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Piloting a Suicide Risk Screening in Jails: Leveraging the Mental Health Research Network Algorithm and Healthcare Data

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Abstract

Background: Suicide in local jails occurs at a higher rate than in the general population, making it a priority to improve risk screening methods. This article describes a research study that will use administrative data and machine learning modeling to improve suicide risk detection at jail booking.

Objective: This research study is primarily focused on gathering preliminary information about the feasibility and practicality of using administrative data and machine learning modeling for suicide risk detection, but also incorporates elements of hypothesis testing pertaining to clinical outcomes.

Methods: The research study validates an existing community suicide risk identification machine learning model – developed and validated by the Mental Health Research Network (MHRN) – on a sample of ~6,000 individuals booked into two diverse jails in a Midwestern state. The model detects suicide risk in jails and post-release by using merged jail, Medicaid, and Vital records data.

Results: The resulting model will be compared to the jails' suicide identification practice-as-usual ('PAU'), to assess risk and detection of identified suicide attempts and deaths from intake through 120 days and 13 months after jail release, and to modeling and PAU together. The research study will also investigate implementation factors, such as feasibility, acceptability, and appropriateness, to optimize jail uptake.

Conclusions: We hypothesize that a combination of intake screening process-as-usual and the machine learning model will be the optimal approach to be evaluated.

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Keywords: suicide, suicide prevention, health risk behaviors, machine learning, jails

Abstract

Suicide in local jails occurs at a higher rate than in the general population, making it a priority to improve risk screening methods. This article describes a research study that will use administrative data and machine learning modeling to improve suicide risk detection at jail booking. This research study is primarily focused on gathering preliminary information about the feasibility and practicality of using administrative data and machine learning modeling for suicide risk detection, but also incorporates elements of hypothesis testing pertaining to clinical outcomes. The research study validates an existing community suicide risk identification machine learning model – developed and validated by the Mental Health Research Network (MHRN) – on a sample of ~6,000 individuals booked into two diverse jails in a Midwestern state. The model detects suicide risk in jails and post-release by using merged jail, Medicaid, and Vital records data. The resulting model will be compared to the jails' suicide identification practice-as-usual ('PAU'), to assess risk and detection of identified suicide attempts and deaths from intake through 120 days and 13 months after jail release, and to modeling and PAU together. The research study will also investigate implementation factors, such as feasibility, acceptability, and appropriateness, to optimize jail uptake. We hypothesize that a combination of intake screening process-as-usual and the machine learning model will be the optimal approach to be evaluated.

Introduction

Suicide Risk in Jails & Standard Screening Procedures

The most recent available data indicate that suicide is the leading cause of death among those incarcerated in jails, and the suicide rate among those detained in jails is approximately four times greater than those in the public (Noonan, 2014; Way et al., 2005). Long-term trends suggest that suicide has been the leading cause of in-jail deaths from 2006 to 2016 following steady increases in suicide mortality since 2000, and it accounted for nearly 30% of all in-jail deaths in 2019 (Carson, 2021). A period of incarceration is also associated with suicide mortality post-release, as evidence indicates that the risk of suicide doubles after jail release (Lim et al., 2012).

Few jails effectively screen for suicide risk at jail booking. Due to the fast-paced booking process, most jails use non-standardized, self-report, and/or single-item measures which can lack cultural sensitivity or are inappropriate for this setting (Boudreaux & Horowitz, 2014; Perry et al., 2010). Given that many jail booking areas are not private, individuals may be less forthcoming in reporting suicidal ideation to jail staff. Current suicide risk identification practices are insufficient given the impracticability of having clinically trained professionals conduct adequate assessments at booking. These deficiencies in suicide risk screening in jail settings exemplify the need to improve risk detection. Improved suicide risk identification could reduce the persistent missingness of behavioral health data in jail facilities (Ray et al., 2022), while also mitigating the adverse impacts that suicide has on detainees, families, jail staff, and the community (The Howard League for Penal Reform, 2016).

Machine Learning for Suicide Risk Screening

Machine learning is the basis for suicide risk identification models. Several studies have indicated that machine learning models considerably improve accuracy and have positive predictive value in detecting risk of suicide compared to practices-as-usual (Linthicum et al., 2019). Suicide risk identification via machine learning detection has already been applied in healthcare systems (Edgcomb et al., 2021) and in cross-sectional (Fernandes et al., 2018; Hettige et al., 2017) and longitudinal (Barak-Corren et al., 2017; Walsh et al., 2017) study designs focused on suicide risk identification, with suicide attempt and suicide death accuracy estimates ranging from the high 0.80s to low .90s, meaning predictions are accurate nearly 90% of the time (Linthicum et al., 2019).

