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Predicting suicide attempts and suicide deaths among adolescents following outpatient visits

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ABSTRACT

Background: Few studies report on machine learning models for suicide risk prediction in adolescents and their utility in identifying those in need of further evaluation. This study examined whether a model trained and validated using data from all age groups works as well for adolescents or whether it could be improved.

Methods: We used healthcare data for 1.4 million specialty mental health and primary care outpatient visits among 256,823 adolescents across 7 health systems. The prediction target was 90-day risk of suicide attempt following a visit. We used logistic regression with least absolute shrinkage and selection operator (LASSO) and generalized estimating equations (GEE) to predict risk. We compared performance of three models: an existing model, a recalibrated version of that model, and a newly-learned model. Models were compared using area under the receiver operating curve (AUC), sensitivity, specificity, positive predictive value and negative predictive value.

Results: The AUC produced by the existing model for specialty mental health visits estimated in adolescents alone (0.796; [0.789, 0.802]) was not significantly different than the AUC of the recalibrated existing model (0.794; [0.787, 0.80]) or the newly-learned model (0.795; [0.789, 0.801]). Predicted risk following primary care visits was also similar: existing (0.855; [0.844, 0.866]), recalibrated (0.85 [0.839, 0.862]), newly-learned (0.842, [0.829, 0.854]).

Limitations: The models did not incorporate non-healthcare risk factors. The models relied on ICD9-CM codes for diagnoses and outcome measurement.

Conclusions: Prediction models already in operational use by health systems can be reliably employed for identifying adolescents in need of further evaluation.

1. Introduction

Reducing suicide attempts among adolescents is a major public health priority. There were over 90,000 incidents of nonfatal self-harm among youth aged 13-17 years (432.64 per 100,000) in 2018. The 2019 Youth Risk Behavior Survey data reveal that 24.1% of females and 13.3% of males aged 14-17 years seriously considered attempting suicide in the 12 months prior to completing the survey (Ivey-Stephenson et al., 2020). Health system efforts to reduce rates of suicide attempt and death such as the Zero Suicide initiative (Education Development Center 2020) could be improved by predicting who is at high risk and targeting services and interventions towards those individuals.

Recent research in estimating machine learning algorithms to predict suicide risk in adults demonstrates these models can accurately identify people when they are at elevated risk. The models have high predictive validity as measured by area under the receiver operating characteristic

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curve (AUC) for prediction of suicide attempt and suicide death, ranging from 0.83 to 0.85. (Kessler et al., 2017; Kessler et al., 2015; Simon et al., 2018; Coleman et al., 2019) Moreover, the models have been implemented as part of routine prevention programs in health systems such as Kaiser Permanente Washington, HealthPartners, and the Veterans Health Administration. (Berg et al., 2018) It has also been demonstrated that suicide risk prediction models developed in one set of health systems perform well when implemented in other health systems. (Kline-Simon et al., 2020) However, little research has been done on how well machine learning algorithms calibrated using the entire population of health systems (i.e., including both adults and adolescents) perform on the subpopulation of adolescents alone.

It might be expected that the factors predicting suicide attempt risk are substantially different for the subpopulation of adolescents, thereby suggesting that new prediction algorithms should be specified, trained, and validated using data from adolescents alone. It is well known that suicide attempt risk is higher among adolescents and lower for suicide death. (Conner et al., 2019) It is also known that the methods of suicide attempt differ between adolescents and adults with, for example, self-harm by poisoning being more common in adolescents. (Hepp et al., 2012; Miller et al., 2004; Spicer and Miller, 2000) Third, diagnosis patterns differ for adolescents with, for example, psychosis being less common (Chan, 2017) and eating disorders being more common (Hoek and van Hoeken, 2003) as does the presence of any known mental health diagnosis (Stone et al., 2018). Fourth, adolescents have different health care utilization patterns (e.g., frequency of visits (Rand and Goldstein, 2018)) and shorter utilization histories, both of which may impact the performance of prediction models.

Recent research on developing machine learning approaches to predict risk of suicide attempt (Walsh et al., 2018; Miché et al., 2020) in adolescents alone is promising. However, Miché and colleagues (Miché et al., 2020) modeled risk using data collected from research clinical interviews rather than data already collected routinely by health systems—thereby limiting the potential for implementation of their model. Walsh and colleagues (Walsh et al., 2018) did use routinely collected health care records data but their results have not yet been validated in a held-out sample of youth. Additionally, neither of these models have included standardized scores for depression or suicidal ideation (Walsh et al., 2018) such as item 9 of the Patient Health Questionnaire (PHQ-9) (Kroenke et al., 2010) or the Columbia-Suicide Severity Rating Scale (C-SSRS) (Posner et al., 2011). The frequency and severity of suicidal ideation are known to be important predictors of future suicide attempts (Posner et al., 2011). We incorporate data on suicidal ideation from item 9 of the PHQ-9 to improve the predictive accuracy of machine learning models of suicide risk for adolescents.

In this study we used the data and coefficients for a suicide risk prediction model (Simon et al., 2018) developed using both adult and adolescent data for seven health systems to measure how well these existing models performed for adolescents alone and compared these results to this same existing model recalibrated to the adolescent only population as well as machine learning models developed de novo using only adolescent data from the same population.

