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Technology Uses in Suicide Prevention

How Data Analytics and Advancements in Technology can Improve Suicide Prevention Strategies

By

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CERTIFICATE OF APPROVAL

This is to certify that the Master's Capstone Project of

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Table of Contents

Abstract

Suicide has been identified as one of the leading causes of death nationally and globally. Because of the complex dynamics of risk factors that contribute to suicidal behavior, predicting and preventing suicide death and attempts requires a varied and multidisciplinary approach. New technologies can complement and provide new opportunities for existing suicide prevention programs through enhanced data collection, identification of at-risk people and technologies that connect people to needed resources. This paper presents an overview of current technologies that have either been developed or are being adopted to aide in suicide prevention at three levels of health care; Individual Providers, Hospital Systems and Public Health/Population Systems.

Part I

Introduction

Research Problem

The objective of this research initiative is to 1) determine what technologies currently exist in suicide prevention, 2) identify how modeling technology can be used to identify patients, 3) explore the role that public health and governmental agencies use technology to aid in suicide prevention programs.

Role of Technologies in Suicide Prevention

Suicide is one of the leading causes of death both in the United States and worldwide. Globally, close to 800,000 people die because of suicide every year and for every person that dies of suicide it is estimated that another 20 have attempted suicide.[1] Among young adults ages 15-29, suicide is the second leading cause of death.[2]

In addition to the human cost that suicide takes on individual families and communities, there is a large economic impact. In the United States alone it is estimated that suicide deaths cost around $26 billion a year in both medical costs of response and treatment as well as lost wages and working days.[3] This economic and human cost makes suicide a serious public health concern in the United States and around the world.

Suicidal behavior is difficult to understand because of the many complex contributing factors including clinical, social, environmental, and psychological phenomenon. This complex combination requires a systems approach that can incorporate data that is collected through different sources across a continuum of life and health care. These sources of data include information collected at outpatient care visits, surveys collected at acute care centers, data aggregated through the medical record and vital statistics data. This data can then be used to incorporate public health strategies and target prevention interventions that are individual to the counties and states it represents.

In the past, suicidal ideation was treated after individuals were identified through mental health services of people who were self-diagnosed or showing signs of suicidal behaviors. With the added technological advancements and data collection, there is a shift in treating individuals to preventing suicide at the population level. This shift demonstrates a movement away from self-diagnosis to risk factor identification through alternative sources and prevention rather than treatment.[4] The technology and technological developments that are advancing these prevention strategies offer exciting opportunities for preventing suicide as the results of decreased suicide attempts and suicide deaths.

Considerations

Benefits

There are numerous benefits to increasingly using technology in suicide prevention. One of the most significant benefits is the collection and aggregation of data coming from electronic medical records, public health resources and survey and self-reported data. The aggregation of this data provides vast opportunities for predicting suicidal behaviors and applying clinical prevention strategies to prevent suicides.[5] Computerized risk screening in combination with machine learning has also been shown to enhance prediction beyond what individual providers are able to foresee.[5] Additionally, technologies have the ability to expand care and identification strategies beyond geographical barriers.[6] Suicide prevention technologies increase the ability to share information and combine resources to strengthen models that identify and predict suicide behaviors.[6]

In addition to data collection and analytics the technologies presented in this research don't rely on self-reporting and identification. This identification of people and populations that are at risk of suicide without self-identifying as 'at risk' adds a significant advantage to timely and successful interventions.[7]

Challenges

There are some challenges that these technologies may introduce or exemplify when they are implemented with their corresponding entities.

Cyber security of data- As with any collection and storage of sensitive information there is a significant looming danger of security compromises and breeches.[8] Because most of technologies that are introduced in this paper exist in hospital and medical systems they are regulated by guidelines established by the Health Insurance Portability and Accountability Act of 1996 (HIPAA) as well as the National Institute of Standards and Technology (NIST), as is all medical record information stored in electronic medical record systems.

Non-standard data collection- Because suicide risk factor data comes from a variety of sources that include public and private healthcare institutions and regional and national public health departments and centers this can present numerous challenges in combining data for use. Challenges include data size, lack of open access, heterogeneity, or uses of antiquated technologies that limit the ways that data can be combined.[9] Better standardization of data such as suicide diagnosis through coroners offices and medical billing would inherently increase the reliability and quality of data that is being collected. Further, enhanced infrastructures and standardization of medical data would increase the availably of data and easier transfer and storage of the data that the research and models rely on.[9]

Part II

Provider Technologies

Accessing Best Practice Research

For people that are at risk of suicide, behavioral health and primary care or family practice physicians offer an entry point for people to connect with professional health either through a formal health system or an individual healthcare provider. Contact with a primary care provider in time leading up to suicide is common, three of four suicide victims had contact with a primary care provider within the year of suicide.[10] For primary health care providers, mental health professionals and trained professionals working on suicide prevention hotlines, having easy access to the most up to date evidence-based treatment information is critical. Evidence based medicine is defined as "The conscientious, explicit and judicious use of current best practice evidence in making decisions about the care of individual patients."[11] In addition to web-based best practice information that is available to providers through sites such as Elsevier, mobile applications such as Suicide Safe provide evaluation tools and triaging information that can help providers talk about suicide with their patients.

