Cross-Sectional Validation of Diabetes Risk Scores for Predicting Diabetes, Metabolic Syndrome, and Chronic Kidney Disease in Taiwanese

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OBJECTIVE — To validate the performance of current diabetes risk scores (DRSs) based on simple clinical information in detecting type 2 diabetes, metabolic syndrome (MetSyn), and chronic kidney disease (CKD).

RESEARCH DESIGN AND METHODS — The performance of 10 DRSs was evaluated in a cross-sectional population screening of 2,759 Taiwanese subjects.

RESULTS — All DRSs significantly correlated with measures of insulin resistance, estimated glomerular filtration rate, and urine albumin excretion. The prevalence of screening-detected diabetes (SDM), MetSyn, and CKD increased with higher DRSs. For prediction of SDM, the Cambridge DRS by Griffin et al. and the Finnish DRS outperformed other DRSs in terms of discriminative power and model fit. For prediction of MetSyn and CKD, the Atherosclerosis Risk in Community Study score by Schmidt et al. outperformed other DRSs.

CONCLUSIONS — Risk scores based on simple clinical information are useful to identify individuals at high risk for diabetes, MetSyn, and CKD in different ethnic populations.

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The use of fasting or postchallenge plasma glucose concentrations has been proposed for the early identification of type 2 diabetes. However, both tests are costly and time-consuming. Therefore, a simple diabetes risk score (DRS) that does not require any laboratory test is needed to identify individuals at high risk. This study aimed to systematically evaluate the performance of current DRSs based on simple clinical information in identifying diabetes in a cross-sectional population screening in Taiwanese. The feasibility of these scores in identifying individuals at high risk for metabolic syndrome (MetSyn) and chronic kidney disease (CKD), two conditions closely related to type 2 diabetes, were also evaluated.

RESEARCH DESIGN AND METHODS

From 8 June 2005 to 22 November 2008, 2,759 participants undergoing community-based screening for type 2 diabetes in the Yun-Lin area in Taiwan were recruited. The exclusion criteria were age <18 years, pregnant women, previously diagnosed diabetes, or previously diagnosed renal disease. Measures of insulin resistance and β-cell function were determined using the homeostasis model assessment (HOMA)-2 with the use of a HOMA calculator (www.dtu.ox.ac.uk). The glomerular filtration rate (GFR) was estimated by the Modification of Diet in Renal Disease (MDRD) Study equation (1). Urine albumin excretion was calculated using a random urine albumin-to-creatinine ratio. Type 2 diabetes was diagnosed by a fasting plasma glucose concentration >126 mg/dl. MetSyn was defined according to the National Cholesterol Education Program Third Adult Treatment Panel guideline with modification for Asian populations (2). CKD was defined as MDRD GFR <60 ml/min per 1.73 m^2 (1). The cutoff values for BMI (24 and 27 kg/m^2) and waist circumference (90 cm for men; 80 cm for women) were modified according to the definition of obesity for Taiwanese and the modified waist circumference criteria for Asians (2). Ten currently available DRSs, including the Atherosclerosis Risk in Community (ARIC) Study, Asian Indian, Cambridge (U.K.), Danish, DESIR (Data from the Epidemiological Study on Insulin Resistance Syndrome) (French), Dutch, FINDRISC (Finnish diabetes risk score), Oman, QDScore (U.K.), and Thai risk scores, were analyzed (3–12). The institutional review board approved this study, and informed consent was obtained from each participant. The area under the receiver operating characteristic (ROC) curves was used to assess the discriminative power of DRSs. Model fitness was assessed by the Hosmer-Lemeshow test, and the DeLong method was used to compare areas under the ROC curves.

