


Risk score model of type 2 diabetes prediction for rural Chinese adults: the Rural Deqing Cohort Study

X. Chen¹ · Z. Wu¹ · Y. Chen² · X. Wang³ · J. Zhu³ · N. Wang¹ · Q. Jiang¹ · C. Fu¹ 

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Abstract

Objective Risk score (RS) model is a cost-effective tool to identify adults who are at high risk for diabetes. This study was to develop an RS model of type 2 diabetes (T2DM) prediction specifically for rural Chinese adults.

Methods A prospective whole cohort study ($n = 28,251$) and a sub-cohort study ($n = 3043$) were conducted from 2006–2014 and 2006–2008 to 2015 in rural Deqing, China. All participants were free of T2DM at baseline. Incident T2DM cases were identified through electronic health records, self-reported and fasting plasma glucose testing for the sub-cohort, respectively. RS models were constructed with coefficients (β) of Cox regression. Receiver-operating characteristic curves were plotted and the area under the curve (AUC) reflected the discriminating accuracy of an RS model.

Results By 2015, the incidence of T2DM was 3.3 and 7.7 per 1000 person-years in the whole cohort and the sub-cohort, respectively. Based on data from the whole cohort, the non-invasive RS model included age (4 points), overweight (2 points), obesity (4 points), family history of T2DM (3 points), meat diet (3 points), and hypertension (2 points). The plus-fasting plasma glucose (FPG) model added impaired fasting glucose (4 points). The AUC was

0.705 with a positive predictive value of 2.5% for the non-invasive model, and for the plus-FPG model the AUC was 0.754 with a positive predictive value of 2.5%. These models performed better as compared with 12 existing RS models for the study population.

Conclusions Our non-invasive RS model can be used to identify individuals who are at high risk of T2DM as a simple, fast, and cost-effective tool for rural Chinese adults.

Keywords Type 2 diabetes · Risk score · Cohort study · Rural China

Introduction

Diabetes is one of the greatest health challenges of the twenty-first century worldwide [1]. In China, the prevalence of type 2 diabetes mellitus (T2DM) has been increasing with aging population, rapid urbanization, and changing lifestyle (obesity or overweight, physical inactivity, and high-calorie food consumption) [2, 3]. In 2010, a national cross-sectional survey of China found that 11.6% of Chinese adults had diabetes and in addition, 8.1% had the disease but undiagnosed [4].

Several large intervention studies have indicated that lifestyle modification or pharmacological intervention targeting population who are at high risk for diabetes can prevent or delay the occurrence of type 2 diabetes [5, 6]. It is important to find people with risk factors for type 2 diabetes using feasible and cost-effective approaches, and the diabetes risk score method has been frequently used [7].

In recent years, a set of risk score (RS) models had been developed and tested, such as the Finnish Risk Score [8], the Cambridge Risk Score [9], the Framingham diabetes mellitus risk score [10], the Australian Type

✉ C. Fu
fcw@fudan.edu.cn

¹ School of Public Health, Key Laboratory of Public Health Safety and Pudong Institute of Preventive Medicine, Fudan University, Shanghai 200032, China

² School of Epidemiology and Public Health, University of Ottawa, Ottawa, ON, Canada

³ Deqing County Center of Disease Prevention and Control, Huzhou, Zhejiang, China

2 Diabetes Risk Assessment Tool [11], and among others. However, there is a lack of RS models constructed based on incidence data for Chinese populations, especially for those living in rural areas. Most existing diabetes RS models work well only in targeted populations and the direct application of these models that were mainly derived from populations of European descent, could underestimate such a risk in the Chinese population [12, 13]. Based on data from the Rural Deqing Cohort Study [14], we aimed to develop a T2DM RS model for rural Chinese population to identify rural residents who are at high risk of developing T2DM.

Materials and methods

Study design and participants

During 2006–2014, 29,229 eligible residents aged ≥ 18 years randomly cluster sampled from eight rural communities including sixty-five villages in Deqing, Zhejiang province, China, participated in the baseline survey of the Rural Deqing Cohort Study with a response rate of 83.5%. Our inclusion criteria were local residents (1) who were currently living in the selected rural communities; (2) who were aged 18 years or more; (3) who agreed to participate in study and signed the informed consents; (4) who were able to complete survey questionnaire and physical examination; and (5) who had no plan to work or move out of Deqing County. Information on demography, lifestyle (smoking, alcohol use, regular physical exercise, diet, and tea consumption), and physical conditions was collected using a questionnaire. Anthropometry data including height, weight, waist, and blood pressure were measured and a total of 5 mL venous blood samples were collected after an overnight fast of at least 8 h to test fasting plasma glucose (FPG) and hemoglobin. The Institutional Review Board of the Fudan University School of Public Health approved the study and all participants gave a written informed consent.

In total, 28,251 participants who were free of diabetes at baseline were followed up and new cases of type 2 diabetes were ascertained from the Deqing electronic health records in November, 2015. No electronic health records were available for 1899 (6.7%). We also conducted a sub-cohort study of 3043 individuals who participated in the baseline survey in 2006–2008 and followed them up through questionnaire interview and free physical examination in 2015, and of them 1205 (39.6%) were lost to follow-up or refused to participate.

