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Implementing Predictive Models Within an Electronic Health Record System: Lessons from an External Validation of a Suicide Risk Model

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Abstract

Over the past 5 years, there has been an increase in the development of EHR-based models for predicting suicidal behaviour. Using the McGinn (2000) framework for creating clinical prediction rules, this study discusses the broad validation of one such predictive model in a context external to its derivation. Along with reporting performance metrics, our paper highlights five practical challenges that arise when trying to undertake such a project including (i) validation sample sizes, (ii) availability and timeliness of data, (iii) limited or incomplete documentation for predictor variables, (iv) reliance on structured data and (v) differences in the source context of algorithms. We also discuss our study in the context of the current literature.

Keywords:

Mental health; prognostic models; informatics implementation; electronic health record

Introduction

Suicide is a widespread public health concern that takes over 800,000 lives globally every year [41]. Within Canada, suicide accounts for 4000 deaths per year, an estimate of 12.3 deaths for every 100,000 people [34], with rates estimated to increase as a result of exacerbating conditions caused due to the coronavirus disease 2019 pandemic [31]. Due to the prevalence of suicide, prevention continues to be a priority, which includes intervening to decrease the likelihood of an attempt when risk factors are present [14]. Prevention interventions, whether including restricting access to lethal means, or pharmacotherapy [22], are most effective when targeted at high risk individuals [5]. Unfortunately, research on suicidal risk factors that has been conducted over the past 50 years has uncovered factors with only limited predictive ability, and those that predict only a small amount of the variance in suicidal behavior [13]. With the advent of electronic health records (EHRs), more representative large samples and longitudinal data collection on a wide variety of predictor variables has allowed for more accurate predictive algorithms [15]. Over the past 5 years, there has been an increase in the development of EHR-based predictive models [1; 9; 17; 18; 29; 33; 36; 40], with models predicting suicidal behavior with relatively good precision, and Area Under the Curve (AUC) values as high as 0.97 in development and testing phases [40]. Some models identify patients within the top 5% of risk, adding more accuracy to predicting outcomes of suicide attempts and deaths [33]. In a review by Belsher et al. [2] that studied over 64 unique prediction models, while classification accuracy was >0.80 in most models (percentage of correct predictions – positive or negative – made by the model), their positive predictive values were extremely low, ranging at 0.01 or below (the percentage of patients with a positive predictive result that will have the suicidal behaviour outcome) [27]. Often, such predictive algorithms are primarily kept in the domain of research and not adopted within clinical practice due to patient safety concerns, legal responsibility [11], clinical burden (including alert fatigue)[20], and clinical interpretability of the predictors behind the suggested clinical decision [4]. Moreover, even predictive models that demonstrate adequate statistic feasibility need to be evaluated appropriately to examine the effects on clinical workflows, patient outcomes, and health care costs [2]. Certain suicide risk algorithms may appear generalizable due to the diverse samples (e.g. millions of patient visits, geographically spread) [33]. However, it is important to understand how these algorithms may be spread across different countries and care settings. Our study focuses on implementing an algorithm that was developed in another setting, beginning with an assessment of model performance within the new context.

Theoretical Framework

Over two decades ago, McGinn et al. detailed the three main steps in creating a clinical prediction rule [23], which have a broader application to predictive models for clinical use, such as suicide risk prediction models. These steps include:

1. Derivation (identification of factors with predictive power)
    a. Validation, including
    b. Narrow Validation (applying the model within a similar clinical setting as its derivation)
2. Broad Validation (applying the model in multiple clinical settings), and
3. Impact Analysis (how the model changes physician behaviour, improves outcomes, reduces costs)

Objective

To measure the generalizability of a suicide-risk prediction model meant for classifying short-term suicide risk of mental health patients within a different context than which it was developed in. We began by performing a broad validation (2b).

