Predicting suicide risks using history of physical illnesses categorized by ICD-10 chapters

Chandan Karmakar[1*], Wei Luo[1], Truyen Tran[1], Michael Berk[2], Svetha Venkatesh[1]

[1]Centre for Pattern Recognition and Data Analytics, Deakin University, Geelong, VIC, Australia

[2]School of Medicine, Deakin University, Geelong, VIC, Australia

*Corresponding author

E-mail: karmakar@deakin.edu.au

Abstract

Although physically illnesses, routinely documented in electronic medical records (EMR), have been found to be a contributing factor to suicides, no automated systems use this information to predict suicide risk. The aim of this study is to quantify the impact of physical illnesses on suicide risk, and develop a predictive model that captures this relationship using Electronic medical Record data. We tested the performance of this model using history of physical illnesses to predict 90 day risk using over historical data over differing time periods ranging from 3 to 48 months. The best predictive results were derived (AUC = 0.71) using combined data across all time periods, which significantly outperformed the clinical baseline derived from routine risk assessment (AUC 0.56). This approach thus shows potential to be incorporated in the broader risk assessment processes used by clinicians.

Introduction

Suicide is a prominent public health concern. All over the world each year, 2% of the population contemplate suicide (1). In 2013, an average of 6.9 suicidal deaths was recorded in Australia each day. Moreover, the relative age-standardized suicide rate was twice as high in both Aboriginal and Torres Strait Islander males and females as non-Indigenous males and females (2.1 and 2.4 respectively) (2). It is estimated that by 2020 suicide will become the 10th most common cause of death in the world (3). Therefore, suicide prevention is important and the process should be integrated within both hospital treatment and general medical practice (4).

In the last decades, large epidemiological studies have identified the number of previous suicide attempts, lethality of previous attempts, psychiatric disorders and social isolation as potential risk factors for suicide (5-10). Besides identifying independent risk or protective factors, these epidemiologic studies also quantified the strength of their relative contribution. Despite the effort to combine these risk factors into risk scores and algorithms to predict suicide risk (11-13), the predictions often have sensitivity and specificity that are too poor to be clinically useful (14, 15). The failure of these approaches may be attributed to the complex nature of suicidal behavior, which consists of an

evolving and multifactorial constellation of components that act together but vary from one individual to another. On the other hand, clinical assessment of suicide risk is primarily done based on the response of the patient, where current suicidal ideation and known risks are integrated. Although suicidality is a prominent risk factor for suicide attempts and completion, only about 30% of patients attempting suicide disclose their suicidal ideation (16-18) and the vast majority of individuals who express suicidal ideation never attempt suicide (19-21).

To improve the clinical assessment or predictive value of suicide risk, researchers have started to look at the broader source of available information such as electronic medical record (EMR) (22) and clinical notes (23). In our previous work (22), we have developed a statistical risk stratification model based on EMR data and the model performance was found to be better than clinical predictions based on an 18-point risk assessment instrument. However, this model was complex and does not generalize to facilities with limited routine data collection. Moreover, since EMR contains a wide variety of information – there is a strong possibility that combinations of them can be asymptotic. Poulin et al (23) have developed linguistics-driven prediction models to estimate the risk of suicide using unstructured clinical notes taken from a national sample of U.S. Veterans Administration (VA) medical records. From the clinical notes, they generated datasets of single keywords and multi-word phrases, and constructed prediction models using a machine-learning algorithm based on a genetic programming framework. Although their result showed an accuracy of 65% or more, it was based on a small veteran population and the method was too complex to derive any symptomatic link with the suicide risk factors.

Recently, Qin et al (24) analyzed the relationship between suicidal death and physical illness, which was the first detailed analysis where physical illness was categorized based on ICD-10 (International Statistical Classification of Diseases and Related Health Problems, 10th Revision) chapters. The results of the study showed that the frequency of hospitalization elevates the risk of committing suicide and this relationship was significant for diseases. However, the study was conducted on the national database of Denmark and the two population groups used were suicidal death and controls.

In this study, using machine learning to analyse EMR, we aim to find the effect of physical illnesses for the at-risk population, considering patients who have received at least one suicide risk assessment but

who did not commit suicide. We hypothesize that the relationship between physical illnesses alone and suicide risk can be exploited for quantitative assessment of suicidal risk using ICD-10 codes. This means that we do not use the "Mental and behavioural disorders" (Chapter V, ICD codes), relying purely on the physical illnesses. We developed a predictive model to obtain a suicide risk score using the history of physical illnesses derived from ICD-10 codes. Finally, we compared the performance of the physical-illness-based risk score with corresponding baseline clinically assessed.