Definition

Body mass index (BMI) was calculated from weight/height² (kg/m²) and overweight was defined as BMI in the range from 25.0 to 29.9 kg/m² and obesity as BMI ≥ 30 kg/m². Family history (FH) was considered to be positive if one or more first-degree relatives had diabetes. Hypertension was defined as having systolic blood pressure ≥ 140 mmHg or diastolic blood pressure ≥ 90 mmHg or a history of hypertension medication. T2DM was diagnosed as having FPG ≥ 7.0 mmol/L alone or self-reported diagnosis of diabetes or use of anti-diabetic medications. IFG (impaired fasting glucose) was defined as FPG range from 6.1 to 6.9 mmol/L.

Development and comparison of risk score models

Cox proportional hazards model was used to identify the predictors, and of 13 variables that were initially examined, only age, BMI, FH, diet preference, hypertension, and FPG were significantly associated to the incidence of T2DM and were given a score for each based on their β -coefficients from the Cox model (1 if $\beta = 0.01$ – 0.20 ; 2 if $\beta = 0.21$ – 0.80 ; 3 if $\beta = 0.81$ – 1.20 ; 4 if $\beta = 1.21$ – 2.20 ; and 5 if $\beta > 2.20$ [8]). The lowest category of each variable was given a score of zero. We constructed two practical risk score models based on the data from the total cohort and the sub-cohort: non-invasive and plus-FPG models. The non-invasive model included age, FH, diet preference, overweight/obesity, and hypertension, and FPG was added to the plus-FPG model. Meanwhile, we compared the performance of existing models derived from other populations, including the Finnish Risk Score, the Cambridge Risk Score, the Framingham Diabetes Mellitus Risk Score, and the Australian Type 2 Diabetes Risk Assessment Tool.

Data analysis

Data were double entered with Epidata 3.1 and statistical analysis was performed in SAS 9.2 (SAS Institute Inc. Cary, N.C.) and R3.3.2. Chi-square or Fisher test was used for categorical variables, and *t* test or ANOVA for continuous variables. Risk factors for T2DM were identified, and their crude hazard ratios (cHRs), adjusted hazard ratios (aHRs), and 95% confidence intervals (95% CIs) were estimated using Cox proportional hazards model. Receiver-operating characteristic (ROC) curves were plotted for RS and the area under curve (AUC) was estimated for the prediction models. In addition, bootstrapping was used to calculate C-statistics, bias-corrected C-statistics, sensitivity, specificity, and their 95% CIs based on 1000 replications. Hosmer–Lemeshow test was employed to test the

goodness-of-fit for the models. All statistical tests were two-sided with a type I error of 0.05, and *p* values <0.05 were considered statistically significant.

Results

By 2015, totally 387 new T2DM cases were identified through the electronic health record system for the whole cohort, with an average 4.2 years of follow-up. The incidence of T2DM was estimated to be 3.3/1000 person-years. In the sub-cohort study with an average 8.7 years of follow-up, 191 new cases were diagnosed and the incidence was 7.7/1000 person-years.

The whole cohort included 12,510 (44.3%) men and 15,741 (55.7%) women. Men were older and were more likely to be a smoker, an alcohol user, or a regular exerciser, while women received higher education, ate more vegetable and fruit, and were more likely to have hypertension and IFG (Table 1).

In the Cox model, increased incidence of T2DM was significantly associated with 40 years of age or above (aHR 5.84, 95% CI 2.84–12.01, 4 points), overweight (aHR 2.15, 95% CI 1.70–2.72, 2 points) or obesity (aHR 4.92, 95% CI 3.11–7.79, 4 points), FH of T2DM (aHR 2.78, 95%

CI 1.51–5.14, 3 points), diet preference (aHR 2.41, 95% CI 1.87–3.11, 3 points), hypertension (aHR 2.00, 95% CI 1.59–2.51, 2 points), and IFG (aHR 4.93, 95% CI 3.86–6.28, 4 points) at baseline (Table 2).

In the non-invasive model, the RSs ranged from 0 to 20 and the optimal cut-off point for incident T2DM was 6. Of 28,251 participants, 11,297 (40.2%) had a score of ≥6, and of them 273 developed T2DM during the follow-up, accounting for 70.5% of all T2DM cases. The AUC of the model was 0.705, the sensitivity and specificity were 70.4 and 60.4%, the positive predictive value (PPV) and the negative predictive value (NPV) were 2.5 and 99.3%, and the positive likelihood ratio (+LR) and the negative likelihood ratio (–LR) were 1.78 and 0.49, respectively. In the plus-FPG model, the RSs ranged from 0 to 22 and the optimal cut-off point was 7. Totally 6954 (24.6%) subjects had a score of ≥7 and 244 of them developed T2DM during the follow-up, accounting for 63.0% of all T2DM cases. We also calculated C-statistic, and found that discrimination capacity of the model was improved after considering time effect. The AUC, C-statistic, sensitivity, and specificity are shown in Table 3 and Fig. 1.