Methods

Setting

This broad validation was conducted at the Centre for Addiction and Mental Health (CAMH) in Toronto, Ontario, which is Canada's largest academic mental health hospital, with close to 13,000 emergency department visits in 2018-2019 [7]. The hospital uses a comprehensive EHR, which was implemented 3 years prior to the beginning of this study. At the time of the study, the hospital had achieved Stage 7 on the HIMSS Electronic Medical Record Adoption Model, signifying a complete electronic health record, data warehousing for data analytics, external health information exchange, >90% physician documentation and computerized provider order entry, and >95% closed-loop medication administration processes, amongst other requirements [16]. The hospital's EHR vendor is Cerner [8], and in an attempt to maximize feasibility of model implementation from a technical perspective, the suicide risk model chosen for implementation into the EHR was one derived by Cerner Math.

Model derivation and narrow validation

The suicide risk prediction model was developed by Cerner Math (DM) using the Cerner Health Facts® data warehouse, which has been used for building risk predictive models for a variety of other clinical outcomes [12]. This data warehouse uses de-identified electronic health record data collected over 20 years. For deriving the suicide risk prediction model, electronic health records were extracted from 119,409 inpatient psychiatry admissions (across 624 U.S. acute care institutions with inpatient psychiatry services between 2000 and 2013). Longitudinal data was gathered for all these patients, and L1 absolute value LASSO regression was used for feature selection of the variables used for building predictive models for the outcome of death by suicides. There were 715 outcomes (deaths), which were further divided into two independent subgroups of equal size, balancing the numbers of cases in each suicidal behaviour category (ideation, intent and plan) in each subgroup. Following this step of identifying outcomes, data from records of patients who had suicidal ideation were matched (age and gender) with controls without suicide attempts or deaths randomly sampled from the balance of the 119,409 admissions. Using Multivariable Poisson regression, 18 statistically significant variables were retained and model performance was measured, achieving >90% sensitivity on the test data sets.

Model implementation

The coefficients for each of the 18 variables in the predictive model were implemented in a Cerner Math predictive mathematical model. This Cerner Math predictive mathematical model was translated into an EHR-based configuration resulting in a real-time risk-score dashboard for all patients in our hospital's EHR, with only the study team having access to this dashboard (see Figure 1). We mapped the predictor variables to our organization's Cerner EHR data fields, assuming some amount of standardization across international databases and institutions with the same vendor.

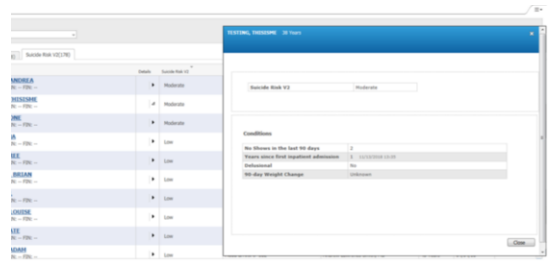

Figure 1– Real-time Suicide risk EHR dashboard

Due to technical challenges (e.g. connecting the mathematical model to our HER over the cloud) in translating the predictive model and issues with mapping our EHR variables to the 18 predictor variables, our study ran for a length of 4 years. Over the course of this time, we implemented two versions of the suicide risk model (version 1 with 5 predictor variables in 2017, and version 2 with 8 predictor variables in 2020). Accurate prediction using the dashboard allowed monitoring of risk at an individual risk level.

The input variables that contributed to Cerner Math's suicide risk model were: (i) number of years with mental illness; (ii) Recent history of loss or bereavement; (iii) Suicidal ideation; (iv) First-degree relative death by suicide; (v) Delusional ideation; (vi) 90-day weight loss more than 2% of baseline weight; (vii) Pessimism/Hopelessness score; (viii) Number of outpatient clinic "no-shows" in past 90 days; (ix) Metrics of non-adherence to regimen; (x) Nightmares duration; (xi) Insomnia duration; (xii) Military deployments history; (xiii) Marital status; (xiv) Trauma history; (xv) Comorbid history of substance abuse; (xvi) Comorbid depression, bipolar disorder, generalized anxiety disorder; (xvii) Assaultive behavior history; and (xviii) Number of psychiatric diagnoses. [24] We were able to map variables (i) – (v) in version 1 of the model implementation, and (i) – (viii) for version 2 of the model implementation, using the expertise and knowledge of clinical application specialists at our organization (MT, BL). See Table 1 for details on the mapping.

