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REVIEW ARTICLE

A systematic review of diabetes risk assessment tools in sub-Saharan Africa

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Abstract

Objectives To systematically review all current studies on diabetes risk assessment tools used in SSA to diagnose diabetes in symptomatic and asymptomatic patients.

Methods Tools were identified through a systematic search of PubMed, Ovid, Google Scholar, and the Cochrane Library for articles published from January 2010 to January 2020. The search included articles reporting the use of diabetes risk assessment tool to detect individuals with type 2 diabetes in SSA. A standardized protocol was used for data extraction (registry #177726).

Results Of the 825 articles identified, 39 articles met the inclusion criteria, and three articles reported tools used in SSA population but developed for the Western population. None was validated in SSA population. All but three articles were observational studies (136 and 58,657 study participants aged between the ages of 15 and 85 years). The Finnish Medical Association risk tool, World Health Organization (WHO) STEPS instrument, General Practice Physical Activity Questionnaire (GPPAQ), Rapid Eating and Activity Assessment for Patients (REAP), and an anthropometric tool were the most frequently used non-invasive tools in SSA. The accuracy of the tools was measured using sensitivity, specificity, or area under the receiver operating curve. The anthropometric predictor variables identified included age, body mass index, waist circumference, positive family of diabetes, and activity levels.

Conclusions This systematic review demonstrated a paucity of validated diabetes risk assessment tools for SSA. There remains a need for the development and validation of a tool for the rapid identification of diabetes for targeted interventions.

Keywords Type 2 diabetes · Validation · Diabetes risk assessment · Africa · Sub-Saharan region · Risk factors

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Introduction

Diabetes mellitus (DM) is a major public health problem globally as the prevalence and burden are uncontrolled in urban areas due to significant lifestyle choices (1, 2). Globally, it was reported in 2016 that more than 422 million adults were living with diabetes and estimated to increase by 55% to over 591.9 million by 2035 (3). Three-quarters of those with diabetes live in low- to middle-income countries (LMICs), and this is projected to increase (4) with a median prevalence estimate at 5% in sub-Saharan Africa (5).

Due to increasing urbanization, demographics, and nutritional changes in the region (6–8), compounded by a lack of awareness of the lifestyle risk factors for diabetes, inadequate healthcare infrastructure, and lack of access to quality healthcare on the sub-continent (2, 9), the prevalence of diabetes is predicted to increase from 4.85% in 2013 to 5.35% in 2035 (10). In addition, the proportion of adults aged 20–79

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years with undiagnosed diabetes was estimated to be 90% of the diabetic population in LMICs compared with 33% in high-income countries (10). The burden of the disease is evident and keeps increasing (2, 9).

Diabetes has become one of four prioritized non-communicable diseases (NCDs) by the World Health Organization (WHO) (11). The projected increase in the prevalence of diabetes mellitus (DM) in SSA will exert considerable economic and human resource costs on the healthcare system that is already lacking in funding and trained human resource (12, 13). To mitigate this effect, there is a need for an effective, non-invasive screening tool for DM in this region such as the diabetes risk assessment tools which are convenient for early screening and detection of diabetes to avoid diabetes-related morbidity, reduce the cost of healthcare, and improve quality of life (11).

Screening for diabetes in general practice by measuring fasting blood glucose levels is feasible, but expensive, invasive, and time-consuming. This could be more efficient if targeted at high-risk patients (14). Different strategies have been suggested to improve diabetes detection including opportunistic screening and population-based screening (15).

Over the last decade, many diabetes risk assessment tools used for identifying previously undiagnosed diabetes and individuals at high risk of diabetes have been developed and validated in various countries. However, these tools were developed for different population groups using both community- and population-based studies (16–27), predominantly among Caucasian (20, 28, 29), Asian (18, 21, 22, 30, 31), and Middle Eastern (32, 33) populations. The tools identified age, sex, obesity, family history of diabetes, and hypertension as the most common factors associated with diabetes (18, 20–22, 28–30, 32, 33). In a population-based systematic review conducted using 5 qualitative analysis tools (two each from Mexico and Peru and another from Brazil), researchers found that the area under the curve (AUC) ranged from 66 to 72% and recommended the use of different diabetes risk scores for the Latin American populations (34).