Based on data from the sub-cohort population, the AUC and C-statistic were 0.638 and 0.662 for the non-invasive model, and at the cut-off point of 6, the sensitivity and

Table 1 Baseline characteristic of whole cohort

Characteristic	Male	Female	χ^2, P
<i>N</i>	12,510 (44.3)	15,741 (55.7)	
Age (years)	57.4 ± 14.7	56.6 ± 14.4	4.52, <0.001
BMI (kg/m ²)	22.5 ± 2.9	22.6 ± 3.0	1.79, 0.071
Famer (%)	8689 (69.6)	11,978 (76.1)	150.47, <0.001
Junior High School education (%)	9232 (74.7)	12,994 (83.4)	317.51, <0.001
Household income			
Low	1852 (14.8)	2256 (14.3)	1.44, 0.487
Median	9655 (77.3)	12,253 (77.8)	
High	980 (7.8)	1232 (7.8)	
Smoker (%)	6112 (48.9)	307 (2.0)	8751.89, <0.001
Alcohol use (%)	4589 (36.8)	692 (4.4)	4792.76, <0.001
Regular exercise (%)	1168 (10.5)	1336 (9.5)	6.10, 0.014
Vegetable consumption (%)	11,121 (90.6)	14,313 (92.6)	38.23, <0.001
Fruit consumption (%)	8265 (68.2)	11,054 (72.4)	57.33, <0.001
Diet			
Vegetable mainly	1692 (13.6)	2134 (13.6)	1.62, 0.446
Meat mainly	1557 (12.5)	1885 (12.0)	
Equally	9238 (74)	11,722 (74.5)	
Family History of T2DM (%)	149 (1.2)	249 (1.6)	7.56, 0.006
Hypertension (%)	2301 (18.4)	3120 (19.8)	8.72, 0.003
IFG	1153 (9.2)	1692 (10.7)	17.65, <0.001

Descriptive statistics were mean ± standard for continuous variable and relative frequencies for categorical variables and analyzed using Student’s *t* test for continuous variable (age and BMI) and Chi-square test for the categorical variables

Table 2 Risk score based on β -coefficient of Cox regression analysis in whole cohort

Predictors	Cox regression			Risk score
	β -Coefficient	aHR (95% CI)	P value	
Age (years)				
<40	–	–	–	0
40–	1.8	5.84 (2.84, 12.01)	<0.001	4
BMI (kg/m ²)				
<25	–	–	–	0
25–	0.8	2.15 (1.70, 2.72)	<0.001	2
30–	1.6	4.92 (3.11, 7.79)	<0.001	4
Family history of T2DM				
No	–	–	–	0
Yes	1.0	2.78 (1.51, 5.14)	<0.001	3
Diet				
Vegetable mainly	–0.3	0.78 (0.55, 1.11)	0.164	–1
Meat mainly	0.9	2.41 (1.87, 3.11)	<0.001	3
Equally	–	–	–	0
Hypertension				
No	–	–	–	0
Yes	0.7	2.00 (1.59, 2.51)	<0.001	2
IFG				
No	–	–	–	0
Yes	1.6	4.93 (3.86, 6.28)	<0.001	4

Predictors were selected by multiple Cox regression analysis using age groups, sex, education, occupation, household income, body mass index categories, smoking, alcohol use, regular exercise, diet, tea consumption, hypertension, and impaired fasting glucose

specificity were 53.4 and 67.3%, for the plus-FPG model the AUC, C-statistic, sensitivity, and specificity were 0.667, 0.707, 59.2, and 65.7%, respectively.

We made a comparison between our RS and 12 existing classic RSs (Table 3). Generally, our RS model provided satisfactory results relative to the existing RS models in terms of AUC, C-statistic, sensitivity, and specificity.

Discussion

The diabetes risk score method is a cost-effective tool to identify individuals who are at high risk for T2DM in areas with limited resources such as rural China [1, 15]. Several

diabetes risk scores have been reported for Chinese population, but few were created for rural population or based on prospective cohort data [16–22]. We developed the current diabetes risk score using data from a longitudinal cohort study of rural population [14], and to our knowledge, is the first one for rural Chinese adults based on large prospective cohort data. In the current study, we developed two practical risk score models, namely non-invasive and plus-FPG models, for rural Chinese adults. The discrimination capability was better for the plus-FPG model compared with the non-invasive model. However, because of the nature of convenience, non-invasiveness, and low cost, the latter is more practical, especially in primary public health settings [23, 24]. Both risk score models showed some discrepancies when different sources of data were used. The optimal risk score was 1-point lower for the sub-cohort population compared with the whole cohort population, and similar differences were reported in previous studies [25].