Suicide Safe was developed by Substance Abuse and Mental Health Services Administration (SAMHSA) to "… to lessen the risk and promote healing and wellness."[12] The app includes patient education materials, conversation starters to ease talking to patients about suicidal ideations or behaviors and interactive suicide assessments that use a five-step evaluation and triage plan to identify risk and protective factors as well as determine the risk level and potential interactions and treatment plans.[12]

Electronic Interventions for Preventative Treatment

As previously mentioned, people frequently make contact with health services prior to their suicide.[13] These providers may be called to evaluate patients who are having suicidal ideations or identify patients who have presented to the system for a chief complaint differing from suicidal thoughts. This contact with primary care providers and emergency room providers can be effective in preventing suicide attempts if the patients can be appropriately identified, evaluated, stabilized during the initial encounter and then followed up on and provided further resources such as contact with specialized psychiatric care.[13,14] Carrigan et al. estimated that the average number of suicide attempts in a family practice is 10-15 patients per year.[14] Electronic assessment tools such as Columbia-Suicide Severity Rating Scale (C-SSRS) are used in emergency rooms and by primary providers to identity patients at risk for suicide through a series of questions that assign points based on yes no answers.[15] Hospital systems establish criteria for these point totals that then determine what to do next for the patient assessed. The C-SSRS tool is often integrated into the electronic health record (EHR) and accessed by either the triage nurse or provider during the initial encounter. Based on the information that is collected in the tool, the Joint Commission requires follow-up actions to be taken which range from urgent psychiatric assessments to diagnosing the patient with depression.[15] A notable feature of the use of computer-automated clinical interviews such as the C-SSRS tool, along with improved patient self-disclosure is the tool providers a consistent way for providers to communicate 'risk' between other providers and outside care.[16] By incorporating the assessment into workflows in the EHR such as the initial nursing triage, the data can easily be referenced through reporting and decision support tools that easily notify providers of high scores.[16] The Harvard Partners Healthcare/Mass General – C-SSRS table below illustrates how the assessment can be incorporated into an electronic workflow and the resulting actions that are taken based on responses.

