Data Driven Strategies for Substance Misuse Identification in Hospitalized Patients

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Rush University Medical Center and Rush Oak Park
Institutional Review Board for the Protection of Human Subjects

Title: Identifying Substance Exposure from the Electronic Medical Record System using Natural Language Processing in Hospitalized Patients: A Quasi-Experimental Clinical Study

Principal Investigator: Hale Thompson, PhD (Rush)

Study Coordinator: Connor McCluskey (Rush)

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Rush Site Principal Investigator: Hale Thompson
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ABSTRACT:

The rate of substance use-related hospital visits in the US continues to increase, and now outpaces visits for heart disease and respiratory failure. The prevalence of substance misuse (nonmedical use of opioids and/or benzodiazepines, illicit drugs, and/or alcohol) in hospitalized patients is estimated to be 15%-25% and far exceeds the prevalence in the general population. With over 35 million hospitalized patients per year, tens of millions of patients are not screened for substance misuse during their stay. Despite the recommendation for self-report questionnaires (single-question universal screens, Alcohol Use Disorders Identification Test [AUDIT], Drug Abuse Screening Tool [DAST]), screening rates remain low in hospitals. Current screening methods are resource-intensive, so a comprehensive and automated approach to substance misuse screening that will augment current clinical workflow would therefore be of great utility.

Substance misuse screening in hospitals is resource-intensive and rarely done. Many hospitalized patients are never offered opioid treatment. An automated approach leveraging routinely captured electronic health record (EHR) data may be easier for hospitals to institute. We previously derived and internally validated an opioid classifier in a separate hospital setting. In the advent of Meaningful Use in the electronic health record (EHR), efficiency for substance misuse detection may be improved by leveraging data collected during usual care. Documentation of substance use is common and occurs in 97% of provider admission notes, but their free text format renders them difficult to mine and analyze. Natural Language Processing (NLP) and machine learning are subfields of artificial intelligence (AI) that provide a solution to analyze text data in the EHR to identify substance misuse. Modern NLP has fused with machine learning, another sub-field of AI focused on learning from data. In particular, the most powerful NLP methods rely on supervised learning, a type of machine learning that takes advantage of current reference standards to make predictions about unseen cases.

We have trained and tested an NLP substance misuse classifier at Rush in a retrospective dataset of over 35,000 hospitalizations that have been manually screened with the universal screens, AUDIT and DAST. Our substance misuse classifier had good

discrimination during external validation. Our model may provide a comprehensive and automated approach to substance misuse identification that augments current workflows and overcomes manual screening barriers. We now aim to test its effectiveness against the current manual screen (usual care) in a pre-post study design at Rush University Medical Center in collaboration with the Substance Use Intervention Team (SUIT). We hypothesize that our automated NLP classifier will be non-inferior to the manual screen and translate into as many or more patients with addiction medicine consults with the SUIT program, medication-assisted treatment, and referrals to outpatient services.

SCIENTIFIC REVIEW:

The COVID pandemic has surfaced major gaps in healthcare, including addiction disease. In 2020, overdose deaths soared to an all-time high with a record 93,000 deaths nationwide during the pandemic year. Substance misuse ranks second among principal diagnoses for unplanned 7-day hospital readmission rates. Despite the availability of Screening, Brief Intervention, and Referral to Treatment (SBIRT) interventions, substance misuse is not part of the admission routine and only a minority of patients are screened for substance misuse in the hospital setting, especially during the COVID pandemic. This is particularly problematic, since among hospitalized inpatients, the prevalence of substance misuse is estimated to be as high as 25%, greater than either the general population or outpatient setting. Practical screening methods tailored for the hospital settings are needed.

Routinely collected data in the electronic health record (EHR) may be leveraged to identify cases of substance misuse. Patients are more likely to disclose substance use to their hospital primary care team than to designated screeners who are not part of the care team. The admission notes and social history sections of notes written by the provider teams frequently contain details about substance use but are rarely accessed for surveillance or screening programs. Computational methods of natural language processing (NLP) can derive discrete representations of clinical notes, from which machine learning can predict substance misuse better than rule-based approaches.

