

Predicting diabetes risk among HIV-positive and HIV-negative women

Karla I. Galaviz^a, Michael F. Schneider^b, Phyllis C. Tien^{c,d},
C. Christina Mehta^e, Ighovwerha Ofotokun^f, Jonathan Colasanti^{a,f},
Vincent C. Marconi^{a,f}, Kartika Palar^c, Gina Wingood^g,
Adaora A. Adimora^h, Maria Alcaideⁱ, Mardge H. Cohen^j,
Deborah Gustafson^k, Roksana Karim^l, Deborah Konkle-Parker^m,
Daniel Merensteinⁿ, Anjali Sharma^o and Mohammed K. Ali^a

Objective: To assess the performance of an adapted American Diabetes Association (ADA) risk score and the concise Finnish Diabetes Risk Score (FINRISC) for predicting type 2 diabetes development in women with and at risk of HIV infection.

Design: Longitudinal analysis of the Women's Interagency HIV Study.

Methods: The women's Interagency HIV Study is an ongoing prospective cohort study of women with and at risk for HIV infection. Women without prevalent diabetes and 3-year data on fasting blood glucose, hemoglobin A1c, self-reported diabetes medication use, and self-reported diabetes were included. ADA and FINRISC scores were computed at baseline and their ability to predict diabetes development within 3 years was assessed [sensitivity, specificity and area under the receiver operating characteristics (AUROC) curve].

Results: A total of 1111 HIV-positive (median age 41, 60% African American) and 454 HIV-negative women (median age 38, 63% African-American) were included. ADA sensitivity did not differ between HIV-positive (77%) and HIV-negative women (81%), while specificity was better in HIV-negative women (42 vs. 49%, $P=0.006$). Overall ADA discrimination was suboptimal in both HIV-positive [AUROC=0.64 (95% CI: 0.58, 0.70)] and HIV-negative women [AUROC=0.67 (95% CI: 0.57, 0.77)]. FINRISC sensitivity and specificity did not differ between HIV-positive (72 and 49%, respectively) and HIV-negative women (86 and 52%, respectively). Overall FINRISC discrimination was suboptimal in HIV-positive [AUROC=0.68 (95% CI: 0.62, 0.75)] and HIV-negative women [AUROC=0.78 (95% CI: 0.66, 0.90)].

^aHubert Department of Global Health, Rollins School of Public Health, Emory University, Atlanta, Georgia, ^bDepartment of Epidemiology, Johns Hopkins Bloomberg School of Public Health, Baltimore, Maryland, ^cDivision of Infectious Diseases, Department of Medicine, University of California-San Francisco, ^dDepartment of Veterans Affairs, San Francisco, California, ^eDepartment of Biostatistics and Bioinformatics, Rollins School of Public Health, Emory University, ^fDivision of Infectious Diseases, Department of Medicine, Emory University School of Medicine, Atlanta, Georgia, ^gDepartment of Sociomedical Sciences, Lerner Center for Public Health Promotion, Mailman School of Public Health at Columbia University, New York, New York, ^hDivision of Infectious Disease, Department of Medicine, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, ⁱDivision of Infectious Diseases, University of Miami Miller School of Medicine, Miami, Florida, ^jDepartment of Medicine, Stroger Hospital and Rush University, Chicago, Illinois, ^kDepartment of Neurology (D.G.), SUNY-Downstate Medical Center, Brooklyn, New York, ^lDepartment of Preventive Medicine, University of Southern California, Los Angeles, California, ^mUniversity of Mississippi Medical Center, Jackson, Mississippi, ⁿDepartment of Family Medicine, Georgetown University Medical Center, Washington, District of Columbia, and ^oDepartment of Medicine, Albert Einstein College of Medicine, Bronx, New York, USA.

Correspondence to Karla I. Galaviz, Assistant Professor, Hubert Department of Global Health, Rollins School of Public Health, Emory University, 1518 Clifton Road NE, CNR Building Room 7041, Atlanta, Georgia, USA.

Tel: +1 404 727 9776; e-mail: kgalavi@emory.edu

Received: 4 June 2018; accepted: 27 July 2018.

Conclusion: Model performance was suboptimal in women with and at risk of HIV, while greater misclassification was generally observed among HIV-positive women. HIV-specific risk factors known to contribute to diabetes risk should be explored in these models.