2. Methods

2.1. Setting

The seven participating sites were five Kaiser Permanente regions (Hawaii, Northwest, Washington, Southern California, Colorado) as well as HealthPartners and Henry Ford Health System. Each system provides insurance coverage and comprehensive health care to a defined population enrolled through employer-sponsored insurance, individual insurance, capitated Medicaid or Medicare, and subsidized low-income programs. All these health systems recommended use of the PHQ-9 for adolescents (and where appropriate, the C-SSRS) at mental health visits and primary care visits for depression, but implementation varied across systems during the study period.

2.2. Data and sampling

Electronic health record (EHR) and administrative claims data were obtained from each health system. Each health system maintains a research data warehouse following the Health Care Systems Research Network's data model (Ross et al., 2011), which includes data from insurance enrollment records, electronic health records, insurance claims, pharmacy dispensings, state mortality records, and U.S. census-derived neighborhood characteristics. Institutional review boards for each health system approved use of these de-identified data for this research.

The study sample included any outpatient visit by an individual aged $\geq$13 years and <18 years either to a specialty mental health provider or to a primary care provider where a mental health diagnosis was recorded. Only visits to integrated health system clinics were included. People were also insured by the health system's insurance plan with the exception of Henry Ford Health System visits and some Medicaid patients. Enrollment and health system criteria maximized the availability of EHR and insurance claims data. There were approximately 45,000 visits where the person was not currently enrolled in a health system insurance plan on the date of the index visit.

The data include all visits from January 1, 2009, through June 30, 2015. Visits were the unit of analysis rather than people and risk was predicted for the 90-day period following every eligible visit for a given individual. The rationale for this approach is that an outpatient visit is an opportunity to conduct suicide prevention and a clinician wants to know the predicted probability of a future suicide attempt at an index visit while the patient is in the room.

Predictors were extracted from health system records for up to five years before each visit. The data domains included: demographic characteristics (age, sex, race, ethnicity, source of insurance, and neighborhood income and educational attainment); diagnoses (current and past mental health and substance use diagnoses, past suicide attempts, other past injury or poisoning diagnoses, general medical diagnoses); prescriptions (dispensed for mental health medication); encounters (past inpatient or emergency department encounters with mental health diagnoses, as well as past outpatient specialty mental health care); and PHQ-9 scores (including total score and item 9 score). Predictors were represented as dichotomous indicators. Each diagnosis category was represented by three overlapping indicators for time: recorded at or within 90 days before the index visit, recorded within 1 year before, and recorded within 5 years before. Each category of medication or of prior mental health utilization was represented by three overlapping indicators for time: occurred (Simon et al., 2016) within 90 days before the index outpatient visit, 1 year before, or 5 years before. To represent temporal patterns of prior PHQ-9 and item 9 scores, indicators were calculated for each index visit to represent the following values over the previous 90, 183, and 365 days: number of unique PHQ-9 observations, maximum PHQ-9 score, modal score, and value of missing PHQ-9. The final set of potential predictors for each encounter included 149 indicators and 164 possible interaction terms. The full list of predictors is available elsewhere (Simon et al., 2018).

2.3. Suicide attempt ascertainment

The prediction target was a composite outcome of fatal and non-fatal suicide attempts. Non-fatal suicide attempts were defined as diagnoses of self-harm or probable suicide attempt, and were ascertained from all injury or poisoning diagnoses recorded in electronic health records and insurance claims accompanied by an ICD-9-CM external cause of injury code indicating intentional self-harm (codes E950–E958) or undetermined intent (codes E980–E989). Ascertainment of suicide attempts was censored at health system disenrollment, after which insurance claims data regarding self-harm diagnoses at external facilities would not be

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available.

Suicide deaths were ascertained from state mortality records. Following common recommendations (Bakst et al., 2016; Cox et al., 2017), all deaths with an ICD-10 diagnosis of self-inflicted injury (codes X60–X84) or injury/poisoning with undetermined intent (codes Y10–Y34) were considered probable suicide deaths. All predictor and outcome variables were completely specified and calculated prior to model training.

We combined fatal and non-fatal suicide attempts as an outcome measure because there were not enough suicide deaths to model these events separately.

Model Specifications –Recalibration andNewly-learned

The goal of this study was to determine if existing models accurately predict risk of suicidal behavior in the subpopulation of adolescents alone or whether newly-learned models using only visits from adolescents are warranted to improve accuracy. Two main sets of analyses were conducted to compare adolescent-specific models to those developed using both adult and adolescent data: newly-learned models in which new variable selection occurred for adolescent prediction models and recalibrated models in which we used the variables selected from models using adult and adolescent data combined but re-estimated the model coefficients using adolescent data alone. A detailed description of each model and modeling step is provided below.

Newly-learned model using only adolescent outpatient visits for model building.

To estimate newly-learning adolescent specific models, separate prediction models were developed using mental health specialty and primary care visits made by adolescents, with a random sample of 65% of each used for model training and 35% set aside for validation. Models included multiple visits per person in order to accurately represent changes in risk within patients over time. For each visit, analyses considered any outcome in the following 90 days, regardless of a subsequent visit in between. This approach uses all data available at the time of the index visit but avoids informative or biased censoring related to timing of visits following the index date.

2.4. Model building approach

There are three steps to model building in this study. In the initial variable selection step, separate models for mental health specialty and primary care visits to predict risk of fatal or non-fatal suicide attempt were estimated using logistic regression with penalized LASSO (least absolute shrinkage and selection operator) variable selection. (Tibshirani, 1996) To avoid overfitting, we used 10-fold cross-validation (Hastie et al., 2009) to select the optimal level of tuning or penalization, measured by the Bayesian information criterion. (Kass and Raftery, 1995)

In the second step, generalized estimating equations (GEE) with logistic link re-estimated coefficients for variables retained by the LASSO model in the training sample in order to properly account for both clustering of visits under patients and bias toward the null in LASSO coefficients.