Materials and Methods

Data

A. Data description

The data was collected retrospectively from the electronic medical records, coded using ICD-10-AM, within Barwon Health, Australia (22). This is a regional hospital serving an area of 350,000 residents. The data consisted of 7,399 mental health patients who were 10 years old or over and were underwent assessment for suicide risk between April 2009 and March 2012. There were 16,858 assessments, each of which was considered as an observational case, from which suicide risk could be predicted. In the follow up period of 90 days after an assessment, the ground truth of suicide risk levels were determined through ICD-10 codes occurring during the period. In this study, we have divided complete population into $Control$ and $Risk$ groups. The $Control$ group consists of assessments of patients who never attempt suicide. Thus, the $Risk$ group consists of assessments of patients who commit at least one suicide attempt.

Ethics approval was obtained from the Hospital and Research Ethics Committee at Barwon Health (number 12/83). Deakin University has reciprocal ethics authorisation with Barwon Health. Although all patients has given written informed consent, patient information was anonymized and de-identified prior to analysis.

B. Clinical risk scoring

Suicide risk assessments were routinely performed by clinicians using an instrument developed internally. The instrument has been in use for 15 years. The checklist has 18 items - suicidal ideation, suicide plan, access to means, prior attempts, anger/hostility/ impulsivity, current level of depression, anxiety, disorientation/disorganisation, hopelessness, identifiable stressors, substance abuse, psychosis, medical status, withdrawal from others, expressed communication, psychiatric service history, coping strategies and supportive others (connectedness).

Based on the ratings (from 1 to 3) for these 18 items, an overall rating of suicide risk ($RiskScore_{Clinical}$) is determined on a scale from 0 (lowest) to 4 (highest). For the purpose of this study, the overall rating was used as the baseline for comparison.

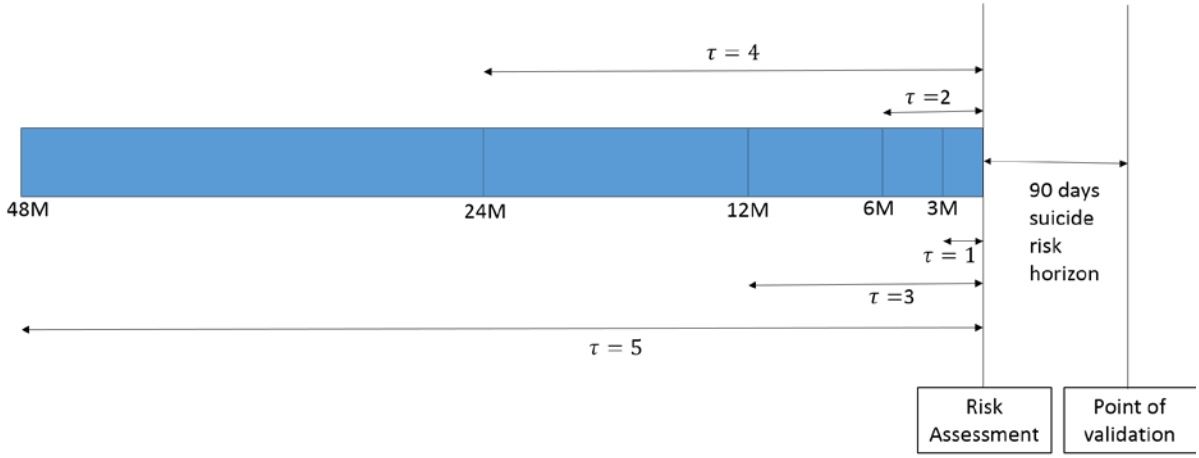

Figure 1: Time periods used to extract the history of physical illnesses from EMR and the suicide risk prediction horizon

C. Selection of ICD-10 chapters and calculating frequency of physical illnesses

ICD-10 (2015 version) has 22 chapters to code all diseases recorded in EMR.

Exclusion: We remove all codes from chapter V, that is all codes related to "Mental and behavioral disorders". We removed chapters XVI and XVII codes altogether as these were absent in the studied population.

Inclusion: We merged chapters VII and VII due to minimal presence of these diagnostic codes. As a result, we finally have 18 chapter headings ($ch = 1, 2, \dots, 18$) corresponding to 19 ICD-10 chapters. *Computing Frequency of codes for each chapter:* We first define the time period (len) over which the patient history EMR is included. Five different time periods are used (see also, Figure 1):

$$\tau = \begin{cases} 1 & , \quad len = 0 - 3Months \\ 2 & , \quad len = 0 - 6Months \\ 3 & , \quad len = 0 - 12Months \\ 4 & , \quad len = 0 - 24Months \\ 5 & , \quad len = 0 - 48Months \end{cases} \tag{1}$$

For each time period, the ICD-10 codes for each assessment are aggregated under selected chapters, wherein each aggregated value represents the total number of occurrences of physical illnesses for the corresponding chapter. Therefore, for each assessment i we obtain a vector $f_i(\tau, ch)$, where $ch = 1, 2, \dots, 18$ and $\tau = 1, 2, \dots, 5$. Assessments with an entry of 0 for all eighteen chapter headings, are counted as an assessment with no history of physical illnesses. For all assessments, we construct the matrix $F_i(\tau, ch)$ as:

$$F_i(\tau, ch) = [f_i(\tau, ch)]_{i=1}^{n} \tag{2}$$

where, n is the total number of assessments.