Several risk scores for T2DM incidence have been developed in both Caucasian populations and Asian populations [8–11, 23, 24, 26–31], and the most common predictors in these models were age, family history of diabetes, obesity, hypertension, and impaired fasting glucose, and our study showed similar results. Although we found that sex, physical activity, smoking, and alcohol use were also significantly associated with incident T2DM, AUC showed no significant improvement, and therefore, our final models did not include these factors.

Although various risk score models included similar risk factors, the discriminative capability was better for those of Caucasian populations [8–11] (AUC 0.78–0.86) than those of Asian populations [23, 24, 29] including ours (AUC 0.67–0.77). Compared to Caucasians, Asians are more susceptible to the development of T2DM [32] and have lower levels of insulin secretion [33].

We compared the performance of several existing risk scores for our study population and found that the AUCs were in the range from 0.56 to 0.73 and C-statistic was in the range from 0.64 to 0.75, which were substantially lower than those from the original study populations. Some existing risk score models showed a higher C-statistic than our study, but not their sensitivity or/and specificity. We used bootstrapping method to validate the performance measures. The bias-corrected C-statistics were similar, and the 95% CIs for the sensitivity and specificity were narrower. For our study population, our risk score models clearly demonstrated a better performance as compared with other existing models developed based on data from non-Chinese populations, suggesting that diabetes risk score models should be designed and developed for specific target populations.

In our non-invasive risk score model, we used predictors that are easily measured and the data can be collected

Table 3 Performance of existing risk score model in whole cohort and sub-cohort

Risk score model	Risk factors in the model				Optimal cut-off in original study	Whole cohort				Sub-cohort					
	AUC in original study	AUC	C-statistic	Hosmer–Lemeshow P value		AUC	C-statistic	Sensitivity	Specificity	AUC	C-statistic	Sensitivity	Specificity		
The Deqing risk score model	0.705	0.705	0.723 (0.694, 0.752) (0.723) ^a	0.867	6	0.705	0.723 (0.694, 0.752) (0.723) ^a	0.867	0.705 (0.656, 0.747)	0.604 (0.599, 0.610)	0.638 (0.618, 0.705) (0.662) ^a	0.662 (0.618, 0.705) (0.662) ^a	0.426	0.534 (0.461, 0.602)	0.672 (0.655, 0.691)
Plus-fasting plasma glucose model: age, BMI, family history of T2DM, diet, hypertension	0.754	0.754	0.769 (0.739, 0.798) (0.769) ^a	0.429	7	0.754	0.769 (0.739, 0.798) (0.769) ^a	0.429	0.631 (0.584, 0.677)	0.759 (0.754, 0.764)	0.667 (0.663, 0.750) (0.707) ^a	0.707 (0.663, 0.750) (0.707) ^a	0.729	0.592 (0.518, 0.655)	0.657 (0.640, 0.677)
USA Framing-ham diabetes mellitus risk score [10] ^A	0.852	0.709	0.739 (0.707, 0.771) (0.739) ^a	<0.001	-	0.709	0.739 (0.707, 0.771) (0.739) ^a	<0.001	0.604 (0.555, 0.655)	0.722 (0.716, 0.727)	0.647 (0.649, 0.738) (0.693) ^a	0.693 (0.649, 0.738) (0.693) ^a	0.044	0.685 (0.620, 0.754)	0.549 (0.531, 0.567)
UK Cambridge Risk Score [9] ^A	0.801	0.607	0.651 (0.621, 0.682) (0.652) ^a	0.074	35	0.607	0.651 (0.621, 0.682) (0.652) ^a	0.074	0.698 (0.651, 0.742)	0.445 (0.439, 0.450)	0.604 (0.584, 0.672) (0.628) ^a	0.628 (0.584, 0.672) (0.628) ^a	0.487	0.560 (0.487, 0.634)	0.591 (0.573, 0.608)
The Finland Diabetes Risk Score [8] ^A	0.857	0.681	0.743 (0.698, 0.788) (0.741) ^a	0.319	9	0.681	0.743 (0.698, 0.788) (0.741) ^a	0.319	0.540 (0.466, 0.609)	0.738 (0.730, 0.747)	0.65 (0.640, 0.741) (0.691) ^a	0.691 (0.640, 0.741) (0.691) ^a	0.056	0.497 (0.417, 0.583)	0.721 (0.701, 0.721)
Australian T2DM Risk Assessment Tool [11] ^A	0.783	0.666	0.726 (0.679, 0.773) (0.725) ^a	0.265	12	0.666	0.726 (0.679, 0.773) (0.725) ^a	0.265	0.568 (0.494, 0.642)	0.694 (0.685, 0.703)	0.622 (0.607, 0.716) (0.662) ^a	0.662 (0.607, 0.716) (0.662) ^a	0.182	0.714 (0.639, 0.790)	0.512 (0.491, 0.533)
Japanese diabetes risk score [23]	0.772	0.727	0.750 (0.706, 0.795) (0.751) ^a	0.654	16	0.727	0.750 (0.706, 0.795) (0.751) ^a	0.654	0.551 (0.477, 0.620)	0.815 (0.808, 0.822)	0.644 (0.636, 0.738) (0.686) ^a	0.687 (0.636, 0.738) (0.686) ^a	0.074	0.748 (0.676, 0.808)	0.483 (0.462, 0.504)