We previously published and made publicly available a substance misuse classifier using NLP and machine learning from the clinical notes. In hospitalized patients, our convolutional neural network (CNN) outperformed a rule-based approach and other machine learning methods. Our CNN substance misuse classifier had greater than 80% sensitivity and specificity, and our results showed that clinical notes from the hospitalization can be used to identify substance misuse and serve as an alternative to manual screening by staff. The trained model comprised of 15,651 medical concepts from 63,301 notes fed into the CNN. The top positive features included terms such as ‘heroin’, ‘opiates’, ‘drug abuse’, and ‘polysubstance abuse’.

RESEARCH PLAN:

In this study, the aim is to prospectively implement our NLP substance misuse classifier to examine its effectiveness in augmenting current practice that features physician referrals in hospitalized adult patients at Rush University Medical Center (RUMC).

STAFF

All work involving patient data will be performed at Rush and Rush staff will gain access to the Rush servers with approved credentialing and authentication by Rush IT. No data will be accessible to external investigators without a fully executed data use agreement and/or IRB approval / SMART IRB reliance agreement.

TRIAL SETTING AND PARTICIPANTS

This pragmatic, quasi-experimental (pre-post) study will be implemented at Rush University Medical Center across the surgical and medical wards. The study will target all adult hospitalized patients over a 24-month period (12 months of manual screen and 12 months under implementation of the NLP tool) and an additional 6-month follow-up for secondary outcomes. Currently, SUIT performs screening for patients identified from physician referrals between 8am-6pm and Monday-Friday and uses Epic (Epic Systems Corporation, Verona, Wisconsin) EHR.

METHODS AND MATERIAL

Overview:

We will use a quasi-experimental, interrupted time series (ITS) design to evaluate the longitudinal effects of the automated screening classifier compared to the manual screen approach at Rush. ITS offers several advantages in making use of our longitudinal data. Our analysis will model the trend in the outcome before the implementation of the automated screen, the change in the outcome that can be attributed to the automated screen and the difference between the slopes in the pre-period versus post-period. It is anticipated that no other interventions that may impact the study outcome will occur during the study period.

A comparison cohort from the manual screen period will extend from August 1, 2022 to July 31st, 2024. The day of switching on the automated screen will mark the start of the intervention period on August 1, 2023 and extend through July 31, 2024. This provides a 30-month total study period (12 months manual screening, and 12 months automated screen, and 6 months additional follow-up for secondary outcomes).

Approach:

Screening, intervention flow sheets, and consult order sets are currently in EHR-driven workflows of both inpatient nurses and social workers at Rush. Leveraging the EHR infrastructure, the manual screen is driven by four key components: (1) connect the nursing and social work navigators into a single workflow that allows both disciplines to document screening information into a common flowsheet in the EHR; (2) a status column in the unit patient list where the social work team indicates the current stage of the intervention for each patient; (3) a consult order to addiction medicine that operates within a work queue managed by the SUIT team; and (4) a flowsheet for the SUIT team to document the details of the intervention. Specifically, if patients report positive to the universal manual screen during the rooming process, an indicator in the substance use column updates to signal a social worker to conduct a full manual screening with the Alcohol Use Disorders Identification Test (AUDIT) and/or Drug Abuse Screening Tool (DAST). Once completed, the social worker is guided by a risk-stratified score (Table) and may provide a brief intervention using motivational interviewing. If the score is high risk, the social worker may recommend a consult to the SUIT team for addiction services. The consult team determines with the

