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Risk Assessment of Type 2 Diabetes Mellitus in the Population of Chonburi, Thailand

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Abstract

This study aims to develop a risk score to identify people at high risk for type 2 diabetes mellitus (T2DM) in the population of Chonburi, Thailand, and to compare this risk score with 2 previous predictive risk scores for T2DM. Data from 7,284 individuals aged ≥ 20 years were collected from the Thai population, using a cross-sectional analytical study method. A screening algorithm was developed based on the first half and validated in the second half of the study population. Logistic regression analysis was used to determine the risk factors for T2DM, by performing a predictive model in which only significant factors were included. Afterwards, our predictive model was compared with the other 2 predictive models, where risk scores were derived from Thai adults. Our results showed that significant predictive variables were age, BMI, hypertension, history of diabetes in parents or siblings, and marital status. A cutoff score of 9 out of 17 produced the optimal sums of sensitivity (74 %) and specificity (97 %). The area under the receiver-operating characteristics curve (AUC) was 0.969. Our predictive model had a higher AUC when compared to the other 2 models. When the risk score was applied, the predictive model selected 425 subjects who should undergo further testing for diagnosing diabetes and 3,259 subjects who should not. A simple T2DM risk score, based on a set of variables, can be used for the investigation of early intervention to delay or prevent T2DM in Thailand.

Keywords: Logistic regression analysis, risk score model, type 2 diabetes mellitus, predictive model

Introduction

Type 2 Diabetes Mellitus (T2DM) is becoming a major public health problem worldwide [1]. Unavoidably, diabetes and its complications will have a huge economic and social cost, particularly in low-income countries [2]. Several global estimates and projection reports indicate that the number of people with diabetes is increasing day by day worldwide [1-3]. According to the International Diabetes Federation (IDF), 77 % of people with diabetes live in low and middle income countries, and the number of diabetic patients will increase from 387 million in 2013 to 592 million by 2035 [3]. The number of people with diabetes will increase because of changes in lifestyle towards urbanization, high population growth, the ageing population, and high economic growth [3]. In Thailand, changes in lifestyle towards urbanization, combined with rapid economic development, increased survival from communicable diseases, and genetic susceptibility, have led to rising numbers of cases of diabetes [4-8]. In addition, the IDF have predicted that the number of Thai diabetic patients will increase from 6.4 % in 2013 to 8.3 % by 2035 [3]. The Ministry of Public Health in Thailand launched several policies in 2011 to decrease the prevalence of diabetes mellitus [9].

Diabetes is associated with health complications, but changes in the lifestyle of people with high risk can prevent diabetes and its complications from occurring [10,11]. Increased awareness about the high risk of diabetes, and detection and control of diabetes with accurate screening tools, may reduce such high risk [12-14]. The blood glucose test is a tool used for diabetes screening, but this tool is not practicable in a resource poor environment such as in Thailand, as it is expensive [1,15-18]. To control T2DM, it is necessary to determine associated risk factors that increase an individual's risk for developing prediabetes and, ultimately, type 2 diabetes. Uncontrollable factors include socio-economic status [10], age [2,8], gender [1,2], marital status [19,20], genetic susceptibility [13,14], and other environmental factors. Controllable factors include obesity [7,8], hypertension [6,7], dyslipidemia [14], physical activity [12,16,21], smoking [14,15], and alcohol intake [15]. Various diabetes risk scores, assessment tools which are designed to predict an individual’s risk of developing type 2 diabetes, have been derived from Caucasian populations [12,16,17,21], but few risk score models are based on Asian ethnic groups [1,4,15]. T2DM risk score models developed in Caucasian populations tend to be poor at predicting high-risk subjects for T2DM in Asian populations [22], because each ethnic group has different and distinctive genetic and environmental characteristics, such as body shape, food and drink, culture, and other lifestyle factors. Therefore, we believe it is ideal to have different models for different populations in order to screen high-risk subjects for diabetes. Numerous studies have been conducted worldwide to develop screening tools based on risk scores in various populations [1,7,12,15,16], but only a few studies have been conducted in Thailand [7,13].