In the final validation step, logistic models derived from the above two-step process were applied in the 35% validation sample to calculate predicted probabilities of suicide attempt in the next 90 days for each visit. Results in this validation data set are reported as receiver operating characteristic (ROC) curves (J.P., 1975) with c-statistics (equivalent to area under the ROC curve) (Bradley, 1997; Hanley and McNeil, 1982), along with predicted and observed rates in prespecified strata of predicted probability. Overfitting was evaluated by comparing classification performance in training and validation samples and by comparing predicted risk and observed risk in the validation sample. Variable selection analyses were conducted using the GLMNET (Friedman et al., 2010) and Foreach (Wallig and Package, 2020) packages for the R statistical package, version 3.4.0. (The R Foundation, 2020) Confidence intervals for c-statistics were calculated via bootstrap with 10,000 replications.

All the statistical code and variable definitions used in this study are available on the Mental Health Research Network Github site. (Mental Health Research Network 2021)

2.5. Recalibrated existing suicide risk prediction model

We have previously reported on the performance of risk prediction models (Simon et al., 2018) developed using both adults and adolescents from the same health systems that participated in the current study. These existing models were developed using the same learning approach described above (LASSO variable selection followed by GEE to re-estimate coefficients) using outpatient visits made by both adults and adolescents. In addition to comparing the existing model as estimated on the full population, we recalibrated the existing model using only the training sample of adolescents. That is, we fit a new GEE model to re-estimate the coefficient values for the variables retained by the adult-and-adolescent LASSO model using only training data from adolescents (see column 2 in Fig. 1 below).

2.6. Comparison to overall population models

We compared all three models (see Fig. 1) by estimating and comparing the AUC, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) on the adolescent-only validation dataset. Additionally, we examined the variables selected for inclusion in the newly-learned adolescent only model to those selected for inclusion in the existing adult-and-adolescent model.

3. Results

Table 1 shows the demographic composition of the sampled visits for individuals aged ≥13 to <18 years. There were 167,029 unique youth in the training sample and 89,794 unique youth in the validation sample for a total sample of 256,823. There were 1,417,880 visits overall with 1,031,932 to specialty mental health and 385,948 to primary care where a mental health diagnosis was recorded. About 54% of visits were made by females, 47% by those of white race, and 34% by those of Hispanic ethnicity. The majority of visits (79%) were covered by commercial insurance and about 14% by state Medicaid programs. (Each of the seven health systems is located in a different state.) In the training sample, 61,826 (7.0%) of visits had a PHQ-9 recorded. There were 3,875 adolescents with at least one suicide attempt, and 17 adolescents whose suicide attempt was fatal, as recorded in electronic health records, administrative claims, or state death data. Females accounted for 71% of all fatal and non-fatal suicide attempts by adolescents.

Table 2 lists the top 20 variables included in each of the models ranked by the size of the positive coefficients. These are the variables most strongly associated with a suicide attempt in the 90 days following a visit. (Note that unlike explanatory models the absolute magnitude of the coefficients is not readily interpreted in predictive models.) The table is divided into mental health and primary care prediction models and further separated into re-estimated and new models.

The re-estimated model for mental health visits includes 94 predictors overall with the top 5 predictors being: any physiological brain disorder diagnosis (including post-concussive syndrome) in the previous 5 years, any depression diagnosis in the previous 5 years, any drug abuse diagnosis in the previous 5 years, any hypnotic medication prescription in the previous 3 months, and any suicide attempt in the previous 3 months. The new model for risk following mental health visits retains only 53 predictors. The majority of predictors are the same as in the re-estimated model; however, the rank order differs. There were 53 predictors retained in the new model. The top five predictors for the new model are: any drug abuse diagnosis in the past five years, any second generation antipsychotic prescription in the last three months, any suicide attempt in the past three months, any antidepressant medication

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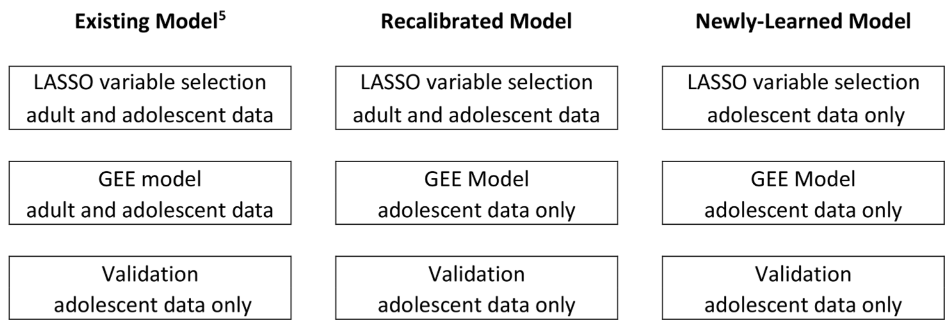

Fig. 1. Data at each model building step in the existing, recalibrated and newly-learned models.

Table 1
Characteristics of sampled visits by youth aged 13 to 17 years to specialty mental health and primary care providers in seven health systems: 2009 to 2015.

