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Evaluating the utility of self-reported questionnaire data to screen for dysglycemia in young adults: Findings from the US National Health and Nutrition Examination Survey

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ABSTRACT

Dysglycemia, including prediabetes and type 2 diabetes, is dangerous and widespread. Yet, the condition is transiently reversible and sequelae preventable, prompting the use of prediction algorithms to quickly assess dysglycemia status through self-reported data. However, as current algorithms have largely been developed in older populations, their application to younger adults is uncertain considering associations between risk factors and dysglycemia vary by age. We sought to identify sex-specific predictors of current dysglycemia among young adults and evaluate their ability to screen for prediabetes and undiagnosed diabetes. We analyzed 2005–2014 data from the National Health and Nutrition Examination Survey for 3251 participants aged 20–39, who completed an oral glucose tolerance test (OGTT), had not been diagnosed with diabetes, and, for females, were not pregnant. Sex-specific stepwise logistic models were fit with predictors identified from univariate analyses. Risk scores were developed using adjusted odds ratios and model performance was assessed using area under the curve (AUC) measures. The OGTT identified 906 (27.9%) and 78 (2.4%) participants with prediabetes or undiagnosed diabetes, respectively. Predictors of dysglycemia status for males were BMI, age, race, and first-degree family history of diabetes, and, in addition to those, education, delivered baby weight, waist circumference, and vigorous physical activity for females. Our male- and female-specific models demonstrated improved validity to assess dysglycemia presence among young adults relative to the widely-used American Diabetes Association test (AUC = 0.69 vs. 0.61; 0.92 vs. 0.71, respectively). Thus, age-specific scoring algorithms employing questionnaire data show promise and are effective in identifying dysglycemia among young adults.

1. Introduction

Type 2 diabetes is highly prevalent, and may be marked by a substantial deterioration of quality of life due to severe physical and psychological comorbidities (Anderson et al., 2001; de Groot et al., 2001; Deshpande et al., 2008; Grigsby et al., 2002; Rochette et al., 2014), as well as an increased risk of premature mortality (Mathers and Loncar, 2006). Since the prevalence of dysglycemia, which includes both type 2 diabetes and its precursor, prediabetes (Goldney et al., 2004; Rubin and Peyrot, 1999), continues to increase worldwide (Guariguata et al., 2014), the condition poses an important threat to public health. In the US, one in three adults was estimated to have prediabetes in 2010 (Bullard et al., 2013), while it is projected that 25–28% of adults will have diabetes in 2050 (Boyle et al., 2010). Increasingly, diabetes is first diagnosed before 40 years of age (Centers for Disease Control and Prevention (CDC), 2003; Mainous et al., 2007), with its global prevalence estimated to double to just under 60 million young adults from 2000 to 2030 (Wild et al., 2004). Since young adults are less likely to be aware of their condition (Kaiser et al., 2012; Satman et al., 2013) yet display more aggressive disease phenotypes than older adults (Dabelea et al., 2017; Huo et al., 2016; Rhodes et al., 2012), there is an increasing need to identify these individuals early to prevent, delay onset, or reduce further morbidity.

Abbreviations: 2h-PG, two-hour plasma glucose; ADA, American Diabetes Association; AUC, area under the receiver-operating characteristic; BMI, body mass index; CANRISK, Canadian Diabetes Risk Questionnaire; DRT, Diabetes Risk Test; FPG, fasting plasma glucose; FINDRISC, Finnish Diabetes Risk Score; HbA1c, glycated hemoglobin; LOESS, locally-estimated scatterplot smoothing; NHANES, National Health and Nutrition Examination Survey; OGTT, oral glucose tolerance test; ROC, receiver-operating characteristic

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Notably, prediabetes is potentially reversible (Tabák et al., 2012; Tuso, 2014), and its progression to diabetes is largely preventable in both randomized-controlled trials (Knowler et al., 2002; Tuomilehto et al., 2001) and community-based studies (Jiang et al., 2013; Kramer et al., 2014; Vita et al., 2016; Vojta et al., 2013). After developing diabetes, comorbidities can be prevented if treatment is started early (Diabetes Control and Complications Trial Research Group et al., 1993; Skyler, 2004). Therefore, many stand to gain from screening tools such as risk prediction scores, which can identify who should seek medical consultation to boost the possibility of prevention and treatment (Paulweber et al., 2010). Risk scores, such as the American Diabetes Association (ADA) Diabetes Risk Test (Bang et al., 2009), are developed using questionnaire data by assigning weights to risk factors based on their associations with prevalent disease in various study populations. Since risk scores can be used to self-assess risk of current disease, they are especially convenient for young adults who are less likely to have medical insurance (Cohen and Bloom, 2010; Fishman, 2001) or regular medical care (Cohen and Bloom, 2010). Previously, studies have validated established risk scores for dysglycemia that use a variety of demographic, health, and behavioral factors in adults over 20 years old using the National Health and Nutrition Examination Survey (NHANES) datasets (Poltavskiy et al., 2016; Zhang et al., 2015). However, it has long been recognized that risk factors for dysglycemia differ between early-onset diabetes in young adulthood and late-onset in older adults (Aguilar-Salinas et al., 2002; Hillier and Pedula, 2001; Song and Hardisty, 2009; Wilmot and Idris, 2014; Yu et al., 2016). Female sex, obesity, sedentary lifestyles, lower socioeconomic status, poor early-life environments, unhealthy diet, and family history of diabetes are more strongly associated with early-onset diabetes than late-onset diabetes (Lascar et al., 2018; Wilmot and Idris, 2014). Since current risk scores have largely been developed in older populations, they demonstrate reduced model performance in the younger age-group (Mainous et al., 2007). Additionally, differences in biology, lifestyle, and environment exposures drive sex disparities in dysglycemia development (Kautzky-Willer et al., 2016). For example, males are more likely to develop diabetes at an earlier age and, especially in young adulthood, at a lower BMI than females, due to sex-differences in insulin sensitivity, fat distribution, and blood lipid levels (Logue et al., 2011). These, and other sex-differences, highlight the need to derive risk scores separately for each sex.

Due to the differential associations between risk factors for dysglycemia by age and sex, we sought to identify sex-specific predictors of prediabetes and undiagnosed diabetes among young US adults (aged 20–39), and to evaluate their utility in screening. Subsequently, due to the few available screening tools tailored specifically for young adults, we created two sex-specific risk scores optimized for this age-group using NHANES data (2005–2014), while comparing them to one in common practice: the ADA Diabetes Risk Test (Bang et al., 2009).

2. Methods

2.1. Study design and participants

For prediction modelling, we used the publicly-available 2005–2014 NHANES data, an annual cross-sectional study conducted in the United States. Detailed methods are described elsewhere (Curtin et al., 2013, 2012; Johnson et al., 2014; Zipf et al., 2013). Briefly, the survey employed a complex, multistage probability sampling design and oversamples elderly, adolescent, low-income, and some minority ethnic groups to produce a representative sample of the non-institutionalized civilian population in the US. NHANES gathered both self-reported and measured health data through interviews, health examinations, and laboratory tests, creating a robust dataset for health research.

Interviews were administered at the participant's home and assessed demographic, socioeconomic, dietary, and health-related factors. Health examinations were comprised of medical, dental, and physiological components, including height, weight, and waist circumference measurements. As well, an array of laboratory tests was performed, including the oral glucose tolerance test (OGTT), a well-established standard for diagnosing dysglycemia (American Diabetes Association, 2018). NHANES participants who were randomly assigned to the morning sessions (vs. afternoon or evening; i.e. ~1/3 of participants) and were 12 years or older were included in the OGTT. Participants who reported pre-existing diabetes, current use of diabetes medication, or could not participate in blood draws or fasting due to health concerns were excluded. For the OGTT, a baseline blood test was conducted the morning after a minimum fast of 9 h. Participants subsequently ingested 75 g of dextrose within 10 min, and an additional blood test was conducted 2 h after. We followed ADA guidelines (American Diabetes Association, 2018) to identify those with dysglycemia, employing both fasting (FPG) and two-hour plasma glucose (2h-PG) values in the OGTT. Specifically, prediabetes was defined by an FPG of 5.6–6.9 mmol/L (100–125 mg/dL) or a 2h-PG of 7.8–11.0 mmol/L (140–199 mg/dL), while diabetes was defined by an FPG ≥ 7.0 mmol/L (≥126 mg/dL) or a 2h-PG ≥ 11.1 mmol/L (≥200 mg/dL).

A total of 9827 participants were 20–39 years old in the 2005–2014 NHANES datasets. Additional inclusion criteria for our analyses were as follows: not pregnant, had both FPG and 2h-PG OGTT results, and did not report pre-existing diabetes. We chose to include participants previously diagnosed with prediabetes as this condition is known to be reversible (Tuso, 2014). Since a subset of the participants underwent OGTT testing, only 3251 (33.1%) participants met these criteria and were included in our analyses. Demographic and anthropometric differences between those included and excluded are displayed in Appendix Table 1. Individuals excluded differed from those included in terms of sex, race, education, and waist circumference, but were similar in age category, BMI, and family history of diabetes.