AIDS 2018, **32**:2767–2775

Keywords: epidemiology, HIV, risk analysis, screening, women's healthcare

Introduction

Type 2 diabetes is a common comorbidity in people living with HIV (PLWH) in the United States, possibly fueling the increased risk of cardiovascular and renal disease and mortality this population is facing [1–3]. PLWH in the United States are two to four times more likely to develop diabetes than their HIV-negative counterparts [4,5], and have a national diabetes prevalence 4% higher than the general adult population [6]. The increased diabetes risk PLWH face has been linked to chronic inflammation, medication-induced dysglycemia, and immunosuppression [7–11]. Furthermore, traditional diabetes risk factors such as older age, minority race, and obesity have been found to have a stronger effect on diabetes risk among HIV-positive than HIV-negative persons [1]. There are 1.2 million PLWH in the United States [12] and those at increased diabetes risk should be identified and treated appropriately to potentially prevent diabetes and its complications.

To minimize the harms of inappropriate glucose testing (e.g. costs, anxiety), expert groups recommend a two-stage diabetes risk screening approach – noninvasive risk assessment followed by glucose testing [13,14]. This approach involves using noninvasive risk scores such as the American Diabetes Association (ADA) diabetes risk score [15] or the Finnish Diabetes Risk Score (FINRISC) [16] to identify those who should be offered diagnostic glucose testing. In the general population, the ADA and FINRISC scores have been found to be effective and practical tools for identifying people with dysglycemia in clinical practice [17–21].

The ADA and FINRISC scores should be tested among PLWH to determine if they are effective diabetes risk screening tools in the setting of HIV infection. Although a recent cross-sectional study tested FINRISC among PLWH, the study did not include an HIV-negative sample for comparing tool performance [22]. Efforts have also been directed towards developing an HIV-specific diabetes risk equation [23] but a practical scoring system has not been developed. It remains unknown what risk score would most accurately identify PLWH at risk for diabetes. Thus, we aimed to assess and compare the performance of the ADA and FINRISC diabetes risk scores in a longitudinal cohort study of HIV-positive and HIV-negative women.

Methods

Study design and population

This was a longitudinal analysis of the Women's Interagency HIV Study (WIHS). WIHS is an ongoing multicentre prospective cohort study established in 1994 in the United States to investigate the progression of HIV in women with and at risk for HIV infection [24]. A total of 4982 women (3678 HIV-positive and 1304 HIV-negative) were enrolled in four waves: 1994–1995 ($n = 2623$), 2001–2002 ($n = 1143$), 2011–2013 ($n = 371$), and 2013–2015 ($n = 845$) from 11 cities (Atlanta, Birmingham, Bronx, Brooklyn, Chapel Hill, Chicago, Jackson, Los Angeles, Miami, San Francisco, and Washington DC). Every 6 months, WIHS participants complete a comprehensive physical examination, provide biological specimens for blood testing, and complete an interviewer-administered questionnaire, which collects information on demographics, disease characteristics, and specific antiretroviral therapy (ART) use. The WIHS study protocol and consent forms have been approved by the Institutional Review Board at each study site, and all participants have provided written informed consent.

Hemoglobin A1c (A1c) and fasting blood glucose (FBG) testing were first introduced in WIHS in October 2000. At each semiannual visit, participants are asked if they use any antidiabetic medication and if they had been told they have diabetes. The index visit was defined as the first visit at which FBG, A1c, self-reported antidiabetic medication use, and self-reported diabetes data were available. Participants with prevalent diabetes (defined as $\text{FBG} \geq 126 \text{ mg/dl}$ or $\text{A1c} \geq 6.5\%$ at the index visit; or self-reported antidiabetic medication use or self-reported diabetes before or at the index visit) were excluded. To be included in our analysis, participants had to have data on FBG, A1c, self-reported antidiabetic medication use, and self-reported diabetes at least once annually for 3 years after the index visit.

Exposures and outcome

Race, age, BMI, and self-reported health insurance status were compared between HIV-positive and HIV-negative women at the index visit. Prediabetes prevalence, defined as either FBG of 100–125 mg/dl or A1c of 5.7–6.4%, was also compared at the index visit. In HIV-positive women, we calculated the prevalence of stavudine use, ritonavir use

or any protease inhibitor use as of the index visit since these HIV medications have been linked to increased diabetes risk [4,10]. Undetectable HIV RNA was defined as HIV-1 RNA less than 80 copies/ml at index visit.

The exposures of interest were ADA and FINRISC diabetes risk scores. The risk scores included the following variables: age, BMI [weight (kg)/height² (meters)], waist circumference (measured in standing position using standardized procedures) [25], history of hypertension (SBP \geq 140 mmHg and DBP \geq 90 mmHg or self-reported hypertension or as self-reported anti-hypertension medication use prior to or at index visit), history of hyperglycemia (FBG measure of 100–125 mg/dl at index visit) and family history of diabetes.