Table 3 continued

Risk score model	Risk factors in the model	AUC in original study	Optimal cut-off in original study	Whole cohort			Sub-cohort				
				AUC	C-statistic	Hosmer–Lemeshow P value	AUC	C-statistic	Hosmer–Lemeshow P value	Sensitivity	Specificity
Korean diabetes risk score [29]	Age, family history of T2DM, hypertension, waist, smoking, alcohol use	0.73	5	0.623	0.645	0.107	0.638	0.653	0.739	0.688	0.540 (0.520, 0.561)
				(0.603, 0.687)	(0.645) ^a	(0.464, 0.608)	(0.677, 0.694)	(0.604, 0.703)	(0.653) ^a	(0.612, 0.758)	
The Thailand diabetes risk score [24]	Age, gender, BMI, waist, hypertension, family history of T2DM	0.748	6	0.627	0.654	0.023	0.621	0.648	0.115	0.822	0.372 (0.352, 0.393)
				(0.613, 0.697)	(0.655) ^a	(0.433, 0.567)	(0.686, 0.703)	(0.598, 0.697)	(0.647) ^a	(0.758, 0.879)	
Diabetes risk score in Taiwan in Chinese [16] ^A	Age, gender, BMI, hypertension, family history of T2DM, WBC, triglyceride, HDL, FPG	0.702	10	0.711	0.737	0.004	0.629	0.666	0.63	0.546	0.665 (0.647, 0.685)
				(0.702, 0.772)	(0.736) ^a	(0.593, 0.645)	(0.752, 0.764)	(0.616, 0.717)	(0.668) ^a	(0.468, 0.630)	
Diabetes risk score in Hong Kong Chinese [22] ^A	Age, gender, BMI, hypertension, hyperlipidemia, family history of T2DM, GDM	0.735	16	0.628	0.692	<0.001	0.654	0.686	0.305	0.728	0.507 (0.488, 0.525)
				(0.661, 0.724)	(0.692) ^a	(0.912, 0.959)	(0.252, 0.258)	(0.642, 0.731)	(0.686) ^a	(0.665, 0.791)	
The Chinese Diabetes Risk Score [20]	Age, gender, BMI, waist, SBP, family history of T2DM	0.748	25	0.566	0.645	0.027	0.642	0.659	0.07	0.583	0.687 (0.668, 0.707)
				(0.601, 0.688)	(0.645) ^a	(0.753, 0.812)	(0.311, 0.328)	(0.608, 0.711)	(0.659) ^a	(0.503, 0.662)	
The Qingdao Diabetes Risk Score [22]	Man: age, family history of T2DM, waist	0.635	17	0.595	0.658	<0.001	0.629	0.664	0.286	0.758	0.450 (0.423, 0.480)
				(0.589, 0.728)	(0.659) ^a	(0.403, 0.625)	(0.674, 0.698)	(0.584, 0.745)	(0.667) ^a	(0.661, 0.855)	
The Diabetes Risk Score in rural Chinese [34]	Women: Age, family history of T2DM, waist	0.689	14	0.555	0.641	0.348	0.65	0.656	0.978	0.663	0.570 (0.543, 0.598)
				(0.587, 0.694)	(0.640) ^a	(0.713, 0.853)	(0.302, 0.325)	(0.593, 0.718)	(0.656) ^a	(0.568, 0.758)	
The Diabetes Risk Score in rural Chinese [34]	Age, BMI, family history of T2DM, family history of T2DM, duration of hypertension	0.763	–	0.627	0.674	0.097	0.646	0.679	0.122	0.669	0.571 (0.551, 0.593)
				(0.632, 0.717)	(0.675) ^a	(0.562, 0.706)	(0.545, 0.563)	(0.630, 0.729)	(0.678) ^a	(0.592, 0.739)	

^A Indicated predictors like HDL, triglyceride, waist, and use of steroids were not included because these variables were not available in whole and sub-cohort