2.2. Identification of risk factors

We reviewed the literature to identify risk factors for dysglycemia using various keywords in combination, such as: prediabetes, diabetes, young adult, youth, early-onset, risk factor, predictor, OGTT. Studies looking at risk factors of diabetes development in young adulthood were selected and examined. Predictors in the NHANES that could be easily assessed by a clinician or individually by a participant were used in the model-building procedure. These included: age, race, education (a proxy for socioeconomic status), self-reported coronary heart disease, self-reported hypertension, self-reported diet healthfulness ("In general, how healthy is {your/his/her} overall diet?"), physical activity (moderate or vigorous), first-degree family history of diabetes, delivered baby weight, measured BMI, measured waist circumference, and tobacco use (ever smoker or current smoker). Though self-reported measures of behavior may be biased (Van De Mortel, 2008), they mirror how individuals who employ the resulting risk scores will respond at home and are thus suitable for risk score development.

Some data cleaning was performed on the selected risk factors. The age variable was categorized into four 5-year groupings (20–24, 25–29, 30–34, and 35–39). The education variable was generated by aggregating "less than 9th grade" and "9–11th grade (includes 12th grade with no diploma)" to "less than high school", "high school grad/GED or equivalent" to "graduated high school", "some college or AA degree" to "some college or university", and "college graduate or more" to "graduated college or university". The race variable combined responses of "Mexican American" and "other Hispanic" to "Hispanic", and kept "White", "Black", and "Other/Multi-racial" categories. For females, we created a classification variable for delivered baby weight that consisted of responses: "nulliparous", "baby weight < 9 lbs", "baby weight ≥9 lbs", or "missing". The "missing" category was added since the question was not asked in the 2005–06 survey, resulting in a large proportion of missing data. Groupings for BMI (Lyznicki et al., 2001)

Table 1
Descriptive characteristics of participants aged 20–39 who provided oral glucose tolerance test results, overall and by sex, NHANES 2005–2014[a].

Characteristics	Total (n = 3251)	Male (n = 1644)	Female (n = 1607)	p-Value[b]
Glycemic status				< 0.0001
Normoglycemia	2266 (69.7)	1028 (62.5)	1238 (77.0)	
Prediabetes[c]	907 (27.9)	570 (34.7)	337 (21.0)	
Undiagnosed diabetes[d]	78 (2.4)	46 (2.8)	32 (2.0)	
Age (years)	29.5 ± 5.8	29.4 ± 5.8	29.6 ± 5.8	0.5
Race				0.41
White	1293 (39.8)	669 (40.7)	624 (38.8)	
Hispanic	978 (30.1)	495 (30.1)	483 (30.1)	
Black	621 (19.1)	296 (18.0)	325 (20.2)	
Other/multi-racial	359 (11.0)	184 (11.2)	175 (10.9)	
Highest attained education				< 0.0001
Less than high school	678 (20.9)	377 (22.9)	301 (18.7)	
Graduated high school	722 (22.2)	430 (26.2)	292 (18.2)	
Some college or university	1074 (33.1)	475 (28.9)	599 (37.3)	
Graduated college or university	776 (23.9)	362 (22.0)	414 (25.8)	
Measured BMI (kg/m^2)	28.2 ± 7.0	28.0 ± 6.2	28.4 ± 7.8	0.10
Measured waist circumference (cm)	94.5 ± 16.6	96.0 ± 15.8	93.0 ± 17.3	< 0.0001
Self-reported hypertension	394 (12.1)	213 (13.0)	181 (11.3)	0.14
Self-reported coronary heart disease	4 (0.12)	2 (0.12)	2 (0.12)	0.98
First-degree family history of diabetes	1161 (36.4)	539 (33.5)	622 (39.4)	0.0005
Participate in moderate PA	1561 (48.0)	781 (47.5)	780 (48.5)	0.56
Participate in vigorous PA	1274 (39.2)	778 (47.3)	496 (30.9)	< 0.0001
Birthed a > 9 lb. baby[e]	–	–	106 (6.6)	–
Self-reported diet healthfulness				0.19
Excellent	195 (6.0)	106 (6.5)	89 (5.5)	
Very good	541 (16.7)	269 (16.4)	272 (16.9)	
Good	1361 (41.9)	659 (40.1)	702 (43.7)	
Fair	902 (27.8)	476 (29.0)	462 (26.5)	
Poor	251 (7.7)	133 (8.1)	118 (7.3)	
Ever smoker[f]	1206 (37.1)	726 (44.2)	480 (29.9)	< 0.0001
Current smoker[g]	798 (24.6)	471 (28.7)	327 (20.4)	0.2

Note. NHANES 2005–2014. Data are mean ± SD or N (%). Actual sample sizes may differ due to missing data. Abbreviations: NHANES, National Health and Nutrition Examination Survey; OGTT, oral glucose tolerance test; PA, physical activity.

[a] Exclusion criteria: pregnant, did not have OGTT results, or had been diagnosed with diabetes.

[b] Testing the differences between sexes using either χ^2 or ANOVA.

[c] Prediabetes = fasting plasma glucose of 5.6–6.9 mmol/L (100–125 mg/dL) or two-hour plasma glucose of 7.8–11.0 mmol/L (140–199 mg/dL) in the OGTT.

[d] Undiagnosed diabetes = fasting plasma glucose of ≥7.0 mmol/L (≥126 mg/dL) or two-hour plasma glucose of ≥11.1 mmol/L (≥200 mg/dL) in the OGTT.

[e] Delivered baby weight includes still and live births.

[f] Based on ≥100 cigarettes smoked in lifetime.

[g] Current cigarette smoking status only asked to those who answered 'yes' to the ≥100 cigarettes smoked question. Percentages represent proportion of current cigarette smokers out of all participants who responded to the ≥100 cigarette smoked in lifetime question.

and waist circumference (Lean et al., 1995; Wang et al., 2005; World Health Organization, 2000) were based on the literature. The "unable to do activity" response, unique to the 2005–06 physical activity data, was re-coded as "no" for having taken part in physical activity (moderate or vigorous) in the last 30 days. Ever smoker variable was based on having smoked ≥100 cigarettes in lifetime. The binary current smoker variable was generated by aggregating the responses of "every day" and "some days" to "yes" and "not at all" to "no". The current smoker question was asked only to those who responded "yes" to the ≥100 cigarettes in lifetime question. The responses "don't know" and "refused" were re-coded as missing for all variables.

2.3. Statistical analyses

Analyses and data management were performed using SAS® 9.4 (SAS Institute, Cary, NC).

2.3.1. Model development

Models were developed separately for each sex. Identified risk factors were input into sex-stratified univariate analyses where the outcome of interest was dysglycemia based on the OGTT. Since prescreening of variables may erroneously reject variables that contribute to the model after adjustment (Collins et al., 2011), we chose to be lenient with our variable selection criteria. Thus, variables which made modest contributions to their sex-specific univariate models based on a measure of statistical significance (likelihood ratio $p < 0.20$) were retained for multivariable model fitting. In order to create an accessible and easily-completed risk prediction tool, similar to other diabetes screening tools (Bang et al., 2009; Lindström and Tuomilehto, 2003; Robinson et al., 2011), we categorized continuous variables that were retained in the final model. A stepwise logistic regression was then run separately for each sex with their respective risk factors using a Wald χ^2 significance level of $p < 0.15$ for the forward selection steps and $p < 0.10$ for the backward elimination steps. Although stepwise functions can enter extraneous variables into the final model, this is not a significant limitation if the goal is to predict an outcome rather than determining the most important factors associated with outcome development (Austin and Tu, 2004). Subsequently, participants missing data for predictors in the final models were excluded, and a dummy variable was created to examine any differences between those included and excluded. A receiver-operating characteristic (ROC) curve was computed to test the predictive ability of the model to correctly identify those with and without dysglycemia (based on the OGTT). An area under the receiver-operating characteristic (AUC) of 0.7–0.79 is considered acceptable, 0.8–0.89 excellent, and ≥0.9 outstanding (Hosmer and Lemeshow, 2000). Additionally, to test the internal calibration of the model between observed and expected probabilities of having dysglycemia, a locally-estimated scatterplot smoothing (LOESS)-based calibration curve was plotted (methods and rationale by Austin and Steyerberg, 2014). This curve is a graphical representation of

Table 2
Unadjusted odds ratios for identified risk factors of dysglycemia in males using participants 20–39 years of age in NHANES 2005–2014[a].