	Visit type (PC/MH)											
	MH (Mental Health)					PC (Primary Care)						
	Number of visits	Percent of visits (column)	Percent of visits (row)	Suicide attempts within 90 days	Suicide deaths within 90 days	Number of visits	Percent of visits (column)	Percent of visits (row)	Suicide attempts within 90 days	Suicide deaths within 90 days	Total Visits	Total Suicide Attempts
Total Visits	1,031,932	100.0%	72.8%	14,004	40	385,948	100.0%	27.2%	2,897	7	1,417,880	16,901
Sex												
Female	570,218	55.3%	74.8%	10,570	24	192,574	49.9%	25.2%	2,113	2	762,792	12,683
Male	461,714	44.7%	70.5%	3,434	16	193,374	50.1%	29.5%	784	5	655,088	4,218
Race												
Asian	44,688	4.3%	68.8%	599	0	20,298	5.3%	31.2%	133	0	64,986	732
Black	74,362	7.2%	71.1%	718	0	30,277	7.8%	28.9%	192	2	104,639	910
Hispanic	351,208	34.0%	72.6%	4,477	16	132,291	34.3%	27.4%	716	1	483,499	5,193
Multiple/ Other	4,189	0.4%	74.1%	81	0	1,463	0.4%	25.9%	24	0	5,652	105
Native American / Alaskan Native	7,971	0.8%	71.6%	140	0	3,166	0.8%	28.4%	38	0	11,137	178
Unknown	56,156	5.4%	72.0%	412	5	21,867	5.7%	28.0%	142	0	78,023	554
White	493,358	47.8%	73.6%	7,577	19	176,586	45.8%	26.4%	1,652	4	669,944	9,229
Median household income <$40K (1/0)												
Missing	111,073	10.8%	75.5%	991	1	35,995	9.3%	24.5%	273	1	147,068	1,264
No	812,995	78.8%	72.6%	11,507	39	306,353	79.4%	27.4%	2,365	6	1,119,348	13,872
Yes	107,864	10.5%	71.2%	1,500	0	43,600	11.3%	28.8%	259	0	151,464	1,759
Neighborhood <25% college-educated												
Missing	111,024	10.8%	75.5%	997	1	35,977	9.3%	24.5%	273	1	147,001	1,270
No	489,579	47.4%	73.3%	7,213	26	178,064	46.1%	26.7%	1,511	4	667,643	8,724
Yes	431,329	41.8%	71.5%	5,794	13	171,907	44.5%	28.5%	1,113	2	603,236	6,907
Enrolled at index												
No	33,598	3.3%	75.0%	130	1	11,170	2.9%	25.0%	43	0	44,768	173
Yes	998,334	96.7%	72.7%	13,874	39	374,778	97.1%	27.3%	2,854	7	1,373,112	16,728
Insurance Coverage at index (multiple categories may apply)												
Medicaid	129,274	12.5%	63.3%	1,675	3	75,007	19.4%	36.7%	543	1	204,281	2,218
Commercial	832,812	80.7%	74.4%	11,601	36	286,779	74.3%	25.6%	2,200	4	1,119,591	13,801
Private pay	43,235	4.2%	70.7%	753	0	17,944	4.6%	29.3%	159	2	61,179	912
State-subsidized	9,217	0.9%	61.6%	121	0	5,737	1.5%	38.4%	64	0	14,954	185
Self-funded	37,827	3.7%	67.0%	629	0	18,643	4.8%	33.0%	259	2	56,470	888
Medicare	552	0.1%	63.2%	11	0	322	0.1%	36.8%	1	0	874	12
Other insurance	240,070	23.3%	75.0%	3,304	14	80,003	20.7%	25.0%	501	1	320,073	3,805
High-deductible	68,320	6.6%	71.1%	957	0	27,721	7.2%	28.9%	143	0	96,041	1,100

prescription in the last three months, and any eating disorder diagnosis in the past five years. There are new coefficients in the top 20 predictors including private pay insurance, an interaction term between Hispanic ethnicity and female gender, history of injury/poisoning diagnosis (last year and last 5 years) and missing PHQ8 score x female gender.

Results for the re-estimated and new models of risk following primary care visits generally show similar predictors as those for mental health (e.g., mental health emergency department visits, previous suicide attempts, injury/poisoning diagnoses). Only 29 variables were retained in the new model compared to 102 in the re-estimated model. The new primary care models give more weight to PHQ-9 observations than the mental health models. Of the top 20 variables in the new model, 7 are predictors related to item 9 of the PHQ-9 and interactions of item 9 with comorbid physical conditions.

Figs. 2 and 3 show the receiver operating characteristic (ROC) curves for the original, re-estimated models, and new models for mental health

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Table 2
Top 20 clinical characteristics selected for prediction of suicide attempt or death within 90 days of visit listed in order of coefficient magnitude in logistic regression models.