^a 1000 bootstrap resampling

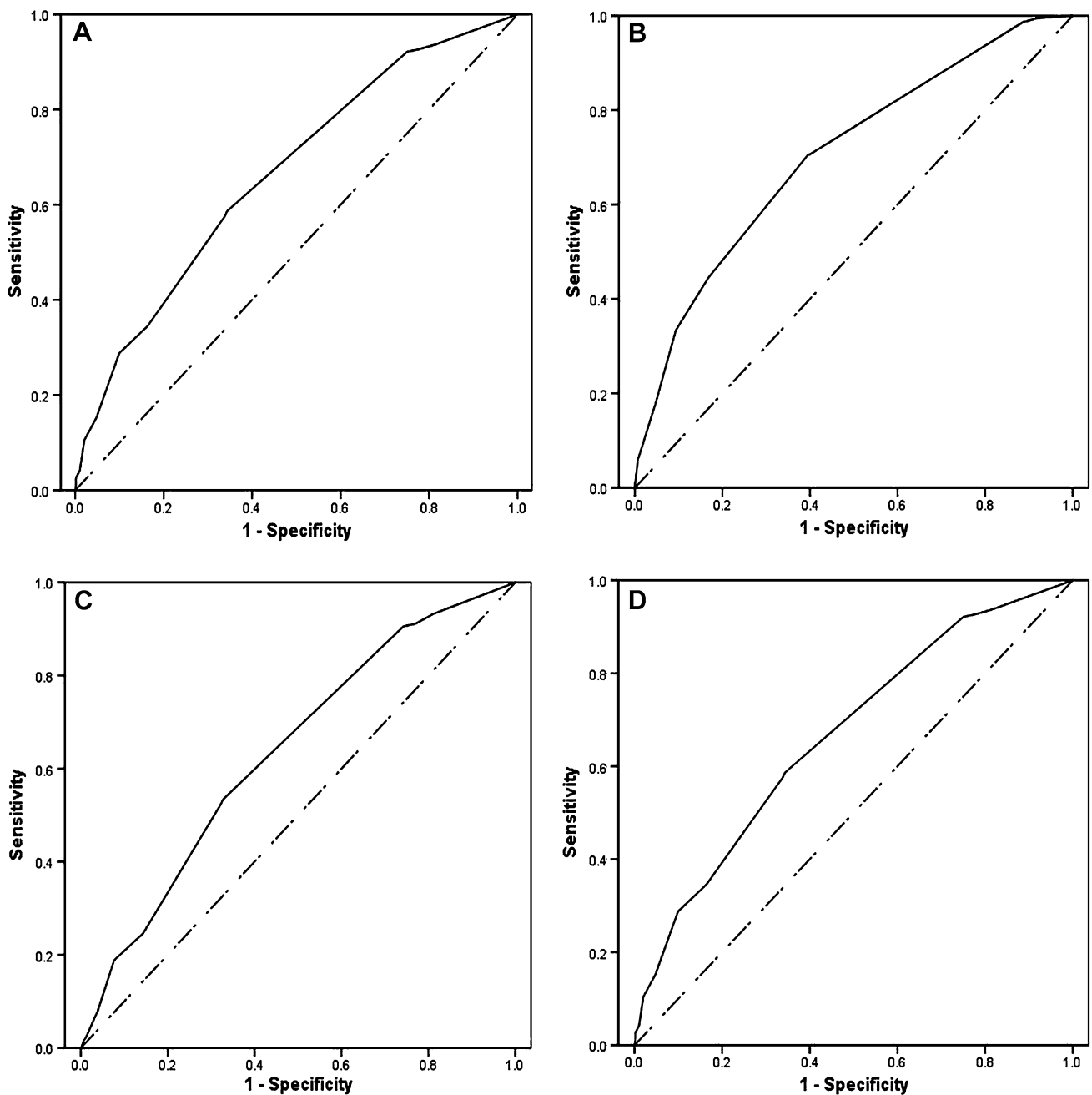


Fig. 1 ROC of the non-invasive model in whole cohort (a); ROC of the plus-fasting plasma glucose model in whole cohort (b); ROC of the non-invasive model in sub-cohort (c); ROC of the plus-fasting plasma glucose model in sub-cohort (d)

in general health care settings with integer point values of risk factors. A non-professional person can also estimate the risk for developing T2DM at home. One limitation was that the incident cases of T2DM were identified through local electronic health records system and there might be some underdiagnosis biases, indicated by the observations from the sub-cohort, which provided additional questionnaire and physical examination information. The local electronic health system currently only had information on annual

community physical examinations, but no electronic medical records from hospitals. People who were diagnosed with T2DM in a hospital but did not participate the annual community physical examination would not be caught in the local electronic health system. Meanwhile, a low attendance rate of physical examination also affects the completeness of the health information system. There is a cautious note about the models' external and internal validities. Although our study population had similar age and sex distributions

as compared to general Chinese rural population, Deqing County is one of top 100 well-developed counties in China. This model needs to be further tested in different rural settings of the country. In addition, nearly 40% of subjects from the sub-cohort were lost to follow-up, which could bias the internal validation of our models to some degree.

Conclusions

In conclusion, our risk score model could be used as a simple, fast, cost-effective tool to identify individuals who are at high risk of type 2 diabetes for rural Chinese adults. Individuals with high score values should be encouraged to take a screening test for type 2 diabetes and to have a healthier lifestyle. It is important to develop a diabetes prevention and control program targeting rural residents to reduce their risk of T2DM.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the Fudan University School of Public Health and the study was approved the Institutional Review Board of the Fudan University School of Public Health.

Informed consent Informed consent was obtained from all individual participants included in the study.