Predictors	Participants	Prevalent dysglycemia[b]	OR (95% CI)	Likelihood ratio p-value[c]
Age (years)				< 0.0001
20–24	430	137	1.0	
25–29	394	119	0.93 (0.69–1.24)	
30–34	413	165	1.42 (1.07–1.89)	
35–39	407	195	1.97 (1.49–2.61)	
Race				0.007
White	669	243	1.0	
Hispanic	495	208	1.27 (1.00–1.61)	
Black	296	90	0.77 (0.57–1.03)	
Other/multi-racial	184	75	1.21 (0.86–1.68)	
Highest attained education				0.04
Less than high school	377	159	1.0	
Graduated high school	430	170	0.90 (0.68–1.19)	
Some college or university	475	168	0.75 (0.57–0.99)	
Graduated college or university	362	119	0.67 (0.50–0.91)	
Measured BMI group				< 0.0001
Not overweight (< 25 kg/m^2)	562	162	1.0	
Overweight (25–29.9 kg/m^2)	580	199	1.29 (1.00–1.66)	
Obese (≥ 30 kg/m^2)	497	251	2.52 (1.96–3.25)	
Measured waist circumference group				< 0.0001
Low risk (< 94 cm)	802	227	1.0	
Increased risk (94-101 cm)	331	138	1.81 (1.39–2.37)	
Substantial risk (≥ 102 cm)	497	243	2.42 (1.92–3.06)	
Self-reported hypertension				0.0008
No	1427	512	1.0	
Yes	213	102	1.64 (1.23–2.19)	
Self-reported coronary heart disease				0.7
No	1641	614	1.0	
Yes	2	1	1.67 (0.10–26.8)	
First-degree family history of diabetes				0.007
No	1072	373	1.0	
Yes	539	225	1.34 (1.09–1.66)	
Participate in moderate PA				< 0.0001
No	863	363	1.0	
Yes	781	253	0.66 (0.54–0.81)	
Participate in vigorous PA				0.0004
No	866	359	1.0	
Yes	778	257	0.70 (0.57–0.85)	
Self-reported diet healthfulness				0.002
Excellent	106	28	1.0	
Very good	269	92	1.45 (0.88–2.39)	
Good	659	241	1.61 (1.01–2.54)	
Fair	476	210	2.20 (1.38–3.51)	
Poor	133	45	1.42 (0.81–2.50)	
Ever smoker[d]				0.4
No	917	352	1.0	
Yes	726	264	0.92 (0.75–1.12)	
Current smoker[e]				0.18
No	255	101	1.0	
Yes	471	163	0.81 (0.59–1.11)	

Note. NHANES 2005–2014. Data for 1644 male participants. Actual sample sizes may differ due to missing data. Abbreviations: NHANES, National Health and Nutrition Examination Survey; OGTT, oral glucose tolerance test; OR, odds ratio; CI, confidence interval; PA, physical activity.

[a] Exclusion criteria: did not have OGTT results or had been diagnosed with diabetes.

[b] Dysglycemia = fasting plasma glucose of ≥ 5.6 mmol/L (≥ 100 mg/dL) or two-hour plasma glucose of ≥ 7.8 mmol/L (≥ 140 mg/dL) in the OGTT.

[c] Likelihood ratios were calculated based on univariate analyses containing the predictor and outcome (OGTT).

[d] Based on ≥ 100 cigarettes smoked in lifetime.

[e] Current cigarette smoking status only asked to those who answered 'yes' to the ≥ 100 cigarettes smoked question.

model goodness-of-fit and is analogous to the Hosmer-Lemeshow test (Austin and Steyerberg, 2014).

2.3.2. Score derivation & comparison to ADA diabetes risk test

Adjusted odds ratios (aOR) from each sex-specific final model were used to assign a score to each variable category (score = [aOR − 1] × 100, rounded to nearest integer). This method was chosen as it assigned a continuous risk score to each predictor category that was directly proportional to its adjusted risk estimate. As well, it conferred a reduced risk of dysglycemia when the aOR was < 1 and an increased risk when the aOR was > 1. The cumulative score was the sum of those risk factor scores for each participant. Subsequently, the effectiveness of these newly developed scores in the assessment of dysglycemia risk were compared to the ADA Diabetes Risk Test (DRT) (Bang et al., 2009).

The DRT employs the following categorical variables: age (< 40, 40–49, 50–59, and ≥ 60 years of age), sex (male, female), first-degree family history of diabetes (yes, no), history of hypertension (yes, no), obesity (not overweight, overweight, obese, extremely obese; based on BMI and waist circumference), and physically active (yes, no). Categorization of these variables was performed as previously described (Bang et al., 2009). For the physically active variable, responses of "yes" for either moderate or vigorous activity and "no" for both were combined. The DRT was run once for each sex to determine its sex-specific performance in young adulthood.

Table 3
Unadjusted odds ratios for identified risk factors of dysglycemia in females using participants 20–39 years of age in NHANES 2005–2014[a].

Predictors	Participants	Prevalent dysglycemia[b]	OR (95% CI)	Likelihood ratio p-value[c]
Age (years)				< 0.0001
20–24	402	52	1.0	
25–29	371	75	1.71 (1.16–2.51)	
30–34	425	115	2.50 (1.74–3.58)	
35–39	409	127	3.03 (2.12–4.34)	
Race				0.002
White	624	128	1.0	
Hispanic	483	139	1.57 (1.19–2.07)	
Black	325	60	0.88 (0.62–1.23)	
Other/multi-racial	175	42	1.22 (0.82–1.82)	
Highest attained education				< 0.0001
Less than high school	301	96	1.0	
Graduated high school	292	83	0.85 (0.60–1.21)	
Some college or university	599	124	0.56 (0.41–0.76)	
Graduated college or university	414	66	0.41 (0.28–0.58)	
Measured BMI group				< 0.0001
Not overweight (< 25 kg/m^2)	642	61	1.0	
Overweight (25–29.9 kg/m^2)	391	84	2.61 (1.82–3.73)	
Obese (≥ 30 kg/m^2)	567	222	6.13 (4.48–8.38)	
Measured waist circumference group				< 0.0001
Low risk (< 80 cm)	394	28	1.0	
Increased risk (80-87 cm)	323	42	1.95 (1.18–3.23)	
Substantial risk (≥ 88 cm)	870	296	6.74 (4.48–10.15)	
Self-reported hypertension				0.0004
No	1424	307	1.0	
Yes	181	61	1.85 (1.33–2.58)	
First-degree family history of diabetes				< 0.0001
No	956	177	1.0	
Yes	622	183	1.84 (1.45–2.33)	
Participate in moderate PA				0.09
No	827	204	1.0	
Yes	780	165	0.82 (0.65–1.04)	
Participate in vigorous PA				< 0.0001
No	1111	298	1.0	
Yes	496	71	0.46 (0.34–0.61)	
Delivered baby weight[d]				< 0.0001
Nulliparous	477	83	1.0	
Baby weight < 9 lb.	652	162	1.57 (1.17–2.11)	
Baby weight ≥ 9 lb.	106	47	3.78 (2.41–5.93)	
Missing	372	77	1.24 (0.88–1.75)	
Self-reported diet healthfulness				< 0.0001
Excellent	89	14	1.0	
Very good	272	33	0.74 (0.38–1.46)	
Good	702	157	1.54 (0.85–2.81)	
Fair	426	119	2.08 (1.13–3.82)	
Poor	118	46	3.42 (1.73–6.76)	
Ever smoker[e]				0.02
No	1126	240	1.0	
Yes	480	129	1.36 (1.06–1.74)	
Current smoker[f]				1.0
No	153	41	1.0	
Yes	327	88	1.01 (0.65–1.55)	

Note. NHANES 2005–2014. Data for 1607 female participants. Actual sample sizes may differ due to missing data. Abbreviations: NHANES, National Health and Nutrition Examination Survey; OGTT, oral glucose tolerance test; OR, odds ratio; CI, confidence interval; PA, physical activity.

[a] Exclusion criteria: pregnant, did not have OGTT results, or had been diagnosed with diabetes.

[b] Dysglycemia = fasting plasma glucose of ≥ 5.6 mmol/L (≥ 100 mg/dL) or two-hour plasma glucose of ≥ 7.8 mmol/L (≥ 140 mg/dL) in the OGTT.

[c] Likelihood ratios were calculated based on univariate analyses containing the predictor and outcome (OGTT).

[d] Delivered baby weight includes still and live births.

[e] Based on ≥ 100 cigarettes smoked in lifetime.

[f] Current cigarette smoking status only asked to those who answered 'yes' to the ≥ 100 cigarettes smoked question.

3. Results

3.1. Sample characteristics

Descriptive statistics for all participants, as well as males and females separately, are provided in Table 1. Of the 3251 participants, 1644 were male and 1607 were female. Participants were, on average, overweight and white, with some college or university education. Based on the OGTT, most of the participants were normoglycemic, while approximately 27.9% and 2.4% were prediabetic and diabetic, respectively.

3.2. Model development

The sex-stratified associations of all predictors and dysglycemia for those 20–39 years of age are displayed in Tables 2 and 3. Due to low prevalence for female participants, the odds ratio for self-reported coronary heart disease could not be estimated reliably. Sex-specific independent predictors of dysglycemia were chosen based on the likelihood ratio ($p < 0.20$).

After sex-specific stepwise functions were fit with the independent predictors, the male model included measured BMI, age, race, and first-

Table 4
Adjusted odds ratio estimates and risk scores for predictors of dysglycemia in young adults included in the final sex-specific regression models[a,b].