In this study, we develop six models to predict suicide risk based on physical illnesses. Five models use the frequency of physical illnesses for the designated time period i.e., $F(\tau, ch), where\ \tau = 1, 2, \dots, 5$, and the sixth model horizontally concatenates frequency matrices from all five individual time periods, $F = [F_i(\tau, ch)]_{\tau=1}^{5}$.

D. Creating the suicide risk lookup table

Definition: A probability lookup table PT is generated from the history of physical illnesses as:

$$PT = (pt_{\tau,ch,j}) \tag{3}$$

where $\tau = 1, 2, \dots, 5$ in the index of the time period used to extract history of physical illnesses, $ch = 1, 2, \dots, 18$ is the index of the ICD-chapter and $j = 1, 2, \dots, 5$ is index of the frequency bin. Each element of this table, $pt(\tau, ch, j)$ is the probability of the ch^{th} chapter using historical data from time

period τ in the j^{th} frequency bin. To calculate $pt(\tau, ch, j)$, we compute the histogram $Hist_j(\ F_i(\tau, ch))$, where j is the bin index and defined as:

$$j = \begin{cases} 1 & , \quad 1 \leq f_i(\tau, ch) \leq 2 \\ 2 & , \quad 3 \leq f_i(\tau, ch) \leq 5 \\ 3 & , \quad 6 \leq f_i(\tau, ch) \leq 10 \\ 4 & , \quad 11 \leq f_i(\tau, ch) \leq 20 \\ 5 & , \quad f_i(\tau, ch) > 20 \end{cases} \tag{4}$$

To separate out the Control and Risk histogram, we introduce the notation $Hist_j^{Contol}$ and $Hist_j^{Risk}$, that are defined as:

$$Hist_j^{Contol}(\tau, ch) = Hist_j\big(F_i(\tau, ch)\big), where\ i \in Control \text{ and } f_i(\tau, ch) \neq 0 \tag{5}$$

$$Hist_j^{Risk}(\tau, ch) = Hist_j\big(F_i(\tau, ch)\big), where\ i \in Risk \text{ and } f_i(\tau, ch) \neq 0 \tag{6}$$

Finally, $pt(\tau, ch, j)$ is defined as:

$$pt(\tau, ch, j) = \frac{Hist_j^{Risk}(\tau, ch)/\sum_j Hist_j^{Risk}(\tau, ch)}{(Hist_j^{Risk}(\tau, ch)/\sum_j Hist_j^{Risk}(\tau, ch)) + (Hist_j^{Control}(\tau, ch)/\sum_j Hist_j^{Conrol}(\tau, ch))} \tag{7}$$

E. Scoring suicide risk of an assessment

The suicide risk score ($RiskScore_{Algorithm}$) is inferred from the suicide risk lookup table PT. This is accomplished using following steps:

i. For a new assessment i and historical time period, extract the frequency of physical illnesses $f_i(\tau, ch)$ from the EMR data for that assessment.

ii. For each chapter ch,

   a. Calculate bin index j from $f_i(\tau, ch)$ using eq. 4.

   b. Extract $P^{Risk}(\tau, ch) = pt_{\tau, ch, j}$ from the lookup table PT.

   c. Use a *Heaviside* step function to convert $P^{Risk}(\tau, ch)$ into:

$$Vote_{Control}^{\tau}(ch) = \begin{cases} 1 & P^{Risk}(\tau, ch) < 0.45 \\ 0 & Otherwise \end{cases} \tag{8}$$

$$Vote^{\tau}_{Risk}(ch) = \begin{cases} 1 & P^{Risk}(\tau, ch) > 0.55 \\ 0 & Otherwise \end{cases} \quad (9)$$

iii. Calculate suicide risk score $RiskScore_{Algorithm}(i)$ as:

$$RiskScore_{Algorithm}(i) = \frac{\sum_{ch} Vote^{\tau}_{Risk}(ch)}{\sum_{ch} Vote^{\tau}_{Risk}(ch) + \sum_{ch} Vote^{\tau}_{Control}(ch)} \quad (10)$$

F. Performance evaluation

The performance of ICD-10 code history based suicide risk scores, clinically evaluated scores and their combination are measured using area under the ROC curve (AUC).

For the clinical score ($RiskScore_{Clinical}$), the performance is evaluated by directly measuring the AUC of the entire study population without dividing them in training or testing sets.

On the other hand, for $RiskScore_{Algorithm}$ we use 90% of the population to generate reference lookup table i.e., training set and the remaining 10% population is used as a test set to measure AUC. This process is repeated 10 times, where there are 10 different test sets and union of them encompass the original population, and the overall performance is presented by the average AUC that are obtained over those reiterations.

Similar approach (90% training and 10% test populations with 10 reiterations) is used for evaluating the performance of combination of clinical and ICD-10 based score. Multi-linear regression is used to combine two variables. The training data set is used to train the regression model and output is generated using test set and the trained model. Finally, the AUC is computed using the output ($RiskScore_{Combined}$) of the model.

