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Comparison of screening scores for diabetes and prediabetes

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ABSTRACT

Aims: There are numerous risk or screening scores for the prediction of type-2 diabetes mellitus (DM). In contrast, few scores are available for preDM. In this paper, we compare the two screening scores from the American Diabetes Association (ADA) and Centers for Disease Control and Prevention (CDC) that can be used for DM as well as preDM.

Methods: Adult participants ($N = 9391$) without known DM from the National Health and Nutrition Examination Surveys 2009–12 were included. We fitted the factors/items in the ADA and CDC scores in logistic regression with the outcomes of undiagnosed DM, preDM, and combination, and assessed the association and discrimination accuracy. We also evaluated the suggested cutpoints that define high risk individuals. We mimicked the original models/settings but also tested various deviations/modifications often encountered in practice.

Results: Both scores performed well and robustly, while the ADA score performed somewhat better (e.g., AUC = 0.77 for ADA and 0.73–0.74 for CDC for DM; 0.72–0.74 and 0.70–0.71 for preDM). The same predictors and scoring rules seem to be reasonably justified with different cutpoints for DM and preDM, which can make usage easier and consistent. Some factors such as race and HDL/LDL cholesterols may be useful additions to health education.

Conclusions: Current DM education and screening focus on the prevention and management of DM. The ADA and CDC scores could further help when we identify individuals at high risk for preDM, and teach the importance of preDM during which lifestyle intervention can be effective and urgently needed.

1. Introduction

There are a number of prediction or screening scores/models for incident and prevalent type-2-diabetes-mellitus (DM) worldwide (http://www.idf.org/epidemiology/risk-prediction). Some are actively being utilized in clinical and community settings or for research purposes, say, for self-assessment, health education and patient-doctor communication/shared decision making. In contrast, there are few screening scores for preDM, and some may question whether we need scores

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for preDM, different from those for DM. To our knowledge, the two scores from the Centers for Disease Control and Prevention (CDC) and the American Diabetes Association (ADA) that have been developed to help screening DM as well as preDM are relatively well known and easy to use (say, in the pencil-and-paper questionnaire): namely, the 'CDC prediabetes screening test', http://www.cdc.gov/diabetes/prevention/pdf/prediabetestest.pdf and the 'ADA diabetes risk test', http://www.diabetes.org/are-you-at-risk/diabetes-risk-test/. The original models for these scores were developed for the outcome of undiagnosed DM from the National Health and Nutrition Examination Survey (NHANES) 2004 or earlier, by statistical modeling [1,2].

Specifically, the ADA score consists of 7 questions (total score of 0–11) on age, sex, gestational DM, family history of DM, hypertension, physical activity, and obesity (based on body mass index (BMI) via a weight-height chart). The CDC score consists of 7 questions on 6 factors (total score of 0–18) based on age, having delivered a baby weighing more than 9 lb, sibling's DM, parent's DM, physical activity, and obesity; see the scoring algorithms in the Fig. S1. Although the original scores were developed to identify individuals at elevated risk for undiagnosed DM, they were also suggested to be used for undiagnosed preDM, with different cutpoints: $\geqslant$5 for DM and 4 for preDM in the ADA score and $\geqslant$10 for DM and 9 for preDM in the CDC score [1–3]. We also found that some modifications or adaptations are often accompanied to handle realistic issues or improve uptake (e.g., related to data unavailable or limited, less user-friendly questions, varying definitions).

In this paper, we evaluated these two scores in terms of prediction/detection of the outcomes – DM; preDM; and DM and preDM combined, all undiagnosed – and if we can support the use of the same score with different cutpoints for DM and preDM. We also conducted sensitivity and exploratory analyses in order to assess the robustness of the models' performance under various modifications/deviations (e.g., in defining or understanding variables) and restrictions (e.g., on age groups), and the value of additional risk factors commonly considered in relevant contexts. This study may provide some lessons to practitioners, researchers, educators, and users regarding how to wisely use good diabetes and other risk assessment tools in practice.