The ADA risk score was computed by summing the risk points obtained for age [$<$ 40 years (0 pts), 40 to $<$ 50 years (1 pt), 50 to $<$ 60 years (2 pts), \geq 60 years (3 pts)], BMI/waist circumference [BMI $<$ 25 kg/m² or waist $<$ 31.5 in (0 pts), BMI 25 to $<$ 30 kg/m² or waist 31.5 to $<$ 35 in (1 pt), BMI 30 to $<$ 40 kg/m² or waist 35.0 to $<$ 49 in (2 pts), BMI \geq 40 kg/m² or waist \geq 49 in (3 pts)], history of hypertension [No (0 pts), Yes (1 pt)], and family history of diabetes [No (0 pts), Yes (1 pt)] [15]. Since all participants were women, sex did not contribute risk points [male (1 pt), female (0 pts)]. Because WIHS lacks physical activity data, this risk factor was excluded from the ADA model.

The FINRISC score was computed by summing the risk points obtained for age [$<$ 45 years (0 pts), 45 to $<$ 55 years (2 pts), \geq 55 years (3 pts)], BMI [$<$ 25 kg/m² (0 pts), 25 to $<$ 30 kg/m² (1 pt), $>$ 30 kg/m² (3 pts)], waist circumference [$<$ 31.5 in (0 pts), 31.5–34.6 in (3 pts), $>$ 34.6 in (4 pts)], FBG [$<$ 100 mg/dl (0 pts), 100 to $<$ 126 mg/dl (5 pts)], and history of hypertension medication use [No (0 pts), Yes (2 pts)] [16]. We used the FINRISC concise model, which excludes physical activity and fruit and vegetable consumption [16].

The outcome of interest was incident diabetes, defined as the first time within 3 years after the index visit at which the participant reported antidiabetic medication use (confirmed with A1c \geq 6.5% or FBG \geq 126 mg/dl), FBG \geq 126 mg/dl (confirmed with a report of antidiabetic medication use or a second FBG measure \geq 126 mg/dl or A1c \geq 6.5%), or self-report of diabetes (confirmed with a report of antidiabetic medication use or two FBG measures \geq 126 mg/dl or concurrent A1c \geq 6.5% and FBG \geq 126 mg/dl) [5].

Statistical analysis

Wilcoxon rank-sum tests were used to test for differences between HIV-positive and HIV-negative women in demographic and clinical characteristics at the index visit. Pearson chi-square tests were used to test for associations

between categorical characteristics and HIV status at the index visit.

For each woman, we calculated an ADA and a FINRISC score at index visit and determined whether diabetes developed within 3 years following the index visit. To categorize women as being at low or high diabetes risk, we chose risk score thresholds (low risk, high risk) that gave equal weight to sensitivity and specificity. We compared the sensitivity, specificity, positive predictive value and negative predictive value of the models between HIV-positive and HIV-negative women using score thresholds selected for this study with two-sample tests of proportions.

We calculated the area under the receiver operating characteristics curves (AUROC) for HIV-positive and HIV-negative women to assess the ability of the models to discriminate those with and without diabetes; values of at least 0.8 were considered indicative of good model discrimination [26]. Ninety-five percent confidence intervals (95% CI) were calculated to quantify the precision in the estimated sensitivity, specificity, positive predictive value, negative predictive value, and AUROC for HIV-positive and HIV-negative women. Significant differences in receiver operating characteristics (ROC) curves between HIV-positive and HIV-negative women (e.g. ROC1 and ROC2) were determined as follows:

$$P \text{ value} = P \left[\chi_1^2 > \left(\frac{(\text{AUROC}_1 - \text{AUROC}_2)^2}{(\text{standard error of ROC}_1^2 + \text{standard error of ROC}_2^2)} \right) \right].$$

We compared diabetes risk classification (via sensitivity, specificity, positive predictive value, negative predictive value, and AUROC) for ADA and FINRISC scores in HIV-positive women at different calendar periods. These were selected based on the years corresponding to early highly active ART (HAART) era (2000–2003) and late HAART era (2010–2013). Specifically, we compared risk score performance between 773 HIV-positive women who had an index visit between October 2000 and March 2003 (early HAART era) and 338 HIV-positive women who had an index visit in the January 2010 to January 2013 period (late HAART era). All statistical analyses were conducted using SAS version 9.4 (SAS Institute Inc 2013 Cary, North Carolina, USA).

Results

From the 1719 eligible women (1225 HIV-positive and 494 HIV-negative), 1565 (1111 HIV-positive and 454 HIV-negative) had complete data to test the ADA and FINRISC models and were included in analyses (see Figure, Supplemental Digital Content 1, <http://links.lww.com/QAD/B361>, which presents the sample selection flow diagram). The excluded women (114 HIV-positive and 40 HIV-negative) were younger than those

Table 1. Participant characteristics by HIV status (N = 1565).