We present the derivation and validation of a new risk prediction algorithm for assessing the risk of developing T2DM in the population of Chonburi, Thailand, and compare it with 2 previous predictive risk scores for T2DM in Thailand. We have designed this scoring system using variables that are readily available, and the system does not require any laboratory testing or physician interpretation. This makes the model reasonable and cost effective.

Materials and methods

Data collection

The Community Health and Learning Center (CHLC), Chonburi, Thailand, has conducted a population-based survey in 7 communities surrounding the oil refinery of the Thaioil Public Company Limited: Ban Ao Udom, Ban Thung, Ban Laem Chabang, Ao Udom market, Ban Chak Yai Chin, Ban Nam Sap, and Wat Manorom. There were 18,380 individuals reported in the Civil Registration database in 7 communities surrounding the oil refinery of Thaioil. When the CHLC conducted a population-based survey in the 7 communities surrounding the oil refinery of Thaioil from October 2010 to April 2015, there were 12,055 subjects who participated in the program. From these 12,055 subjects, we selected an adult population of age 20 years or above in order to develop a risk assessment score. 7,284 out of 12,055 subjects fitted the identified criteria for risk factors. Therefore, the sample size comprised 7,284 subjects (**Table 1**). The criteria used were age, gender, marital status, educational level, occupation, previously diagnosed T2DM, and hypertension. This study population was divided into 2 groups, based on their screening number. A screening algorithm was developed based on the first half and validated through use in analysis of the second half of the study population.

Definitions

In the survey process, the socio-demographic characteristics, collected by use of a structured questionnaire, were (1) age (20 - ≥60 years with 10 year intervals), (2) gender, (3) marital status, (4) educational level, (5) occupation, (6) previously diagnosed T2DM, and (7) hypertension. Personal information was collected using a structured questionnaire during the survey process, including (1) family history of diabetes (defined as positive if at least one first or second degree relative had diabetes), (2) weight, and (3) height. Body mass index (BMI) was calculated by dividing weight (kg) by the square of height (m^2) (World Health Organization [WHO]). Being overweight was defined as being of a BMI of ≥ 25 kg/m^2 and < 30 kg/m^2, obesity corresponded to a BMI of ≥ 30 kg/m^2, and underweight to a BMI of < 18.5 kg/m^2.

Table 1 Socio-demographic characteristics of the diabetic and non-diabetic subjects studied (N = 7,284) and risk factors.

Variable	Diagnosed diabetes; $N = 464$	Non-diabetics; $N = 6,820$	Statistical
Age (mean ± SD)	59.4 ± 12.1	42.0 ± 14.3	$t_{556} = -29.555^{*}$ $P < 0.001$
Age group			$\chi^2_4 = 712.308^{****}$
20 - 29	4 (0.9)	1,464 (21.5)	$P < 0.001$
30 - 39	17 (3.7)	1,800 (26.4)	
40 - 49	72 (15.5)	1,692 (24.8)	
50 - 59	124 (26.7)	1,009 (14.8)	
≥ 60	247 (53.2)	855 (12.5)	
Gender			$\chi^2_1 = 10.290^{**}$
Male	178 (38.4)	3,139 (46.0)	$P = 0.001$
Female	286 (61.6)	3,681 (54.0)	
Marital status			$\chi^2_2 = 87.366^{***}$
Single	48 (10.3)	1,432 (21.0)	$P < 0.001$
Married	313 (67.5)	4,719 (69.2)	
Divorced/widowed	103 (22.2)	669 (9.8)	
Education status			$\chi^2_4 = 242.298^{****}$
Illiterate	55 (11.9)	447 (6.6)	$P < 0.001$
Primary	325 (70.0)	2,601 (38.1)	
Secondary	37 (8.0)	1,868 (27.4)	
High School	18 (3.9)	874 (12.8)	
University	29 (6.2)	1030 (15.1)	
Occupation			$\chi^2_7 = 206.158^{*****}$
Retired/not working	131 (28.2)	766 (11.2)	$P < 0.001$
Worker	118 (25.4)	3,590 (52.6)	
Farmer/Fisherman	10 (2.2)	71 (1.0)	
Government	9 (1.9)	136 (2.0)	
House wife	82 (17.7)	728 (10.7)	
Army/Police	1 (0.2)	23 (0.3)	
Self-employed	113 (24.4)	1,333 (19.5)	
Student	0 (0.0)	173 (2.5)	
Body mass index			$\chi^2_2 = 90.991^{***}$
< 25 (normal)	247 (53.2)	4,890 (71.7)	$P < 0.001$
25 - 30 (overweight)	138 (29.7)	1,446 (21.2)	
> 30 (obese)	79 (17.0)	484 (7.1)	
Family history of diabetes			$\chi^2_1 = 2327.231^{**}$
No	14 (3.0)	6,067 (89.0)	$P < 0.001$
Yes	450 (97.0)	753 (11.0)	
Hypertension			$\chi^2_1 = 467.289^{**}$
No	289 (62.3)	6,311 (92.5)	$P < 0.001$
Yes	175 (37.7)	509 (7.5)	