HARVARD PARTNERS HEALTHCARE/MASS GENERAL – C-SSRS WITH RISK AND PROTECTIVE FACTORS

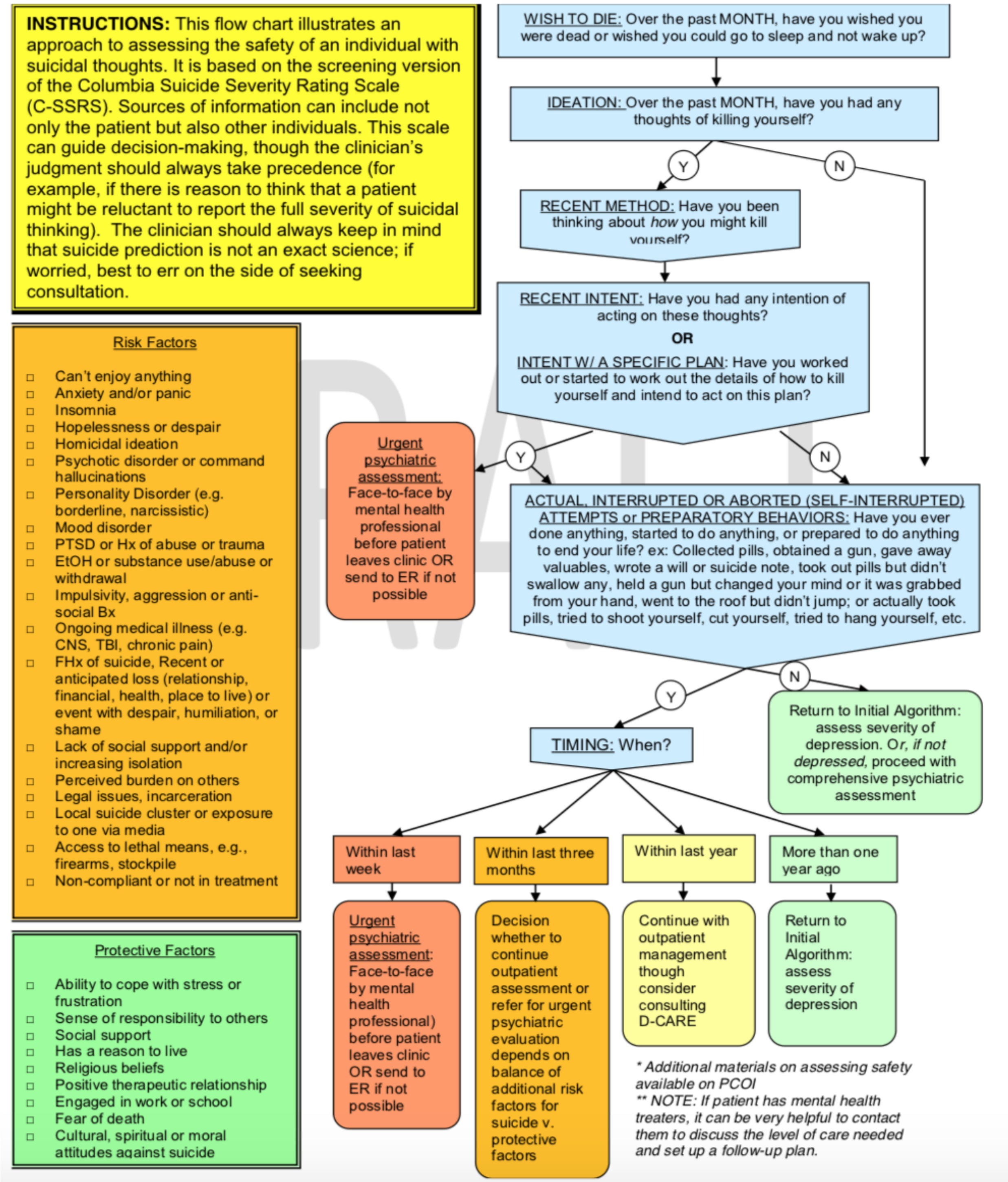

Chart 1. C-SSRS flowchart illustrating the flow of C-SSRS questions and implementation of workflow.[17]

Access and Reminders for Follow-up Care

For patients that are either seen outpatient for suicide ideation or admitted to an inpatient unit, the highest risk period for a relapse is immediately following the visit or in the weeks following discharge.[18] Being able to reach recent patients helps patients continuity of care by connecting them with outpatient providers through appointment reminders and online scheduling. Mobile applications (apps) that allow patients to communicate with providers and schedule appointments have been shown to increase overall appointment adherence rates[19]. Text messaging has also been used to send reminders of treatment appointments.[19]

Practitioner Opportunity for Personal Correspondence and Outreach

Another potentially effective use of technology in the prevention of suicide in recently seen or discharged patients is the use of email for sending personal correspondences or 'caring letters' to patients[20]. Motto et. al. found that patients that were contacted with a short email for five years had a lower suicide rate across all five years then the control group.[20] In a recent review of literature that examined the effectiveness of using technologies such as email and text messaging, it was observed that the use of multimedia correspondence that were easily used by the patient decreased the risk of new attempts of suicide in the post discharge period.[21] These email based programs are helpful in populations that are mobile such as adolescents and military personnel because they are not defendant on having a current address on file.[21]

Mobile technologies- texting and other chat/text platforms

Texting and other mobile applications have been integrated into many if not all aspects of day-to-day living such as driving, banking, eating and medical and mental health interventions. In addition to increased cell phone ownership per household, more adolescents and adults prefer to communicate by texting over traditional voice communication.[22] With this change in preference crisis hotlines have had to adapt to better serve their populations. Texting and online access to crisis hotlines may also serve an important role in aiding rural communities and other underserved populations. [22,23] In a study that evaluated the technological preferences of suicidal adolescents, online access to mental health professionals through online communication such as chatting or social networking and support groups promoted increased disclosure of suicidal ideation.[23] The authors suggested that texting and chat rooms increased anonymity and promoted an increase in the type and amount of personal information that the participant was willing to provide.[23]

Part III

Hospital System Technologies

Identification of 'at-risk' populations through Predictive Models

The identification of patients at-risk of suicide has typically relied on methods such as suicide assessments and self-reported data that comes from the patient themselves. These types of assessments do not consider how risk factors work together to cause suicidal ideation and behaviors.[24] These assessments have produced variable results with results that are marginally better than a coin flip in identifying at-risk patients.[24,25] It's clear that a better way to predict these at-risk populations is necessary. Technologies such as predictive modeling and machine learning may be able to supplement hospital based suicide assessments by modeling relationships between variables and apply complex machine learning techniques to large data sets that that can analyze these complex relationships through an optimized algorithm.

Data mining, statistical algorithms, machine learning and artificial intelligence

As technological power increases and more and more information is stored in electronic means such as electronic medical records there is numerous opportunities for application of precision medicine and risk prediction in identifying populations at risk for suicide.[26.] Three recent analysis used different modeling techniques to identify risk factors from electronic medical records data to predict suicide death. These studies included prediction models developed for Veterans Health Administration, *Predicting suicides after outpatient mental health visits in the Army Study to Assess Risk and Resilience in Servicemembers (Army STARRS).* Another study completed by Barak-Corren and collogues, *Predicting Suicidal Behavior From Longitudinal Electronic Health Records*, used data collected from two large academic hospitals in the outpatient setting to predict suicide attempt and deaths. Lastly, Kaiser Permanente created a model that combined electronic health record data with a supplemental depression questionnaire to predict suicide attempt and death within 90 days of either an outpatient primary care visit or an outpatient mental health visit in research titled, *Predicting Suicide Attempts and Suicide Deaths Following Outpatient Visits Using Electronic Health Records*. This section will review the three studies, the type of model that was developed and compare the positive predictive coefficients of identified risk factors and characteristics of the models and compare the sensitivity, specificity, positive predictive values (PPV) and negative predictive value (NPV) of these models for the given populations.

