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Predictive Apriori Algorithm in Youth Suicide Prevention by Screening Depressive Symptoms from Patient Health Questionnaire-9

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Abstract **–This study employed the Predictive A priori algorithm in identifying significant questions of Patient Health Questionnaire-9 (PHQ-9) for suicide tendency prediction by using PHQ-9 and suicidal screening form (8Q). The random forest was applied to calculate the classification accuracy of PHQ-9 and 3 feature selection algorithms were applied to determine the attribute importance. The Predictive Apriori algorithm was applied to find the meaningful association rules. The classification accuracy of PHQ-9 is 92.12% and item no. 1 and no. 9 of PHQ-9 are less important. The significant risk factors associated with suicidal ideation are Item no. 2, no. 4, and no. 5.**

Keywords **– Depression, Feature selection, Predictive Apriori algorithm, Random forest, Suicidal risk.**

1. Introduction

Suicide related depression among youth is a major global public health concern which is increasing worldwide [1]. It is the second leading cause of death among females, and the third leading cause among male aged 10-24 years [1],[2]. Suicidal often emerges in youth as across 32 low-and middle-income countries. The pooled prevalence of suicide ideation is 16.2% among females and 12.2% among males whereas the ideation with a plan are 8.3% among females and 5.8% among male [1].

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In Thailand, adolescents risk for depression is 44% and diagnosed with major depressive disorder of 18% [3]. It also associates with functional impairments and increased morbidity and mortality [4]. Due to its high prevalence, it is imperative to improve the screening access in this population [1], [4]. Suicide is a complex clinical challenge and always related to depression. Most youth are at risk for suicide is depressed [1],[3]. The prevalence of undiagnosed suicide in the depression may indicate the presence of completed suicide [4]. Assessment and early identification suicide could be enhanced with screening tools that look beyond depression [2]. Although the suicide related depression screening is very complex, particularly in adolescents. Nonetheless, it is a first valuable step to improve mental health care [5].

Patient Health Questionnaire-9 (PHQ-9) is universally accepted as an effective tool for screening depression and identifying suicide risk in suicidal screening form (8Q) referrals to mental health care providers, potentially improving morbidity and mortality among youth [6]. Assessing depressive symptoms that trigger suicide risk among youth is needed. Pettit et al. presented recommendations for conducting risk assessments, followed by an algorithm for designating risk in children and adolescents [7]. Vladimir et al. used the data from PHQ-9, Suicide Behaviors Questionnaire and Social-demographic survey to identify demographic risk factors associated with suicide and depression in Serbian medical school students [8]. Moreover, Li et al. also used the data from PHQ-9 to identify the risk factors which were significantly associated with suicidal ideation [9].

Clinicians are sometimes reluctant to broach the topic of suicide with youth, concerning that talking about suicide might inadvertently create a risk that was not already present or might damage rapport with a client [7]. Literatures suggest that the suicide risk screening does not enhance risk in youth. Verkleij et al. evaluated the sensitivity of items of standard clinical psychological assessment [5]. Furthermore, understanding the origins in symptoms of depression is the first step in preventing suicide, especially among youth patients with limbic system proactive with depression [4].

Data mining is the process for automated recognition of implicit and interesting patterns in huge data sets [10]. The most commonly used data mining techniques include classification, clustering, association rule mining, anomaly or outlier detection, regression analysis and prediction. Lui et al. employed the random forest and Gini index to predict the end-stage renal disease (ESRD) among Asian people with immunoglobulin A nephropathy (IgAN) [11]. Besga et al. applied the random forest to discriminate between Alzheimer's Disease and Late Onset Bipolar Disorder [12]. Abuhamad et al. used 3 feature selection algorithms to identify the best features for dengue outbreaks detection for Malaysian health agencies [13]. Association rule mining (ARM) plays an important role in the process of mining data for discovering interesting relations between a set of items that often appear together in a transactional dataset. Ivancevic et al. extracted the association rules used in identifying risk factors for early childhood caries by the association rule mining [14]. Toti et al. used ARM to analyze the correlation between pediatric asthma exacerbation and exposure to pollutant mixtures [15]. Wright et al. conducted ARM to infer associations between medications and problems [16].

Apriori algorithm is commonly implemented in ARM for finding frequent item set and uncovering the hidden information. A number of studies have been conducted on the Apriori algorithm. Bansal & Bhambhu used the Apriori algorithm and the Predictive Apriori algorithm in Weka to extract the crimes concerning women [17]. Hrovat et al. explored and compared the temporal trend for large healthcare database by using the algorithm and linear model-based recursive partitioning [18]. Paoin used the Apriori algorithm in Weka to produce association rules of linkage among cancer of lung, hypertension and cerebrovascular diseases [19]. Fernandez-Arteaga et al. used the Apriori algorithm in Weka to find the association rule between suicide and environment temperature [20].