Data presented in the form of mean ± SD and *n* (%).
[*]Unpaired Student's t-test, df = 556;
[**]Chi-Square test, df = 1;
[***]Chi-Square test, df = 2;
[****]Chi-Square test, df = 4;
[*****]Chi-Square test, df = 7.

Statistical analysis and validation

Data were analyzed using SPSS 17.0 and described using the mean (±SD) for continuous variables and proportions for categorical variables. Difference between the age mean was assessed by an unpaired student t-test. Chi-square tests were performed to see the frequency differences between the first and second half data. Binary logistic regression analysis was used to produce a model that permitted the prediction of binary variable values from a set of illustrative variables. Each variable was adjusted in relation to others using a stepwise forward elimination. The association measure computed in this model was the odds ratio, which quantified the strength of the association between an event's occurrence (represented by illustrative variables) and the factors that could influence it (represented by illustrative variables).

A simple predictive model was developed using a scoring system. Points were assigned to each variable based on the magnitude of its regression coefficient [14]. A point was calculated by dividing each coefficient by the lowest coefficient value of the significant variable and rounding them up to the nearest integer. For example, the lowest coefficient value was 0.896. The score for the divorced/widowed group (i.e. 2) was calculated by (1.981/0.896) = 2.211, and then rounded up to 2.00. A total T2DM risk score for each subject was calculated as the sum of points for each variable. This score was related to actual observed incidence.

The predictive performance of the risk score was evaluated with respect to the area under the curve (AUC) of a receiver operating characteristics (ROC) curve, sensitivity (the probability of a positive test, given the subject truly does have T2DM), specificity (the probability of a negative test, given the subject does not have T2DM), Positive Predictive Value (PPV) (the probability of T2DM, given a positive test), and Negative Predictive Value (NPV) (the probability of no T2DM, given a negative test). At the cutoff point of the predictive model, the number of subjects who would need to be referred for further testing to diagnose diabetes was calculated, as was the number of subjects with undiagnosed diabetes who would be missed. The Hosmer-Lemeshow goodness-of-fit test was used to determine if the observed incidence rates of diabetes differed significantly from the expected incidence rate. If the observed incidence of diabetes is close to the predicted probabilities, the predictive model is considered to be well calibrated. The ability of the predictive model values to predict the incidence of diabetes was examined with ROC curves and their respective areas under the curve (AUC), in which sensitivity was plotted as a function of 1-specificity. The AUC is a global summary statistic of the discriminative value of a model describing the probability that the score will be higher in a subject developing T2DM than in a subject not developing T2DM.

The algorithm developed by DeLong *et al*. [23] was used to compare the AUC. We compared our predictive model with other 2 predictive models, Aekplakorn *et al*. [13] and Keesukphan *et al*. [7], using the second half of the data and the AUC. A 2-side P-value of less than 0.05 was considered statistically significant in all tests.

Ethics statement

This study was approved by the Ethical Clearance Committee on Human Rights Related to Researches Involving Human Subjects, Walailak University (016/2014).