Comparison of Predictive Models

Kessler et. al. (2017)[27]

Kessler et. al. conducted a study that would explore the validity of using medical record data to predict suicides among outpatient mental health visits in non-deployed US Army soldiers. Because soldiers predominantly seek treatment from the Veterans Administration (VA) system, the data that is being collected over the entire spectrum of care is typically extensive.

The researchers used de-identified Hospital Anxiety and Depression Scale data (HADS) from two major health systems and cross-tabulated the data distinguished by general medical vs mental health specialty index admission, prior psychiatric hospitalization, gender and deployment status. The model was then developed through estimating univariate associations of predictor of suicide death compared to other outcomes including other death, separation from service and end-of follow-up period. The researches then used machine learning with various R packages to select the best classifier for predicting suicide death for each sampled person this calculated value was then combined was then aggregated over a 12 month period for a sample of 100,000 soldiers. They then used the predictive values from the person-level coefficients estimated in earlier years to predict future suicides.

The model analysis found a high positive predictive value for the highest risk patients (1047.1/ 100,000) in the 5 weeks after an outpatient visit. The authors concluded that this PPV was high enough to have implications for targeting preventive interventions. Suggesting that their research was consistent with other literature showing that statistical methods outperformed expert judgement in predicting suicide risk for this population and although the model was not created to replace human judgement, it could be used as an additional tool in assessing suicide risk. One of the limitations of the study is that it relied heavily on administrative and personal data from a comprehensive military database limiting the results from being generalized to the general population.

Barak-Corren et. al. (2017)[28]

Barak-Corren et. al. researched weather they could develop a model based off of historical EHR data to predict future risk of suicidal behavior. The patient population for the data analysis came from the Partners Healthcare Research Patient Data Registry which, at the time, had information on 4.6 million patients from Boston General Hospital and Brigham and Women's Hospital. From this patient base patients were chosen for analysis based on inclusion criteria of three or more visits, patients age at appointment between 10 and 90. Demographic, diagnostic, procedure, laboratory and medication data was collected for all visits.

The model was then created using the case definitions defined by diagnostic codes and death certificates. Baysesian classifier models were created, dividing out men and women and creating a training and test subcohorts to account for differences in gender. The researchers then assigned a partial risk-score, classified as "protective" or "adverse" to each input variable including demographic characteristics, diagnostic codes, laboratory results and prescribed medications.

This study found that variables such as psychological conditions and substance were the most highly weighted variables in the model. The final model that was created produced sensitivity of 33%-45% and specificity of 90%-95% prediction of suicidal behavior 3-4 years in advance. One of the key strengths of the model is that it highlighted unsuspected risk factors such as wounds, infections and chronic conditions because it was able to search the diagnostic breadth of the EHR data. Limitations of this model included variabilities in how conditions were coded and because this model relies heavily on coded data this may limit the generalization of the model. In addition, continuity of care is difficult to understand because patients may have left the geographic care area or be treated beyond the studied hospital system in private, outpatient settings.

Simon and Colleagues (2018)[29]

In a similar study, Simon et. al. sought to develop a model that would incorporate both electronic medical record data with self-reporting questionnaires to understand if the combination of both of the resources could better predict suicide death after an outpatient visit (either a primary care visit or a specialty mental health specialty visit). Potential risk factors were pulled out of the data set and represented as dichotomist indicators. These categories included, demographic information and factors such as medication usage and an inpatient or emergency visit within 90 days of the outpatient index admission. Data from the Patient Health Questionnaire – 9 (PHQ-9), a selfassessment for leading major depressive symptoms was a used to supplement the demographic information that was obtained from the EHR.

Prediction models were then created to divide out mental health specialty from primary care visits. To establish the initial variables logistic regression was used with LASSO (least absolute shrinkage and selection operator) penalization factors to estimate coefficients of the variables. Next a sample of 35% of the data was applied to the remaining data as a validation sample to calculate the predictive probability for each risk factor.

This research suggest that, for this population, the biggest risk factors included mental health diagnosis, substance abuse diagnosis, the use of mental health resources and a history of self-harm. One of the strongest aspects to this research was that it was able to sample over 20 million patient visits by 30 million patients. The depth of this medical history strongly benefited the high sensitivity created by the models. A limitations of the research included high false positive rate. This could primarily be due to the poor identification of suicide deaths by the medical examiner. The predictive model that was created by this research showed that prediction models that incorporate both EHR data and data from questionnaires may outperform certain predictive models that only use EHR data or self-assessments.[29]

Although this is a large sample size, the model has a specific target and population that was used to develop the model. In order to create more generalized results, this study may have benefited from using machine learning to train the model rather than an independent sample.[30]