Characteristics	HIV-positive, n = 1111	HIV-negative, n = 454	P value
African-American race, N (%)	663 (60)	284 (63)	0.299
Age [years, median (IQR)]	41 (34, 47)	38 (29, 46)	<0.001
BMI [kg/m ² , median (IQR)]	27 (24, 32)	28 (24, 34)	0.064
Health insurance, N (%)	1023 (92)	301 (66)	<0.001
Prediabetes, N (%)	283 (25)	149 (33)	0.003
History of stavudine use, N (%)	475 (43)	NA	NA
History of any protease inhibitor use, N (%)	597 (54)	NA	NA
History of ritonavir use, N (%)	269 (24)	NA	NA
CD4 ⁺ cell count [cells/ μ l, median (IQR)]	463 (300, 653)	953 (753, 1191)	<0.001
Undetectable HIV RNA, N (%)	458 (41)	NA	NA

IQR, interquartile range; NA, not applicable.

included, while HIV-negative women excluded were more likely to be African American than those included (see Table, Supplemental Digital Content 2, <http://links.lww.com/QAD/B361>, which presents demographic data of excluded women by HIV status).

Participant median age was 40 years and 61% were African-American. As shown in Table 1, HIV-positive women were on average 3 years older than HIV-negative women (41 vs. 38 years, $P < 0.001$). The prevalence of prediabetes was lower in HIV-positive than in HIV-negative women (25 vs. 33%, $P = 0.003$). More HIV-positive than HIV-negative women reported having health insurance (92 vs. 66%, $P < 0.001$). Forty-three percent of the HIV-positive women had a history of stavudine use, 24% had a history of ritonavir use, 41% were virally suppressed, and 50% had a median CD4⁺ cell count between 300 and 653 cells/ μ l (Table 1).

The risk factor prevalence and score distribution for ADA and FINRISC by HIV status are reported in Table 2. The median ADA risk score was 3 for both HIV-positive and negative women, and the median FINRISC score was 6 for both groups. In both models, obesity was the most prevalent risk factor, present in 53% of HIV-positive and 54% of HIV-negative women according to ADA (based on BMI and waist circumference) and in 35% of HIV-positive and 43% of HIV-negative women according to FINRISC (based on BMI). According to ADA, history of hypertension was also common, present in 46% of HIV-positive and 41% of HIV-negative women; this was followed by family history of diabetes, present in nearly 30% of both women groups. Three years after the index visit, 69 (6%) HIV-positive and 21 (5%) HIV-negative women developed diabetes.

To evaluate ADA model performance, the sensitivity and specificity of all possible risk score cutoffs were explored by HIV status (see Table, Supplemental Digital Content 3A, <http://links.lww.com/QAD/B361>, which presents sensitivity and specificity values for all ADA score cutoffs). The score cutoff ADA uses to indicate high diabetes risk (≥ 5) had a poor sensitivity (28%) in both HIV-positive and HIV-

negative women. A score of at least 3 was deemed the best performing for identifying high-risk HIV-positive (sensitivity = 77%, specificity = 42%) and HIV-negative (sensitivity = 81%, specificity = 49%) women in this study (see ROC curves in Fig. 1). Using this cutoff, the ADA model classified 60% of HIV-positive and 52% of HIV-negative women as having high diabetes risk (Table 3). ADA model discrimination was suboptimal in both HIV-positive [AUROC = 0.64 (95% CI: 0.58, 0.70)] and HIV-negative women [AUROC = 0.67 (95% CI: 0.57, 0.77)].

The sensitivity and specificity of all possible FINRISC score cutoffs were also explored by HIV status (see Table, Supplemental Digital Content 3B, <http://links.lww.com/QAD/B361>, which presents sensitivity and specificity values for all FINRISC score cutoffs). The score cutoff FINRISC uses to indicate high diabetes risk (≥ 9) had a suboptimal sensitivity in HIV-positive (42%) and HIV-negative women (62%). A score of at least 6 was deemed the best performing for identifying high-risk HIV-positive (sensitivity = 72%, specificity = 49%) and HIV-negative (sensitivity = 86%, specificity = 52%) women in this study (see ROC curves in Fig. 1). Using this cutoff, the FINRISC model classified 52% of HIV-positive and 50% of HIV-negative women as having high diabetes risk (Table 3). FINRISC model discrimination was suboptimal in both HIV-positive [AUROC = 0.68 (95% CI: 0.62, 0.75)] and HIV-negative women [AUROC = 0.78 (95% CI: 0.66, 0.90)].