2. Methods

2.1. Survey design and participants

We used the NHANES 2009–12, the most recent waves at the time of the study. We restricted our analyses to the adult population, who are $\geqslant$20 years old. We excluded individuals with (1) diagnosed DM (i.e., doctor told you or currently on DM medication) or (2) missing outcomes data (i.e., fasting glucose, A1C, and 2-h plasma glucose by oral glucose tolerance test (OGTT) unmeasured). In the analyses where preDM is the sole outcome, we further excluded those with undiagnosed DM and diagnosed preDM (e.g., doctor told you). Publicly available data were used in our study (http://www.cdc.gov/nchs/nhanes.htm).

2.2. Outcomes and predictors

We focused on the variables that are needed in the derivation or use of the two screening scores. We defined predictors and outcomes following the original definitions or the current practice guidelines [4,5] as closely as possible in the primary analyses. Some modifications/adaptations were addressed in the sensitivity/ancillary analyses. To reflect the most common scenario, if data on risk factor is missing, we assigned the score of 0, so we equated the answers of 'No' and 'I don't know'.

The outcomes of type-2 DM and preDM are defined as follows: If a person has fasting glucose $\geqslant$ 7.0 mmol/L, A1C $\geqslant$ 48 mmol/mol, or 2-h glucose $\geqslant$ 11.1 mmol/L, then this person has DM. If a person does not meet the DM criteria, but has 5.6 $\leqslant$ fasting glucose < 7.0, 39 $\leqslant$ A1C < 48, or 7.8 $\leqslant$ 2-h glucose < 11.1, then this person has preDM.

Predictors are defined in the following manner. Age is categorized with the cutpoints of 40, 50 and 60 for the ADA score and of 45 and 65 for the CDC score. Hypertension is defined based on diagnosis (i.e., told by doctor), medication use, or blood pressure (systolic $\geqslant$140 mmHg or diastolic $\geqslant$90 mmHg using the higher value of the first two measurements). Family history of DM is defined based on parent and sibling's DM. [Of note, NHANES we used did not collect family history information separately for parent and sibling so we combined the 2 questions into 1 in the CDC score and assigned the score of 1 in the main analyses. We also assigned the score of 2 and a combination of 1 and 2 in sensitivity analyses.] Pregnancy history data were available so we coded as Yes/No. We created obesity categories as specified in the two scores. The paper version of the both scores provides a small table of weight and height, where the classification corresponds to BMI cutpoints of 25/30/40 for the ADA score (4 groups) and of 27 for the CDC score (2 groups). Finally, there are numerous ways to assess physical activity. The CDC score asks "Get little or no exercise in a typical day?" and the ADA score askes "Are you physically active?" but the same questions were not utilized in the NHANES. Considering these and currently available recommendations from the ADA and CDC (http://www.diabetes.org/are-you-at-risk/lower-your-risk/activity.html and http://www.cdc.gov/diabetes/living/beactive.html), we derived a binary variable by checking if 5 or more days in a typical week of any of the following activities: vigorous or moderate work, recreational work, walk or bicycle.

We described the variables used in sensitivity and ancillary analyses in Appendix. We tried to address frequently encountered situations in a variety of realistic settings where risk scores are used.

2.3. Statistical analyses

We combined the NHANES 2009–10 and 2011–12 and accounted for complex survey design in relevant analyses according to the NHANES's analytic guidelines. We repeated some analyses with different weights (e.g., medical exam weight in place of fasting subsample weight) or no weight to include maximum sample/information available, where these 3 different weighting schemes may achieve lowest bias and

higher efficiency in estimation, and closeness to real practice (like a convenient sample in community screening). We indicated which weight was used in each analysis in tables' footnotes. We described the study participants by summary statistics and computed the prevalence of undiagnosed DM and preDM for each total score of the ADA and CDC scores.

We fitted logistic regression with the predictors and each outcome described above, and computed odds ratio (OR) with 95% confidence interval (CI) and *p*-value for quantifying associations, and the area under the receiver-operating-characteristic curve (AUC) for assessing discrimination ability. In addition, we calculated standard performance measures – the percent of high risk individuals, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV).

We performed sensitivity and subgroup analyses of practical importance, and tested the predictiveness of additional factors that are not included in the two scores. In these exploratory analyses, we analyzed ordinal and continuous variables as continuous predictors and nominal and binary variables as categorical predictors in regression. Analyses were conducted in SAS 9.3 (SAS Institute, Cary, NC).