Predictors	Male		Female	
	aOR (95% CI)	Score[c]	aOR (95% CI)	Score[c]
Age (years)				
20–24	1.0	0	1.0	0
25–29	0.92 (0.67–1.24)	−9	2.00 (1.31–3.11)	101
30–34	1.30 (0.97–1.75)	30	2.36 (1.56–3.61)	136
35–39	1.72 (1.28–2.31)	72	2.95 (1.94–4.55)	195
Race				
White	1.0	0	1.0	0
Hispanic	1.25 (0.98–1.61)	25	1.24 (0.89–1.72)	24
Black	0.71 (0.52–0.96)	−29	0.55 (0.37–0.80)	−45
Other/multi-racial	1.41 (1.00–2.00)	41	2.89 (1.77–4.72)	189
Measured body mass index				
Not overweight (< 25 kg/m^2)	1.0	0	1.0	0
Overweight (25–29.9 kg/m^2)	1.20 (0.92–1.55)	20	1.47 (0.87–2.49)	47
Obese (≥30 kg/m^2)	2.29 (1.76–3.01)	129	3.04 (1.73–5.42)	204
First-degree family history of diabetes				
No	1.0	0	1.0	0
Yes	1.21 (0.97–1.51)	21	1.39 (1.07–1.82)	39
Measured waist circumference group				
Low risk (< 80 cm)	–	–	1.0	0
Increased risk (80-87 cm)	–	–	1.77 (1.00–3.17)	77
Substantial risk (≥88 cm)	–	–	3.27 (1.68–6.44)	227
Highest attained education				
Less than high school	–	–	1.0	0
Graduated high school	–	–	1.13 (0.76–1.70)	13
Some college or university	–	–	0.72 (0.50–1.04)	−28
Graduated college or university	–	–	0.61 (0.39–0.94)	−39
Participation in vigorous PA				
No	–	–	1.0	0
Yes	–	–	0.63 (0.45–0.86)	−37
Delivered baby weight[d]				
Nulliparous	–	–	1.0	0
Baby weight < 9 lb.	–	–	0.73 (0.51–1.05)	−27
Baby weight ≥9 lb.	–	–	1.62 (0.96–2.73)	62
Missing	–	–	0.64 (0.42–0.95)	−37

Note. NHANES 2005–2014. Data for 1607 males and 1558 females. Participants with any missing data were excluded. Abbreviations: NHANES, National Health and Nutrition Examination Survey; aOR, adjusted odds ratio; CI, confidence interval; PA, physical activity.

[a] All these factors were included simultaneously in the model.

[b] Exclusion criteria: pregnant, did not have OGTT results, or had been diagnosed with diabetes.

[c] Scores = (aOR − 1) ∗ 100, rounded to nearest integer.

[d] Delivered baby weight includes still and live births.

degree family history of diabetes. Though race and first-degree family history of diabetes no longer statistically contributed to the model (p = 0.07 and p = 0.06, respectively), they were included into the final male score because they increased its internal discrimination (AUC = 0.63 vs. 0.69) and calibration (data not shown). The female model contained measured BMI, race, age, education, delivered baby weight, first-degree family history of diabetes, vigorous physical activity, and measured waist circumference. The final sex-specific multivariable logistic models are displayed in Table 4. The tool, which is suitable for self-administration, is shown in Appendix Table 2, with a score of ≥51 for males and ≥320 for females indicating a high risk of having dysglycemia.

Black young adults (aged 20–39) displayed significantly reduced odds of having dysglycemia (excluding diagnosed diabetes) compared to whites based on the OGTT (Table 4; Appendix Table 3). The same trend was found in older adulthood (aged ≥40) and all adults (aged ≥20) before adjustment (Appendix Table 3). However, when glycated hemoglobin (HbA1c) was employed alone or in conjunction with the OGTT to diagnose dysglycemia, blacks became significantly more likely to have dysglycemia compared to whites in all age groups (Appendix Table 3).

3.3. Model performance & comparison to ADA diabetes risk test

The number of responses and assigned scores for predictors included in the DRT are displayed in Table 5. We compared the DRT model with our sex-specific models based on their performance when run with young adult males and females separately.

Pearson correlation coefficients between the DRT and our scores were 0.71 for males and 0.76 for females (data not shown). Fig. 1A demonstrates the discriminatory ability of the DRT when run with male participants through an AUC of 0.61 (95% CI 0.58–0.64), while Fig. 1B denotes poor internal calibration. Using the DRT, the respective sensitivity and specificity for young adult males were 6.7% and 97.9% using the established cut-point score of five (data not shown). On the other hand, our male-specific model had a greater AUC of 0.69 (95% CI 0.66–0.71) (Fig. 1C) and displayed good model fitness (Fig. 1D). The sensitivity and specificity of our male-specific model were 71.3% and 50.7%, respectively, at a cut-point score of 51 (data not shown).

When implemented for females, the DRT AUC increased to 0.71 (95% CI 0.68–0.73; Fig. 2A) and model fitness improved (Fig. 2B). The respective sensitivity and specificity for young adult females were 2.8% and 99.4% when using the DRT at a cut-point score of five (data not shown). Our female-specific model also exhibited a higher discriminatory ability (AUC = 0.92 (95% CI 0.91–0.94); Fig. 2C) and improved internal calibration, exemplified by a linear LOESS-based calibration curve with thin confidence limits (Fig. 2D). For our female-specific model, the sensitivity and specificity were 80.1% and 58.4%, respectively, at a cut-point score of 320 (data not shown).

Notably, neither sex-specific risk score was significantly affected in terms of internal discrimination or calibration when self-reported BMI

Table 5
Number of responses stratified by sex and assigned risk scores for predictors included in the American Diabetes Association Diabetes Risk Test.

Predictors	Male	Female	Score[a]
Age (years)			
< 40	1605 (100)	1572 (100)	0
40–49	–	–	1
50–59	–	–	2
≥60	–	–	3
Sex			
Female	–	1572 (100)	0
Male	1605 (100)	–	1
First-degree family history of diabetes			
No	1068 (66.5)	953 (60.6)	0
Yes	537 (33.5)	619 (39.4)	1
History of hypertension[b]			
No	1298 (80.9)	1365 (86.8)	0
Yes	307 (19.1)	207 (13.2)	1
Obesity[c]			
Not overweight or obese	540 (33.6)	383 (24.4)	0
Overweight	504 (31.4)	319 (20.3)	1
Obese	475 (29.6)	736 (46.8)	2
Extremely obese	86 (5.4)	134 (8.5)	3
Physically active[d]			
No	543 (33.8)	663 (42.2)	0
Yes	1062 (66.2)	909 (57.8)	−1

Note. NHANES 2005–2014. N = 3177. Data are N (%). Participants with any missing data were excluded. Abbreviations: NHANES, National Health and Nutrition Examination Survey.

[a] Scores from Bang et al. (2009).

[b] History of hypertension was based on hypertension diagnosis and/or medication, four systolic blood pressure readings ≥140 mm Hg, and four diastolic blood pressure readings ≥90 mm Hg.

[c] Obesity was based on measured waist circumference in sex-specific categories and measured BMI.

[d] Physically active was based on participation in moderate and/or vigorous physical activity.

values were input as responses rather than measured BMI values (data not shown). Using the same cut-point scores as above, self-reported BMI did not affect the sensitivity and specificity of either the male- (72.6% and 48.2%) or female-specific (79.6% and 57.6%) models (data not shown).

3.4. Missing data

Thirty-seven (2.3%) males and 49 (3.1%) females were excluded from our final sex-specific models due to missing data, mostly for the family history of diabetes variable (33/37 and 29/49, respectively). Excluded males were more likely to report worse diets, while excluded females were more likely to be other/multi-racial; no other significant differences were found (data not shown). Inclusion of participants with missing data did not significantly alter the internal discrimination or calibration of either sex-specific model (data not shown).

4. Discussion

Altogether, our study found that important predictors of dysglycemia development in young adulthood were age, race, BMI, and first-degree family history of diabetes for males and, in addition to those, waist circumference, education, vigorous physical activity, and delivered baby weight for females. Employing these predictors, our male- and female-specific risk models displayed varying discriminatory abilities (AUCs of 0.69 and 0.92, respectively), but high goodness-of-fit. In comparison, the widely-used DRT did not perform well in this age-group, with lower discrimination (males, 0.61; females, 0.71) and goodness-of-fit than our models. These findings indicate that it is necessary to account for age when using survey data to assess the risk of current dysglycemia, though this approach works better for females

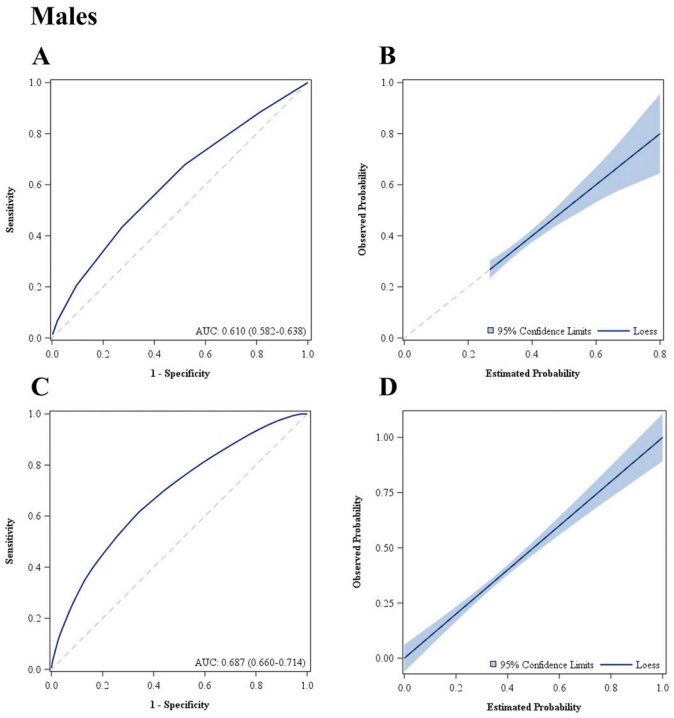

Fig. 1. Model performance of the American Diabetes Association Diabetes Risk Test (DRT) run with young adult, male participants (A, B) compared to our male-specific (C, D) risk score optimized for this age-group. Receiver-operating characteristics (A, C), which test the internal discrimination of the model between true positive and true negative states, and LOESS-based calibration curves (B, D), which test the internal calibration of the model between observed and expected probabilities of suffering with dysglycemia, are displayed. Areas under the receiver-operating curve (AUC) were calculated with 95% confidence limits. Models were validated on NHANES 2005–2014.

than males.