Comparison of Methods

Study	Analysis	Data Source	Population	n	NPV	PPV	Sensitivity	Specificity	C-statistic for prediction of suicide
Kessler et. al[27]	Naïve Bayes Random Forest Support vector regression Elastic net penalized regression Machine learning	Administrative data from the Department of Defense and comprehensive suicide risk assessments.	Male Outpatient (Primary care and Mental Health Specialty) Non-deployed US Army Soldiers 2004-2009	975,057	52.9-71.6[1]	602.3 – 1076.8[2]	24%-48%	85%-95%	
Barak-Corren et. al.[28]	Bayesian models	EHR demographic and medical data from two academic hospitals. Death Certificate data.	Inpatient and Outpatient visits Documented previous suicidal behavior 1998-2012	20,246	0.99 and 0.99[3]	0.04 and 0.064[3]	33%-45%	90%-95%	
Simon et. al.[29]	Logistic regression with LASSO	EHR data in combination with depression questionnaire.	Outpatient visit (primary care or mental health clinic) by a Kaiser Permenate member over the age of 13 2009-2015	2,960,929					0.853

Table 1. Overview of comparison data from the 3 predictive models

1. (1-NPV) NPV = Negative Predictive Value expressed as the number of suicide deaths per 100,000 person years.
2. PPV = Positive Predictive Value expressed as a number of suicide deaths per 100,000 person-years. Range expresses PPV of suicides in the 26 weeks after index outpatient visit.
3. Overall (Male and Female) for 90% and 95% specificity respectively
4. (1-NPV) NPV = Negative Predictive Value expressed as the number of suicide deaths per 100,000 person years.

Clinical Implications and Decision Support

Table 1 demonstrates how these models and other models that predict suicide behavior can be a powerful tool in identifying patients that are at risk for suicidal behaviors. Among the highest risk individuals identified Simon et. al.'s model showed a 20 times increase in risk of suicide attempt or death.[31] Although the risk factors identified by most of the studies seem intuitive - substance abuse, mental health diagnosis and depression, the continued computerized results may help providers feel more confident in interpreting the prediction of these risk factors. These models do have significant limitations that make them unfit to replace the judgement of a practitioner including the incorporation of social determinants that are not captured in the medical record.[31]

Predictive models also rely on the input of much if not all information into the system to be done manually such as diagnosis and treatment thus requiring clinical judgment. The predictive models exists as a tool to better understand the clinical diagnosis and judgements of providers that may not been understood at a patient level analysis.[33]

Additionally, these predictive tools are only useful if they are operationalized and able to be integrated into clinical workflows that can use the information to actually predict suicides. These models work as a decision support tool and not a quantitative risk assessment. Barak-Corren et. al. suggest incorporating these models into dashboards with a user-friendly visualization that would categorize the patient risk over different time frames (short, medium and long term) suicide risks.[33] These risk assessments could also be incorporated as alerts that notify the provider if a patient reaches a defined threshold for clinical risk.[33] At this point it is unclear if and how clinical judgement could be impacted with the use of decision support tools such as alerts for suicide prevention.

Uses of Natural Language Processing and Machine Learning

From the three studies listed above it is clear how the cohorts for the studies were carefully constructed to mitigate bias but inherently have strong selection bias. Patient self-selection, limiting cohorts based on clinical care and billing (VA patient population and Kaiser Permanente members) and inconsistent outcome data (classification of cause of death) can cause misleading or non-generalizable studies.

Machine learning may be best suited to combat these biases by improving the accuracy of predictions through incorporating algorithms that can help researchers and clinicians understand the complex and non-linear relationships between the data.[34] Additionally, the use of predictive models in combination of use with machine learning have been shown to outperform clinical judgement alone but there is no amount of computing power that would be able to account for information that is not present in data and is contained in either other sources of information or in free text data elements.[34]

Without incorporating sociodemographic information and social determinants of health data predictive models that rely on clinical data alone will still have very limited predictive value.[35] Because so much medical data is held in text notes that are completed by the providers machine learning, in combination with natural language processing, may be best suited as the form of analysis for this type of information that is held outside of a traditional structured database.[36]

One study used machine learning to mine clinical text notes for risk factors that were identified as having the most influence on suicide risk of a select population of patients with a Fibromyalgia diagnosis.[37] What differentiates this study from the predictive modeling examples that were explored previously is the identification of risk factors through machine learning and natural language processing of free text notes that could better capture social information and risk factors not identified in other structured sources such as the EHR.

In a retrospective study that identified the cohort through records public health department records, researchers were able to link the public health information with the medical information from the EHR and create regression models that could be applied to a current patient population to predict suicide.[37] The study compared the prediction accuracy of only clinical data vs. data from natural language processing of hospital discharge and other narrative notes. Machine learning and natural language processing techniques were used to incorporate free text information that was contained in the provider discharge notes to improve risk stratification. When clinical information was combined with data from the natural language processing analysis prediction substantially improved.[38]

In conclusion, these studies demonstrate the feasibility of incorporating unstructured data and machine learning techniques to predictive models and highlight how being able to extract different types of information and combine it with normalized clinical data can increase the power of a predictive model and make the model more generalizable to other populations.