RESULTS

All DRSs correlated significantly with components of MetSyn, HOMA2–insulin resistance, high-sensitive C-reactive protein, and uric acid levels, all of which were markers of insulin resistance (supplementary Table S1, found in an online appendix at http://care.diabetesjournals.org/cgi/content/full/dc09-0694/DC1). However, HOMA2-β, a measure of insulin secretion, did not

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Table 1—*The predictive performance of 10 diabetes risk scores for screening-detected diabetes, metabolic syndrome, and CKD*

Model	ROC area (95% CI)	H-L *P* value	Sensitivity	Specificity	Correctly classified	LR^+	LR^-	Youden index	Number of predictors
Screening-detected diabetes									
ARIC (U.S.)	0.74 (0.70–0.77)	0.01	0.68	0.70	0.69	2.23	0.46	0.39	6
QDScore (U.K.)	0.74 (0.70–0.77)	<0.0001	0.73	0.63	0.64	1.99	0.42	0.38	9
Cambridge (U.K.)	0.73 (0.69–0.76)	0.23	0.64	0.67	0.67	1.95	0.54	0.31	7
FINDRISC (Finnish)	0.73 (0.69–0.77)	0.78	0.67	0.67	0.67	2.01	0.49	0.34	8
Oman	0.72 (0.69–0.75)	0.08	0.65	0.67	0.67	1.99	0.52	0.32	5
Danish	0.72 (0.68–0.76)	0.07	0.63	0.70	0.69	2.08	0.58	0.33	6
Thai	0.71 (0.67–0.74)	0.04	0.71	0.62	0.62	1.87	0.47	0.33	6
Asian Indian	0.70 (0.66–0.74)	0.0005	0.63	0.69	0.68	2.01	0.54	0.32	5
Dutch	0.69 (0.64–0.73)	0.016	0.61	0.70	0.70	2.03	0.56	0.31	4
DESIR (French)	0.67 (0.64–0.71)	0.009	0.55	0.70	0.69	1.82	0.64	0.28	4
Metabolic syndrome									
DESIR (French)	0.82 (0.81–0.84)	0.002	0.70	0.83	0.79	4.06	0.37	0.53	4
Thai	0.82 (0.81–0.84)	<0.0001	0.77	0.75	0.75	3.03	0.30	0.52	6
ARIC (U.S.)	0.81 (0.79–0.83)	0.62	0.74	0.73	0.73	2.72	0.35	0.47	6
Cambridge (U.K.)	0.80 (0.79–0.82)	<0.0001	0.77	0.69	0.71	2.48	0.33	0.47	7
Asian Indian	0.78 (0.76–0.80)	<0.0001	0.71	0.73	0.72	2.66	0.40	0.45	5
FINDRISC (Finnish)	0.77 (0.75–0.79)	<0.0001	0.71	0.67	0.68	2.12	0.43	0.40	8
QDScore (U.K.)	0.77 (0.75–0.79)	<0.0001	0.73	0.68	0.69	2.26	0.39	0.41	9
Danish	0.77 (0.76–0.79)	0.002	0.79	0.62	0.66	2.08	0.37	0.41	6
Dutch	0.73 (0.71–0.75)	<0.0001	0.57	0.77	0.71	2.46	0.55	0.33	4
Oman	0.73 (0.71–0.74)	<0.0001	0.76	0.62	0.66	2.02	0.39	0.41	5
CKD									
ARIC (U.S.)	0.71 (0.68–0.73)	0.46	0.64	0.68	0.67	1.97	0.53	0.31	6
Cambridge (U.K.)	0.68 (0.66–0.70)	0.002	0.69	0.55	0.58	1.54	0.56	0.25	7
QDScore (U.K.)	0.68 (0.65–0.70)	<0.0001	0.64	0.61	0.61	1.64	0.59	0.28	9
Danish	0.67 (0.65–0.69)	<0.0001	0.62	0.63	0.63	1.63	0.63	0.27	6
Dutch	0.66 (0.64–0.69)	<0.0001	0.59	0.74	0.72	2.27	0.55	0.33	4
Oman	0.66 (0.64–0.69)	<0.0001	0.58	0.65	0.63	1.64	0.65	0.22	5
Asian Indian	0.65 (0.62–0.67)	<0.0001	0.63	0.59	0.60	1.53	0.63	0.24	5
FINDRISC (Finnish)	0.62 (0.59–0.64)	0.006	0.68	0.49	0.52	1.32	0.66	0.17	8
Thai	0.61 (0.58–0.63)	<0.0001	0.56	0.59	0.59	1.38	0.74	0.16	6
DESIR (French)	0.60 (0.58–0.63)	0.01	0.77	0.40	0.47	1.28	0.58	0.17	4