We found obesity, based on either measured BMI or waist circumference, to be the strongest predictor of dysglycemia presence in both male (OR = 2.52 and OR = 2.42, respectively) and female young adults (OR = 6.13 and OR = 6.74, respectively). Yet, after adjustment for BMI, waist circumference was only predictive of dysglycemia presence in females. Similarly, waist circumference change was associated independently of BMI change to diabetes development in Japanese females with large waist circumference, but not males (Tatsumi et al., 2015). BMI and waist circumference also differ more between non-diabetic and diabetic females than males (Wannamethee et al., 2012), suggesting a greater impact to diabetes development in females. Thus, we believe both measures of adiposity are important in a female-specific model. Though few published diabetes risk scores include both, this may be due to being developed for both sexes. Further, our results suggest black young and older adults have lower odds of having dysglycemia (excluding diagnosed diabetes) compared to whites when defined by FPG alone, 2h-PG alone, or OGTT. Based on FPG alone, blacks were also found to be less likely to have prediabetes in the NHANES (Cowie et al., 2006), though based on HbA1c (employed alone or with the OGTT), blacks were more likely to have prediabetes and undiagnosed diabetes compared to whites (Cowie et al., 2010; Marcinkevage et al., 2013; Menke et al., 2015). Indeed, when dysglycemia was defined by HbA1c or HbA1c and OGTT, we found that blacks were at higher risk than whites; nonetheless, these results are misleading. Baseline HbA1c is known to be higher in blacks than whites (Chalew and Hamdan, 2018; Dagogo-Jack, 2010; Herman and Cohen, 2012; Ziemer et al., 2010), resulting in an over-estimation of the prevalence of dysglycemia in the black population (Ziemer et al., 2010). Some advise against using HbA1c altogether, especially for non-

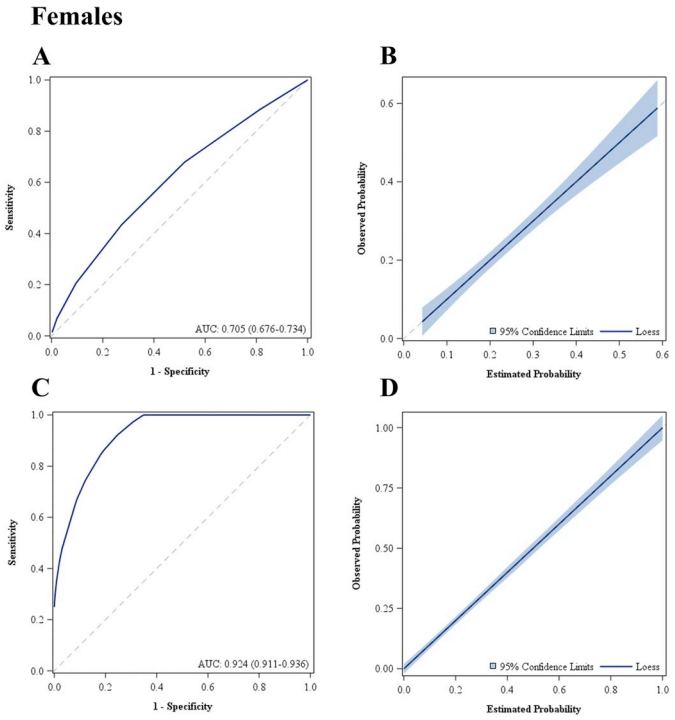

Fig. 2. Model performance of the American Diabetes Association Diabetes Risk Test (DRT) run with young adult, female participants (A, B) compared to our female-specific (C, D) risk score optimized for this age-group. Receiver-operating characteristics (A, C), which test the internal discrimination of the model between true positive and true negative states, and LOESS-based calibration curves (B, D), which test the internal calibration of the model between observed and expected probabilities of suffering with dysglycemia, are displayed. Areas under the receiver-operating curve (AUC) were calculated with 95% confidence limits. Models were validated on NHANES 2005–2014.

Caucasians (Dagogo-Jack, 2010). Thus, we retained the OGTT definition and created sex-specific risk scores to assess young adult dysglycemia risk.

Several risk scores have been previously developed to predict dysglycemia presence in clinical practice. When run using the same dataset used to create the respective model, the DRT had an AUC of 0.79 (cut-point of five: sensitivity, 0.82; specificity, 0.63) (Bang et al., 2009), Canadian Diabetes Risk Questionnaire (CANRISK) had an AUC of 0.75 (cut-point of 29: sensitivity, 0.80; specificity, 0.55) (Robinson et al., 2011), and Finnish Diabetes Risk Score (FINDRISC) had an AUC of 0.85 (cut-point of nine: sensitivity, 0.78; specificity, 0.77) (Lindström and Tuomilehto, 2003). The CANRISK and FINDRISC studies employed the World Health Organization dysglycemia definitions (Lindström and Tuomilehto, 2003; Robinson et al., 2011), while the DRT used the ADA guidelines (Bang et al., 2009). Our sex-specific models fared well in comparison, with our female-specific score outperforming and our male-specific score slightly underperforming in terms of AUC measures when trained and validated on the same dataset. However, none of these risk scores produced sex-specific risk scores, even though sex disparities in dysglycemia development and its risk factors exist (Kautzky-Willer et al., 2016). Studies have found that a positive FINDRISC test is more often accurate for males than females due to these sex-differences (Jølle et al., 2016; Saaristo et al., 2005; Zhang et al., 2014). Similarly, a positive FINDRISC test was found to be more accurate for older adults than young adults (Jølle et al., 2016; Saaristo et al., 2005; Zhang et al., 2014). To determine if the DRT is likewise affected by age and sex, we established its performance compared with our sex-specific models when male and female young adults were tested separately.

Despite the strong positive correlation between our risk scores and the DRT (male models, $\rho = 0.71$; female models, $\rho = 0.76$), both of our male- and female-specific risk models displayed better discriminatory abilities (0.69 vs. 0.61; 0.92 vs. 0.71, respectively) and goodness-of-fit. Due to being developed with older populations in mind, age represented one-third of the DRT's maximum risk score. Thus, the DRT cut-point of five was inappropriate in this demographic as the maximum scores young adult females and males could receive were six and five, respectively. As a result, our models demonstrated better sensitivity compared to the DRT (male models, 71.3% vs. 6.7%; female models, 80.1% vs. 2.8%), but low specificity overall (male models, 50.7% vs. 97.9%; female models, 58.4% vs. 99.4%). Nevertheless, since being identified at high risk for dysglycemia has few negative repercussions regardless of true health status (lifestyle changes and seeking medical consultation), a lower specificity is arguably less important than a high sensitivity. Finally, both our risk score and the DRT demonstrated poorer discrimination for males compared to females, which has been shown previously in other models (Balkau et al., 2008; Saaristo et al., 2005; Zhang et al., 2014). As well, nearly all the risk factors studied, both those subjective and objective, were more predictive of dysglycemia status in females based on univariate analyses. This could not be explained by sex differences in FPG or 2hPG distributions, self-report bias, heterogeneity in pathology, age of onset, or demographics. More work must be done to identify important predictors of dysglycemia status in young adult males.

4.1. Study limitations and strengths

Firstly, an important limitation of our study is the lack of external validation. Unfortunately, we were unable to find a comparable US dataset which combined both self-reported and measured health variables. Secondly, we found that participants excluded from our study differed from those included in terms of some demographic and anthropometric factors, though were similarly distributed between measured BMI and age groups. These differences may affect the models' generalizability. As well, we excluded participants with missing data from the final model, which can generate selection bias and influence model building and performance. However, the model performance did not suffer when participants with missing data were included in the final model and there was a low proportion of missing data, suggesting the overall effect of this bias on the model building procedures may be negligible. Thirdly, it is important to note that due to a largely white sample, these risk scores may not perform well in other populations where the ethnic majority is not Caucasian. Further, BMI and waist circumference groupings employed were based on Caucasian populations and may poorly define obesity for other races. Finally, the use of different definitions of dysglycemia may be affecting model building and performance and should be studied. Current definitions were developed in older populations and must be revised to determine their validity in young adulthood (Nadeau et al., 2016). Limitations notwithstanding, the NHANES is a well-established survey of a representative US sample. Its continuous data collection of objective health data lends itself to studying unfolding public health issues and is therefore well-suited for risk score development. To our knowledge, this is the first study to optimize a dysglycemia risk score for young adulthood in a sex-specific manner.