Part IV

Population and Public Health Systems

Introduction

Suicide has been considered a serious public health concern, in a report that was published by the World Health Organization (WHO) in 2014, it was estimated that 804,000 suicide deaths occurred worldwide in 2012 representing a global rate of 11.4 suicides per 100,000 people.[39]

In contrast to the suicide prevention and patient identification methods that were discussed in the Provider Technologies and Hospital Technologies sections, public health uses a population approach to suicide prevention rather than an individual approach. According to the Centers for Disease Control and Prevention (CDC), there are four main differences that separate the public health approach from the treatment of individuals. The main differences include 1) a population approach 2) prevention of suicide behavior 3) understanding suicide through science and 4) multi-disciplinary collaboration.[41]

Despite overwhelming public health data and evidence for rising suicide rates, suicide remains a low priority for policy makers and government entities. This lack of resources for research and other public health campaigns have made public health's local and federal role in suicide prevention primarily focused on the collection and distribution of suicide mortality and suicide attempt injury data. These public health monitors include tracking suicide trends, evaluating interventions and determining how to best implement interventions.

A recent article published by the CDC highlighted main ways that states and communities could help prevent suicide with many of the recommendations dependent or supported by the county and state level public health departments. Primarily, the CDC recommends placing effort into the systems and networks that identify and support people at risk of suicide.[41] For both suicide death data and suicide attempt data, availability and quality of vital suicide information remains the most important requirement for effective suicide prevention. This section will review how suicide mortality and behavior data is collected, analyzed and accessed through all levels of the public health from county to federal level. This section will also explore concerns with how these types of data are collected and stored.

Public health surveillance (Mortality Data)

One of the major roles that public health departments and systems play is the collection, aggregation and reporting of suicide attempt data and suicide deaths.

Mortality data is collected through the vital statistics program which, under federal law, records every death on death certificates. States that have funding from National Violent Death Reporting System (NVDRS), a division of the CDC, to record more specific information about violent deaths including suicides and deaths of undetermined intent.[42] Both vital statistics reporting and NVDRS data is reviewed by a coroner or medical examiner where the death certificate originates with the professional determining the cause of death.[43] In the case of a suicide death the cause of death section in the death certificate will be included in a category of sudden, violent, or non-natural death, representing the medical opinion of physicians and other medical professionals.[43] After the county in which the death took place completes the death certificate it is sent to the National Vital Statistics program where the data can be aggregated and analyzed along with data from the rest of the country. Demographic information is stored similarly- starting at the local health department and moving through to state and national level collection systems.[43]

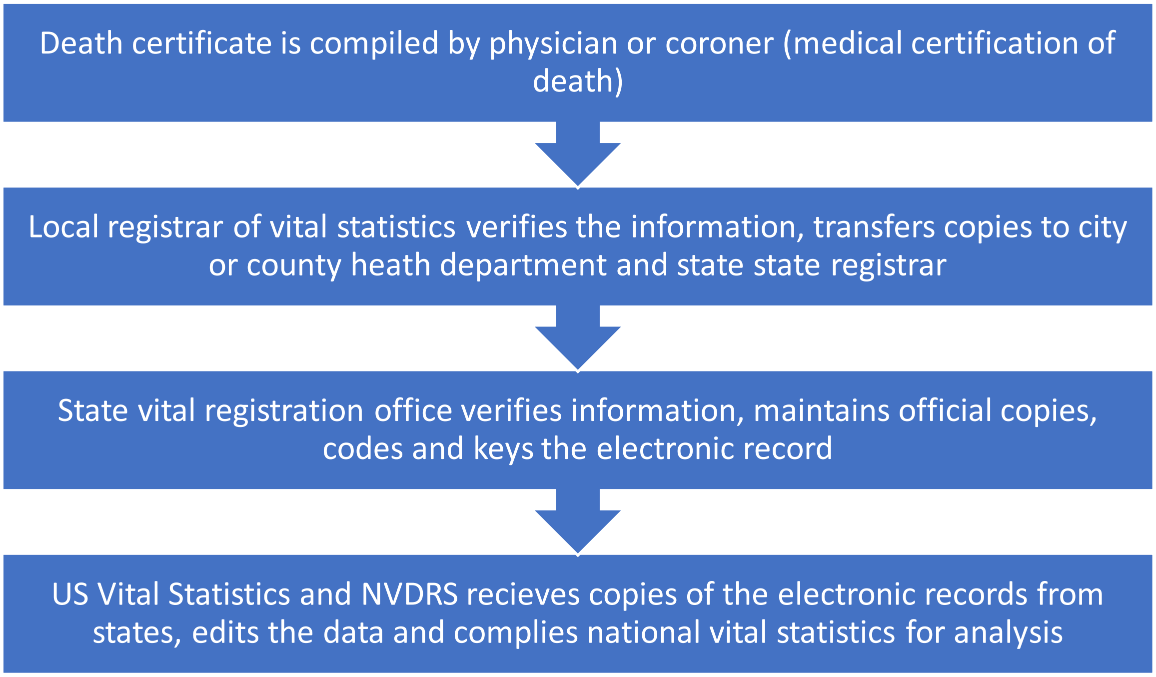

Table 2. Process of collection of vital statistics from local to federal level[43]