Among the 1111 HIV-positive women, we found ADA and FINRISC model performance differed according to period of index visit (Table 4). For the ADA model, the specificity was better among women whose index visit was in 2000–2003 than among those whose index visit was in 2010–2013 (47 and 29%, respectively). The positive predictive value was also better among women whose index visit was in 2000–2003 than among those whose index visit was in 2010–2013 (10 and 5%, respectively). For the FINRISC model, the specificity of the model was better among women whose index visit was in 2000–2003 than among those whose index visit was in 2010–2013 (55 and 36%, respectively).

Table 2. Risk factor prevalence, risk scores, and diabetes incidence by HIV status.

Risk factors included in models	Risk points	HIV-positive, <i>n</i> = 1111	HIV-negative, <i>n</i> = 454
ADA model			
Age, <i>N</i> (%)			
<40 years	0	527 (47)	263 (58)
40 to <50 years	1	431 (39)	129 (28)
50 to <60 years	2	135 (12)	51 (11)
≥60 years	3	22 (2)	11 (2)
BMI/waist circumference, <i>N</i> (%)			
<25 kg/m ² or waist <31.5 in	0	211 (19)	102 (22)
25 to <30 kg/m ² or waist 31.5 to <35 in	1	314 (28)	106 (23)
30 to <40 kg/m ² or waist 35.0 to <49 in	2	498 (45)	200 (44)
≥40 kg/m ² or waist ≥49 in	3	88 (8)	46 (10)
History of hypertension, <i>N</i> (%)			
No	0	595 (54)	266 (59)
Yes	1	516 (46)	188 (41)
Family history of diabetes, <i>N</i> (%)			
No	0	761 (69)	325 (72)
Yes	1	350 (31)	129 (28)
Risk score [median (IQR)] ^a		3 (2, 4)	3 (1, 4)
FINRISC model			
Age, <i>N</i> (%)			
<45 years	0	749 (67)	336 (74)
45 to <55 years	2	302 (27)	86 (19)
55–65 years	3	60 (5)	32 (7)
BMI, <i>N</i> (%)			
<25 kg/m ²	0	355 (32)	141 (31)
25 to <30 kg/m ²	1	369 (33)	123 (27)
≥30 kg/m ²	3	387 (35)	195 (43)
Waist circumference, <i>N</i> (%)			
<31.5 in	0	239 (22)	118 (26)
31.5 to <34.6 in	3	288 (26)	100 (22)
≥34.6 in	4	584 (53)	241 (53)
Fasting blood glucose, <i>N</i> (%)			
<100 mg/dl	0	1011 (91)	413 (91)
100 to <126 mg/dl	5	98 (9)	40 (9)
History of hypertension medication use, <i>N</i> (%)			
No	0	922 (83)	396 (87)
Yes	2	190 (17)	59 (13)
Risk score [median (IQR)] ^a		6 (4, 7)	6 (3, 7)
Diabetes within 3 years, <i>N</i> (%)		69 (6)	21 (5)

ADA, American Diabetes Association; FINRISC, Finnish Diabetes Risk Score; IQR, interquartile range.

^aRisk score obtained by summing the risk points for all risk factors.

Discussion

Early identification of PLWH at risk for diabetes can facilitate prompt initiation of preventive measures to forestall the development of diabetes and its complications. To inform such efforts, we assessed the performance of the concise FINRISC model and an adapted ADA model in a predominantly minority population of HIV-positive and HIV-negative women. Our assessment showed that performances of the concise FINRISC and adapted ADA models were broadly similar among HIV-positive and HIV-negative women. However, model performance was suboptimal in both groups, while greater misclassification was generally observed among HIV-positive women. Exploring the contribution of HIV-specific risk factors in these models could unmask performance differences and could improve risk classification in HIV-positive women.

At baseline, HIV-positive women had a lower prediabetes prevalence than HIV-negative women (25 vs. 33%); yet, a

similar proportion of HIV-positive and negative women developed diabetes within 3 years (6 and 5%, respectively). This may be an early signal that PLWH could be moving from prediabetes to diabetes faster than HIV-negative populations. We also observed an annual diabetes incidence of ~2%, which is higher than the ~1% annual incidence observed in the United States general population [27]. This is likely because over half of WIHS women have overweight or obesity compared with the 38% obesity prevalence reported in the general population [28]. Overall, HIV-positive women have a high prevalence of diabetes risk factors and may develop the disease faster than HIV-negative women.

