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Invited Commentary | Statistics and Research Methods

Efficient Determination of Social Determinants of Health From Clinical Notes for Timely Identification of Suicidality Among US Veterans

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The article by Mitra et al[1] provides a novel approach for measuring social determinants of health (SDOHs) in the context of determining risk factors for suicidality among US military veterans. The authors found that SDOHs extracted automatically from clinical notes included in the electronic health record (EHR) of past medical encounters via a natural language processing (NLP) algorithm can efficiently capture the association with death by suicides and can measurably enhance SDOHs obtained from structured EHR data. Importantly, the results show that the NLP-extracted SDOHs have a higher degree of association compared with those obtained from structured data, suggesting that we might be able to efficiently identify at-risk individuals even when structured data on the relevant variables are missing or incomplete.

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Assessing Risk of Suicide for Timely Intervention

As discussed in a 2012 editorial in the *American Journal of Public Health*,[2] veterans have significantly higher risk of suicide (up to 4 times) relative to the general population during the first 4 years following military service. A reliable ability to universally screen veterans for depression and suicide risk and to refer them for appropriate treatment would save numerous lives, and any such tool would arguably be applicable with little modification to the general population.

In 2016, The Joint Commission[3] highlighted that a significant number of individuals dying from suicide were not receiving mental health care but had a recent medical interaction and could possibly have disclosed suicidal ideation (SI) had they been asked directly. As a direct result of such emerging evidence, the Veterans Health Administration (VHA) Office of Mental Health and Suicide Prevention established an interdisciplinary workgroup of experts to identify an evidence-informed approach to detect suicide risk among veterans.[4] These efforts might have contributed to recent decrease in suicides[5]; in 2020 there were 343 fewer veteran suicides than in 2019, and the number of veteran suicides was lower than each prior year since 2006. However, adjusting for population age and sex differences, the current suicide rate for veterans is still 57.3% greater than for nonveteran US adults; the unadjusted rate of suicide in 2020 among US veterans was 31.7 per 100 000,[5] about twice that of the general population (13.5 per 100 000). The work of Mitra et al[1] can enable new cost-efficient interventions to close this gap.

Estimating Suicidality From EHRs Using Machine Learning

Large EHR databases with detailed records of past diagnoses and medical encounters combined with sophisticated pattern recognition enabled by cutting edge machine learning (ML) algorithms are poised to revolutionize how we think about disease risk and personalized preventive health care. Assessing the risk for suicide risk is no different. Several studies[6] have highlighted the association of mental disorders with SI and suicide attempt (SA) in veterans, and diagnostic code patterns recorded in individual history of medical interactions has the potential to accurately flag patients with comorbidities that elevate SI and SA risk. Arguably, if a predictive association can be established, we can achieve operationally better odds of effective interventions compared with the current approach centered around standardized questionnaires that aim to assess SI/SA risk.

The challenge remains that many at-risk veterans might not be receiving adequate metal health care[3]; ergo, they may not have the relevant diagnoses on record of an associated mental disorder necessary to flag them for SI/SA risk. Even if we were to universally deploy some form of diagnostic code–based risk assessment, the impact might be marginal. Additionally, new procedures, even if comprising relatively short questionnaire-based assessments, are often ignored by clinicians due to typically high workloads. Thus, while such predictive models have existed for some time in the literature, universal deployment and uptake of these tools has not happened. Simply establishing a predictive model is not enough, we must consider the consequences for clinician productivity and minimize workflow deviations for successful adoption within existing health care systems.

This is where the approach of Mitra et al[1] to assess risk from SDOHs extracted automatically from EHR codes and clinical notes could be helpful. It is conceivable that such tools can deduce a risk flag from existing patient data and notify the clinician even before patient encounter starts.

Thus, while the use of SDOHs to assess SI/SA risk has indeed been explored before, as discussed by the authors,[1] the novelty here lies in the source of this information. SDOH data are typically not available publicly for various privacy reasons, and manually collecting such information can be expensive. Mitra et al[1] suggest that we generate such information from the clinical notes included in standard EHR via NLP. Thus, the authors' approach can indeed provide the foundation for addressing the key hurdles in enacting efficient universal assessment for suicide risk among the veterans and perhaps in the general population.

However, even with better odds, it is doubtful that such technology can make a measurable impact in the very near term. This work should be seen as a proof of concept, and several hurdles remain before we have a deployment-ready application that incorporates the ideas set forth here and integrates seamlessly with existing EHR systems. Barriers to the uptake of digital technology in health care are beginning to be understood,[7] and validated performance along with seamless integration are key to eventual adoption.

Future Improvements

There are problems with administrative data. EHR data are typically error prone, especially in socially vulnerable areas. Clinical notes might involve similar uncertainty. Although if the objective is to raise flags, we might be able to arrange for the downside to be simply a high false-positive rate. Depending on how we handle such spurious flags, we might be able to live with it. The impact of EHR noise needs to be investigated in a clinical setting.

Keyword-based NLP systems have limitations. There are limitations to language models in how well they can extract meaning from human-generated text, although rapid progress in ML and artificial intelligence (AI) is changing that. The authors use a keyword-based NLP system and show that it works reasonably well. However, perhaps a more sophisticated AI/ML system can do better. Currently, deploying such cutting edge models on data is quite simple and might provide radically improved results.

On similar lines, here the putative SDOH factors are manually selected, as are the keywords needed to train the NLP system. It is entirely conceivable that a language model learns directly from text using technology similar to modern ML models similar to the Generative Pre-trained Transformer (ChatGPT)[8] and should be explored in the future. Importantly, manual selection of putative factors might have left out important factors, eg, religiosity, which has been shown to have a nontrivial protective effect among US youth.[9]

Can we verify self-reported SDOH values? The SDOHs we can extract in the proposed approach are essentially self-reported. Maybe we can think about frameworks where we can have more verifiability, while not losing individual privacy. Additionally, it might be helpful to compare these results with traditional estimates of SDOH and the recently reported Social Vulnerability Metric.[10]

Conclusions

Suicide is an urgent public health issue, especially for military veterans. Our current approach to identifying individuals who need help is inadequate. Novel technologies that leverage existing information and resources to enable life-saving interventions, such as the approach proposed by Mitra et al,[1] are greatly welcome and should be explored for creating universal screening deployments.

ARTICLE INFORMATION

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