Table. Cutoffs to categorize patients into risk zones for substance misuse

	AUDIT Score		Description of Category
	Male	Female	
Zone 1	0	0	No alcohol use
Zone 2	1-7	1-4	Low-risk alcohol use
Zone 3	8-15	5-12	Mild/moderate alcohol use
Zone 4	≥16	≥13	Severe alcohol use*
	DAST Score		
Zone 1	0		No drug use
Zone 2	1-2		Low-risk drug use
Zone 3	3-5		Mild drug use
Zone 4	6-8		Moderate drug use
Zone 5	9-10		Severe drug use*

*at-risk for substance use disorder (SUD)

patient whether to initiate medication and linkage to outpatient services upon discharge. If ready, patients may begin medication and, upon discharge, receive individual and group psychotherapy, case management, continued medication treatment at an outpatient addiction medicine clinic. The study coordinator will collect the following elements: (1) documentation and modality of SBIRT was performed by the provider (Yes/No); (2) dose assessed by documentation of brief intervention, motivational interview, or referral to treatment; and (3) reasons for no receipt (e.g., patient refusal).

Clinical decision support (CDS) with substance misuse NLP classifier:

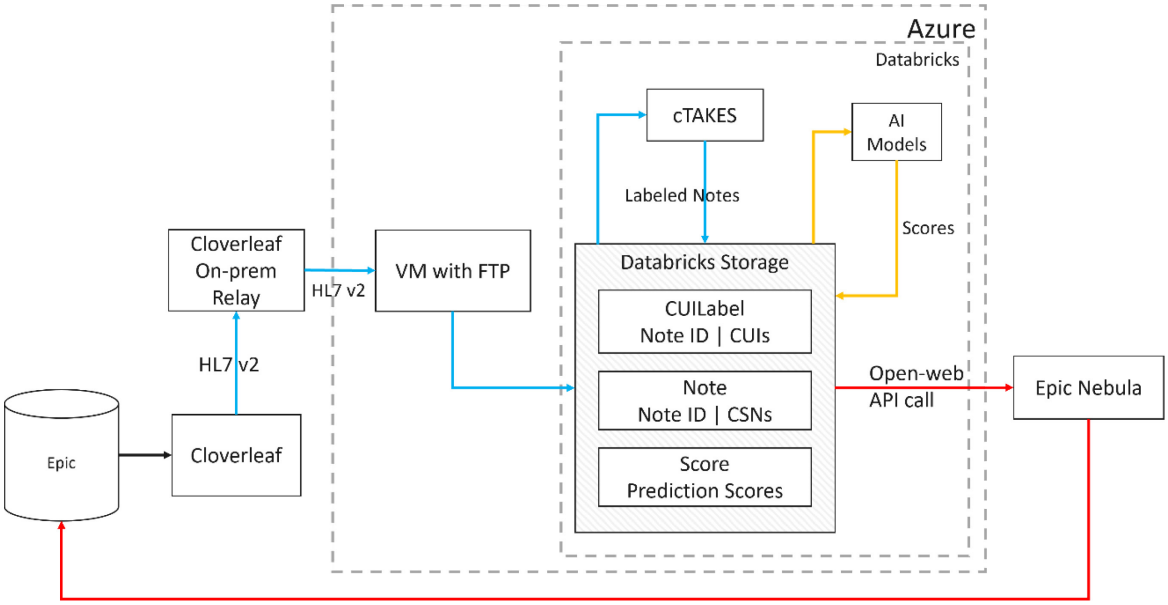
All analytics for the NLP classifier will be performed on Rush Servers by the Rush Addiction Data Science Lab. Linguistic processing of all clinical documents for the NLP classifier is performed in the clinical Text and Knowledge Extraction System version 4.0 (cTAKES) open-source Apache software tool (https://ctakes.apache.org/). These include linguistic pre-processing modules for breaking the text into sentences and tokens, and tagging the tokens with parts of speech (e.g., noun, adjective). Next, candidate phrases are matched to a dictionary of concepts, by default SNOMED CT and RxNORM, and tagged with concept codes from the original dictionary, and a Concept Unique Identifier (CUI) from the National Library of Medicine's Universal Medical Language System (UMLS) Metathesaurus. For the concept codes, cTAKES recognizes the words or phrases from the notes as medical terms that represent the domain concepts (named entity mentions) to understand the relations between the identified concepts. The Unified Medical Language System (UMLS) includes over 2 million concepts from nearly 9 million distinct names from 152 sources that are merged into the Metathesaurus. The spans of the UMLS named entity mentions (diseases, symptoms, anatomy, and procedures) will be identified and organized into CUIs. For instance, the named entity mention for *'heroin abuse'* is assigned C0600241 as its CUI. '*Heroin abuse'* is mapped to a separate CUI than 'history of heroin abuse' which is C3266350. The classifier is fed all the CUI predictors/features as inputs into the machine learning model that will serve as the automated screening tool. The software has been developed and is currently available in the Rush Addiction Data Science Lab (led by Dr. Hale Thompson) at https://github.com/Rush-SubstanceUse-AILab/SubstanceMisuse.