3. Results

The characteristics of 9391 participants included in our study, excluding diagnosed DM, are described in Table 1. The average age was 46 years [range: 20 to >80] and 48% were men. Obesity status based on BMI showed a higher proportion of 'higher than normal weight', compared to that based on self-report (67% vs. 57%). Of note, the NHANES did not allow 'obese' as an answer to the question "How do you consider your weight?" A total of 45% of participants reported they were physically active for 5 or more days of a week. Approximately 7% were shown to have undiagnosed DM and 48% to have undiagnosed preDM under the optimal setting (e.g., 3 DM diagnostic tests were performed, and the best-suited weights were used for estimation). The prevalence varies depending on the tests available and analysis samples/weights/methods used [6]. Nonetheless, only 4.5% of participants reported they were told by doctor they had preDM.

When we fitted the logistic regression for the outcome of undiagnosed DM, which was the primary outcome in the original studies [1,2], all predictors except for 'macrosomic baby (>9 lb)' were statistically significant, with the AUC of 0.77 for

Table 1 – Characteristics of adult participants without diagnosed DM in NHANES 2009–12 (N = 9391).

Predictors included in the ADA and CDC scores	Mean (standard error) or percentage
Age, year	45.9 (0.48)
Men	47.8%
Body mass index, kg/m^2	28.3 (0.12)
25–30 (overweight)	34.3%
30–40 (obese)	27.3%
⩾40 (extreme obese)	5.2%
Overweight (self-report)	57.3%
Waist circumference, cm – Women	94.7 (0.36)
Men	100.0 (0.45)
Systolic blood pressure, mmHg	122.9 (0.38)
Diastolic blood pressure, mmHg	73.0 (0.39)
Hypertension	34.8%
Family history of DM	32.8%
Physically active	45.0%
Having a baby >9 lb (women only)	11.4%
Gestational diabetes (women only)	3.9%
Outcomes-related	
Fasting glucose, mmol/L, *n* = 4290	5.5 (0.02)
A1C, % or mmol/mol, *n* = 9380	5.5 (0.01) or 36.3 (0.10)
2-h glucose, mmol/L, *n* = 3883	6.4 (0.05)
Diabetes status: normal/preDM/DM	
by fasting glucose only	57.5/38.9/3.6%
by A1C only	72.7/25.0/2.3%
by 2-h glucose only	80.8/13.8/5.5%
by glucose/A1C/2-h glucose*	45.4/47.7/6.9%
PreDM told by doctor	4.5%

Adult participants are those of 20 years old or older.
Those with missing outcomes data (i.e., all of fasting glucose, A1C and 2-h glucose) were excluded.
Fasting glucose and 2-h glucose were collected from subsamples.
All summary statistics were weighted with interview, medical exam, fasting or oral glucose tolerance test (OGTT) sample weight.
Sample sizes, total N and *n*, were unweighted.
DM denotes type 2 diabetes mellitus.
* OGTT weight was used to estimate the prevalence more validly, following the NHANES analytic guidelines. When medical exam weight or no weight was used, which can include larger N, prevalence turns out to be 60.0/35.5/4.5% and 55.0/38.5/6.4%, respectively. DM denotes type 2 diabetes mellitus.

the ADA score and 0.73–0.74 for the CDC score. When we fitted the same set of predictors for the outcome of undiagnosed preDM (*N* = 8442 after excluding undiagnosed DM and diagnosed preDM), the observed ORs were attenuated toward the null, with the directions of the association being preserved. The AUC decreased to 0.72–0.74 and 0.70–0.71, respectively, for the ADA and CDC score, which is anticipated as preDM includes a wider range of patients away from the tail of the risk spectrum; see Table 2. When we combined DM and preDM as composite outcome, the corresponding AUCs slightly increased (0.73–0.76 and 0.71–0.72), also as anticipated. Fig. S2 demonstrates the increasing trend of the disease prevalence as the total score increases.