Results

Table 1 shows the socio-demographic characteristics of diabetic and non-diabetic studied subjects. The mean age of the diabetic and non-diabetic subjects was significantly different. The proportion of diagnosed diabetic subjects was particularly high in the over 60 years age group (53.2 %), followed by 50 - 59 (26.7 %), and then 40 - 49 (15.5 %). The proportion of T2DM diagnosed subjects was higher in females (61.6 %) than males (38.4 %), higher in the married group (67.5 %) than in other marital status groups, higher in the low educated group than in the high educated group, and higher in subjects that had a history of diabetes in a first-degree relative (mother, father, brother, or sister) (97.0 %) than where there was no history of diabetes. Significant differences were observed between diabetic and non-diabetic subjects in terms of marital status, educational status, occupation, BMI, family history of diabetes, and hypertension. Although the proportion of T2DM diagnosed subjects was likely to have a normal BMI (53.2 %), it was increased in diagnosed diabetes subjects who were overweight (increased from 21.2 to 29.7 %) and obese (increased from 7.1 to 17.0 %), while it was decreased in subjects of normal BMI, from 71.7 to 53.2 %. Similarly, the proportion of T2DM diagnosed subjects were increased from 7.5 to 37.7 %.

Binary logistic regression analysis was used to determine the risk factors for T2DM in the first half data of the adult subjects (**Table 2**). In the final model, 5 variables were found to be predictive of screen detected T2DM: age, marital status, BMI, family history, and hypertension. The total score ranged between 1 and 17. At a score of 9 or higher, the sum of sensitivity and specificity was maximized (sensitivity = 74 %; specificity = 97 %; accuracy = 95 %). The model had an area under the ROC curve (AUC) of 0.969, with acceptable agreement between the observed and predicted estimates (Hosmer-Lemeshow test: χ^2_8 = 2.305, P = 0.970). The predictive model was successfully validated using internal data from the second half population; the AUC was 0.979 (P < 0.001), the PPV was 94.6 %, and the NPV was 93.3 %. The AUC in the second half of the population was better than the first half of the population (AUC 0.969 vs 0.979, P < 0.01) and better than other predictive models (Aekplakorn *et al*. predictive model: AUC 0.969 vs 0.927, P < 0.001; Keesukphan *et al*. predictive models: AUC 0.969 vs 0.720, P < 0.001). The comparative performance of the predictive models is shown in **Figure 1**.

When the risk score was applied as shown in **Table 3**, the predictive model selected 425 subjects who should undergo further testing for diagnosis of diabetes (the sum of the true positive value and the false negative value), and 3,259 subjects who should not. The prevalence of T2DM in the validation group was 206 (5.6 %). Only 11 (the false positive value) out of 206 (5.34 %) were missed by the predictive model. When the risk score was applied, screening of 3,248 (88.2 %) people could be avoided.

Table 2 Predictors for diabetes mellitus in adults of the communities surrounding the refinery of Thaioil using multiple logistic regression analysis.

Independent variables	OR (95% CI)	β-Coefficient	*P*-Value	Score
Age group				
20 - 29	Reference			0
30 - 39	2.516 (0.518 - 12.221)	0.923	0.252	0
40 - 49	12.013 (2.771 - 52.079)	2.486	0.001*	3
50 - 59	31.100 (7.219 - 133.988)	3.437	0.000*	4
≥ 60	36.117 (8.413 - 155.049)	3.587	0.000*	4
Marital status				
Single	Reference			0
Married	3.022 (1.485 - 6.150)	1.106	0.002*	1
Divorced/widowed	7.248 (3.156 - 16.646)	1.981	0.000*	2
Body mass index				
< 25 (normal)	Reference			0
25 - 30 (overweight)	1.197 (0.778 - 1.840)	0.179	0.413	0
> 30 (obese)	2.451 (1.379 - 4.355)	0.896	0.002*	1
Family history of DM				
No	Reference			0
Yes	171.524 (89.630 - 328.243)	5.145	0.000*	6
Hypertension				
No	Reference			0
Yes	3.193 (2.025 - 5.036)	1.161	0.000*	1
Area under the ROC curve	0.969 (0.960 - 0.977)			

Risk factor was significantly associated with T2DM (*P* < 0.05).
The score value was calculated by dividing each coefficient by the lowest coefficient value of significant variable and rounding them up to the nearest integer. For example, the lowest coefficient value was 0.896. The score of the divorced/widowed group (i.e. 2) was calculated by (1.981/0.896) = 2.211, and then rounded up to 2.00.