Our team will work to integrate the automated screen into the EHR established SUIT as an email alert from the backend data warehouse. Prior to switching on the automated screen, all inpatient nurses and social workers in participating units will be asked to participate in a brief in-service training on the tool and termination of the manual screening program on the day when the automated screener is initiated. Additional emails will be sent to inform providers who could not attend the training session.

Option 1 Email Alert System: During the implementation period, an alert will run every 24 hours after a nightly data extraction from the front-end EHR (Epic) into the back-end data mart (Clarity) at Rush. The automated screener will operate off the data mart and patients flagged by the system during each nightly data load will be reported the next morning. The report will be routed through a secure environment from a standard relational database for viewing. At Rush, the flagged patients will be reported with an e-mail routed to the SBIRT provider each morning detailing the patients that flagged positive, after the server is refreshed with the last 24 hours of data and the substance misuse classifier has been executed on the notes. With an average time of 1.6 days from a patient's admission to receipt of a SUIT during usual care, there is ample time for the automated screener to operate and report after admission notes are collected.

Successful implementation of the classifier in hospitalized patients is a step towards an automated and comprehensive universal screening system for substance misuse. We expect our results to demonstrate the automated screener will increase the proportion of hospitalized patients with substance misuse who screen positive and receive a brief intervention or referral to treatment. Dissemination of the expected results from this research would allow standardized and scalable 'NLP-capable' measures for healthcare systems to identify patients with substance misuse.

Option 2: Epic Best Practice Alert (if available at time of study roll out): The Rush IT Operations team is currently in the process of implementing a real-time NLP system to support clinical decision support tools such as our automated classifier. Our team will work with the Rush IT team to integrate the opioid classifier into health systems, using the HL7 interface. The real-time data feeds, including a cTAKES NLP pipeline will be incorporated using both the Rush Azure cloud computing environment and Epic's Nebula cloud computing environment. Ultimately, the modeling of notes data as data feeds into the opioid classifier will include the following protocol: (1) rendering clinical documents in HL7 exchange as input from the hospital encounter; (2) notes will be moved into Rush's HIPAA secure Azure environment; (3) run cTAKES in Azure cloud to generate set of CUIs; (5) application calls the ML algorithm microservice, which uses the set of CUIs from NLP to generate outputs. (6) cloud service associates the output into Epic's Nebula system for integration back into Rush Epic as a best practice alert. The diagram below is a draft schematic for the architecture:



Eligibility criteria:
Inclusion Criteria:

- Ages 18 years old to 89 years old
- Inpatient status during hospitalization

Exclusion Criteria:

- Cannot participate in the usual care SBIRT intervention

Study Outcomes:

While our prior aims validated the automated screener as a process measure, this study is examining the tool as an outcome measure to identify patients with substance misuse in practice using a pragmatic, quasi-experimental design. We hypothesize that the natural language processing algorithm can provide a standardized and interoperable approach for an automated daily screen on all hospitalized patients and provide better implementation fidelity for screening, brief intervention, and referral to treatment.