The sensitivity (77–81%) and specificity (42–49%) of the adapted ADA model observed in this study differ from the sensitivity (89–98%) and specificity (4–40%) observed in the United States general population [17]. Differences in populations, risk score cutoffs, and in risk factors included in the models (e.g. physical activity, race and

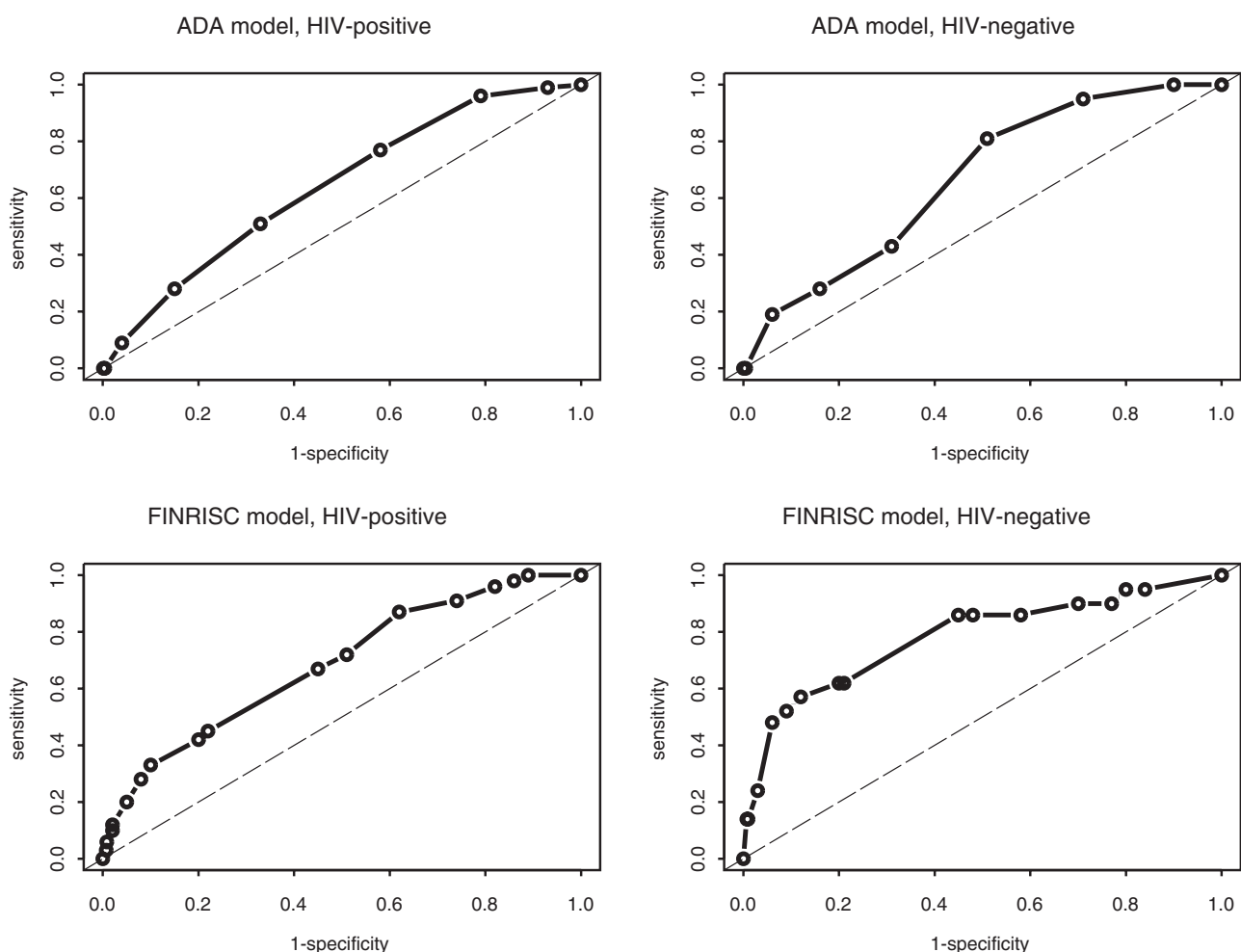


Fig. 1. Receiver operating characteristics curves for American Diabetes Association and Finnish Diabetes Risk Score models by HIV status.

dyslipidaemia) may explain these differences. The sensitivity (72–86%) and specificity (49–52%) of the concise FINRISC model observed in this study were similar to the sensitivity (79%) and specificity (49%)

observed in the United States general population [18]. Regarding FINRISC performance in HIV-positive populations, the model has been found to be more specific (90%) and sensitive (65%) among HIV-positive

Table 3. Risk model performance assessment by HIV status.