Results

This study included 2,072 suicide risk cases and 14,786 control cases, comprising of 1,080 male and 992 female suicide risk cases and 7,215 male and 7,571 female control cases. In the study population,

the percentage of suicide risk and control cases over five different time ranges with a history of hospitalization are (73.12% and 45.14%), (80.07% and 53.27%), (87.93% and 62.50%), (92.18% and 73%) and (95.90% and 83.09%) over the past 3, 6, 12, 24 and 48 months respectively (Table 1). This indicates that the number of subjects having physical illness is higher in suicide risk population than the control population irrespective of the time range. In addition, although the percentage of population having no ICD codes is decreased with increasing time range in both the control and risk groups, it is reduced to 4.10% in risk group in contrast to 16.91% in control group.

Table 1: Distribution of suicide risk associated with diagnostic groups according to ICD-10 category (without chapter V - Mental and behavioral disorders) for five different time ranges.

	$\tau = 1$ (0-3M)				$\tau = 2$ (0-6M)				$\tau = 3$ (0-12M)				$\tau = 4$ (0-24M)				$\tau = 5$ (0-48M)			
	Control		Risk		Control		Risk		Control		Risk		Control		Risk		Control		Risk	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
History of ICD codes																				
No	8112	54.86	557	26.88	6909	46.73	413	19.93	5545	37.50	250	12.07	3992	27.00	162	7.82	2501	16.91	85	4.10
Yes	6674	45.14	1515	73.12	7877	53.27	1659	80.07	9241	62.50	1822	87.93	10794	73.00	1910	92.18	12285	83.09	1987	95.90
Frequency of ICD codes																				
0	8112	54.86	557	26.88	6909	46.73	413	19.93	5545	37.50	250	12.07	3992	27.00	162	7.82	2501	16.91	85	4.10
1-2	2914	19.71	500	24.13	2925	19.78	430	20.75	2881	19.48	365	17.62	2733	18.48	238	11.49	2517	17.02	179	8.64
3-5	1641	11.1	319	15.40	1870	12.65	305	14.72	2044	13.82	277	13.37	2213	14.97	254	12.26	2379	16.09	216	10.42
6-10	1317	8.91	356	17.18	1666	11.27	315	15.20	1999	13.52	332	16.02	2286	15.46	336	16.22	2532	17.12	267	12.89
11-20	657	4.44	247	11.92	1028	6.95	366	17.66	1499	10.14	345	16.65	2089	14.13	386	18.63	2338	15.81	383	18.48
>20	145	0.98	93	4.49	388	2.62	243	11.73	818	5.53	503	24.28	1473	9.96	696	33.59	2519	17.04	942	45.46

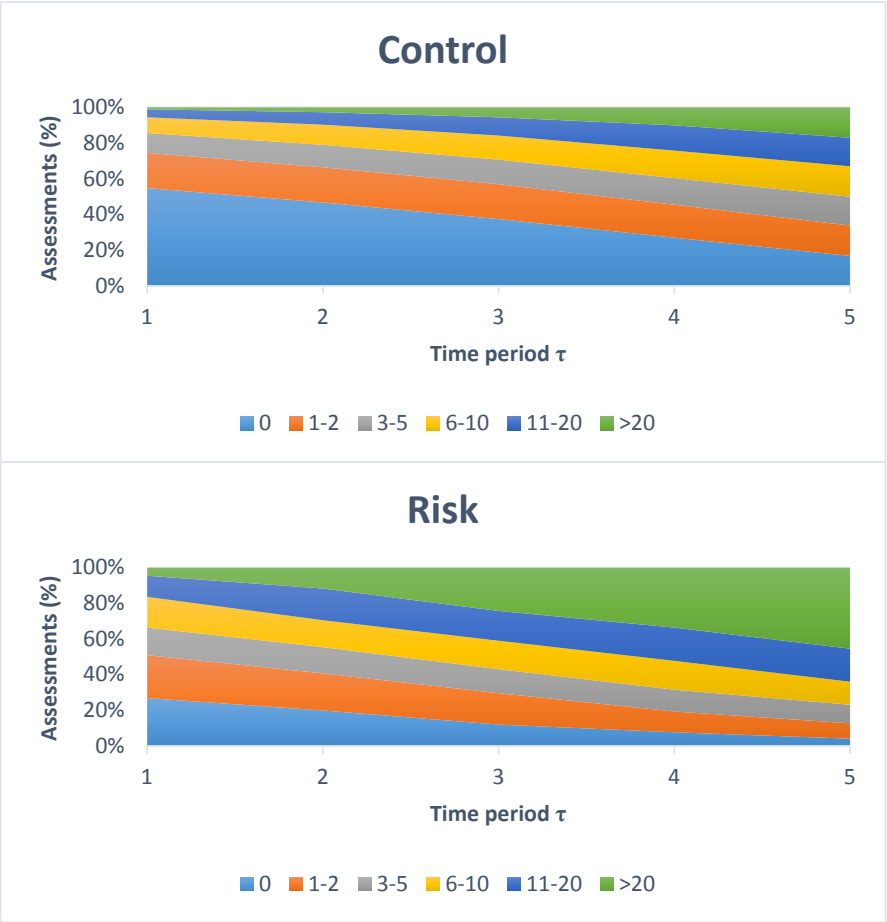

Figure 2: Distribution of assessments with respect to frequencies of ICD-codes (*without* chapter V - Mental and behavioral disorders) and time periods. Different color represents the frequencies of ICD-codes.