The Mental Health Research Network (MHRN) developed and validated a suicide risk identification machine learning model which detects suicide attempt and death risk based on historical health and insurer (including Medicaid) data (Simon et al., 2018). Among a general population sample, the MHRN model has shown effectiveness in identifying increased risk for suicide attempts and deaths using general and behavioral health records and claims data across seven healthcare systems (Simon et al., 2018) and from claims data alone (Simon et al., 2019). The MHRN model generates a suicide risk score which can be used to alert health personnel to the possibility of heightened suicide risk and prompt further screening and service provision. The MHRN model gathers 313 unique factors such as demographic and clinical characteristics from five years of historical healthcare data. The MHRN model outperformed other suicide screens and machine learning models with a C-statistic, area under the ROC curve, of 0.853 (95% CI: [0.849, 0.857]) compared to the REACH VET model which has a C-statistic of 0.761 (95% CI: [0.751, 0.771]) (McCarthy et al., 2015), with the top 5% of risk scores identifying over 43% of suicide attempts/deaths 90-days following a healthcare visit. The MHRN model includes a comprehensive set of clinical indicators, is intended to be used at the point of encounter, and shows promising results for improved suicide risk identification among a general population sample. A similar identification process for incarcerated individuals, available at jail booking, could help detect those at risk for in-jail and post-release suicide attempts and deaths. Because there is no standardized process for identification of suicide risk across jails, an objective data-driven risk indicator would greatly enhance such screening.

Study Aims

Our protocol includes three interrelated aims. The first is to validate the MHRN model using retrospective data from approximately 6,000 individuals booked into two geographically and demographically diverse jails in a midwestern state to assess model generalizability. Jail administration data will be linked with historic (i.e., pre-booking) Medicaid claims data so the MHRN model can generate suicide risk scores. Since Medicaid is the insurer for 73% of the jail population in the study's state (Comartin et al., 2021), most of the jail population will be included in the analysis. The second aim seeks to compare the accuracy of the MHRN flag in identifying risk of suicide attempt and death to current suicide risk identification practice-as-usual (PAU) over 120 days and 13-months from initial jail booking among individuals who have been released from jail. This involves merging jail records and prospective Medicaid, pharmacy, and Vital Records data to examine if the MHRN model improved suicide risk detection in jails and post-release as compared to the jails' PAU. The research team hypothesizes that the MHRN model will be validated as an effective screening tool to detect risk for suicide attempts/deaths as evidenced by a C-statistic (area under the ROC curve) of at least 0.75 and a positive predictive value that exceeds the base rate of suicide attempts/deaths through 13-months post booking. The pilot testing is included in the third aim, which will evaluate implementation outcomes related to integrating the MHRN model in jails.

This pilot project benefits from having a substantive *N* that will allow for an evaluation of the implementation of the MHRN model in jails, but to also conduct hypothesis testing on select clinical outcomes. For instance, if the MHRN model improves jails' PAU, increased opportunities to connect individuals at risk of suicide with interventions to reduce suicide attempts/deaths in jail and post-release will be created. The research team hypothesizes that more individuals with subsequent suicide attempts/deaths will be identified by the model or a combination of the model and screening versus screening only.

Materials & Methods

Two participating jails will provide data on booking and suicide risk identification PAU results for their jail population over a six-month period (09/01/2021–02/28/2022). To assess suicide risk, the MHRN model will be applied to five years of Medicaid encounter data prior to jail booking (09/01/2016–08/31/2021). We will compare accuracy of the MHRN model, the jail's screening PAU in identifying suicide attempts and deaths in jail and over 13-months post-jail release, using Medicaid and pharmacy data for suicide attempts and Vital Records data for suicide deaths (both sources, Medicaid and pharmacy data as well as Vital Records data, 03/01/2022–03/31/2023). This study is funded by the National Institute of Mental Health (NIMH) to the National Center for Health and Justice Integration for Suicide Prevention (NCHATS), and is approved by the authors' Institutional Review Board (#22064717). NCHATS research studies are grounded in application of data analytic approaches to identify individuals at risk for suicide across different intercepts of the sequential intercept model (Munetz & Griffin, 2006). The current project focuses on suicide risk detection during incarceration whereas other NCHATS projects focus on suicide risk detection and prevention before and after incarceration.