The primary outcome is the count of patients who received the composite outcome of any of the following: naloxone dispensing [prescription, free kit from clinic, or order for home kit], medication assisted treatment [buprenorphine, methadone, naltrexone, acamprosate, gabapentin, disulfiram], addiction consult, referral to outpatient treatment, brief intervention/motivational interviewing for substance misuse. Each component will be indicated separately in the flowsheet for the encounter, along with the type of SUIT team involvement: formal consultation, curbside consultation, or supporting other service. The design is an interrupted time-series prospective observational study. [Time Frame: 30 months]

The secondary outcome is all-cause re-hospitalizations following 6-months from the Index hospital encounter. We will compare healthcare utilization outcomes in all patients between manual screen period and automated screen period controlling for all patient demographic and clinical characteristics. [Time Frame: 24 months of evaluation with 6 months follow-up for rehospitalization] Further exploratory outcomes include analyzing each component of the primary outcome separately: naloxone dispensing, medication assisted treatment, addiction consult, referral to outpatient treatment, brief intervention/motivational interviewing for substance misuse.

Analysis Plan:

Overall approach: Demographic and clinical characteristics between the manual and automated screen periods will be examined using bivariate statistics. We will also perform descriptive analysis to examine the proportion of hospitalized patients with substance misuse who received any component of the composite outcome (naloxone dispensing, medication-assisted treatment, addiction consult, referral to outpatient treatment, brief intervention/motivational interviewing for substance misuse) within each month of the study period, and we will plot these proportions using mixed-effects logistic regression, with time (month of observation) modeled using restricted cubic splines. The primary analysis for aim 1 will consist of an interrupted time series approach utilizing autoregressive integrated moving average (ARIMA) models to determine the effect of the automated screener to the manual screen for this outcome. ARIMA models are preferable to alternatives such as segmented regression which may inadequately control for seasonality and autocorrelation in time series data. We will also perform sensitivity analyses to confirm the results of aim 1 using generalized linear mixed-effects models (GLMM) that include random intercepts to account for multiple index encounters over the follow-up time period and adjust for important patient demographics and clinical characteristics including: age, sex, race/ethnicity, insurance status, diagnosis, and comorbidities. GLMMs will also be used to analyze secondary endpoints.

Specific aim 1: First, we will plot the counts of hospitalized patients who received any component of the composite outcome to examine seasonality, trends, and outlying values. A transformation will be applied to stabilize the variance over time if data are heteroscedastic. Differencing will be applied to induce stationarity, such as a difference to account for linear trend (d=1, degree of non-seasonal differencing) and autocorrelation functions (ACF) will be plotted to verify stationarity. After differencing,

ACFs and partial ACFs will be used to determine the orders of autoregression (AR) or moving average (MA) that will correct for the remaining autocorrelation. We hypothesize that the intervention will promote a step change (binary indicator for a level shift when intervention begins) and possibly a ramp effect (variable takes the value of 0 before the intervention and increases by 1 for each month following the beginning of the intervention). Fit statistics (AIC, BIC) and residual analysis (Ljung-Box test for white noise) will be used to identify a parsimonious and appropriate model based on AR/MA orders, differencing assumptions, and parameters for intervention impact (step, pulse, or ramp).

Specific aim 2: The number of hospitalizations in the 6 months following the index encounter will be regressed on time period of index hospitalization (manual screen or automated screen) and patient demographic and clinical characteristics using mixed-effects Poisson regression models. GLMMs with appropriate link and distributions specified will consider other follow-up utilization outcomes (e.g., costs, any encounter).