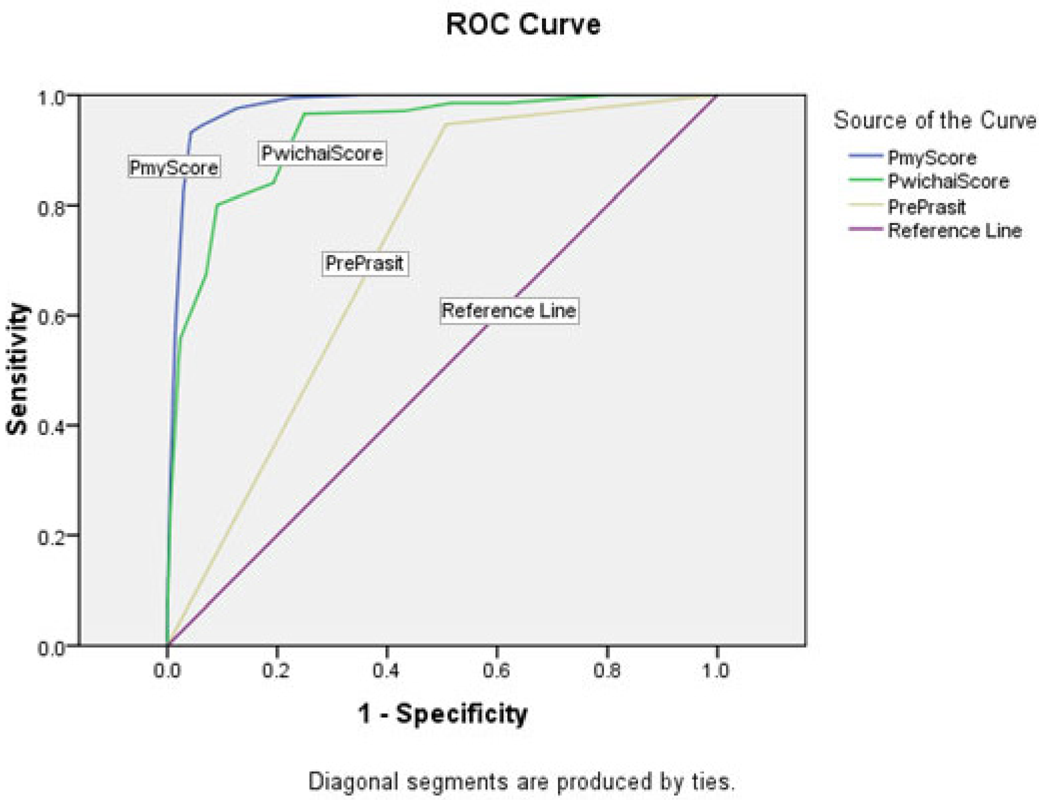

Figure 1 ROC curves for this study's predictive model (PmyScore), the predictive model of Aekplakorn *et al*. (PwichaiScore), and the predictive model of Keesukphan *et al*. (Preprasit).

Table 3 Performance of risk score in each validation group.

	Score ≥ 9	**Score < 9**	**Total**
Diabetics	195	11	206 (5.6 %)
Non-diabetics	230	3,248	3,478 (94.4 %)
Total	425 (11.5 %)	3,259 (88.5 %)	3,684 (100 %)

For the cutoff point of the T2DM risk score ≥ 9, the true positive value was 195, the false positive value was 11, the false negative value was 230, and the true negative value was 3,248.

Discussion

Many studies have attempted to develop risk functions for diabetes screening, but little has been done in Thailand [7,13]. When we compare diabetic and non-diabetic groups, diabetes tends to occur in subjects who are elderly, are divorced/widowed, those with low educational attainments (illiterate or having only completed primary school), those with a high BMI, those with a family history of diabetes, and those with high hypertension. It is possible that these individuals have the least information about dietary factors and the importance of self-care. In this study, we present a simple and practical tool to identify the early detection of T2DM in the Thai population. Binary logistic regression showed that, after taking into account all the variables studied, age, marital status, BMI, family history of diabetes, and hypertension proved to be the principle risk factors for developing diabetes.

Our results indicated that age was significantly correlated with a high risk of T2DM in Thailand, where older people had higher risks of T2DM than younger people [5,6,14]. This could possibly be due to the fact that Thailand is having a demographic transition, with an increase in life expectancy leading to an increasingly elderly population. This is the root of the drastic increase of diabetes in Thailand.