Multiple ICD codes were more common amongst risk cases relative to the control cases (Table 1, Figure 2). For $\tau = 1$ (0-3Months) percentages of risk cases were always higher than control cases for ICD codes more than zero. This trend changed with the increasing time length where distribution of control populations become approximately equal over all five frequency ranges used in this study (Figure 2, top panel). On the other hand, for risk population the frequency of ICD codes increased with time ranges and therefore, approximately 45% of the total population had ICD code frequency >20 (Figure 3, bottom panel).

The prevalence of physical illness of both suicide risk and control groups grouped according to ICD-10 categories (Chapter headings) has been summarised in Table 2 and Figure 3. Except for ICD-10 chapters

II (Neoplasms) and [VII, VIII] (Sensory organ disease), a significantly higher prevalence of physical illness was observed in suicide risk cases than in control cases. However, the percentages of populations in those two chapters were insignificant across all organs or systems of the body. Interestingly, the most prevalent physical illness found for both control and suicide risk groups across all time ranges was Factors influencing health status and contact with health services (ICD-10 Chapter XI), where the percentage of population continually increased from 20.38% to 53.54% and 39.29% to 78.38% for control and suicide risk groups respectively (Table 2). Interestingly, a significant (>20%) population showed prevalence of multiple ICD-10 chapters in suicide risk cases at shorter time ranges than control cases. For $\tau = 1$ and $\tau = 2$, ICD-10 chapter XXI were prevalent in more than 20% of control cases in contrast with five chapters (XVIII, XIX, XX, XXI, XXII) in suicide risk cases. This indicates that comorbidity is more prevalent and observable in shorter time range in suicide risk cases than control cases (Figure 4).

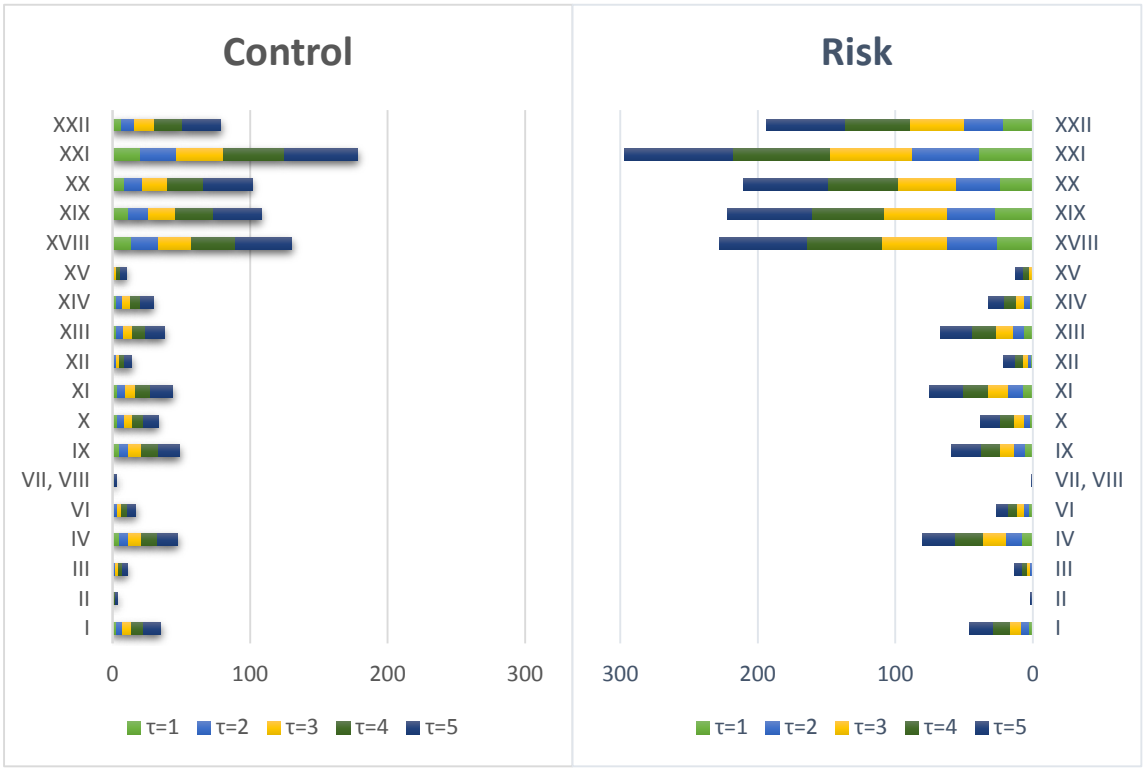

Figure 3: Cumulative percentage of cases in control and suicide risk groups over five time periods grouped on ICD-10 category (Excluded chapters: chapter V - Mental and behavioral disorders, chapter XVI - Certain conditions originating in the perinatal period, and chapter XVII - Congenital malformations, deformations and chromosomal abnormalities).