The Predictive Apriori algorithm is an improved version of the Apriori algorithm, which maximizes the probability of making an accurate prediction and resolves the issue of balance between support and confidence [21]. The Predictive Apriori algorithm, combines support and confidence into a single value called predictive accuracy. This value is used to generate the Apriori association rule [22]. Sharma et al. found the best and strong association rules and the results indicated that the Predictive Apriori algorithm performs better, and it is based on the predictive accuracy with various statistical measures [23].

This study uses the random forest to find the classification accuracy of PHQ-9 and then employs the feature selection algorithms to define importance of attribute by the statistical measures; namely Chi-Square, Gini Index and Information gain. The Predictive Apriori algorithm is applied to find the association rules between the PHQ-9 and 8Q for identifying the significant questions of PHQ-9 which can predict the suicide tendency in undergraduate students. The hypothesis is that the youth suicide screening could be improved by analyzing a combination of certain questions in PHQ-9. These results provide the understanding and enhancing sensitivity of stakeholders to detect suicide warning sign in depressive symptoms.

2. Materials and Methods

2.1. Ethical Consideration

Permissions for the study were obtained from the Ethics Committee of Walailak University, Thailand (Protocol Number WUEC-18-060-01). The ethical issues involved the participants' independence, intimacy, and anonymity. The participants were informed of the objectives and details of the study.

2.2. Patient Health Questionnaire-9 (PHQ-9)

PHQ-9 is a self-assessment questionnaire developed from DSM-IV-TR [24]. It assesses depression symptoms by asking about the situation of symptom over the past 2 weeks and how often the subjects has been bothered by any of the problems. Table 1 shows the attributes of PHQ-9. The subjects should rate the 9 questions on a 4-point Likert scale (0- Not at all, 1- Several day (1-7 days), 2- Nearly every day (> 7days) and 3-Every day) [25]. The score is classified into 4 levels, namely minimal, minor, major and severe.

2.3. Suicidal screening form (8Q)

8Q was developed from the suicidality module of Mini International Neuropsychiatric Interview (Thai version 5.0.0, revised 2007) [24]. It is a self-report type of questionnaire consisting of 8 questions to determine the type of suicidal ideation and behaviors, as well as the risk of suicide or self-harm. Table 1 shows the attributes of 8Q. The subjects should rate the 8 questions on a Dichotomous Scales (0 - No, 1-10 - Yes). The score is classified into 4 levels, namely minimal, minor, major and severe. They had the right to refuse to join or could withdraw from this project at any time. Each participant willingly gave permission for informed consents were gained from the participants who agreed to be involved in the study.

Table 1. Attributes of PHQ-9 and 8Q used for each student

PHQ-9 Attribute	Description	8Q Attribute	Description
Q1	Little interest or pleasure in doing things	Q1	Think about you would be better if you dead or wish you were dead
Q2	Feeling down, depressed or hopeless	Q2	Want to harm yourself or to hurt or to injure yourself
Q3	Trouble falling asleep, staying asleep, or sleeping too much	Q3	Thinking about suicide
Q4	Felling tired or having little energy	Q4	Have a suicide plan
Q5	Poor appetite or overeating	Q5	Take any active steps to prepare to injure you or to prepare for a suicide attempt in which you expected or intended to die
Q6	Feeling bad about yourself – or that you're a failure or have let yourself or your family down	Q6	Intentionally injure yourself without deliberate to kill yourself
Q7	Trouble concentrating on things, such as reading the newspaper or watching television	Q7	Have you ever suicide attempt which intend to actually dead
Q8	Moving or speaking so slowly that other people could have noticed. Or, the opposite – being so fidgety or restless that you have been moving around a lot more than usual	Q8	Did you ever make a suicide attempt
Q9	Thoughts that you would be better off dead or of hurting yourself in some way		

2.4. Data Set Characteristics

The data used in this study are obtained from PHQ-9 and 8Q questionnaires, implemented on 1,549 undergraduate students from a university in the south of Thailand. The data are from both male and female students between 17-22 years old from 14 faculties. The detailed scores of PHQ-9 and 8Q are shown in Table 2. Then, the data was analyzed by using random forest and 3 feature selection algorithms in RapidMiner as well as the Predictive Apriori algorithm in Weka (Figure 1.). Since this research aims to identify significant questions of the PHQ-9 that related to the suicide tendency, the data from PHQ-9 and 8Q is therefore selected to create the desired data sets. Then, these data sets will be integrated to generate association rules of prediction depressive symptoms for suicidal risk. The sample data from PHQ-9 and 8Q transformed into the format required by the Predictive Apriori algorithm are shown in Table 3.