	ADA model ^a		<i>P</i> value	FINRISC model ^b		<i>P</i> value
	HIV-positive, <i>N</i> = 1111	HIV-negative, <i>N</i> = 454		HIV-positive, <i>N</i> = 1111	HIV-negative, <i>N</i> = 454	
Diabetes risk, <i>N</i> (%) ^c						
Low risk	450 (40)	218 (48)	0.006	533 (48)	226 (50)	0.517
High risk	661 (60)	236 (52)		578 (52)	228 (50)	
Sensitivity, % (95% CI)	77 (67, 87)	81 (64, 98)	0.774	72 (62, 83)	86 (71, 100)	0.216
Specificity, % (95% CI)	42 (39, 45)	49 (45, 54)	0.006	49 (46, 52)	52 (47, 56)	0.447
PPV, % (95% CI)	8 (6, 10)	7 (4, 10)	0.689	9 (6, 11)	8 (4, 11)	0.728
NPV, % (95% CI)	96 (95, 98)	98 (96, 100)	0.221	96 (95, 98)	99 (97, 100)	0.093
AUROC (95% CI)	0.64 (0.58, 0.70)	0.67 (0.57, 0.77)	0.597	0.68 (0.62, 0.75)	0.78 (0.66, 0.90)	0.141

ADA, American Diabetes Association; AUROC, area under the receiver operating characteristics curve; CI, confidence interval; FINRISC, Finnish Diabetes Risk Score; NPV, negative predictive value; PPV, positive predictive value.

^a Values obtained using a score cutoff of at least 3 for both HIV-positive and HIV-negative participants.

^b Values obtained using a score cutoff of at least 6 for both HIV-positive and HIV-negative participants.

^c Low-risk participants were those achieving a score of less than 3 for ADA and less than 6 for FINRISC. High-risk participants were those achieving a score of at least 3 for ADA and at least 6 for FINRISC.

Table 4. Risk prediction model performance assessment of 1111 HIV-positive women by date of index visit.

	ADA model ^a			FINRISC model ^b		
	Index visit ^c 10/00–4/03, n = 773	Index visit 10/10–3/13, n = 338	P value	Index visit 10/00–4/03, n = 773	Index visit 10/10–3/13, n = 338	P value
Sensitivity, % (95% CI)	75 (63, 86)	86 (67, 100)	0.494	67 (55, 80)	93 (79, 100)	0.091
Specificity, % (95% CI)	47 (44, 51)	29 (24, 34)	<0.001	55 (52, 59)	36 (31, 41)	<0.001
PPV, % (95% CI)	10 (7, 13)	5 (2, 8)	0.026	10 (7, 14)	6 (3, 9)	0.063
NPV, % (95% CI)	96 (94, 98)	98 (93, 100)	0.541	96 (94, 98)	99 (97, 100)	0.091
AUROC (95% CI)	0.66 (0.59, 0.73)	0.63 (0.48, 0.78)	0.677	0.69 (0.62, 0.76)	0.74 (0.62, 0.87)	0.456

ADA, American Diabetes Association; AUROC, area under the receiver operating characteristics curve; CI, confidence interval; FINRISC, Finnish Diabetes Risk Score; NPV, negative predictive value; PPV, predictive value.

^aValues obtained using a score cutoff of at least 3.

^bValues obtained using a score cutoff of at least 6.

^cWe refer to the first visit at which fasting blood glucose, hemoglobin A1c, self-reported antidiabetic medication use, and self-reported diabetes data were available as the index visit. Time frames were selected based on the years corresponding to early HAART era (2000–2003) and late HAART era (2010–2013).

individuals from London [22] than among WIHS women in this study. In addition to population characteristics, these differences could be related to the different score cutoffs we used to improve model discrimination and the different observation periods and models tested (i.e. FINRISC concise vs. full).

The performance of the adapted ADA and the concise FINRISC models did not significantly differ between HIV-positive and HIV-negative women. However, a greater percentage of HIV-positive than negative women were misclassified as having (lower specificity) or not having diabetes (lower sensitivity). It is possible that misclassification occurred more often in HIV-positive women due to HIV-related factors that are not measured in these models. Indeed diabetes risk classification has been found to be better among HIV-positive individuals when HIV-specific risk factors are included [22]. Inclusion of HIV-specific risk factors such as CD4⁺ cell count could potentially unmask differences in the performance of these tools and improve risk classification among HIV-positive women.

Identifying asymptomatic persons with dysglycemia through targeted screening in healthcare settings has been recommended by numerous organizations [14,29,30]. Though HIV clinical guidelines mirror these screening recommendations [31], risk management in HIV-positive populations has fallen below the recommended standards [32]. This is compounded by the lack of HIV-specific risk screening tools [32]. Diabetes risk screening in HIV care can help estimate, communicate and monitor risk to motivate adherence to lifestyle change or therapies, and to allocate scarce prevention resources and strategies appropriately [32]. For this, a high performing, practical risk screening tool to conduct targeted glucose testing in HIV care is needed.