When different cutpoints were evaluated for different outcomes, sensitivity was highest when these scores were used for the identification of DM, 0.83 for the ADA score and 0.79 for the CDC score. When we aimed at the identification of preDM (after excluding undiagnosed DM artificially), sensitivity was somewhat lowered, but PPV markedly increased (e.g., ~0.10 to >0.50), which is not unexpected as PPV depends on the disease prevalence. The performance of these scores was slightly enhanced when it was used to identify DM and preDM together – rather than preDM alone – which could reflect a more realistic scenario in practice because persons with undiagnosed DM or preDM are unaware of their condition so eligible to use the score; see Table 3. As noted before, the CDC score includes parent's DM and sibling's DM as separate predictors but the NHANES did not collect these variables separately. Thus, we tried 4 scenarios: (1) assign the score of 1 for the family history of DM; (2) assign the score of 2; (3) assign the score of 2 or 1, where 2 to 25% of those who had DM; and (4) repeat the third scenario but replacing 25% by 50%. These 4 experiments yielded the identical results.

When we introduced various modifications on variables' definitions, the AUC values were quite robust, which may justify some modification(s) are acceptable (Table 4). We observed that fasting glucose alone in the outcome definition yielded the lowest AUCs. Discrimination ability of the scores was consistently higher in younger age group, less than 60 years old. However, when the outcome was preDM, AUCs were the highest when younger and older groups were combined. We found that knowing accurate obesity status in more than two categories seems to be important because when we used a binary status (overweight vs. normal/underweight) based on self-report, the lowest AUC was resulted and regression analyses clearly demonstrated strong monotonic

Table 2 – Logistic regression with predictors in the ADA and CDC scores.

	ADA (AUC = .77/.77/.77)			CDC (AUC = .73/.74/.73)	
Predictor	OR (95% CI)	*p*-value	Predictor	OR (95% CI)	*p*-value
a. Outcome = Undiagnosed DM (N = 9391)					
Age 40–49	2.3 (1.5–3.6)	<0.001	Age <65 and physically inactive	1.6 (1.2–2.1)	<0.001
50–59	3.5 (2.3–5.4)	<0.001	45–64	2.8 (2.2–3.6)	<0.001
⩾60	6.3 (4.3–9.3)	<0.001	⩾65	8.0 (5.6–11.6)	<0.001
Men	1.5 (1.1–2.0)	0.007			
Hypertension	1.5 (1.3–1.9)	<0.001			
Family DM	1.7 (1.3–2.1)	<0.001	Parent DM Sibling DM	1.8 (1.4–2.3)	<0.001
BMI 25–29.9	1.5 (1.0–2.2)	0.035	BMI ⩾ 27	2.8 (2.1–3.6)	<0.001
30–39.9	3.1 (2.1–4.7)	<0.001			
⩾40	7.3 (5.0–10.7)	<0.001			
Physically inactive	1.5 (1.2–1.9)	<0.001	Physically inactive	See "age" above	
Gestational DM (women only)	2.5 (1.3–5.0)	0.006	>9 lb baby (women only)	1.0 (0.6–1.5)	0.92
	ADA (AUC = .72/.74/.72)			CDC (AUC = .70/.71/.70)	
Predictor	OR (95% CI)	*p*-value	Predictor	OR (95% CI)	*p*-value
b. Outcome = Undiagnosed preDM (N = 8442)					
Age 40–49	2.1 (1.7–2.5)	<0.001	Age < 65 and physically inactive	1.0 (0.9–1.1)	0.96
50–59	2.8 (2.3–3.4)	<0.001	45–64	2.7 (2.3–3.1)	<0.001
⩾60	5.0 (4.1–6.2)	<0.001	⩾65	4.9 (4.1–5.9)	<0.001
Men	1.5 (1.3–1.7)	<0.001			
Hypertension	1.3 (1.1–1.4)	<0.001			
Family DM	1.2 (1.0–1.3)	0.01	Parent DM Sibling DM	1.2 (1.1–1.4)	0.002
BMI 25–29.9	1.4 (1.2–1.7)	<0.001	BMI ⩾ 27	1.9 (1.7–2.3)	<0.001
30–39.9	2.1 (1.7–2.6)	<0.001			
⩾40	3.4 (2.6–4.5)	<0.001			
Physically inactive	1.0 (0.9–1.1)	0.82	Physically inactive	See "age" above	
Gestational DM (women only)	2.0 (1.3–3.0)	0.002	>9 lb baby (women only)	1.0 (0.8–1.3)	0.91

Regression fits were from weighted analyses by medical exam weight. Three AUCs are from regressions with medical exam weight/fasting weight/unweighted, respectively. BMI, body mass index.