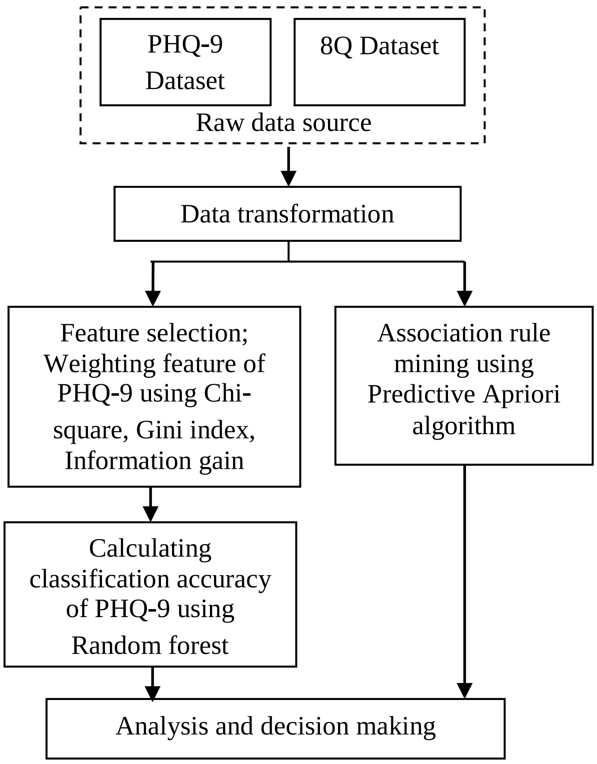

Figure 1. An approach for the search of association rule between PHQ-9 and 8Q

Table 2. PHQ-9 scores and 8Q scores

Depression /Suicide Diagnosis	Depression				Suicide			
	Symptom severity	PHQ-9 score	N	%	Symptom severity	8Q score	N	%
0	Minimal	0 - 6	821	53.04	Minimal	0	1,396	90.18
1	Minor	7-12	567	36.63	Minor	1-8	122	7.88
2	Major	13-18	130	8.39	Major	9-16	25	1.62
3	Severe	19-27	30	1.94	Severe	17-52	5	0.32

Table 3. Sample data from PHQ-9 and 8Q for the Predictive Apriori algorithm

Stud_id	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Depression Diagnosis	Suicide Diagnosis
1	3	2	2	2	2	2	1	0	3	2	3
2	1	2	2	2	2	2	0	0	1	1	3
3	3	3	3	3	2	3	2	2	2	3	3
4	2	1	0	3	1	2	0	1	1	1	2
5	2	3	2	1	0	3	3	0	1	2	2

3. Results and Discussion

In the experiment, the random forest indicates that the classification accuracy of PHQ-9 is 92.12%. Table 4 shows that all items of the PHQ-9 are important to predict the depression symptoms and Item no. 1 and 9 are less important in the same manner for all 3 statistical measures. The Predictive Apriori algorithm finds 1,000 possible association rules, including 168 association rules of the PHQ-9 whose accuracy are greater than 0.89257. Moreover, it can search out 6 association rules between PHQ-9 and 8Q with the accuracy between 0.84544 - 0.89257. Table 5 shows a list of the top 10 rules with the highest predictive accuracy of the rule in PHQ-9 and a list of the association rules between the PHQ-9 and 8Q. The results show that association rules in the PHQ-9 almost answering the questions at scale 2 (Nearly every day); there will be a tendency of major depression. Moreover, the 6 association rules between the PHQ-9 and 8Q are discovered which related to suicidal risk. The details are in the discussion section. Using this information as a basis, it means that there exists an association between depression and suicide. Therefore, the physician can give careful consideration to students who have the score of 2 or higher in these Item no. of the PHQ-9.

Table 4. Weight vector for all attributes weightening operations by the statistical measures; Chi-Square, Gini Index and Information gain

Chi-Square		Gini Index		Information gain	
Attributes	Weight	Attributes	Weight	Attributes	Weight
Q8	1	Q4	1	Q4	1
Q6	0.932	Q8	0.978	Q6	0.926
Q4	0.891	Q6	0.955	Q7	0.907
Q7	0.881	Q7	0.950	Q8	0.852
Q5	0.474	Q2	0.715	Q2	0.714
Q2	0.437	Q3	0.601	Q3	0.597
Q3	0.227	Q5	0.508	Q5	0.534
Q1	0.158	Q1	0.247	Q1	0.372
Q9	0	Q9	0	Q9	0

Table 5. Meaningful association rules of PHQ-9 and association rules between PHQ-9 and 8Q