These findings should be interpreted in light of the study limitations. First, we did not include men in this analysis,

which limits conclusions about the performance of these tools in HIV-positive populations to women only. Second, since physical activity and fruit and vegetable consumption data were not complete in WIHS, we excluded physical activity from the ADA model and used the concise FINRISC model. Third, this analysis focused on diabetes as the outcome and did not explore dysglycemia at-large (i.e. prediabetes *and* diabetes). Finally, we only explored diabetes risk over 3 years, which does not correspond with the time period FINRISC assesses (i.e. 10-year diabetes risk). The analysis may also be limited due to the small number of diabetes cases we could detect and to the lack of score validation over a shorter time interval.

Diabetes is an increasingly important comorbidity in PLWH. Diabetes risk screening in HIV care can help estimate, communicate and monitor risk to motivate adherence to lifestyle change or therapies, and to allocate scarce prevention resources and strategies appropriately. To inform such efforts, we assessed the performance of the concise FINRISC model and an adapted ADA model in a predominantly minority population of HIV-positive and HIV-negative women. Our assessment showed that the performance of the models was broadly similar between women with and at risk of HIV, though greater misclassification was generally observed among women with HIV. Inclusion of HIV-specific risk factors known to contribute to diabetes risk may improve identification of HIV-positive individuals at increased diabetes risk. Long-term studies in multiethnic, mixed-gender longitudinal cohorts in this area are needed.

Acknowledgements

K.I.G. and M.K.A. designed the study, provided guidance for statistical analyses, provided interpretation of study findings, and drafted the article. M.F.S. conducted the

statistical analyses, contributed to interpretation of findings, critically revised the article and approved submission. P.T., C.C.M., and I.O. contributed to study design, provided guidance for statistical analyses and study conduction, contributed to interpretation of findings, critically revised the article and approved submission. J.C., V.C.M., and K.P. contributed to interpretation of findings, provided guidance for study conduction, critically revised the article and approved submission. G.W., A.S., D.G., D.M., R.K., M.H.C., A.A.A., M.A., and D.K.P. contributed to interpretation of findings, critically revised the article and approved submission.

The current study was funded by the National Institute of Allergy and Infectious Diseases through the WIHS (U01AI103408-04). M.K.A. was partially supported by the Georgia Center for Diabetes Translation Research (P30DK111024).

Data in this article were collected by the Women's Interagency HIV Study (WIHS). The contents of this publication are solely the responsibility of the authors and do not represent the official views of the National Institutes of Health (NIH). WIHS (Principal Investigators): UAB-MS WIHS (Mirjam-Colette Kempf and Deborah Konkle-Parker), U01-AI-103401; Atlanta WIHS (Ighovwerha Ofotokun and Gina Wingood), U01-AI-103408; Bronx WIHS (Kathryn Anastos and Anjali Sharma), U01-AI-035004; Brooklyn WIHS (Howard Minkoff and Deborah Gustafson), U01-AI-031834; Chicago WIHS (Mardge Cohen and Audrey French), U01-AI-034993; Metropolitan Washington WIHS (Seble Kassaye), U01-AI-034994; Miami WIHS (Margaret Fischl and Lisa Metsch), U01-AI-103397; UNC WIHS (Adaora Adimora), U01-AI-103390; Connie Wofsy Women's HIV Study, Northern California (Ruth Greenblatt, Bradley Aouizerat, and Phyllis Tien), U01-AI-034989; WIHS Data Management and Analysis Center (Stephen Gange and Elizabeth Golub), U01-AI-042590; Southern California WIHS (Joel Milam), U01-HD-032632 (WIHS I–WIHS IV). The WIHS is funded primarily by the National Institute of Allergy and Infectious Diseases (NIAID), with additional co-funding from the Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD), the National Cancer Institute (NCI), the National Institute on Drug Abuse (NIDA), and the National Institute on Mental Health (NIMH). Targeted supplemental funding for specific projects is also provided by the National Institute of Dental and Craniofacial Research (NIDCR), the National Institute on Alcohol Abuse and Alcoholism (NIAAA), the National Institute on Deafness and other Communication Disorders (NIDCD), and the NIH Office of Research on Women's Health. WIHS data collection is also supported by UL1-TR000004 (UCSF CTSA), UL1-TR000454 (Atlanta CTSA), and P30-AI-050410 (UNC CFAR).

Conflicts of interest

There are no conflicts of interest.

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