4.2. Conclusions

Current diabetes risk scores were developed in older populations and have to be revised to increase their validity in young adulthood. This study shows that age- and sex-specific risk scores improve dysglycemia status prediction in young adulthood, particularly in females. However, our findings do not demonstrate unequivocally that our algorithm is superior to the widely-used ADA test. We recommend that our algorithm be applied to other datasets of young adults to evaluate whether our findings are generalizable to other populations. Further, more work must be done to determine predictors of dysglycemia status in young adult males and on stratifying model development by

ethnicity, given that waist circumference (Park et al., 2008), BMI (Mainous et al., 2007), and family history of diabetes (Mainous et al., 2007) show race-dependent associations with diabetes development in young adulthood.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ypmed.2019.01.002.

References

Aguilar-Salinas, C.A., Rojas, R., Gómez-Pérez, F.J., García, E., Valles, V., Ríos-Torres, J.M., Franco, A., Olaiz, G., Sepúlveda, J., Rull, J.A., 2002. Prevalence and characteristics of early-onset type 2 diabetes in Mexico. Am. J. Med. 113, 569–574.

American Diabetes Association, 2018. Classification and diagnosis of diabetes: standards of medical care in diabetes—2018. Diabetes Care 41, S13–S27. https://doi.org/10.2337/dc18-S002.

Anderson, R.J., Freedland, K.E., Clouse, R.E., Lustman, P.J., 2001. The prevalence of comorbid depression in adults with diabetes: a meta-analysis. Diabetes Care 24, 1069–1078.

Austin, P.C., Steyerberg, E.W., 2014. Graphical assessment of internal and external calibration of logistic regression models by using loess smoothers. Stat. Med. 33, 517–535. https://doi.org/10.1002/sim.5941.

Austin, P.C., Tu, J.V., 2004. Automated variable selection methods for logistic regression produced unstable models for predicting acute myocardial infarction mortality. J. Clin. Epidemiol. 57, 1138–1146. https://doi.org/10.1016/j.jclinepi.2004.04.003.

Balkau, B., Lange, C., Fezeu, L., Jean, T., de Lauzon-Guillain, B., Czernichow, S., Fumeron, F., Froguel, P., Vaxillaire, M., Cauchi, S., Ducimetière, P., Eschwège, E., 2008. Predicting diabetes – clinical, biological and genetic approaches: the D.E.S.I.R. study. Diabetes Care. https://doi.org/10.2337/dc08-0368.

Bang, H., Edwards, A.M., Bomback, A.S., Ballantyne, C.M., Brillon, D., Callahan, M.A., Teutsch, S.M., Mushlin, A.I., Kern, L.M., 2009. Development and validation of a patient self-assessment score for diabetes risk. Ann. Intern. Med. 151, 775–783. https://doi.org/10.7326/0003-4819-151-11-200912010-00005.

Boyle, J.P., Thompson, T.J., Gregg, E.W., Barker, L.E., Williamson, D.F., 2010. Projection of the year 2050 burden of diabetes in the US adult population: dynamic modeling of incidence, mortality, and prediabetes prevalence. Popul. Health Metrics 8, 29. https://doi.org/10.1186/1478-7954-8-29.

Bullard, K.M., Saydah, S.H., Imperatore, G., Cowie, C.C., Gregg, E.W., Geiss, L.S., Cheng, Y.J., Rolka, D.B., Williams, D.E., Caspersen, C.J., 2013. Secular changes in U.S. prediabetes prevalence defined by hemoglobin A1c and fasting plasma glucose: National Health and Nutrition Examination Surveys, 1999–2010. Diabetes Care 36, 2286–2293. https://doi.org/10.2337/dc12-2563.

Centers for Disease Control and Prevention (CDC), 2003. Prevalence of diabetes and impaired fasting glucose in adults—United States, 1999–2000. MMWR Morb. Mortal. Wkly Rep. 52, 833–837.

Chalew, S., Hamdan, M., 2018. Racial disparity in HbA1c persists when fructosamine is used as a surrogate for mean blood glucose in youth with type 1 diabetes. Pediatr. Diabetes. https://doi.org/10.1111/pedi.12696.

Cohen, R.A., Bloom, B., 2010. Access to and utilization of medical care for young adults ages 20–29 years: United States, 2008. NCHS Data Brief 1–8.

Collins, G.S., Mallett, S., Omar, O., Yu, L.-M., 2011. Developing risk prediction models for type 2 diabetes: a systematic review of methodology and reporting. BMC Med. 9, 103. https://doi.org/10.1186/1741-7015-9-103.

Cowie, C.C., Rust, K.F., Byrd-Holt, D.D., Eberhardt, M.S., Flegal, K.M., Engelgau, M.M., Saydah, S.H., Williams, D.E., Geiss, L.S., Gregg, E.W., 2006. Prevalence of diabetes and impaired fasting glucose in adults in the U.S. population: National Health and Nutrition Examination Survey 1999–2002. Diabetes Care 29, 1263–1268. https://doi.org/10.2337/dc06-0062.

Cowie, C.C., Rust, K.F., Byrd-Holt, D.D., Gregg, E.W., Ford, E.S., Geiss, L.S., Bainbridge, K.E., Fradkin, J.E., 2010. Prevalence of diabetes and high risk for diabetes using A1C criteria in the U.S. population in 1988-2006. Diabetes Care 33, 562–568. https://doi.org/10.2337/dc09-1524.

Curtin, L.R., Mohadjer, L.K., Dohrmann, S.M., Montaquila, J.M., Kruszan-Moran, D., Mirel, L.B., Carroll, M.D., Hirsch, R., Schober, S., Johnson, C.L., 2012. The National Health and Nutrition Examination Survey: sample design, 1999–2006. Vital Health Stat. 2, 1–39.

Curtin, L.R., Mohadjer, L.K., Dohrmann, S.M., Kruszon-Moran, D., Mirel, L.B., Carroll, M.D., Hirsch, R., Burt, V.L., Johnson, C.L., 2013. National Health and Nutrition Examination Survey: sample design, 2007–2010. Vital Health Stat. 2, 1–23.

Dabelea, D., Stafford, J.M., Mayer-Davis, E.J., D'Agostino, R., Dolan, L., Imperatore, G., Linder, B., Lawrence, J.M., Marcovina, S.M., Mottl, A.K., Black, M.H., Pop-Busui, R., Saydah, S., Hamman, R.F., Pihoker, C., SEARCH for Diabetes in Youth Research Group, 2017. Association of type 1 diabetes vs type 2 diabetes diagnosed during childhood and adolescence with complications during teenage years and young adulthood. JAMA 317, 825–835. https://doi.org/10.1001/jama.2017.0686.

Dagogo-Jack, S., 2010. Pitfalls in the use of $HbA_1(c)$ as a diagnostic test: the ethnic conundrum. Nat. Rev. Endocrinol. 6, 589–593. https://doi.org/10.1038/nrendo.2010.126.

de Groot, M., Anderson, R., Freedland, K.E., Clouse, R.E., Lustman, P.J., 2001. Association of depression and diabetes complications: a meta-analysis. Psychosom. Med. 63, 619.

Deshpande, A.D., Harris-Hayes, M., Schootman, M., 2008. Epidemiology of diabetes and diabetes-related complications. Phys. Ther. 88, 1254–1264. https://doi.org/10.2522/ptj.20080020.

Diabetes Control and Complications Trial Research Group, Nathan, D.M., Genuth, S., Lachin, J., Cleary, P., Crofford, O., Davis, M., Rand, L., Siebert, C., 1993. The effect of intensive treatment of diabetes on the development and progression of long-term complications in insulin-dependent diabetes mellitus. N. Engl. J. Med. 329, 977–986. https://doi.org/10.1056/NEJM199309303291401.

Fishman, E., 2001. Aging out of coverage: young adults with special health needs. Health Aff. (Millwood) 20, 254–266. https://doi.org/10.1377/hlthaff.20.6.254.

Goldney, R.D., Phillips, P.J., Fisher, L.J., Wilson, D.H., 2004. Diabetes, depression, and quality of life: a population study. Diabetes Care 27, 1066–1070. https://doi.org/10.2337/diacare.27.5.1066.

Grigsby, A.B., Anderson, R.J., Freedland, K.E., Clouse, R.E., Lustman, P.J., 2002. Prevalence of anxiety in adults with diabetes: a systematic review. J. Psychosom. Res. 53, 1053–1060. https://doi.org/10.1016/S0022-3999(02)00417-8.

