H., Kleiman, E. M., Huang, X., Musacchio, K. M., Jaroszewski, A. C., Chang, B. P., & Nock, M. K. (2017). Risk factors for suicidal thoughts and behaviors: A meta-analysis of 50 years of research. *Psychological Bulletin*, 143(2), 187.
- Horwitz, A. G., Smith, D. L., Held, P., & Zalta, A. K. (2019). Characteristics of veteran and civilian suicide decedents: A sex-stratified analysis. *American Journal of Preventive Medicine*, 56(5), e163-e168.
- Ravindran, C., Morley, S. W., Stephens, B. M., Stanley, I. H., & Reger, M. A. (2020). Association of Suicide Risk With Transition to Civilian Life Among US Military Service Members.
 JAMA Network Open, 3(9), e2016261. <u>https://doi.org/10.1001/jamanetworkopen.2020.16261</u>
- U.S. Department of Veterans Affairs. (2023). 2023 National Veteran Suicide Prevention Annual Report. Office of Mental Health and Suicide Prevention.