Direct relationships between BMI, as well as obesity, and diabetes has been observed around the world, in places such as in Thailand, Korea, the Netherlands, Pacific island countries, Taiwan, and Jeddah and other areas of Saudi Arabia [13,15-17,24,19,25]. Our study shows that BMI is one of the principle risk factors for developing diabetes, and highlights the importance of the impact of nutritional transition. The acceleration of urbanization in Thailand and the rise in obesity play important roles in increased diabetes prevalence. The prevalence of diabetes in Thailand is increasing with lifestyle changes due to rapid urbanization. Urban communities have changed their diet, consuming more refined sugar and more saturated fat, and having less of a fiber intake, and engage in less physical activities. In addition, divorce rates have tended to increase with an increase in urbanization. Our results indicate that marital status (widowed and divorced persons) contributes significantly in increasing T2DM risk in Thailand, similar to some places such as Jeddah [19] and the United States [20], but not to other places like Portugal [21] and African-American [26].

Previous studies observed that family history of diabetes, as well as hypertension, contributed significantly to increased T2DM risk in Jeddah [19], Qatar [2], Portugal [21], and Pakistan [27]. Although both hypertension and diabetes occur independently, they are known to exacerbate each other [28]. A greater proportion of patients developed hypertension after diabetes diagnosis (43.1 %), as compared with 23.1 % of patients in whom hypertension was diagnosed prior to the diagnosis of diabetes [28].

Previous studies in Portugal [21] and Taiwan [24] reported gender as a risk factor for T2DM. However, studies [7,13] done in Thailand could not find any association between gender and T2DM. Our study also did not find any association between gender, education status, and occupation and T2DM. Similar findings were observed in Qatar and Iran [2,29], but not in Jeddah [19].

In this study, we assessed the validity of 2 previous T2DM risk scores in Thailand [7,13]. The model by Aekplakorn *et al*. [13] was derived from 2,667 Thai adults who were employees of a state enterprise, the Electric Generation Authority of Thailand (EGAT) and was performed in separate population comprising 2,420 employees. Most of the employees were urban dwellers of a middle-income social class. Follow-up health interviews and examination surveys were performed after 12 years. The model by Keesukphan *et al.* [7] was derived from 429 Thai adults without a previous history of diabetes derived from the outpatient clinic of the Department of Family Medicine, Faculty of Medicine, Ramathibodi Hospital, Mahidol University, Bangkok, and was performed in separate population comprising 1,617 adults with at least one risk factor for diabetes. The findings showed that risk factors were age, BMI, and hypertension. All these scoring models performed well in their study populations. Risk scores cannot always be generalized from one population to another, so a scoring model must be validated before widespread application can be made. When we compared our model with these 2 previous models [7,13], the Keesukphan *et al*. model [7] had a lower predictive ability than our model and the Aekplakorn *et al*. model [13]. This might be due to 2 possible reasons. First, the Keesukphan *et al*. model was derived from a small population size (i.e., 429 Thai adults), but our model was derived from a large sample size (i.e., 7,284 Thai adults). Second, predictive variables differed among models. The predictive variables in the model of Keesukphan *et al*. [7] were age, BMI, and hypertension, and in Aekplakorn *et al*., the predictive variables in the model were age, BMI, hypertension, sex, history of diabetes in parents or siblings, and waist circumference. Our model's predictive variables were age, BMI, hypertension, history of diabetes in parents or siblings, and marital status.

Conclusions

We have developed a simple self-assessment risk score for detecting the risk of currently undiagnosed T2DM in Thai adults. We were able to establish a simple risk score model based on socio-demographic and personal information without performing any laboratory tests. Therefore, this predictive model would be easy and convenient enough so that an non-medically trained person could perform a self-assessment of T2DM risk in real life. In addition, this score can be applied in primary medical care practice and by the public as a self-assessment tool to identify subjects at high risk of T2DM. Using the simple risk score in this model should render a more cost-effective approach to diabetes screening. Subjects with a high score should be referred for further blood tests and their lifestyles changed to a healthier one as primary prevention. For future work, a simple risk assessment model for T2DM screening using web-based technology is needed.

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