Guariguata, L., Whiting, D.R., Hambleton, I., Beagley, J., Linnenkamp, U., Shaw, J.E., 2014. Global estimates of diabetes prevalence for 2013 and projections for 2035. Diabetes Res. Clin. Pract. 103, 137–149. https://doi.org/10.1016/j.diabres.2013.11.002.

Herman, W.H., Cohen, R.M., 2012. Racial and ethnic differences in the relationship between HbA1c and blood glucose: implications for the diagnosis of diabetes. J. Clin. Endocrinol. Metab. 97, 1067–1072. https://doi.org/10.1210/jc.2011-1894.

Hillier, T.A., Pedula, K.L., 2001. Characteristics of an adult population with newly diagnosed type 2 diabetes: the relation of obesity and age of onset. Diabetes Care 24, 1522–1527. https://doi.org/10.2337/diacare.24.9.1522.

Hosmer, D., Lemeshow, S., 2000. Chapter 5: assessing the fit of the model. In: Applied Logistic Regression. Wiley Series in Probability and Statistics John Wiley and Sons, New York, NY, pp. 160–164.

Huo, X., Gao, L., Guo, L., Xu, W., Wang, W., Zhi, X., Li, L., Ren, Y., Qi, X., Sun, Z., Li, W., Ji, Q., Ran, X., Su, B., Hao, C., Lu, J., Guo, X., Zhuo, H., Zhang, D., Pan, C., Weng, J., Hu, D., Yang, X., Ji, L., 2016. Risk of non-fatal cardiovascular diseases in early-onset versus late-onset type 2 diabetes in China: a cross-sectional study. Lancet Diabetes Endocrinol. 4, 115–124. https://doi.org/10.1016/S2213-8587(15)00508-2.

Jiang, L., Manson, S.M., Beals, J., Henderson, W.G., Huang, H., Acton, K.J., Roubideaux, Y., Special Diabetes Program for Indians Diabetes Prevention Demonstration Project, 2013. Translating the diabetes prevention program into American Indian and Alaska native communities: results from the special diabetes program for Indians diabetes prevention demonstration project. Diabetes Care 36, 2027–2034. https://doi.org/10.2337/dc12-1250.

Johnson, C.L., Dohrmann, S.M., Burt, V.L., Mohadjer, L.K., 2014. National Health and nutrition examination survey: sample design, 2011–2014. Vital Health Stat. 2, 1–33.

Jølle, A., Midthjell, K., Holmen, J., Tuomilehto, J., Carlsen, S.M., Shaw, J., Åsvold, B.O., 2016. Impact of sex and age on the performance of FINDRISC: the HUNT study in Norway. BMJ Open Diabetes Res. Care 4, e000217. https://doi.org/10.1136/bmjdrc-2016-000217.

Kaiser, A., Vollenweider, P., Waeber, G., Marques-Vidal, P., 2012. Prevalence, awareness and treatment of type 2 diabetes mellitus in Switzerland: the CoLaus study. Diabet. Med. 29, 190–197. https://doi.org/10.1111/j.1464-5491.2011.03422.x.

Kautzky-Willer, A., Harreiter, J., Pacini, G., 2016. Sex and gender differences in risk, pathophysiology and complications of type 2 diabetes mellitus. Endocr. Rev. 37, 278–316. https://doi.org/10.1210/er.2015-1137.

Knowler, W.C., Barrett-Connor, E., Fowler, S.E., Hamman, R.F., Lachin, J.M., Walker, E.A., Nathan, D.M., Diabetes Prevention Program Research Group, 2002. Reduction in the incidence of type 2 diabetes with lifestyle intervention or metformin. N. Engl. J. Med. 346, 393–403. https://doi.org/10.1056/NEJMoa012512.

Kramer, M.K., Miller, R.G., Siminerio, L.M., 2014. Evaluation of a community diabetes prevention program delivered by diabetes educators in the United States: one-year follow up. Diabetes Res. Clin. Pract. 106, e49–e52. https://doi.org/10.1016/j.diabres.2014.10.012.

Lascar, N., Brown, J., Pattison, H., Barnett, A.H., Bailey, C.J., Bellary, S., 2018. Type 2 diabetes in adolescents and young adults. Lancet Diabetes Endocrinol. 6, 69–80. https://doi.org/10.1016/S2213-8587(17)30186-9.

Lean, M.E., Han, T.S., Morrison, C.E., 1995. Waist circumference as a measure for indicating need for weight management. BMJ 311, 158–161.

Lindström, J., Tuomilehto, J., 2003. The diabetes risk score: a practical tool to predict type 2 diabetes risk. Diabetes Care 26, 725–731. https://doi.org/10.2337/diacare.26.3.725.

Logue, J., Walker, J.J., Colhoun, H.M., Leese, G.P., Lindsay, R.S., McKnight, J.A., Morris,

A.D., Pearson, D.W., Petrie, J.R., Philip, S., Wild, S.H., Sattar, N., Scottish Diabetes Research Network Epidemiology Group, 2011. Do men develop type 2 diabetes at lower body mass indices than women? Diabetologia 54, 3003–3006. https://doi.org/10.1007/s00125-011-2313-3.

Lyznicki, J.M., Young, D.C., Riggs, J.A., Davis, R.M., Council on Scientific Affairs, American Medical Association, 2001. Obesity: assessment and management in primary care. Am. Fam. Physician 63, 2185–2196.

Mainous, A.G., Diaz, V.A., Everett, C.J., 2007. Assessing risk for development of diabetes in young adults. Ann. Fam. Med. 5, 425–429. https://doi.org/10.1370/afm.705.

Marcinkevage, J.A., Alverson, C.J., Narayan, K.M.V., Kahn, H.S., Ruben, J., Correa, A., 2013. Race/ethnicity disparities in dysglycemia among U.S. women of childbearing age found mainly in the nonoverweight/nonobese. Diabetes Care 36, 3033–3039. https://doi.org/10.2337/dc12-2312.

Mathers, C.D., Loncar, D., 2006. Projections of global mortality and burden of disease from 2002 to 2030. PLoS Med. 3, e442. https://doi.org/10.1371/journal.pmed.0030442.

Menke, A., Casagrande, S., Geiss, L., Cowie, C.C., 2015. Prevalence of and trends in diabetes among adults in the United States, 1988–2012. JAMA 314, 1021–1029. https://doi.org/10.1001/jama.2015.10029.

Nadeau, K.J., Anderson, B.J., Berg, E.G., Chiang, J.L., Chou, H., Copeland, K.C., Hannon, T.S., Huang, T.T.-K., Lynch, J.L., Powell, J., Sellers, E., Tamborlane, W.V., Zeitler, P., 2016. Youth-onset type 2 diabetes consensus report: current status, challenges, and priorities. Diabetes Care 39, 1635–1642. https://doi.org/10.2337/dc16-1066.

Park, J., Mendoza, J.A., O'Neil, C.E., Hilmers, D.C., Liu, Y., Nicklas, T.A., 2008. A comparison of the prevalence of the metabolic syndrome in the United States (US) and Korea in young adults aged 20 to 39 years. Asia Pac. J. Clin. Nutr. 17, 471–482.

Paulweber, B., Valensi, P., Lindström, J., Lalic, N.M., Greaves, C.J., McKee, M., Kissimova-Skarbek, K., Liatis, S., Cosson, E., Szendroedi, J., Sheppard, K.E., Charlesworth, K., Felton, A.-M., Hall, M., Rissanen, A., Tuomilehto, J., Schwarz, P.E., Roden, M., Paulweber, M., Stadlmayr, A., Kedenko, L., Katsilambros, N., Makrilakis, K., Kamenov, Z., Evans, P., Gilis-Januszewska, A., Lalic, K., Jotic, A., Djordevic, P., Dimitrijevic-Sreckovic, V., Hühmer, U., Kulzer, B., Puhl, S., Lee-Barkey, Y.H., AlKerwi, A., Abraham, C., Hardeman, W., Acosta, T., Adler, M., AlKerwi, A., Barengo, N., Barengo, R., Boavida, J.M., Charlesworth, K., Christov, V., Claussen, B., Cos, X., Cosson, E., Deceukelier, S., Dimitrijevic-Sreckovic, V., Djordjevic, P., Evans, P., Felton, A.-M., Fischer, M., Gabriel-Sanchez, R., Gilis-Januszewska, A., Goldfracht, M., Gomez, J.L., Greaves, C.J., Hall, M., Handke, U., Hauner, H., Herbst, J., Hermanns, N., Herrebrugh, L., Huber, C., Hühmer, U., Huttunen, J., Jotic, A., Kamenov, Z., Karadeniz, S., Katsilambros, N., Khalangot, M., Kissimova-Skarbek, K., Köhler, D., Kopp, V., Kronsbein, P., Kulzer, B., Kyne-Grzebalski, D., Lalic, K., Lalic, N., Landgraf, R., Lee-Barkey, Y.H., Liatis, S., Lindström, J., Makrilakis, K., McIntosh, C., McKee, M., Mesquita, A.C., Misina, D., Muylle, F., Neumann, A., Paiva, A.C., Pajunen, P., Paulweber, B., Peltonen, M., Perrenoud, L., Pfeiffer, A., Pölönen, A., Puhl, S., Raposo, F., Reinehr, T., Rissanen, A., Robinson, C., Roden, M., Rothe, U., Saaristo, T., Scholl, J., Schwarz, P.E., Sheppard, K.E., Spiers, S., Stemper, T., Stratmann, B., Szendroedi, J., Szybinski, Z., Tankova, T., Telle-Hjellset, V., Terry, G., Tolks, D., Toti, F., Tuomilehto, J., Undeutsch, A., Valadas, C., Valensi, P., Velickiene, D., Vermunt, P., Weiss, R., Wens, J., Yilmaz, T., 2010. A European evidence-based guideline for the prevention of type 2 diabetes. Horm. Metab. Res. 42 (Suppl. 1), S3–36. https://doi.org/10.1055/s-0029-1240928.