The performance of proposed physical illnesses (*without* ICD-10 chapter V) based suicide risk scoring model is shown in Table 3. The AUC value using $RiskScore$ is 0.64, 0.67, 0.68, 0.68, 0.69 for individual time ranges. This sequential increment of ROC area values with increased length of history of physical illnesses shows longer history length provides better suicide risk assessment than the shorter one. The maximum AUC 0.71 is obtained using physical illnesses from all time ranges, which indicates that overlapping history of physical illnesses improves the performance of the model than using a physical illnesses from a single time period. In addition, for all of the lengths of the history of physical illnesses the $RiskScore_{Algorithm}$ performed better than clinically assessed risk score $RiskScore_{Clinical}$ (AUC=0.56).

The performance of regression model output $RiskScore_{Combined}$ is shown in Table 3. Similar to physical illnesses based $RiskScore_{Algorithm}$, the AUC values increase with increasing length of history of physical illnesses (AUC 0.65, 0.67, 0.68, 0.69 and 0.70 respectively) and maximum AUC 0.72 is obtained for history of physical illnesses of all time ranges. Although AUC values of multi-linear regression model is higher than physical illnesses based model, the improvement is marginal and statistically significant.

Table 3: AUC obtained using suicide risk scoring model based on physical illnesses, clinically assessed score and their combinations.

Length of history of physical illness	AUC		
	$RiskScore_{algorithm}$	$RiskScore_{Clinical}$	$RiskScore_{Combined}$
0-3Months ($\tau = 1$)	0.64	0.56	0.65
0-6Months ($\tau = 2$)	0.67	0.56	0.67
0-12Months ($\tau = 3$)	0.68	0.56	0.68
0-24Months ($\tau = 4$)	0.68	0.56	0.69
0-48Months ($\tau = 5$)	0.69	0.56	0.70
$combined\ \tau = [1, 2, \dots, 5]$	**0.71**	0.56	**0.72**

Table 2: Distribution of suicide risk and control cases associated with diagnostic groups according to ICD-10 category for five different time ranges.

		$\tau = 1$ (0-3M)				$\tau = 2$ (0-6M)				$\tau = 3$ (0-12M)				$\tau = 4$ (0-24M)				$\tau = 5$ (0-48M)			
		Control		Risk		Control		Risk		Control		Risk		Control		Risk		Control		Risk	
		n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
I	Certain infectious and parasitic diseases	440	2.98	73	3.52	638	4.31	115	5.55	944	6.38	157	7.58	1352	9.14	259	12.5	1816	12.28	346	16.7
II	Neoplasms	28	0.19	1	0.05	45	0.30	5	0.24	67	0.45	7	0.34	131	0.89	10	0.48	194	1.31	17	0.82
III	Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism	142	0.96	22	1.06	190	1.28	25	1.21	269	1.82	47	2.27	417	2.82	78	3.76	577	3.90	100	4.83
IV	Endocrine, nutritional and metabolic diseases	724	4.90	165	7.96	994	6.72	252	12.16	1331	9.00	340	16.41	1740	11.77	420	20.27	2223	15.03	483	23.31
VI	Diseases of the nervous system	230	1.56	60	2.90	324	2.19	79	3.81	454	3.07	104	5.02	599	4.05	134	6.47	858	5.80	166	8.01
VII, VIII	Sensory organ disease	16	0.11	1	0.05	26	0.18	1	0.05	46	0.31	3	0.14	102	0.69	9	0.43	184	1.24	9	0.43
IX	Diseases of the circulatory system	748	5.06	120	5.79	1022	6.91	163	7.87	1347	9.11	220	10.62	1766	11.94	291	14.04	2329	15.75	426	20.56
X	Diseases of the respiratory system	548	3.71	53	2.56	700	4.73	88	4.25	898	6.07	142	6.85	1199	8.11	216	10.42	1533	10.37	282	13.61
XI	Diseases of the digestive system	534	3.61	154	7.43	790	5.34	227	10.96	1145	7.74	297	14.33	1650	11.16	384	18.53	2347	15.87	502	24.23
XII	Diseases of the skin and subcutaneous tissue	188	1.27	37	1.79	257	1.74	51	2.46	345	2.33	71	3.43	521	3.52	113	5.45	755	5.11	166	8.01
XIII	Diseases of the musculoskeletal system and connective tissue	428	2.89	138	6.66	699	4.73	171	8.25	1004	6.79	256	12.36	1412	9.55	361	17.42	2037	13.78	471	22.73
XIV	Diseases of the genitourinary system	444	3.00	57	2.75	598	4.04	86	4.15	844	5.71	113	5.45	1098	7.43	183	8.83	1389	9.39	237	11.44
XV	Pregnancy, childbirth and the puerperium	90	0.61	8	0.39	152	1.03	15	0.72	216	1.46	45	2.17	386	2.61	85	4.10	617	4.17	114	5.50
XVIII	Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified	2079	14.06	547	26.40	2804	18.96	759	36.63	3660	24.75	978	47.20	4690	31.72	1125	54.3	6041	40.86	1311	63.27
XIX	Injury, poisoning and certain other consequences of external causes	1677	11.34	574	27.70	2175	14.71	729	35.18	2934	19.84	946	45.66	4023	27.21	1095	52.85	5205	35.20	1254	60.52
XX	External causes of morbidity and mortality	1315	8.89	495	23.89	1867	12.63	668	32.24	2727	18.44	872	42.08	3912	26.46	1064	51.35	5169	34.96	1260	60.81
XXI	Factors influencing health status and contact with health services	3013	20.38	814	39.29	3911	26.45	1010	48.75	5053	34.17	1231	59.41	6476	43.80	1470	70.95	7916	53.54	1624	78.38
XXII	Codes for special purposes	989	6.69	455	21.96	1391	9.41	595	28.72	2086	14.11	808	39.00	3070	20.76	984	47.49	4106	27.77	1165	56.23