Jail County Sites

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Two county jails are participating in the study. Jails were selected based on their varying geographic settings and jail populations. County A is a metropolitan sized county on the west side of the state with a population near 670,000 people. The jail has 1,285 beds and booked 24,000 individuals in 2019. County B, on the east side of the state, is an urban county, with over 370,000 people. The jail has 404 beds and 8,300 bookings in 2019. These jails vary in screening methods for suicide risk at jail booking, which reflects variability nationally. County A uses several scripted questions about current and/or past suicide ideation or attempts, and County B uses several scripted questions and a truncated version of the Columbia Suicide Severity Rating Scale (Posner et al., 2011).

The two jail populations vary demographically. County A is just under half White (46.5%) while County B is less White (39.4%). County A (71.4%) has a smaller proportion of males than County B (76.4%). Both jail populations are similar in age, with County A having 51.3% of people 31 years or older and County B with 51.5%. Medicaid is the insurer for 96% of people in jail in County A and 78% of people in jail in County B. Prior studies show varying rates of mental health needs, assessed by a modified cut score on the Kessler-6 (Kubiak et al., 2012), with County A (21.5%) reporting higher proportions than County B (16.8%). According to the Bureau of Justice Statistics (Zeng, 2022), the average jail length of stay nationally was 33 days in 2021, an increase of 5 days from the previous year (28 days in 2020).

Data Sources and Assessments

Jail data. Jail data will include admission and discharge dates and jail medical records, including results from the suicide identification PAU (positive/negative), intervention and/or referral related to suicide risk, veteran's status, and information on suicide attempts/deaths while in jail. To determine if a death occurred within the jail, the research team will use jail admissions and discharge dates and date of death from Vital Records data to determine if the death occurred inside the facility. Self-injury Vital Records deaths that occur within 24-hours of jail discharge, will be considered an in-custody suicide, accounting for jail to hospital transfer.

Community health and death data. So that individuals can be matched across datasets, the research team will provide identifiers to the state's Department of Health and Human Services, which oversees Medicaid, pharmacy, and Vital Records data. To account for the average time spent in jail, the post-release period will be extended to 120 days and 13-months, as opposed to 90 days and 12-months (Simon et al., 2018). Physical and behavioral health Medicaid encounter data and pharmacy data include: date of service between 09/01/2016–03/31/2023; current procedural terminology code; procedure code; diagnosis related groups code; national drug code; medication class, generic name, dose; medication provider; medication days of supply and fill date; member ID type; quantity of service/length of stay; transactional control number; national provider ID; diagnosis code and sequence; encounter or provider type; zip code; census tract; and member-months. Identifiers such as date of birth and first and last name will be needed for record linkage purposes. The research team will employ the MHRN model definition for suicide attempt which includes ICD-10 diagnosis of suicide attempt (ex. codes: suicide attempt [T14.91]; self-inflicted injury/poisoning due to asphyxiation [T71.X]) as measured using Medicaid encounter data. Vital Records data requested consists of the following variables between 03/01/2022–03/31/2023: state and county of occurrence; state, county, and zip code of residence; census tract; date of death; age; sex; race; marital status; autopsy; underlying cause of death code (Code800); related cause of death; if the case was referred to the medical examiner and the certifier of the death record; place and manner of death; and the decedent's first and last name and birth date. ICD-10 diagnosis of self-inflicted injury (codes X60–X84) or injury/poisoning with undetermined intent (codes Y10–Y34) will be used to capture suicide deaths from the Vital Records data. To ensure the accuracy of the match and determine missingness, the research team will conduct intense data cleaning on these sources, removing individuals not found in Medicaid data. If individuals are not found in the Vital Records data, it is assumed death did not occur since these are official records. Table 1 outlines the key identification methods and post-year outcomes, along with corresponding data sources.

[insert table 1 about here]

Quantitative Data Analysis

This study will determine if the model is successful at identifying suicide attempts and deaths during and after jail detention. Assessment of drops in predicted probability for every 1% increment between 5% and 10% will inform the creation of a cutoff percentile for this population. Univariate analyses in identifying suicide outcomes from intake through 120 days and 13-months after jail release will include three suicide risk identification methods: (a) model only, (b) PAU only, and (c) model and PAU. Risk identification methods will be compared within each jail separately and in both jails together. Frequencies of suicide risk identification will be summarized and associations between identification method and suicide outcomes will be examined using chi-square analyses. Predictive validity of risk identification methods in assessing suicide attempts/deaths (separately and combined) will be calculated using ordinal logistic regression models. Adjusted odds ratios and their 95% confidence intervals will be estimated. Non-independence of observations within jails will be considered using robust standard errors that account for the intra-cluster correlation. A secondary set of analyses will also include suicide attempts reported within jails. Moderation analyses will explore whether MHRN and PAU accuracy vary by sex; race/ethnicity; past suicide attempt; past behavioral health treatment; county; the Area Deprivation Index which reflects income, education, employment, and housing quality; Mental Health Professional Shortage Area score; and per capita incarceration.