In b, undiagnosed DM and diagnosed preDM were excluded. When we combined the outcomes (undiagnosed preDM and undiagnosed DM), AUC = .73/.76/.73 for the ADA score and .71/.72/.71 for the CDC score. DM denotes type 2 diabetes mellitus.

Table 3 – Performance of the ADA and CDC scores.

Model/cutpoint	Outcome, undiagnosed	% of high risk	Sensitivity	Specificity	PPV	NPV
ADA ⩾ 4	preDM/DM	60	78	54	57	76
⩾4	preDM	58	76	54	53	77
⩾5	DM	46	83	57	12	98
CDC ⩾ 9	preDM/DM	58	74	54	56	73
⩾9	preDM	56	72	54	51	74
⩾10	DM	52	79	50	10	97

Analyses were unweighted, assuming we have convenient sample in a community screening setting.
The CDC model yielded the same results with score of 1, 2, or a combination of 1 or 2 for family DM.
For outcome = preDM, undiagnosed DM and diagnosed preDM cases were excluded. For outcome = preDM/DM, diagnosed preDM cases were excluded.
In all analyses, diagnosed DM cases were excluded.
DM denotes type 2 diabetes mellitus; PPV = positive predictive value; NPV = negative predictive value.

Table 4 – AUCs in the sensitivity and ancillary analyses.

	Undiagnosed DM		Undiagnosed preDM	
	ADA	CDC	ADA	CDC
Original model	.766	.731	.718	.697
Task 1: Different outcome definition				
Fasting glucose alone	**.765**	**.729**	**.717**	**.682**
A1C alone	**.785**	.738	.733	.720
2-h glucose alone	.768	**.743**	**.746**	**.729**
Task 2: Age subgroups				
Age ⩾60 years old	.637	.598	.575	.577
<60 years old	.774	.723	.701	.666
Task 3: Modification in predictor				
Clinical measures				
No blood pressures available	.764	NA	.717	NA
Obesity				
Add WC as new predictor	.773	.760	.721	**.709**
Combine BMI + WC in obesity categories	.767	NA	.719	NA
Over vs. normal/underweight based on self-assessment	**.744**	**.718**	**.705**	**.680**
BMI	.772	.757	.719	.704
WC	.774	.761	.720	**.709**
Waist-to-height ratio	**.784**	**.771**	**.724**	.707
Physical activity				
>30 min/day of recreational activity	.767	.732	.718	.698
Add 'hours of sedentary activity' as new predictor	.766	.731	.719	.700
Medical history No pregnancy data	.762	.731	.717	.697
No family DM data	.760	.722	.717	.693
Task 4: Additional predictor added				
Race (black, hispanic, white, others)	**.779**	**.746**	.723	.705
HDL cholesterol	.773	**.746**	.722	.708
LDL cholesterol	.769	.738	**.738**	**.710**
Total cholesterol	.766	**.733**	.720	.702
Alcohol (average number of drinks/day)	.776	.741	.721	.697
Smoking (current vs. others)	.769	.738	.714	.692
(average number of cigarettes/day)	**.764**	.752	.719	**.689**
Healthy diet (in 5 levels)	.769	.738	.719	.701
Total sugar	.768	.735	**.718**	.700
Total fat	.769	.734	**.718**	.699

Predictors were included as continuous variable in logistic regression, unless stated otherwise.
Analyses were weighted with medical exam weight.
Largest AUCs in each model under different tasks are in bold and smallest AUCs are in italicized bold.
Sample sizes of complete data and types of variables (e.g., continuous vs. binary) are different so comparisons need some caution.
DM denotes type 2 diabetes mellitus; NA, not applicable; AUC = area under the receiver-operating-characteristic curve; BMI = body mass index; WC = waist circumference.

associations in obesity grade and DM as well as preDM risk. Also, when waist circumference (WC) was added to the existing models where BMI-based categories were already in (as in Table 2), WC was highly significant (p's < 0.001). Notably, when BMI vs. WC vs. waist-to-height ratio (WHtR; or waist-to-stature ratio (WSR)) were compared, WHtR yielded the highest AUC, confirming previous findings [7,8]. Among additional predictors tested, race yielded the largest increase in AUC for DM and LDL did for preDM [9,10]. It is inherently difficult to measure the types and amounts of physical activity precisely. Assessment by three different ways led to substantially similar AUC values.