Table 1– Mapping of predictor variables

Predictor Variable	***Mapped to***	***Details***
i	Number of years since the **date of first admission encounter within our hospital**	Could be different than year since first diagnosis, especially if the patient was diagnosed outside of hospital
ii	**Recent history of loss or bereavement (in the last year)** data field, with multi-select options	Mandatory fields within the standard Suicide Risk Assessment done across the hospital primarily by nurses, (but also carried
iii	**Presence of Suicidal Ideation/ Intent/ Plan** data field	

iv	**Family Member that died by suicide** data field, with multi-select options	out by allied health and/or psychiatrists)
v	**Thought Content** data field, with Delusions as an option	An option within a data field on the Mental Status Exam – a nursing assessment that is frequently carried out on all inpatients
vi	**Weight** data field	Field was rarely filled out at our organization
vii	**Patient Health Questionnaire (PHQ) – 9 data field** that asks "Over the past two weeks, how often have you been bothered by any of the following problems: Feeling down, depressed, irritable or hopeless?"	Since implementation of a patient portal, this field can also be filled out by patients during self-assessments
viii	**Scheduling** data field with the outcome of "no shows"	This data field was not used widely across the hospital (especially for inpatients)

Broad validation of the model

Following implementation of the model into the EHR, we allowed the algorithm to run in the background and score patients prospectively. However, since the outcome of death by suicide is a low-base rate phenomenon, we also manually calculated the score prior to the outcome for several individuals with this outcome. We performed a validation of the model using the most recently available algorithm score prior to the outcome of death by suicide and attempted suicide, as well as algorithm scores for patients with non-events (i.e. patients with no previous suicide attempt OR death by suicide). The categorical model scores (low, medium, high) were initially gathered manually through retrospective calculation (for pa-tients with outcomes), or through the dashboard for version 1 of the model (for patients with no outcomes). We were able to gather numerical scores (with the associated categorical scores) for patients using a database query for version 2 of the model.

Ethical considerations

Ethics approval has been granted through the CAMH and University of Toronto Research Ethics Boards. Since this data originates from a vulnerable population, all records were de-identified, and all data was stored on a secure, password-protected server.

Results

Model performance

Following implementation of version 1 of the Cerner Math predictive mathematical model, initial validation results in 2018 demonstrated very low sensitivity of the model (22.9%) for the outcome of death by suicide (N=44), and even lower sensitivity (20.5%) for the event of suicide attempt (N=83). Outcomes were compared with model scores just prior to the event, to simulate clinical utility of using this model as a clinical decision support tool. A true positive was noted when the categorical model score was "High". Specificity for the model was high (81.0%), as would be expected in a low base-rate phenomenon [21]. Model scores for patients with no outcome of suicide attempt or death by suicide (N=279) were gathered, and a true negative was notified when the model score read as "Low". The accuracy of version 1 of the model was 0.73 for the outcome of death by suicide and 0.67 for the outcome of suicide attempt.

Given the low sensitivity results, the model ran in the background over the next two years, and sensitivity was re-measured following implementation of version 2, with added patient outcome data (i.e. suicide attempts). Updated results in 2021 demonstrated a continued low sensitivity (22.3%) for the outcome of suicide attempt (N=458).

Practical challenges when completing external validation

We experienced several practical challenges while completing an external validation of the model, listed below for consideration by other organizations prior to undertaking such a project.

1. Validation sample sizes: Number of outcomes

The comprehensive EHR across our organization went live 3 years prior to the beginning of the study. At the time of the first validation (2018), there was only 4 years' worth of structured data within the EHR, meaning that event data for the primary outcome of death by suicide was limited. Additionally, since our only data source for suicide deaths was our hospital's database, there is uncertainty that we had captured all death by suicides of patients within our observed time frame, since we relied on data from those deaths that were communicated to the hospital. Moreover, our secondary outcome of suicide attempts was not collected within the first three years of the system being live. This data collection field was added as an option to an existing mandatory field within the EHR as a result of our research study; however, even post-implementation there could have been outcomes missed in our dataset due to clinicians choosing an alternate overlapping option (see Figure 2). The option was added to the multi-disciplinary assessment, filled out by clinicians when patients arrive at the emergency department at CAMH (the only emergency department in the province that provides 24/7 emergency assessment and treatment focused on adults with mental health and substance use issues) [6].