Data Collection Concerns

There are two main concerns about suicide data collection in the public health domains these include timeliness and quality of suicide data. Practices around medical examination and the classification of cause of death can vary between counties due to differences in the training and profession of the person completing the death certificate, and to the different practices in collecting the final cause of death.[44] Suicides can be miscoded as drug overdoses and other types of non-natural death such as a motor vehicle accident. In addition, societal pressures and the community disapproval that is associated with suicide may cause added pressure to miscode the death certificates.[44]

The second concern around the current collection of mortality data is the lack of timeliness of national estimates of suicide deaths. As highlighted above, the certification and reporting process is complex. In addition to the multiple layers of reporting and aggregation there is a two-year lag in the calculation of a suicide rate by the CDC.[45] This delay from reporting to getting the information returned can have a big impact on programs that are relying on the data to determine the effectiveness of programs and initiatives aimed at decreasing suicide rates.

This lack of current information has led to individual counties collecting and storing data that is being collected during the death investigation process that goes above and beyond the collection of the standard medical examiners data. Washington County Public Health department developed a program that imbeds an epidemiologist into the medical exam process to complete more thorough data collection called Consolidated Risk Assessment Profile.[46] This data is collected near real time and available immediately helping get the information to interested groups at the local level much faster. Dr. Kimberly Repp, Chief Epidemiologist with Washington County Public Health spoke about a direct example of how having the data accessible immediately was beneficial as a tool in suicide prevention.[46]

> "In the span of a month, we noticed that the MDIs [medicolegal death investigators or deputy medical examiners] each had a case where the decedent surrendered their pet at a shelter shortly before the suicide," said Repp.
>
> "Within two months, our suicide prevention team had provided training to every staff, volunteer and veterinarian at the county's animal shelter."
>
> "Within three months of receiving this training, shelter staff had already identified and intervened with seven people surrendering their animals who stated they were going to harm

themselves after being asked by staff if they were planning suicide. These individuals were immediately connected to the county crisis line."

Because the problems with quality and timeliness of data collected about suicide mortality there is a clear need for more localized, community level data collection.[46] Collecting and storing data locally can provide the professionals that are actively addressing suicide in the community the information they need to evaluate their programs and begin to apply community level diagnostics.

Suicide attempt and suicide behavior information is collected differently than suicide mortality data. Because the nature of the data (pre and post) that is being collected, attempt and behavior data is collected through hospital sources such as billing and coding diagnosis and self-reported survey information.

These sources of information include the National Electronic Injury Surveillance System- All injury Program (NEISS-API), which is national information collected from states hospital emergency departments to estimate self-harm injuries (WISQARS).[47] The information can be accessed publicly and currently is reporting data from 2000-2016. Similar to the NEISS-API is the National Hospital Ambulatory Medical Care Survey (NAMCS) and the National Inpatient Sample (NIS) that collect information about ambulatory and inpatient hospital stays and visits to track utilization and charges resulting in injuries resulted from suicide attempts.[47] On a national level, suicide statistical reporting systems include the National Violent Death Reporting System (NVDRS) and the National Vital Statistics Systems.[47]

Self-reported data about suicidal behavior is typically collected through surveys and interviews such as the Youth Risk Behavior Surveillance System (YRBSS) and the National Survey on Drug

Use and Health (NSDUH).[48] While the NSDUH survey collects face to face interviews with US civilians over age 12 who are not institutionalized, the YRBSS survey targets young adults in high school.[48]

Information and data about suicides and prevention (Behavior Data)

The CDC developed the Youth Risk Behavior Surveillance System (YRBSS) in 1990 to monitor and better understand the major risk factors that lead to death among youth and adults in the United States. From 1991-2017, the YRBSS collected data from more than 4.4 million high school students through a survey.[47] Among other risk factors such as drug use the YRBSS includes suicide data on suicidal thoughts and behavior.

From the 2019 Standard High School YRBBS, the following questions were included to gather information about sadness, suicide ideation and planning, attempted suicide and the severity of suicide attempts among this population. In contrast to the mortality data that is collected in the vital statistics program, the data that is collected from these surveys aims to understand the factors and behaviors of teens and their perceived thoughts about attempting suicide rather than deaths caused by suicide.[49] The suicide behavior related questions from the survey include:

25. During the past 12 months, did you ever feel so sad or hopeless almost every day for two weeks or more in a row that you stopped doing some usual activities?
26. During the past 12 months, did you ever seriously consider attempting suicide?
27. During the past 12 months, did you make a plan about how you would attempt suicide?
28 During the past 12 months, how many times did you actually attempt suicide?
29. If you attempted suicide during the past 12 months, did any attempt result in an injury, poisoning, or overdose that had to be treated by a doctor or nurse?

Results for the entire survey are released in summarized reports called Youth Risk Behavior Survey Data Summary & Trends Report. The different areas in the survey are broken up by topic and questions are analyzed and summarized at the national level. For the Mental health and suicide questions, “At-A-Glance” variables are summarized in a trended table.