The optimal cutoff value was defined as the one with the least $(1 - \text{sensitivity})^2 + (1 - \text{specificity})^2$. Youden index was defined as the maximum of (sensitivity + specificity − 1). H-L, Hosmer-Lemeshow goodness-of-fit test; LR^+, positive likelihood ratio; LR^-, negative likelihood ratio.

strongly correlate with DRSs (supplementary Table S1). All DRSs were associated with reduced MDRD GFR and with increased urine albumin excretion (supplementary Table S1). The prevalence of screening-detected diabetes (SDM), MetSyn, and CKD increased significantly with increasing DRSs (all *P* for trend <0.0001, supplementary Figs. S1–S3).

The predictive performance of 10 DRSs for SDM, MetSyn, and CKD are summarized in Table 1. The best area under the ROC for SDM was 0.74 (95% CI 0.70–0.77, Table 1), with 68% sensitivity and 70% specificity using optimal cutoff values. There were no statistical differences in the area under the ROC for SDM among ARIC, QDScore, Cambridge, FINDRISC, Oman, Danish, and Thai scores. However, the Cambridge risk score and the FINDRISC outperformed the other DRSs in model fit. Using stepwise logistic regression, we identified age, waist circumference, medication for hypertension, and family history of diabetes as independent predictors for SDM. The area under ROC of the logistic regression model based on these predictors was 0.75 (95% CI 0.71–0.78) for SDM, similar to those of DRSs.

The best area under the ROC for MetSyn was 0.82 (95% CI 0.81–0.84, Table 1) with 70% sensitivity and 83% specificity. There were no statistical differences in the areas under the ROC among the DESIR, Thai, and ARIC scores for MetSyn. However, the ARIC score outperformed other DRSs in model fit.

The best area under the ROC curves for CKD was 0.71 (95% CI 0.68–0.73) (supplementary Fig. S2). The sensitivity was 64% and specificity 68% to detect CKD. The ARIC score outperformed other DRSs in discriminative performance for CKD and model fit.

CONCLUSIONS

This study validated the predictive performance of currently available DRSs based on simple clinical information for type 2 diabetes in a cross-sectional screening program in Taiwan. The predictive performance of these DRSs among Taiwanese was comparable to those in other European populations (13). These data indicate that DRSs based on simple clinical information without laboratory test are

also applicable for cross-sectional screening across different ethnic populations. All DRSs strongly correlate with markers of insulin resistance and are strong predictors for MetSyn. Therefore, DRSs are actually predictors of insulin resistance, which in turn predicts type 2 diabetes.

Another key finding of this study was that all DRSs correlated with GFR and urine albumin excretion and are fair predictors of CKD. Although a great deal of effort has been exerted to develop a renal risk score to identify individuals at high risk of CKD, there is currently no simple and widely established renal risk score (14). Most proposed scoring models use serum creatinine and urine protein as the main predictors, which are often not available in large-scale population screening (14). Although the predictive performance of DRSs cannot surpass current renal risk models, the results here demonstrate the potential feasibility of developing a simple renal risk score to select high-risk individuals for further laboratory screening.

This study has some limitations. First, an oral glucose tolerance test was not performed and 2-h glucose concentration was not included in the definition of diabetes. Second, other DRSs including the American Diabetes Association risk tool, the Second National Health and Nutrition Survey questionnaire by Herman et al., the German risk score by Shulze et al., and the new ARIC risk scores by Kahn et al. were not included in the analyses because of the lack of delivery history, gestational diabetes history, detailed dietary information, and ethnic-specific cutoff values for weight and height (15–17).

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