Re-estimated Models	
Mental Health Specialty Visit	Primary Care Visit
Of 94 Predictors Retained	Of 102 Variables Retained
Dementia diagnosis in past 5 years	Depression diagnosis in past 5 years
Depression diagnosis in past 5 years	Hypnotic prescription in previous 3 months
Drug abuse diagnosis in past 5 years	Suicide attempt in past 5 years
Hypnotic prescription in past 3 months	Drug abuse diagnosis in past 5 years
Suicide attempt in past 3 months	Suicide attempt in past 3 months
Second generation antipsychotic fill in past 3 months	Suicide attempt in past 5 years, interacted with alcohol abuse diagnosis in past 5 years
Female gender	Insurance status: self-funded
Antidepressant prescription in past 3 months	Female gender
Laceration or violent suicide attempt in past 5 years	Personality disorder dx in past 5 years
Eating disorder diagnosis in past 5 years	Maximum PHQ9 item 9 in last 12 months = 1
Maximum PHQ9 item 9 in last 90 days = 2	Antidepressant prescription in past 3 months
MH-related ED utilization in past 3 months	Laceration or violent suicide attempt in past 5 years
Benzodiazepine fill in past year	Other psychosis dx in past 5 years
MH-related IP utilization in past year	PHQ item 9 = 2 at visit, interacted with Charlson score
Maximum PHQ9 item 9 in last year = 1	MH specialty outpatient visit in past 3 months
MH-related ED utilization in past 5 years	PHQ item 9 = 3 at visit, interacted with Charlson score
Maximum PHQ9 item 9 in last year = 3	PHQ item 9 = 1 at visit, interacted with Charlson score
Antidepressant fill in past year	Hispanic ethnicity, interacted with bipolar dx in past 5 years
MH specialty outpatient visit in past 5 years	Injury or poisoning diagnosis in past year
Benzodiazepine fill in past 3 months	Any MH-related inpatient utilization in past 5 years
Newly-learned Models	
Mental Health Specialty Visit	Primary Care Visit
Of 53 Predictors Retained	Of 29 Predictors Retained
Drug abuse diagnosis in past 5 years	Suicide attempt in the past 3 months
Second generation antipsychotic fill in past 3 months	PHQ9 not asked at index visit, interacted with female gender
Any suicide attempt in past 3 months	MH-related IP visit in past year
Antidepressant fill in past 3 months	Drug abuse diagnosis in past 5 years
Eating disorder diagnosis in past 5 years	PHQ9 Item 9 = 1, interacted with Charlson score
Laceration or violent suicide attempt in past 5 years	PHQ9 Item 9 = 2, interacted with Charlson score
Insurance: Private Pay	Antidepressant fill in past 3 months
Female Gender	MH specialty visit in past 3 months
Antidepressant fill in past year	MH-related ED visit in past year
MH-related ED visit in past 3 months	Injury or poisoning diagnosis in past year
MH-related IP visit in past year	MH-related IP visit in past 3 months
Hispanic ethnicity, interacted with female gender	MH-related ED visit in past 3 months
MH-related IP visit in past 3 months	Depression diagnosis in past 5 years, interacted with age
Depression diagnosis in past 5 years, interacted with female gender	PHQ9 Item 9 = 3, interacted with PHQ9 1-8 total
Any injury or poisoning diagnosis in past 5 years	Number of PHQ9 measures in past 90 days
No PHQ measure at index visit, interacted with female gender	PHQ9 Item 9 = 1, interacted with PHQ9 1-8 total
Any suicide attempt in past 5 years, interacted with Charlson score	PHQ9 Item 9 = 2, interacted with age
Any injury or poisoning diagnosis in past year	Any suicide attempt in past 5 years, interacted with age
MH-related ED visit in past 5 years	PHQ9 Item 9 = 2, interacted with PHQ9 1-8 total
PHQ9 Item 9 = 3 at index visit, interacted with age	Number of PHQ9 measures in past year

and primary care. Fig. 1 clearly shows that shape of the curves is virtually identical between among the three models. There is also no statistically significant difference in the area-under-the-curve (AUC) for the original model including all individuals (i.e., including adults) and the re-estimated or new models. Similar results for primary care visits are evident in Fig. 3. While the new model appears to perform slightly worse at higher cut-points, the confidence intervals for the three AUCs overlap.

Table 3 shows the actual proportion of individuals making a suicide attempt within 90 days of a visit stratified by risk percentiles and re-estimated versus new models. The top 5% of risk in the re-estimated mental health visits model accounts for 26.1% of all suicide attempts compared to 26.5% of suicide attempts for the new model. The top 5% of risk in the re-estimated primary care visits model accounted for 37.4% of suicide attempts whereas the new model accounted for 38.7% of suicide attempts. Across all models, there were minimal drops in performance between training and validation models with no appreciable difference/ improvement for the new models.

Table 4 reports the sensitivity, specificity, PPV, and NPV for each of the four models at pre-specified cut-offs. There are only minor differences in these performance metrics between re-estimated and new models.

4. Discussion

In this study of over 1.4 million visits by 167,029 adolescents in seven health systems, prediction models developed using EHR and claims data for adolescents alone did not outperform models developed using both adolescent and adult data as measured by AUC. The AUCs are generally considered “very good” (Hosmer and Lemeshow, 2000), at about 0.795 for 90-day risk following a mental health visit and 0.85 following a primary care visit.

Similar to results reported for adults (Simon et al., 2018), the models have low sensitivity but very high negative predictive value. The low prevalence of fatal and non-fatal suicide attempt indicate that NPV is the more useful measure of clinical utility. The model in this study and other similar models are currently used in health systems to identify people who need additional evaluation (e.g., with the Columbia Suicide Severity Rating Scale (Posner et al., 2011) instrument) rather than immediately triggering any specific treatment or intervention. Any specific recommendation or treatment should not be based on a prediction model alone. This may be especially true when false positives do trigger treatment or intervention at considerable cost to the delivery system. Reducing false positives is a challenge for the future as risk prediction algorithms become more widely adopted. These results suggest that there may be substantial efficiency to be gained by estimating suicide risk for the entire population of a health system rather than fitting separate models for adults and adolescents. Several health systems (e.g., Kaiser Permanente, HealthPartners) now calculate suicide risk using machine learning models and make risk scores available at the point of care to guide clinicians’ efforts at suicide prevention. Maintaining only two population-level models (one for those people treated in specialty mental health and one for those treated in primary care) rather than several subpopulation models would significantly reduce the burden on information technology staff and time—resources that are often highly constrained.