Power analysis:

A simulation study was designed to examine potential step effects in a non-inferiority design. In 2020, there were 95 ± 10 addiction consults per month and an autocorrelation AR(1) of ϕ=0.4. Additionally, we performed silent testing of the automated screener in 2020 where it detected ~70 additional cases of substance misuse per month that did not receive consults by the usual care approach. We propose that a non-inferiority margin of 15 consults is acceptable and a step effect of 20 is a feasible goal with the implementation of automated screening. Assuming a similar consult rate of 95 ± 10 per month in this study's pre-period (July 2022-June 2023) and ϕ=0.4, we have 80% power to detect a step effect of +20, resulting in 115±10 consults per month in the post-period (July 2023-June 2024).

Data Elements:

RUSH EHR

The following electronic health record data elements will be included in the data sets used for analysis. Most data will be obtained through direct extraction of EPIC; however, some data may be computed from EHR data and obtained through the Rush Clinical Research Analytics team or transformed from EHR data by the research team (NLP mapped concepts from the text):

- MRN
- Address with Geocoding
- Census Tract Identifiers
- Encounter ID and type
- Date / time Stamps for all EHR data (e.g. admission / discharge, procedures, assessments, notes, etc. (time-shifted for final analysis))
- De-identified concept unique identifiers (CUIs) from all clinical documentation in the EHR (process described below)
- Nursing assessments and flowsheets including AUDIT, DAST, and universal screens
- Clinical / nursing assessments, flowsheets, documentation including SUIT data
- Insurance status
- Vital signs (including respirator settings and data)
- Co-morbidities
- ICD and CPT codes

- Cost, charges and reimbursement data associated with all the CPT, ICD9/10, and medications
- patient location
- laboratory results
- radiological orders
- interventional orders including addiction consult orders
- diagnostic test orders
- medication ordered and administered
- sex
- age
- race / ethnicity
- primary and secondary diagnoses
- date of admission
- date of discharge
- dates related to notes, assessments, procedures, orders, reports, vitals, observations, events, diagnoses, etc.
- discharge disposition
- adverse events during hospitalization, defined as Rapid Response Team activations, ICU transfer, cardiac arrest, or mortality
- OR procedures
- OR admission and discharge

DURATION
It is expected that participant enrollment will begin by January 1, 2018 and that human subjects activities will be complete by June 30, 2024. In this pre-post design, a manual screen cohort of patients will provide the comparison. The automated screen period will run prospectively on hospitalized patients over a 12-month period between July 1, 2023 and June 30, 2024. During these study periods, all patient data (for patients ages 18 and above) will be collected.

LOCATION
Research will be conducted at Rush University Medical Center by study staff from Rush. Staff from ITM Loyola and UW-Madison may consult on analyses. All data will be housed at Rush and analyzed on our systems. PHI will not be released outside of Rush.

TYPE AND NUMBER OF SUBJECTS
EHR data for adult (ages 18 and above) patients will be collected. The target study population is adult (ages 18 and above)- male or female – that were identified by the manual or automated screening for substance misuse at Rush University Medical Center. Additionally, patients meeting only the age criteria within the specified time-frame for the study may be included for analyses regardless of potential of or screening for substance misuse. Investigators at Rush University anticipate approximately 57,800 RUMC patients will be included in the analysis, based on preparatory research planning.

POTENTIAL RISKS & BENEFITS
The main risk to subjects is breach of confidentiality. All data is maintained electronically and stored on password-protected computers using secured servers with limited access maintained at Rush University Medical Center. For analysis, Rush will access a delimited file containing patient notes and then process the data, load the model, and make a prediction for each patient. The software will generate output in the

form of a delimited file linking each patient's unique identifier (such as MRN) to a prediction about the patient's alcohol, opioid, non-opioid, and polysubstance use statuses. All these activities will be performed locally within Rush's HIPAA-secure servers.