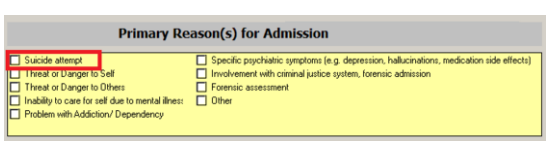

Figure 2– Data collection field for outcome of suicide attempt

2. Availability and timeliness of data

We had access to a higher number of outcomes than reported in our validation results; however, the model was only able to calculate scores for 38.5% of patients with the outcome of death by suicide, and 45.5% of patients with the outcome of suicide attempt because the remainder of the patients with these outcomes did not have any data for the predictors in the EHR prior to the outcome. Additionally, the length of time between the last available score and the outcome ranged from a few days to over 600 days. This range of time between predictive scores and outcomes affects the timeliness of data required for prediction and subsequently clinical decisions, and any decisions to reduce this window would have led to a further drop in sample size.

3. Limited or incomplete documentation for predictor variables

Of the variables we had mapped to within our organization's EHR, several data fields had missing data. Within our initial validation of version 1 of the algorithm, data fields such as "Recent History of Loss" had a 27.4% missing data rate. Other variables such as "Suicidal Ideation" that were a required organizational practice had 0% missing data rates. The amount of documentation present in the patient's chart varied depending on how long they had spent in the hospital, whether they were in inpatient or outpatient care (since there are different documentation requirements), and the severity of their clinical history.

4. Reliance on structured data

Another challenge that affected our results was the algorithm's reliance on structured data found within admission and nursing assessments. We were only able to map 8 out of the 18 variables, as information on 10 variables were present in free-text documentation and not captured in structured fields across our organization's EHR. We did not use any Natural Language Processing software required to parse out relevant information from free text notes.

5. Differences in algorithm source context

Given that the model was developed using data from U.S. inpatient psychiatry records, certain variables such as "Military deployments history" were found to be significant predictors of suicide, whereas these variables are not often collected across many Canadian primary or tertiary care contexts. A reason for this could be the differences in numbers of Veterans, where they make up close to 7% of the population in the U.S., [32], as compared to only 1.6% within Canada [38].

Discussion

Few health systems have implemented suicide risk assessment models into practice [30] or carried out a prospective validation of EHR-based, real-time suicide risk model [39]. Walsh et al. (2021) acknowledges that performance can be different amongst clinical settings within a medical center including behavioral health, adult hospital and emergency de-partments. Walsh et al.[39] state the importance of model recalibration and updating prior to deployment in new settings, with their model reaching area under the Receiver operating characteristic curve (AUROC) values of 0.836 for suicidal ideation and 0.797 for suicidal attempt across the entire medical center setting. Recalibration is an important step that we have considered for future validations.

Rare events are not unique to psychiatry, but present across healthcare in cardiology (e.g. sudden cardiac death) [25] and immunology (e.g. severe vaccine adverse effects) [3]. Recent methods have stated the importance of situating model sensitivity in relation to prevalence of the outcome, focusing on metrics such as Positive Predictive Value and area under the precision recall curve (AUPRC), as compared to AUROC [28]. Calculating such metrics is an important next step for our research project.

In additional to statistical challenges, the technical challenges of implementing the algorithm within the EHR is an important aspect to consider prior to validation. Retrospective validation using data from the clinical data warehouses [10] can be a first approach to validation prior to implementing the algorithm on the back-end, since this can reduce the time and effort required for validation.

Finally, expanding the type of EHR data used can increase the sample size of outcomes as well as allow mapping to a larger number of predictor variables. Tsui et al. found [37] a significantly greater accuracy in model performances when using both unstructured and structured data as compared to structured data alone, suggesting that the number of predictor variables can increase using this method. Additionally, complementing EHR data with data from more frequent inputs such as social media posts [26] and ecological momentary assessments [19; 35] can help in building more accurate and real-time predictions, as well as validating predictions with more timely information.

Conclusions

Our research demonstrates that it is important to study the generalizability and replicability of predictive models for clinical outcomes such as suicide. We list out five practical challenges that affect the implementation of such models in contexts different from their derivation, which should be considered prior to embarking on a validation project.

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