References

- International Diabetes Federation (2015) IDF Diabetes atlas, seventh edition. http://www.idf.org/sites/default/files/Atlas-poster-2015_EN.pdf. Accessed 1 Dec 2015
- Chinese Diabetes Society (2014) China guideline for type 2 diabetes. *Chin J Diabetes* 22(8):2–42
- Zuo H, Shi Z, Hussain A (2014) Prevalence, trends and risk factors for the diabetes epidemic in China: a systematic review and meta-analysis. *Diabetes Res Clin Pract* 104(1):63–72. doi:10.1016/j.diabres.2014.01.002
- Xu Y, Wang L, He J, Bi Y, Li M, Wang T, Wang L, Jiang Y, Dai M, Lu J, Xu M, Li Y, Hu N, Li J, Mi S, Chen CS, Li G, Mu Y, Zhao J, Kong L, Chen J, Lai S, Wang W, Zhao W, Ning G, 2010 China Noncommunicable Disease Surveillance Group (2013) Prevalence and control of diabetes in Chinese adults. *JAMA* 310(9):948–959. doi:10.1001/jama.2013.168118
- Turner RC, Cull CA, Frighi V, Holman RR (1999) Glycemic control with diet, sulfonylurea, metformin, or insulin in patients with type 2 diabetes mellitus: progressive requirement for multiple therapies (UKPDS 49). UK Prospective Diabetes Study (UKPDS) Group. *JAMA* 281(21):2005–2012
- Gong Q, Gregg EW, Wang J, An Y, Zhang P, Yang W, Li H, Li H, Jiang Y, Shuai Y, Zhang B, Zhang J, Gerzoff RB, Roglic G, Hu Y, Li G, Bennett PH (2011) Long-term effects of a randomised trial of a 6-year lifestyle intervention in impaired glucose tolerance on diabetes-related microvascular complications: the China Da Qing Diabetes Prevention Outcome Study. *Diabetologia* 54(2):300–307. doi:10.1007/s00125-010-1948-9
- Baan CA, Ruige JB, Stolk RP, Witteman JC, Dekker JM, Heine RJ, Feskens EJ (1999) Performance of a predictive model to identify undiagnosed diabetes in a health care setting. *Diabetes Care* 22(2):213–219
- Lindstrom J, Tuomilehto J (2003) The diabetes risk score: a practical tool to predict type 2 diabetes risk. *Diabetes Care* 26(3):725–731
- Park PJ, Griffin SJ, Sargeant L, Wareham NJ (2002) The performance of a risk score in predicting undiagnosed hyperglycemia. *Diabetes Care* 25(6):984–988
- Wilson PW, Meigs JB, Sullivan L, Fox CS, Nathan DM, D'Agostino RB Sr (2007) Prediction of incident diabetes mellitus in middle-aged adults: the Framingham Offspring Study. *Arch Intern Med* 167(10):1068–1074
- Chen L, Magliano DJ, Balkau B, Colagiuri S, Zimmet PZ, Tonkin AM, Mitchell P, Phillips PJ, Shaw JE (2010) AUSDRISK: an Australian Type 2 Diabetes Risk Assessment Tool based on demographic, lifestyle and simple anthropometric measures. *Med J Aust* 192(4):197–202
- Jiang H, Xu H, Xiao S, Li G (2012) Performance of 3 diabetes screening questionnaires for a rural sample in China. *Zhong Nan Da Xue Xue Bao Yi Xue Ban* 37(11):1108–1111. doi:10.3969/j.issn.1672-7347.2012.11.005
- Xu L, Jiang CQ, Schooling CM, Zhang WS, Cheng KK, Lan TH (2014) Prediction of 4-year incident diabetes in older Chinese: recalibration of the Framingham diabetes score on Guangzhou Biobank Cohort Study. *Prev Med* 69:63–68. doi:10.1016/j.ypmed.2014.09.004
- Fu CW, Chen Y, Wang F, Wang XC, Wang WB, Zhao GM, Jiang QW (2012) Chronic diseases in adults living in rural communities of China. World Congress on Public Health World Health Organization
- Herman WH, Smith PJ, Thompson TJ, Engelgau MM, Aubert RE (1995) A new and simple questionnaire to identify people at increased risk for undiagnosed diabetes. *Diabetes Care* 18(3):382–387
- Chien K, Cai T, Hsu H, Su T, Chang W, Chen M, Lee Y, Hu FB (2009) A prediction model for type 2 diabetes risk among Chinese people. *Diabetologia* 52(3):443–450. doi:10.1007/s00125-008-1232-4
- Liu M, Pan C, Jin M (2011) A Chinese diabetes risk score for screening of undiagnosed diabetes and abnormal glucose tolerance. *Diabetes Technol Ther* 13(5):501–507. doi:10.1089/dia.2010.0106
- Ye X, Zong G, Liu X, Liu G, Gan W, Zhu J, Lu L, Sun L, Li H, Hu FB, Lin X (2014) Development of a new risk score for incident type 2 diabetes using updated diagnostic criteria in middle-aged and older Chinese. *PLoS One* 9(5):e97042. doi:10.1371/journal.pone.0097042
- Luo S, Han L, Zeng P, Chen F, Pan L, Wang S, Zhang T (2014) A risk assessment model for type 2 diabetes in Chinese. *PLoS One* 9(8):e104046. doi:10.1371/journal.pone.0104046