This study involves "no more than minimal risk." There are no planned interventions that would pose any significant risk. All of the instruments used in this study have been previously used and studied in psychiatric research studies. The completion of psychiatric diagnostic instruments and psychological assessments can involve the recollection of past symptoms and previous history. Recollection of events always poses some degree of risk in that individuals may experience distress if their past histories are particularly traumatic. The SBIRT program used in the study is currently in place and part of usual care. The program has been well studied in multiple populations, and no adverse events as a consequence of this patient-centered care are foreseeable. Universal screening is already performed on all hospitalized patients so consenting patients is not feasible but the social workers using the universal screen will have the opportunity to opt-out of using the substance misuse classifier. Nevertheless, a data safety and monitoring board (See SAFETY MONITORING section below) has been formed to track and monitor for any unintended consequence of the automated screener as a universal screen for SBIRT.

There is no direct benefit to patients whose electronic health records we will use. However, there is potential future benefit to new patients. The proposed research will provide new screening tools that may be used in patients hospitalized and at-risk for substance misuse. Tools developed with the methodologies we investigate will improve our ability to perform clinical decision support. In addition, creating improved and scalable methodologies for text processing will allow health providers in other domains to access detailed information about patient symptoms, the course of disease onset, diagnosis, treatment, and social history. This previously unavailable knowledge will enable more accurate and complete data on screening for preventable and treatable health conditions.

PLAN TO PROTECT IDENTIFIERS FROM IMPROPER USE AND DISCLOSURE:
The confidentiality of data will be ensured by limiting the acquisition, access to, and transmission of all data. All electronic patient data will be obtained through Rush University and Rush University Medical Center. Databases will be stored on secured servers behind the Rush firewall with access only to authorized users and will be accessible only to users approved by the IRB. Subject names will not be used in any scientific or other publications. Raw data will not be shared outside of the study investigators and IRB-approved personnel. Additionally, raw data will not be released outside of Rush University Medical Center. A text file for NLP dataset will be stored on the research directory in the department of Psychiatry at Rush in the Addiction Data Science Lab led by Dr. Hale Thompson. The datasets will be analyzed from there and imported into R, Python, cTAKES, or other statistical programs for analysis. A physical machine onto a dedicated server was established with secure login for access to the data loaded into cTAKES for analysis by IRB approved data scientists. All data analyses with PHI will be performed on the Rush server. No identifying information will be in the file name.

PLAN TO DESTROY IDENTIFIERS:

Identifiers will be destroyed immediately following completion of study. In addition, extraction of data elements for analysis do not include any unnecessary PHI.

WHO WILL HAVE ACCESS TO THE PROTECTED HEALTH INFORMATION:

Access to the protected health information will be limited to the Rush investigators and study staff listed in this IRB. A physical machine on a dedicated Rush server was established with secure login for access to the data loaded into cTAKES for analysis by IRB approved data scientists. No identifying information will be in the file name. Also, no data containing PHI will be used during NLP analysis performed outside the server.

SAFETY MONITORING

A data safety monitoring board has been established to ensure that the data remain confidential and that the participants are not experiencing any harm from the intervention. A committee to ensure that the plan is followed will be formed. The committee will meet every three to six months during the 24-month study period. Members of the data safety monitoring board will include individuals who have demonstrated expertise in the areas related to the project and have agreed to serve in this capacity. Richard S. Cooper, MD, is a Professor and Chair of Public Health Sciences in the School of Medicine at Loyola University Chicago and will serve as the Chair of the Data Safety Monitoring Board (letter of support). He has extensive experience in clinical trials and has extensive experience in health inequities research. He has conducted numerous clinical studies and has more than 20 years of NIH funding. Dr. Suthat Liangpunsakul, MD, is an Associate Professor at Indiana University and a practicing Hepatologist with several NIH/NIAAA-funded grants examining patients with alcoholic hepatitis. He has performed multiple clinical studies in hospitalized patients and involved in clinical trials for alcohol hepatitis treatment. Dr. Ellen Burnham, MD, is an Associate Professor at University of Colorado and a critical care physician and currently the PI of a NIAAA R24 multi-site collaboration collecting patient samples for alcohol research. She is familiar with the potential harms in performing alcohol research in hospitalized patients. Finally, Dr. Dr. Ramon Durazo, PhD, is a Professor of Biostatistics at University of California San Diego and has served on data safety monitoring boards for clinical trials and will help to evaluate the statistical analyses and reports provided by the study team. Of note, the study team will provide the proportion screened and identified to have substance misuse as one of the important metrics to determine any harm that is being incurred in patients missed for SBIRT by the substance misuse NLP classifier.