Association rules of PHQ-9	
Best rules found	**Accuracy**
1. attr1=Q1_2 attr3=Q3_2 attr6=Q6_2 attr7=Q7_2 28 ==> depress=C2 28	0.99159
2. attr1=Q1_2 attr4=Q4_2 attr5=Q5_2 attr6=Q6_2 28 ==> depress=C2 28	0.99159
3. attr1=Q1_2 attr4=Q4_2 attr6=Q6_2 attr7=Q7_2 attr8=Q8_2 22 ==> depress=C2 22	0.98974
4. attr4=Q4_2 attr5=Q5_2 attr9=Q9_2 21 ==> depress=C2 21	0.98929
5. attr1=Q1_2 attr5=Q5_2 attr9=Q9_2 21 ==> depress=C2 21	0.98929
6. attr3=Q3_2 attr5=Q5_2 attr7=Q7_2 attr9=Q9_2 21 ==> depress=C2 21	0.98929
7. attr3=Q3_2 attr4=Q4_2 attr9=Q9_2 20 ==> attr7=Q7_2 depress=C2 20	0.98877
8. attr3=Q3_2 attr5=Q5_2 attr8=Q8_2 attr9=Q9_2 20 ==> depress=C2 20	0.98877
9. attr5=Q5_2 attr6=Q6_2 attr8=Q8_2 attr9=Q9_2 20 ==> depress=C2 20	0.98877
10. attr2=Q2_2 attr5=Q5_2 attr6=Q6_2 attr7=Q7_2 attr8=Q8_2 19 ==> depress=C2 19	0.98819
Association rules between PHQ-9 and 8Q	
Best rules found	**Accuracy**
1. attr2=Q2_2 attr3=Q3_2 attr4=Q4_2 attr5=Q5_2 attr6=Q6_3 3 ==> suicide=2 3	0.89257
2. attr2=Q2_2 attr4=Q4_2 attr5=Q5_2 attr7=Q7_2 attr9=Q9_3 3 ==> suicide=2 3	0.89257
3. attr3=Q3_2 attr4=Q4_2 attr5=Q5_2 attr7=Q7_2 attr9=Q9_3 3 ==> suicide=2 3	0.89257
4. attr1=Q1_0 attr6=Q6_2 depress=C1 2 ==> suicide=1 2	0.84544
5. attr1=Q1_2 attr3=Q3_2 attr6=Q6_3 2 ==> suicide=2 2	0.84544
6. attr8=Q8_2 attr9=Q9_3 depress=C3 2 ==> suicide=2 2	0.84544

Depression concept consists of 4 groups of symptoms change: emotional, cognition, behavioral, and physical change [6]. This research results reveal that only emotional and physical changes with 3 items of the PHQ-9 are significant in predicting risk of suicide in the 8Q among undergraduate students: Item no. 2 “Feeling down, depressed or hopeless”, Item no. 4 “Feeling tired or having little energy”, and Item no. 5 “Poor appetite or overeating”. Na et al. suggested that Item no. 9 of the PHQ-9 was insufficient for the suicide risk and suicide ideation. Thus, the 8Q was used to confirm suicidal risk and these research results fill the gaps for finding the impact items of suicide risk enhancing the effective in early detection [26].

For Item no. 2 “Feeling down, depressed or hopeless”, emotional change is the main symptom change in depression [4]. Hopelessness is mediated significantly associated with depression and self-injury [27]. Emotional difficulties also are significantly predicted by hopelessness [28]. Emotional symptoms and depression are costly and potentially disabling conditions, affecting a considerable proportion of adolescent with risk for suicide among youth [29].

Item no. 4 “Feeling tired or having little energy” and Item no. 5 “Poor appetite or overeating” are indicated risks for suicide among undergraduate students. These 2 items are physical symptom change that always appears in the severe depression level related to suicide among youth [30]. Greater occurrence and severity of fatigue were associated with depressive symptoms and the lower level of physical activity [31]. Literatures confirmed that vegetative symptoms such as appetite and weight change, loss of energy and insomnia occur in adolescent MDD more frequently than those in adults MDD [28]. Disturbances in eating behavior are common in depression, negative emotions such as depression are one of the most proximate psychological factors related to disorder eating [32], [33]. Some individuals eat more than others while suffering depressive symptoms because the depression was positively correlated with the emotional eating [33].

The results of this study reflect the risk of suicide in depressed adolescents’ state in emotional and physical changes. Implementation of PHQ-9 depression screening protocol identifies the suicide risk among adolescent accessing facilitating referrals to mental health providers, potentially improving morbidity and mortality among youth. For practice implications, the depressive symptom is common among youth and associated with increased suicide rate and the functional impairments. Due to its high prevalence, it is imperative to improve depression screening access for identify risk of suicide youths.

4. Conclusion

In this paper, we have described the association rules of PHQ-9 and 8Q and how it can be utilized to screen the depression symptom. Our finding suggests that, for the effective prevention of suicide in undergraduate students, the focus should be on these 3 questions from Item no. 2, 4, 5 from PHQ-9. In this sense, the association rule mining can be useful for predicting the depressive symptom and identifying undergraduate students who require special attentions.

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