20. Zhou X, Qiao Q, Ji L, Ning F, Yang W, Weng J, Shan Z, Tian H, Ji Q, Lin L, Li Q, Xiao J, Gao W, Pang Z, Sun J (2013) Non-laboratory-based risk assessment algorithm for undiagnosed type 2 diabetes developed on a nation-wide diabetes survey. *Diabetes Care* 36(12):3944–3952. doi:[10.2337/dc13-0593](https://doi.org/10.2337/dc13-0593)
21. Gao WG, Dong YH, Pang ZC, Nan HR, Wang SJ, Ren J, Zhang L, Tuomilehto J, Qiao Q (2010) A simple Chinese risk score for undiagnosed diabetes. *Diabet Med* 27(3):274–281. doi:[10.1111/j.1464-5491.2010.02943.x](https://doi.org/10.1111/j.1464-5491.2010.02943.x)
22. Ko G, So W, Tong P, Ma R, Kong A, Ozaki R, Chow C, Cockram C, Chan J (2010) A simple risk score to identify Southern Chinese at high risk for diabetes. *Diabet Med* 27(6):644–649. doi:[10.1111/j.1464-5491.2010.02993.x](https://doi.org/10.1111/j.1464-5491.2010.02993.x)
23. Doi Y, Ninomiya T, Hata J, Hirakawa Y, Mukai N, Iwase M, Kiyohara Y (2012) Two risk score models for predicting incident type 2 diabetes in Japan. *Diabet Med* 29(1):107–114. doi:[10.1111/j.1464-5491.2011.03376.x](https://doi.org/10.1111/j.1464-5491.2011.03376.x)
24. Aekplakorn W, Bunnag P, Woodward M, Sritara P, Cheepudomwit S, Yamwong S, Yipintsoi T, Rajatanavin R (2006) A risk score for predicting incident diabetes in the Thai population. *Diabetes Care* 29(8):1872–1877
25. Glumer C, Vistisen D, Borch-Johnsen K, Colagiuri S, DETECT-2 Collaboration (2006) Risk scores for type 2 diabetes can be applied in some populations but not all. *Diabetes Care* 29(2):410–414
26. Schmidt MI, Duncan BB, Bang H, Pankow JS, Ballantyne CM, Golden SH, Folsom AR, Chambless LE, Atherosclerosis Risk in Communities Investigators (2005) Identifying individuals at high risk for diabetes: The Atherosclerosis Risk in Communities study. *Diabetes Care* 28(8):2013–2018
27. Nelson KM, Boyko EJ, Third National Health Nutrition Examination Survey (2003) Predicting impaired glucose tolerance using common clinical information: data from the Third National Health and Nutrition Examination Survey. *Diabetes Care* 26(7):2058–2062
28. Schulze MB, Hoffmann K, Boeing H, Linseisen J, Rohrmann S, Möhlig M, Pfeiffer AF, Spranger J, Thamer C, Häring HU, Fritsche A, Joost HG (2007) An accurate risk score based on anthropometric, dietary, and lifestyle factors to predict the development of type 2 diabetes. *Diabetes Care* 30(3):510–515
29. Lee YH, Bang H, Kim HC, Kim HM, Park SW, Kim DJ (2012) A simple screening score for diabetes for the Korean population: development, validation, and comparison with other scores. *Diabetes Care* 35(8):1723–1730. doi:[10.2337/dc11-2347](https://doi.org/10.2337/dc11-2347)
30. Mohan V, Deepa R, Deepa M, Somannavar S, Datta M (2005) A simplified Indian Diabetes Risk Score for screening for undiagnosed diabetic subjects. *J Assoc Physicians India* 53:759–763
31. Al-Lawati JA, Tuomilehto J (2007) Diabetes risk score in Oman: a tool to identify prevalent type 2 diabetes among Arabs of the Middle East. *Diabetes Res Clin Pract* 77(3):438–444
32. Shai I, Jiang R, Manson JE, Stanfer MJ, Willett WC, Colditz GA, Hu FB (2006) Ethnicity, obesity, and risk of type 2 diabetes in women: a 20-year follow-up study. *Diabetes Care* 29(7):1585–1590
33. Khoo CM, Sairazi S, Taslim S, Gardner D, Wu Y, Lee J, van Dam RM, Shyong Tai E (2011) Ethnicity modifies the relationships of insulin resistance, inflammation, and adiponectin with obesity in a multiethnic Asian population. *Diabetes Care* 34(5):1120–1126. doi:[10.2337/dc10-2097](https://doi.org/10.2337/dc10-2097)
34. Xin Z, Yuan J, Hua L, Ma YH, Zhao L, Lu Y, Yang JK (2010) A simple tool detected diabetes and prediabetes in rural Chinese. *J Clin Epidemiol* 63(9):1030–1035. doi:[10.1016/j.jclinepi.2009.11.012](https://doi.org/10.1016/j.jclinepi.2009.11.012)