Poltavskiy, E., Kim, D.J., Bang, H., 2016. Comparison of screening scores for diabetes and prediabetes. Diabetes Res. Clin. Pract. 118, 146–153. https://doi.org/10.1016/j.diabres.2016.06.022.

Rhodes, E.T., Prosser, L.A., Hoerger, T.J., Lieu, T., Ludwig, D.S., Laffel, L.M., 2012. Estimated morbidity and mortality in adolescents and young adults diagnosed with type 2 diabetes mellitus. Diabet. Med. 29, 453–463. https://doi.org/10.1111/j.1464-5491.2011.03542.x.

Robinson, C.A., Agarwal, G., Nerenberg, K., 2011. Validating the CANRISK prognostic model for assessing diabetes risk in Canada's multi-ethnic population. Chronic Dis. Inj. Can. 32, 19–31.

Rochette, L., Zeller, M., Cottin, Y., Vergely, C., 2014. Diabetes, oxidative stress and therapeutic strategies. Biochim. Biophys. Acta 1840, 2709–2729. https://doi.org/10.1016/j.bbagen.2014.05.017.

Rubin, R.R., Peyrot, M., 1999. Quality of life and diabetes. Diabetes Metab. Res. Rev. 15, 205–218. https://doi.org/10.1002/(SICI)1520-7560(199905/06)15:3<205::AID-DMRR29>3.0.CO;2-O.

Saaristo, T., Peltonen, M., Lindström, J., Saarikoski, L., Sundvall, J., Eriksson, J.G., Tuomilehto, J., 2005. Cross-sectional evaluation of the Finnish diabetes risk score: a tool to identify undetected type 2 diabetes, abnormal glucose tolerance and metabolic syndrome. Diab. Vasc. Dis. Res. 2, 67–72. https://doi.org/10.3132/dvdr.2005.011.

Satman, I., Omer, B., Tutuncu, Y., Kalaca, S., Gedik, S., Dinccag, N., Karsidag, K., Genc, S., Telci, A., Canbaz, B., Turker, F., Yilmaz, T., Cakir, B., Tuomilehto, J., 2013. Twelve-year trends in the prevalence and risk factors of diabetes and prediabetes in Turkish adults. Eur. J. Epidemiol. 28, 169–180. https://doi.org/10.1007/s10654-013-9771-5.

Skyler, J.S., 2004. Effects of glycemic control on diabetes complications and on the prevention of diabetes. Clin. Diabetes 22, 162–166. https://doi.org/10.2337/diaclin.22.4.162.

Song, S.H., Hardisty, C.A., 2009. Early onset type 2 diabetes mellitus: a harbinger for complications in later years—clinical observation from a secondary care cohort. QJM 102, 799–806. https://doi.org/10.1093/qjmed/hcp121.

Tabák, A.G., Herder, C., Rathmann, W., Brunner, E.J., Kivimäki, M., 2012. Prediabetes: a high-risk state for diabetes development. Lancet 379, 2279–2290. https://doi.org/10.1016/S0140-6736(12)60283-9.

Tatsumi, Y., Watanabe, M., Nakai, M., Kokubo, Y., Higashiyama, A., Nishimura, K., Kobayashi, T., Takegami, M., Nakao, Y.M., Watanabe, T., Okayama, A., Okamura, T., Miyamoto, Y., 2015. Changes in waist circumference and the incidence of type 2 diabetes in community-dwelling men and women: the Suita study. J. Epidemiol. 25, 489–495. https://doi.org/10.2188/jea.JE20140160.

Tuomilehto, J., Lindström, J., Eriksson, J.G., Valle, T.T., Hämäläinen, H., Ilanne-Parikka, P., Keinänen-Kiukaanniemi, S., Laakso, M., Louheranta, A., Rastas, M., Salminen, V., Uusitupa, M., Finnish Diabetes Prevention Study Group, 2001. Prevention of type 2 diabetes mellitus by changes in lifestyle among subjects with impaired glucose tolerance. N. Engl. J. Med. 344, 1343–1350. https://doi.org/10.1056/NEJM200105033441801.

Tuso, P., 2014. Prediabetes and lifestyle modification: time to prevent a preventable disease. Perm. J. 18, 88–93. https://doi.org/10.7812/TPP/14-002.

Van De Mortel, T.F., 2008. Faking it: social desirability response bias in self-report research. Aust. J. Adv. Nurs. 25, 40.

Vita, P., Cardona-Morrell, M., Bauman, A., Singh, M.F., Moore, M., Pennock, R., Snow, J., Williams, M., Jackson, L., Milat, A., Colagiuri, S., 2016. Type 2 diabetes prevention in the community: 12-month outcomes from the Sydney diabetes prevention program. Diabetes Res. Clin. Pract. 112, 13–19. https://doi.org/10.1016/j.diabres.2015.11.010.

Vojta, D., Koehler, T.B., Longjohn, M., Lever, J.A., Caputo, N.F., 2013. A coordinated national model for diabetes prevention: linking health systems to an evidence-based community program. Am. J. Prev. Med. 44, S301–S306. https://doi.org/10.1016/j.amepre.2012.12.018.

Wang, Y., Rimm, E.B., Stampfer, M.J., Willett, W.C., Hu, F.B., 2005. Comparison of abdominal adiposity and overall obesity in predicting risk of type 2 diabetes among men. Am. J. Clin. Nutr. 81, 555–563. https://doi.org/10.1093/ajcn/81.3.555.

Wannamethee, S.G., Papacosta, O., Lawlor, D.A., Whincup, P.H., Lowe, G.D., Ebrahim, S., Sattar, N., 2012. Do women exhibit greater differences in established and novel risk factors between diabetes and non-diabetes than men? The British regional heart study and British women's heart health study. Diabetologia 55, 80–87. https://doi.org/10.1007/s00125-011-2284-4.

Wild, S., Roglic, G., Green, A., Sicree, R., King, H., 2004. Global prevalence of diabetes: estimates for the year 2000 and projections for 2030. Diabetes Care 27, 1047–1053.

Wilmot, E., Idris, I., 2014. Early onset type 2 diabetes: risk factors, clinical impact and management. Ther. Adv. Chronic Dis. 5, 234–244. https://doi.org/10.1177/2040622314548679.

World Health Organization, 2000. Obesity: preventing and managing the global epidemic. In: WHO Technical Report Series (Geneva, Switzerland).

Yu, H., Xie, L.-F., Chen, K., Yang, G.-Y., Xing, X.-Y., Zhao, J.-J., Hong, T.-P., Shan, Z.-Y., Li, H.-M., Chen, B., Tang, X.-L., Qi, L., Yang, J., Fang, Y., Li, T., Wang, S.-S., Liang, X., Yin, Y.-Q., Mu, Y.-M., 2016. Initiating characteristics of early-onset type 2 diabetes mellitus in Chinese patients. Chin. Med. J. 129, 778. https://doi.org/10.4103/0366-6999.178959.

Zhang, L., Zhang, Z., Zhang, Y., Hu, G., Chen, L., 2014. Evaluation of Finnish diabetes risk score in screening undiagnosed diabetes and prediabetes among U.S. adults by gender and race: NHANES 1999–2010. PLoS One 9, e97865. https://doi.org/10.1371/journal.pone.0097865.

Zhang, Y., Hu, G., Zhang, L., Mayo, R., Chen, L., 2015. A novel testing model for opportunistic screening of pre-diabetes and diabetes among U.S. adults. PLoS ONE 10. https://doi.org/10.1371/journal.pone.0120382.

Ziemer, D.C., Kolm, P., Weintraub, W.S., Vaccarino, V., Rhee, M.K., Twombly, J.G., Narayan, K.M.V., Koch, D.D., Phillips, L.S., 2010. Glucose-independent, black-white differences in hemoglobin A1c levels: a cross-sectional analysis of 2 studies. Ann. Intern. Med. 152, 770–777. https://doi.org/10.7326/0003-4819-152-12-201006150-00004.

Zipf, G., Chiappa, M., Porter, K.S., Ostchega, Y., Lewis, B.G., Dostal, J., 2013. National Health and Nutrition Examination Survey: plan and operations, 1999–2010. In: Vital Health Stat. Ser 1 Programs Collect. Proced. pp. 1–37.