<u>The Progress of Study and Safety of Patients</u>**:**

The following data will be examined to evaluate safety issues: adverse events and rates of adherence to Screening, Brief Intervention, and Referral to Treatment (SBIRT) at all contact points. In order to provide a level of protection to all patients, the following will be specifically included for monitoring and follow-up: (1) number (if any) of patients who were identified by the care team to have substance misuse but was not captured by the automated screener; (2) number (if any) of patients who received screening but refused any intervention; (3) number (if any) of patients who began medication or were referred for treatment; (4) number (if any) who had withdrawal syndrome. Of note, the risks involved with this study are considered low and the manual screen in the control group is an approved intervention for substance misuse by the United States Preventive Services Task Force (USPSTF), the National Institute of Drug Abuse (NIDA), the Center for Disease Control and Prevention (CDC), and the Substance Abuse and Mental Health Service Administration.

(1) *Compliance with the reporting of adverse events:* Determining whether all adverse events and/or unanticipated problems were reported in writing to Rush University Medical Center and the IRB within 48 hours of discover of the incident. Priority of the DSMB is to analyze presence of any level of harm to patients.

(2) *Data Accuracy and Protocol Compliance:* Evaluating records for the training of personnel and other protocol documents as needed. All research staff personnel will be required to have human subjects training, HIPPA training, and training on all study protocols. Drs. Afshar and Thompson will have weekly lab meetings with the project staff and co-investigators. The Substance Use Intervention Team have already been trained for SBIRT and addiction counseling in their practice of usual care currently in place at Rush. At baseline and every six months thereafter, the following will be done by Dr. Afshar, Dr. Thompson, and the staff to ensure compliance: (1) reviewing study documents; (2) auditing the data collection forms for missing data and reasons for missing data; (3) performing analyses of the performance of the substance misuse classifier to ensure no major deviance and harm is occurring. Priorities of the DSMB are to ensure the accurate reporting of the safety data including: 1) manual and automated screening estimates; 2) screen fails; 3) missing data.

RECRUITMENT & WAIVER OF INFORMED CONSENT FOR DATA PULL AND ANALYSES:

Patients include all adults admitted to the inpatient wards and recorded into the EHR. We are requesting a waiver of informed consent based on the following: (1) the project presents minimal risk to subjects; (2) there is no intervention, so the only risk is breach of confidentiality, which will be minimized as described in “Protections against risk”; (3) a waiver of consent will not adversely affect the rights or welfare of patients; and (4) the research cannot be carried out without the waiver because the study consists of retrospectively reviewing records collected during usual care in the EHR.

WAIVER of HIPAA

We are additionally requesting a waiver of HIPAA authorization, as the information we collect about patients will contain protected health information (PHI). Only the minimum necessary PHI needed will be retained and utilized, the medical record is the best source of the PHI. It would be difficult to obtain written authorization given that the study team will not interact with the patients whose information will be used for the research.

PAYMENT

No payment will be made to participants.

DESCRIBE THE USE OF THE DATA (publication, presentation, etc.).

The data will be utilized in multiple facets including the following: abstract presentations at international conferences, national conferences, other presentations, and publications. Data generated from this study will support the PI’s, Co-I’s and study staff’s publications in peer-reviewed scientific journals. The results will also serve as preliminary data for larger NIH grants and potentially other sources of funding.

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