THE PERCENTAGE OF HIGH SCHOOL STUDENTS WHO:	2007 Total	2009 Total	2011 Total	2013 Total	2015 Total	2017 Total	Trend
Experienced persistent feelings of sadness or hopelessness	28.5	26.1	28.5	29.9	29.9	31.5	
Seriously considered attempting suicide	14.5	13.8	15.8	17.0	17.7	17.2	
Made a suicide plan	11.3	10.9	12.8	13.6	14.6	13.6	
Attempted suicide	6.9	6.3	7.8	8.0	8.6	7.4	
Were injured in a suicide attempt	2.0	1.9	2.4	2.7	2.8	2.4	

*For the complete wording of YRBS questions, refer to Appendix. | Source: National Youth Risk Behavior Surveys, 2007-2017

Graph 3. Example of output from Youth Risk Behavior Survey Data Summary Report[30]

The results from the YRBS survey are available to free of charge and no permission is needed to download or use the data that is collected. Datasets that include national, state and large urban school district data can be downloaded from the YRBSS website as zip files, Access files, SPSS and SAS files for immediate use. Having this type of data easily available to community members and educators allows for program evaluation, proposals for funding and raising awareness to certain health behaviors in communities and among populations.

The survey results sets are also useful to researchers both external of the Centers for Disease Control and Prevention and in academia. Examples of recent journal articles relying heavily on the YRBS data include:

Sexual Orientation Discordance and Nonfatal Suicidal Behaviors in U.S. High School Students Annor FB, Clayton HB, Gilbert LK, Ivey-Stephenson AZ, Irving SM, David-Ferdon C, Kann LK *American Journal of Preventive Medicine* 2018

Association Among Television and Computer/Video Game Use, Victimization, and Suicide Risk Among U.S. High School Students
Rostad WL, Basile KC, Clayton HB
Journal of Interpersonal Violence 2018. https://doi.org/10.1177/0886260518760020

Harassment and Mental Distress Among Adolescent Female Students by Sexual Identity and BMI or Perceived Weight Status
Johns MM, Lowry R, Demissie Z, Robin L
Obesity 2017;25(8):1421-1427

Conclusion

In conclusion, technologies play an important role in suicide prevention and will continue to expand and grow within the healthcare system nationally and globally. Technology provides an extra tool for practitioners to assist in preventing suicide. These tools are not meant to replace clinical decision making by trained professionals but help identify trends and connections in data that may not be recognized alone with clinical judgment. The technologies presented in this paper help health practitioners access best practice information, assist practitioners in reaching at-risk populations, help identify at-risk patients without self-identification and help assist in population-level risk analysis for suicide prevention.

Many of the technologies in suicide prevention were recently developed and are most likely changing as this paper is being written. As these technologies are being incorporated into clinical and public health workflows further evaluation is needed to better identify best practice for the use of technology in suicide prevention. Further research is needed to understand the costs and benefits of implementing these technologies.

Operationalizing the use of the predictive models and data collection provide the added benefit of the technology in suicide prevention therefore the data collection and model strength will only be as useful as the ways it is implemented to create change. Continued innovation and integration of technologies in local outpatient offices to federal public health departments are beneficial for estimating the risk of suicide and further strengthening prevention programs globally.

Glossary of Key Terms

Clinical Best Practice – Recommendations for clinicians about the care of patients with specific conditions. Recommendations are based upon the best available research evidence and practice experience.

Joint Commission – An independent, not-for-profit group in the United States that administers voluntary accreditation programs for hospitals and other healthcare organizations.

Machine Learning – The application of artificial intelligence that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.

Natural Language Processing – Ability of a computer program to understand human language as it is spoken.

Parasuicide – act of self-harm without the realistic expectation of death

Primary Care (Family Care and Outpatient Care) – Health care at a basic rather than specialized level for people making an initial approach to a doctor or nurse for treatment.

R (R Packages) – A programming language and free software environment for statistical computing and graphics.

Suicide – death caused by self-directed injurious behavior with intent to die as a result of the behavior.

Suicide Attempt – a non-fatal, self-directed, potentially injurious behavior with intent to die as a result of the behavior. A suicide attempt might not result in injury.

Suicidal Ideation – thinking about, considering, or planning suicide.

Acronyms

C-SSRS	Columbia-Suicide Severity Rating Scale
HIPAA	Health Insurance Portability and Accountability Act
NIST	National Institute of Standards and Technology
EHR	Electronic Health Record
VA	Veterans Health Administration
HADS	Hospital Anxiety and Depression Scale
PHQ	Patient Health Questionnaire
WHO	World Health Organization
CDC	Centers for Disease Control and Prevention
NVDRS	National Violent Death Reporting System
NEISS-API	National Electronic Injury Surveillance System- All injury Program
WISQARS	Web-based Injury Statistics Query and Reporting System
NAMCS	Ambulatory Health Care Data Homepage
NIS	Nationwide Inpatient Sample
YRBSS	Youth Risk Behavior Surveillance System
SAMHSA	Substance Abuse and Mental Health Services Administration

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