4. Discussion

In this study, we evaluated and compared the two preDM screening scores. They were originally derived for undiagnosed DM as an outcome, but have been proposed to use for preDM with different cutpoints. The ADA and CDC scores performed well for DM as well as preDM in independent data, recent NHANES, and we view this as external, temporal validation. The ADA score performed somewhat but nearly uniformly better, and we believe this is partly due to multiple categories used for age and obesity which show strong monotonicity in disease prevalence. Both scores are easy, cheap and noninvasive to administer in the format of pencil-and-paper or online calculator, so either one may be used depending on the preference.

The observed AUC values, the discrimination statistic, for the ADA and CDC scores were comparable to those for well-known risk scores in cardiovascular disease and DM/preDM [11–13], and quite robust when various, small changes were incorporated. For example, when blood pressure or pregnancy-related data were unavailable, which are common in some situations where risk assessment is done (say, with or without interview, or using administrative or health record database), the AUC values were not discernibly reduced. However, our study suggests that it could be important to know the accurate status of a person's obesity, which supports the inclusion of the existing BMI table in the paper version of these scores, designed to be user-friendly for intended users, say, based on weight (in pound) and height (in inches) in the US. We also observed WC – particularly, WHtR – appears to be more predictive of DM and preDM than BMI. The limitations of BMI are well documented, and some risk scores include WC [8,14–16]. Yet, based on our own and others' experiences, WC has other issues, for instance, not normally collected in medical record, not easy to measure accurately (often leading to under-estimation), or patient does not know or feel comfortable to be measured [17,18]. Possibly, a currently recommended threshold of 0.5 for WHtR is easy to remember and may carry an educational value. More discussion is warranted regarding how to choose and use anthropometric measures for risk assessment and screening, and for different races or regions/countries [16,19–21]. Until then, weight and height in the screening score, and WC or WHtR in the accompanying educational materials may be ideal.

Our study may have some implications in the development, validation and utilization of risk score. Development of risk score or prediction model is basically dictated by data availability. For example, if the history of gestational DM is not available, researcher cannot include this variable in the model, which is common in the risk scores developed using secondary data. Yet, subjective decision to add gestational DM might be justified with a score assigned in an ad-hoc manner (say, minimal score such as 1), if compelling evidence is available in the literature. A similar issue can happen when data were not systematically measured, which is common when multiple datasets or disparate cohorts are merged [22,23]. On the other hand, it is not always good to include all covariates that are statistically significant and clinically explainable, especially, those with small effect size, costly, less user-friendly or conflicting/controversial variables [24–28]. Moreover, prediction models can be different depending on goal, e.g., patient's self-assessment vs. shared decision making by patient-doctor vs. policy. Indeed, some arbitrariness/subjectivity in the final predictor selection, score assignment and cutpoint determination was involved in the developments of the ADA and CDC tools [2,29]. The ultimate justification will be tested when the scores will be validated independently with necessary data for the intended goal. As other scientific findings, risk scores can be adapted and evolve naturally whenever sufficient evidence calls for [30]. Furthermore, the same score (with or without small adaptations) may be justified for closely-related conditions; it may help a smaller number of models/scores be developed, so that good models available are used more widely, systematically and wisely, and patients and users become less confused but more comfortable and familiar [16,24,31,32].

Based on our exploratory investigation, diabetes prevention program may emphasize race disparity if that helps the awareness, healthy lifestyle education or more targeted screening; in our study, Hispanics showed the highest (unadjusted) prevalence of undiagnosed DM and Blacks showed the highest prevalence of undiagnosed preDM. The screening scores could be more effective and useful for younger persons, where a high risk group can be recommended to receive blood test or advice from healthcare providers. In addition to well-validated predictors already included in the scores, more emphasis on additional modifiable factors that lay persons can understand easily (e.g., WC, LDL/HDL cholesterols, and diet/nutrition) may be worthwhile.