While many of the same predictors are identified in the top 20 according to positive association with suicide attempt between models, the difference in the rank order of variables between the new models and original or re-estimated models also makes it clear that different factors were identified as most important in adolescents compared to adults. This finding may have important implications for clinicians who find the overall risk scores to be a “black box” and who wish to focus on a short list of predictors with their patients. Though, none of the predictors identified by the new models were particularly unexpected. Currently, only a flag indicating the overall risk is above the 95th percentile for

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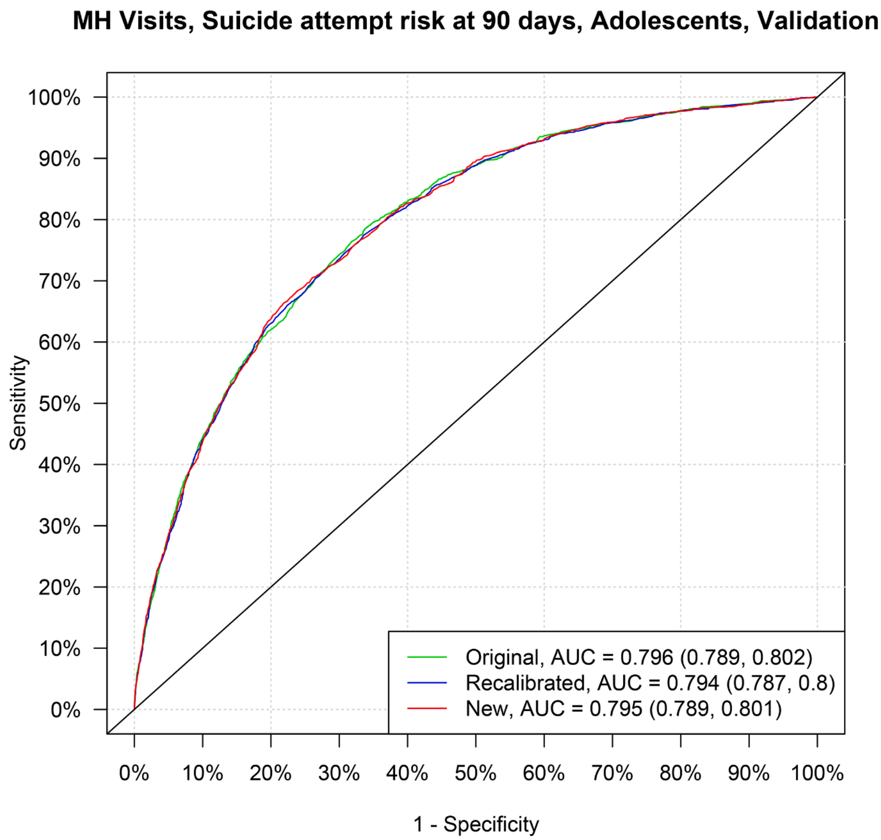

Fig. 2. ROC Curves for Mental Health Visit Models.

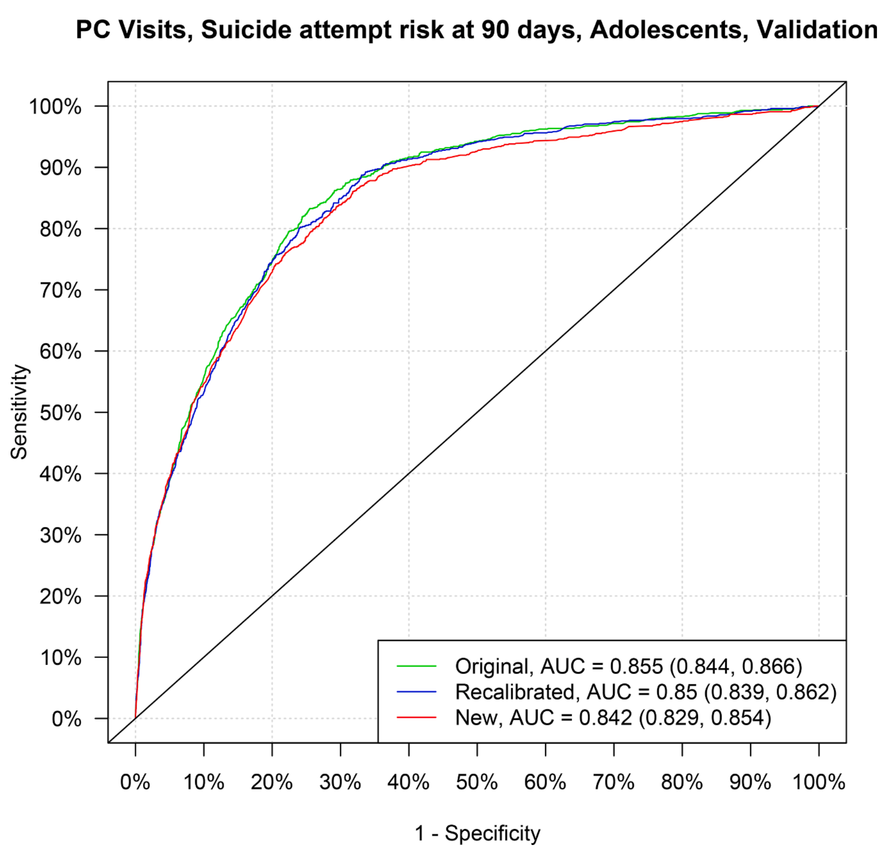

Fig. 3. ROC Curves for Primary Care Visit Models.