Discussion

To our knowledge, this study is the first to only use the patient's history of physical illnesses (ICD-10 codes, *without* chapter V (Mental and behavioral disorders) to predict suicide risk. This study has demonstrated how to exploit the physical illnesses to predict suicide risk using EMR of a single regional hospital (Barwon Health). The ready availability of EMR shows promise that such tools can be integrated within hospital systems for effective decision support.

The findings of this study, based on all patients of Barwon Health who had the mandated suicide risk assessment between April 2009 and March 2012, shows that the percentage of the population having a history of physical illness are higher in risk group than the control. This supports previously reported findings that hospitalization for a physical illness significantly increases the risk of subsequent suicide (9, 24). Although this higher prevalence of physical illnesses in our risk group is found over five different time periods ranging from 3 moths to 48 months, the difference in prevalence between two groups decreases with increasing time (Table 1, Figure 3). This indicates that time period over which history is considered is a critical parameter in predicting risk.

The results of this study showed that the frequency of physical illness (11-20, >20) is higher in suicide risk population than control for all time periods, which is similar to the findings reported by P. Qin et al (24). However, for smaller frequency values, the percentage of control cases exceeds the percentage of suicide risk cases with increasing historical time period. Although this contradicts the findings of Qin et al (24) where they have used much longer time period than 48 months, this can be attributed to the cohort difference – they have reported 1.13% of suicide cases with physical illnesses frequency >20 in contrast to 0.27% of control; in our study for a 48 month period, we found these frequencies to be 45.46% and 17.04% for the risk and control group respectively.

The performance of ICD-10 based (*without* chapter V) suicide risk score, $RiskScore_{Algorithm}$, performed better than 18-point risk checklist based clinical assessment ($RiskScore_{Clinical}$) for all time periods used in this study. This indicates that three or more months of history of physical illnesses can better predict the suicide risk than clinical assessment. This supports the previous findings that

additional information is required in designing a more effective and automated suicide risk assessment systems suitable for clinical settings (14, 15). $RiskScore_{Combined}$ showed a marginal improvement in suicide risk prediction than physical illnesses based score $RiskScore_{Algorithm}$ but substantial improvement over clinical assessment. Therefore, adding history of physical illnesses with regular clinical assessments can improve the performance of suicide risk prediction. Since physical illnesses based models are tested using 10-fold cross validation, the performance can be considered to be robust.

A limitation of this study is that we have considered only physical illnesses that resulted in hospitalization. However, this is an inherent and unavoidable limitation of any study based on electronic medical records (EMRs). Therefore, the effect of mild illnesses that resulted in no hospitalization or treated outside hospitals was not considered. Furthermore, we did not consider the effect of age or gender on the distribution of physical illnesses and developed a single model for scoring the suicide risk, which may provide some bias. The small number of suicide risk cases restricted us to stratify by age or gender as this would result in a sparse lookup table.

This study has following clinical implications: i) The results of this study shows that hospital clinicians who are not specialists in mental health can use our decision support for assessing a patient's suicide risk and that this may improve patient care; ii) Clinical assessors with mental health expertise can use patient's history of physical illnesses through our proposed tool to improve suicide risk prediction, especially for patients with a history of multiple hospitalizations; and, iii) Our tool can also assist primary care providers with access to EMR to recognize early signs of risk and refer patients to specialty care.

In conclusion, this study provides a novel approach to exploit the history of physical illnesses extracted from EMR (ICD-10 codes *without* chapter V-Mental and behavioural disorders) to predict suicide risk, and this model outperforms existing clinical assessments of suicide risk.