After excluding known DM, we found that 2–7% of the participants had newly diagnosed DM. 14–48% were shown to have preDM but less than 5% reported doctors told them they had preDM [6]. We think these statistics are alarming. If either screening score were used for preDM in a similar population (e.g., general population in a community in the US), >50% of people would be declared to be at high risk of preDM, and 1 out 2 of them to be revealed to have preDM.

Our study has some limitations. First, the NHANES did not collect parent and sibling's DM history separately. When we implemented multiple scenarios including conservative and liberal ones, the results were unchanged. Second, sample sizes for variables were different (e.g., fasting and OGTT subsamples, non-response) but some were enforced by design. We handled this issue by applying different weighting schemes and reached robust answers. The strengths of our study are data availability and quality – recent, large, multi-year, representative samples with detailed outcomes-

related information (i.e., fasting glucose, A1C and 2-h glucose) and all of the necessary predictors measured. Although cross-sectional data are appropriate for undiagnosed or prevalent disease, the use of prospective data could provide additional useful insight or lessons (e.g., prediction of incident disease, if new risk score and/or new risk factor is needed; if more complicated model is warranted).

In conclusion, the ADA and CDC scores performed well and comparably, and performance was robust to different data availability and deviations/modifications often entailed in practice. The same score may be used for DM and preDM. This direction may help active identification of preDM cases, which deserves to be a new focus of screening, by patients as well as healthcare providers in an efficient and seamless manner. While having preDM, one still has a chance to delay DM or even reverse the condition, during which some interventions have been shown to be effective and cost-effective. Despite limitations, self-assessment of DM and preDM risks has a potential to be the cheapest, easiest and safest way to learn about the risk and key risk factors, and to promote patient empowerment and patient-centered care.

Conflicts of interest

None.

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Appendix A.

A. *Variables used in sensitivity analyses*

For the sensitivity analyses, the following modifications were considered:

DM and preDM: We derived the outcomes based on fasting glucose only, A1C only, or 2-h glucose only.

Hypertension: We used self-report, without blood pressure measurements.

Obesity: We added WC as a continuous covariate/predictor, in addition to BMI-based categories. Also, we derived the obesity categories by combining BMI and WC [2]. We tested the binary variable, overweight vs. under/normal weight based on self-assessment without anthropometric measures. The answer choice did not allow obese in the NHANES so this scenario represents a situation with underreporting of obesity, where no patients perceived they are obese [18]. Finally, we tested BMI vs. WC vs. WHtR when they were separately included as continuous predictor. Of note, another commonly considered measure, waist-hip ratio was not included in comparison because hip circumference was not available.

Physical activity: We derived two additional variables for physical activity. First, we derived a binary variable: Yes or No if >30 min of having recreational activities in a typical day. Second, we included 'hours of sedentary activity in a typical day'.

Medical history: We simulated the scenarios where no pregnancy or family history data are available, which are common when these scores are used with administrative data or in some clinical settings [18].

B. *Additional predictors tested in ancillary analyses*

The following variables are not included in the original scores but we examined them as they are supported by the literature and could be useful for education or targeted screening [33,34]. We focused on *modifiable* factors among clinical, behavioral and dietary variables that patients are familiar with, in addition to race which is currently being used in various DM education programs. Thus, some of the variables may be used in future regression analyses or health education materials (e.g., information to be added to the back of the score card, in the follow-up step of the risk assessment) if educators or users wish.

Race: is categorized into 4 groups: black (non-hispanic); white (non-hispanic); hispanic; and others.

Alcohol consumption: 'Average number of alcoholic drinks per day for the past 12 months' was used.

Smoking: was analyzed in 2 manners: binary variable (current smoker vs. others) and continuous variable (average number of cigarettes per day for the past 30 days). Note that the NHANES did not use the same duration of time for alcohol and smoking.

Healthy diet: We used the answer (1: excellent to 5: poor) to "how healthy is your diet?"

Clinical and dietary: HDL, LDL, and total cholesterols, total sugar, and total fat were considered.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.diabres.2016.06.022.

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