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Table 3
Classification accuracy in predefined strata for prediction of suicide attempt or death within 90 days of a mental health or primary care visit.

Existing Model - Percentile Cutoffs for Predicted Risk of a Suicide Attempt within 90 days of a Visit						
	Mental Health Visits			Primary Care Visits		
Percentile	Event rate in training	Event rate in validation	% Attempts	Event rate in training	Event rate in validation	% Attempts
99.5-100	15.4%	15.9%	6.1%	15.4%	12.2%	8.2%
99.0-99.4	12.1%	7.5%	2.7%	10.1%	10.9%	7.7%
95-98	6.8%	6.1%	18.5%	4.6%	4.0%	22.4%
91-94	4.3%	4.3%	15.7%	1.8%	2.4%	16.6%
76-90	2.4%	2.1%	24.9%	1.3%	1.3%	27.4%
51-75	1.0%	1.1%	20.9%	0.4%	0.3%	11.7%
0-50	0.3%	0.3%	11.1%	0.1%	0.1%	6.0%
Re-estimated Models - Percentile Cutoffs for Predicted Risk of a Suicide Attempt within 90 days of a Visit						
	Mental Health Visits	s		Primary Care Visit		
Percentile	Event rate in training	Event rate in validation	% Attempts	Event rate in training	Event rate in validation	% Attempts
99.5-100	18.0%	14.7%	5.5%	18.6%	11.3%	6.9%
99.0-99.4	12.4%	7.2%	2.7%	9.0%	11.8%	7.6%
95-98	7.1%	6.1%	17.8%	4.8%	4.2%	22.9%
91-94	4.1%	4.3%	16.4%	2.2%	2.2%	15.4%
76-90	2.3%	2.2%	25.6%	1.1%	1.3%	27.6%
51-75	1.0%	1.1%	20.8%	0.4%	0.4%	13.6%
0-50	0.3%	0.3%	11.2%	0.1%	0.1%	6.0%
Newly-Learned Models - Percentile Cutoffs for Predicted Risk of a Suicide Attempt within 90 days of a Visit						
	Mental Health Visits			Primary Care Visits		
Percentile	Event rate in training	Event rate in validation	% Attempts	Event rate in training	Event rate in validation	% Attempts
99.5-100	17.6%	13.6%	5.5%	15.9%	12.2%	8.1%
99.0-99.4	13.0%	9.2%	3.5%	10.5%	10.4%	8.0%
95-98	7.1%	6.1%	17.5%	4.5%	4.2%	22.6%
91-94	4.2%	4.0%	15.5%	2.1%	2.2%	15.4%
76-90	2.2%	2.3%	27.0%	1.1%	1.2%	24.5%
51-75	1.0%	1.1%	20.6%	0.5%	0.4%	13.8%
0-50	0.3%	0.3%	10.4%	0.1%	0.1%	7.5%

Table 4
Performance Characteristics of models by setting.

Mental Health					
Existing Model					
Cutoff	Percentile	Sensitivity	Specificity	PPV	NPV
0.129	>99th	0.089	0.991	0.117	0.988
0.0478	>95th	0.274	0.953	0.072	0.99
0.0275	>90th	0.432	0.906	0.058	0.992
0.0126	>75th	681	0.752	0.035	0.994
0.00672	>50th	0.889	0.499	0.023	0.997
Recalibrated Model					
Cutoff	Percentile	Sensitivity	Specificity	PPV	NPV
0.116	>99th	0.083	0.991	0.11	0.988
0.0476	>95th	0.261	0.954	0.071	0.99
0.0296	>90th	0.424	0.905	0.057	0.992
0.0144	>75th	0.681	0.751	0.035	0.994
0.00696	>50th	0.889	0.5	0.023	0.997
Newly-Learned Model					
Cutoff	Percentile	Sensitivity	Specificity	PPV	NPV
0.116	>99th	0.09	0.991	0.114	0.988
0.0473	>95th	0.265	0.954	0.072	0.99
0.0295	>90th	0.42	0.905	0.056	0.991
0.0144	>75th	0.69	0.752	0.036	0.994
0.007	>50th	0.896	0.5	0.023	997

Primary Care					
Existing Model					
Cutoff	Percentile	Sensitivity	Specificity	PPV	NPV
0.0935	>99th	0.108	0.994	0.109	0.993
0.0246	>95th	0.405	0.945	0.051	0.995
0.0141	>90th	0.601	0.875	0.034	0.997
0.00635	>75th	0.814	0.736	0.022	0.998
0.00211	>50th	0.94	0.502	0.014	0.999
Recalibrated Model					
Cutoff	Percentile	Sensitivity	Specificity	PPV	NPV
0.081	>99th	0.145	0.992	0.116	0.994
0.0271	>95th	0.376	0.952	0.055	0.995
0.0169	>90th	0.529	0.902	0.038	0.996
0.007	>75th	0.804	0.752	0.023	0.998
0.00212	>50th	0.94	0.504	0.014	0.999
Newly-Learned Model					
Cutoff	Percentile	Sensitivity	Specificity	PPV	NPV
0.0733	>99th	0.161	0.991	0.112	0.994
0.0252	>95th	0.388	0.953	0.057	0.995
0.0189	>90th	0.479	0.922	0.043	0.996
0.0078	>75th	0.787	0.748	0.022	0.998
0.00249	>50th	0.925	0.495	0.014	0.999

mental health specialty visits is displayed in operational use. However, transparency regarding the factors included in risk prediction (e.g., mental health diagnoses, history of suicide attempt, PHQ9 item score) is likely to increase clinician and health system engagement in suicide prevention. That is, communicating the most highly weighted predictors will increase acceptability of the algorithms by clinicians and health systems. While clinicians may not know which particular variables resulted in the person being flagged at any point in time, knowing the set of variables and agreeing with their face validity will facilitate uptake/ use of these algorithms as triggers for follow-up - even when there are false positives. More research is needed on how best to communicate the information provided by risk prediction models. Such work is ongoing in

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the Mental Health Research Network.