Validation of the model will be done using Statistics Analysis System (SAS). SAS will return the predicted probabilities and percentile groupings across the sample. The same percentile groups used in the MRHN study will be used for analysis in this pilot (5th percentile), with expansion to higher test-levels (10th percentile) to allow state-level partners and jail staff to assess any gains that could be made at each 1% interval in probable scores (Simon et al., 2018).

Cost Analysis

To facilitate replication, the study team will track the hours spent in negotiating access to the linkable data sets, programming the linkage and scoring, and developing a user interface appropriate to the jail setting. Costs for those three tasks will be reported that include salaries, fringe benefits, overhead, and any other direct costs (e.g., for data storage).

Administrator Interviews

Through semi-structured interviews with state-level administrators involved in the health and jail data linkage study and jail staff across both jail sites, the research team will assess the facilitators and barriers of utilizing the MHRN model as a suicide risk flag. These interviews will assess the jails information technology and software capacity for, and barriers to embedding the MHRN model at jail booking as well as institutional policies, procedures, and practices that hinder or facilitate future implementation of the MHRN model in jails. Guided by the Institute for Healthcare Improvement Framework for Going to Full Scale (Barker et al., 2016), broad and jail-specific implementation factors of acceptability, feasibility, and appropriateness will be assessed per the Acceptability of Intervention Measure, Intervention Appropriateness Measure,

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and Feasibility of Intervention Measure (Weiner et al., 2017). This information will be used to design potential implementation approaches for future testing.

Qualitative Analyses

All interviews will be audio-recorded and transcribed and analyzed by multiple coders using a grounded theory approach to understand facilitators and barriers to implementation through content-analytic matrix and by jail staff role through role-ordered matrix (Miles et al., 2014; Strauss & Corbin, 1997). Findings will be used in the creation of a data integration toolkit that will provide summarized recommendations to state and jail partners on what is needed to efficiently and effectively implement the MHRN model into the jails' systems. The toolkit will also include recommended actions needed to respond to suicide risk in jails.

Discussion

This article describes a research protocol for validating a community suicide risk identification machine learning model with jail populations by comparing the model to other validated instruments and screening practices to improve data surveillance and treatment linkage for a highly vulnerable population. By integrating data across general health, behavioral health, and criminal-legal systems, providers could leverage an existing high performing suicide risk model to detect risk of suicide in a novel jail population (Simon et al., 2018). Using data linkage to ensure access to critical and life-saving information at jail bookings would greatly increase the probability of appropriate intervention. While this is a complicated endeavor, marked by information technology infrastructure and data sharing legality challenges, authors and state-level officials in the study state are engaged in ongoing efforts to better integrate community and jail health data.

More accurate and efficient ways of identifying vulnerable individuals at high risk of suicide and rapidly connecting them to treatment are needed. This project attempts to fill this gap using an automated, algorithmic screening tool that has demonstrated effectiveness in prior medical settings (Simon et al., 2018). Should the MHRN model prove to be a stronger alternative to jails' PAU or to improve accuracy when combined with the PAU, the next steps will be to understand how it might be replicated in other areas. Project implementation analyses will identify implementation facilitators and develop strategies to address potential implementation barriers, such as limited medical health care in carceral settings (Vandergrift & Christopher, 2021), wide ranging variations in service quality in carceral settings (Brinkley-Rubinstein, 2013), and mental health stigma (Melnikov et al., 2017).

Conclusion

There is a growing interest in using machine learning to detect suicide risk, and through this study, this promising methodology will be applied to an incarcerated population. Machine learning to detect suicide risk among incarcerated individuals holds promise for improving the identification and prevention of suicide. However, it is important to rigorously validate machine learning algorithms and carefully consider pros and cons of use before they are widely implemented. This project will: (1) accomplish this important next step, validating the models overall and by sex, race/ethnicity, and other important moderators; and (2) explore implementation strategies to be tested in future trials, should tested algorithms prove effective.

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Supplementary Files

Figures

Analysis Model.