References:

1. Borges G, Nock MK, Abad JMH, Hwang I, Sampson NA, Alonso J, et al. Twelve-Month Prevalence of and Risk Factors for Suicide Attempts in the World Health Organization World Mental Health Surveys. J Clin Psychiat. 2010;71(12):1617-28.
2. Statistics ABo. Australian Bureau of Statistics 2015.
3. Murray CJ, Lopez AD. Mortality by cause for eight regions of the world: Global Burden of Disease Study. The Lancet. 1997;349(9061):1269-76.
4. Druss B, Pincus H. Suicidal ideation and suicide attempts in general medical illnesses. Archives of Internal Medicine. 2000;160(10):1522-6.
5. Gonda X, Fountoulakis KN, Kaprinis G, Rihmer Z. Prediction and prevention of suicide in patients with unipolar depression and anxiety. Ann Gen Psychiatry. 2007;6(1):23.
6. Gonda X, Pompili M, Serafini G, Montebovi F, Campi S, Dome P, et al. Suicidal behavior in bipolar disorder: epidemiology, characteristics and major risk factors. Journal of affective disorders. 2012;143(1):16-26.
7. Haw C, Hawton K. Living alone and deliberate self-harm: a case–control study of characteristics and risk factors. Social psychiatry and psychiatric epidemiology. 2011;46(11):1115-25.
8. Martin-Fumadó C, Hurtado-Ruíz G. Clinical and epidemiological aspects of suicide in patients with schizophrenia. Actas Esp Psiquiatr. 2012;40(6):333-45.
9. Perry IJ, Corcoran P, Fitzgerald AP, Keeley HS, Reulbach U, Arensman E. The incidence and repetition of hospital-treated deliberate self harm: findings from the world's first national registry. PLoS One. 2012;7(2):e31663.
10. Sapyta J, Goldston DB, Erkanli A, Daniel SS, Heilbron N, Mayfield A, et al. Evaluating the predictive validity of suicidal intent and medical lethality in youth. Journal of consulting and clinical psychology. 2012;80(2):222.
11. Fountoulakis KN, Pantoula E, Siamouli M, Moutou K, Gonda X, Rihmer Z, et al. Development of the Risk Assessment Suicidality Scale (RASS): a population-based study. Journal of affective disorders. 2012;138(3):449-57.
12. Stefansson J, Nordström P, Jokinen J. Suicide Intent Scale in the prediction of suicide. Journal of affective disorders. 2012;136(1):167-71.
13. Waern M, Sjöström N, Marlow T, Hetta J. Does the Suicide Assessment Scale predict risk of repetition? A prospective study of suicide attempters at a hospital emergency department. European Psychiatry. 2010;25(7):421-6.
14. Bolton JM, Spiwak R, Sareen J. Predicting suicide attempts with the SAD PERSONS scale: a longitudinal analysis. The Journal of clinical psychiatry. 2012;73(6):e735-41.
15. Ryan CJ, Large MM. Suicide risk assessment: where are we now. Med J Aust. 2013;198(9):462-3.
16. Denneson LM, Basham C, Dickinson KC, Crutchfield MC, Millet L, Shen X, et al. Suicide Risk Assessment and Content of VA Health Care Contacts Before Suicide Completion by Veterans in Oregon. Psychiat Serv. 2010;61(12):1192-7.
17. Kaplan MS, McFarland BH, Huguet N, Valenstein M. Suicide Risk and Precipitating Circumstances Among Young, Middle-Aged, and Older Male Veterans. Am J Public Health. 2012;102:S131-S7.
18. Kovacs M, Beck AT, Weissman A. The communication of suicidal intent: A reexamination. Archives of general psychiatry. 1976;33(2):198-201.
19. Borges G, Angst J, Nock MK, Ruscio AM, Walters EE, Kessler RC. A risk index for 12-month suicide attempts in the National Comorbidity Survey Replication (NCS-R). Psychol Med. 2006;36(12):1747-57.
20. E. CA, B. H, G. OLA, E. PS, J. G. Suicidal thoughts and behaviors among adults aged ≥18 years-United States, 2008-2009. MMWR Surveill Summ. 2011;60(SS-13).
21. Kessler RC, Berglund P, Borges G, Nock M, Wang PS. Trends in suicide ideation, plans, gestures, and attempts in the United States, 1990-1992 to 2001-2003. Jama-J Am Med Assoc. 2005;293(20):2487-95.

22. Tran T, Luo W, Phung D, Harvey R, Berk M, Kennedy RL, et al. Risk stratification using data from electronic medical records better predicts suicide risks than clinician assessments. Bmc Psychiatry. 2014;14.
23. Poulin C, Shiner B, Thompson P, Vepstas L, Young-Xu Y. Predicting the Risk of Suicide by Analyzing the Text of Clinical Notes (vol 9, e85733, 2014). Plos One. 2014;9(3).
24. Qin P, Webb R, Kapur N, Sorensen HT. Hospitalization for physical illness and risk of subsequent suicide: a population study. J Intern Med. 2013;273(1):48-58.