Currently, suicide risk prediction models are being used in Kaiser Permanente Washington, HealthPartners and the VA to predict risk in adults. Clinicians do not receive information about the individual-level predictors. Rather, clinicians or care managers receive an alert in the electronic health record or care management system that a patient's risk is at the top of the distribution. Clinicians and/or care managers then follow-up with the CSSRS, diagnostic interviews and/or care management outreach. Again, the predictors in the models are mostly ones that are usually clinically considered and available in the EHR. The gain in efficiency comes in two areas. First, clinicians do not need to review years of records data to tally every risk factor. Second, the model gives every factor the correct weight for consideration. A clinician might be able to do both these things but it would take away from time better spent by clinicians.

The difference in the relative importance of the PHQ-9, specifically item 9 regarding thoughts of death or self-harm, between the specialty mental health setting and primary care is notable. Having an item 9 score of 3 (daily thoughts of death or self-harm) and having a missing PHQ-9 interacted with female gender were the only two PHQ-9-related predictors among adolescents seen in specialty mental health. However, seven predictors were PHQ-9 related in the primary care population of adolescents. Indeed, the interaction between total PHQ-8 score and level of item 9 endorsement at each of 1, 2 or 3 were all important predictors. Walsh and colleagues (Walsh et al., 2018) recently called for the inclusion of traditional clinical assessments in machine learning models and the results reported here suggest that the PHQ-9 and item 9 in particular are highly valuable in predicting 90-day risk of suicide attempt in adolescents.

4.1. Limitations

This study has many strengths including a large population of youth, data from seven health systems in seven different states, and EHR/claims data classified both proximally (within 90 days) and distally (in the last 5 years) to suicide attempt. We also stratified analyses by individuals at higher risk of suicide attempt (those seen in specialty mental health) and those at lower risk (people treated in primary care for mental health issues).

This study was limited to the use of health care data from EHRs and administrative claims. Previous work by Miché and colleagues (Miché et al., 2020) used self-reported data on factors such as negative life events, sexual trauma, parental loss, and parental psychopathology but did not include assessment scores measuring depression severity or severity of suicidal ideation. An ideal model would include both health care data and non-health care data to optimize prediction accuracy.

This study was also limited by the use of ICD-9-CM external cause of injury codes for outcome ascertainment. Recording of E-codes is known to vary by provider and health system. (Lu et al., 2014) Although use of E-codes varied across the United States during the study period, (Lu et al., 2014) participating health systems were selected for high and consistent rates of E-code use. Record review (Simon et al., 2016) also supports the positive predictive value of this definition for identification of true self-harm in these health systems. Furthermore, subsequent observation of coding changes across the transition from ICD-9 to the more specific ICD-10 coding scheme indicates that most "undetermined" ICD-9 diagnoses actually reflect self-harm. (Stewart et al., 2017)

Finally, only one modelling approach was used to develop risk predictions. We took this approach to focus on comparing results between adolescents and adults using the same pool of predictors. It is possible that the model reported here offers minimal improvement over traditional logistic regression methods or that more advanced machine learning models (random forest, neural network) might improve prediction performance as measured by the AUC. See Christodoulou (2019) (Christodoulou et al., 2019) for a systematic review of comparisons between machine learning and logistic regression.

5. Conclusion

Machine learning models for suicide risk prediction and risk stratification for outreach programs are becoming important tools for preventing suicide. Using health care data alone, the results in this study suggest that separate models for adults and adolescents are not needed to accurately target prevention efforts. Further research is needed regarding the incorporation of multiple data streams including health care, education, juvenile justice, child protection, and self-reported questionnaire data.

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Author statement

All authors have approved the final article.

Contributors

Robert Penfold led the drafting of the manuscript and participated in the design of the study and interpretation of results.

Eric Johnson conducted the statistical modeling and participated in editing the manuscript

Susan M. Shortreed designed the statistical analysis, oversaw the modeling and participated in editing the manuscript

Rebecca A. Ziebell led the database programming and participated in editing the manuscript

Frances L. Lynch participated in producing the data from KPNW, the interpretation of results and participated in editing the manuscript

Greg N. Clarke participated in the interpretation of results and editing the manuscript

Karen J. Coleman participated in producing the data from KPSC, the interpretation of results and participated in editing the manuscript

Beth E. Waitzfelder participated in producing the data from KPHI, the interpretation of results and participated in editing the manuscript

Arne L. Beck participated in producing the data from KPCO, the interpretation of results and participated in editing the manuscript

Rebecca C. Rossom participated in producing the data from HPRI, the interpretation of results and participated in editing the manuscript

Brian K. Ahmedani participated in producing the data from HFHS, the interpretation of results and participated in editing the manuscript

Gregory E. Simon conceived of the overall study design, participated in the interpretation of results and participated in editing the manuscript.

Role of the funding source

The funder played no role in the conduct of this research.

Declaration of Competing Interest

The authors have no conflicts of interest to disclose.

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