In Africa, there is paucity of data on the use of non-invasive tools for diabetes risk assessment despite the growing population and prevalence of diabetes. For example, in a population-based study conducted in Egypt on 1032 individuals without a history of diabetes, the authors found that a predictive model could easily detect undiagnosed diabetes (35). Another study conducted on 3094 Mauritian Indians using risk prediction models found that the AUC was 62% for men and 64% for women (36). In Ogun State, Nigeria, using a community-based diabetes risk assessment tool on 56,567 individuals, authors found higher risk scores for diabetes and a higher rate of obesity among females than males. The study by Alebiosu et al. suggested that current evidence should be examined in order to implement diabetes preventative strategies (37). Overall, these studies (35–37) are in agreement that diabetes assessment tools are limited to the population for which they were developed, and when used in different populations including among SSAs, their validity could be affected resulting in an inferior predictive model.

Therefore, this study was designed to provide evidence on the availability and use of diabetes risk assessment tools in SSA by systematically reviewing all current studies on diabetes risk assessment tools within the region. This was supported by reviewing studies conducted outside SSA countries on diabetes risk assessment tools so that the findings are generalizable to a wider population. Identifying the diabetes risk assessment tool models available in the SSA region would be valuable at the primary care level, for clinicians and public health workers to facilitate early detection of DM among those who are unaware of their status. Also, the study will provide evidence of the risk factors and diabetes risk scores that could be further studied in different SSA countries or integrated into the guidelines for policy-makers as a standard of practice for diabetes screening at the population level. Findings can also be used to develop diabetes prevention and education programs across SSA communities.

Research design and methods

This study was conducted in conformance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement on reporting items for systematic reviews and meta-analyses (38) following a protocol for this systematic review which was registered in Prospero (registry #177726). The search was performed in the following databases: PubMed, Ovid, Google Scholar, and the Cochrane Library. The databases were searched and articles published from January 2000 to January 2020 were included and no language limits were applied. A literature search strategy was developed and implemented using the Population, Intervention, Comparison, Outcome, and Study (PICOS) framework, as shown in Table 1. The search goals were first to identify studies on the development of tools for non-invasive diabetes risk assessment in Africa, and then to expand that search to other continents. Search terms included diabetes risk assessment tools, diabetes mellitus risk assessment tools, diabetes risk assessment tools in Africa, "diabetes" AND "risk assessment tools" AND Africa.

Search strategy and selection criteria

Two experienced reviewers, EE and GO, independently carried out the searches on two separate dates. PubMed and Ovid databases were searched on January 13, 2020, while Cochrane Library was searched on January 15, 2020. Both reviewers used the same predefined search terms as detailed in the Supplementary file (S1). The search hits were then manually screened for relevance and collated for more detailed scrutiny

Table 1 The search strategy for literature selection

PICOS	Description
Population	Indigenous African population aged 15 years and over
Intervention	Application of diabetes risk assessment tools
Comparison	Comparison of DM risk tools to other previously validated tools
Outcome	Accuracy levels of risk assessment tools
Study	All studies including but not limited to clinical trials, cohort, case-control, cross sectional, and reviews

using predefined inclusion and exclusion criteria. All articles selected by both reviewers were collated for data extraction. A third experienced reviewer, KO, adjudicated disputed articles. The full electronic search strategy for PubMed database, including the limits used, is presented (S1).

Data extraction and quality assessment

A total of 825 articles were selected for review of the abstracts, and 786 articles were excluded after duplicate removal and after applying the inclusion and exclusion criteria below. Data were extracted after assessing the quality of the studies by using Cochrane collaboration's tool for assessing risk of bias in publications. The following data were extracted from each study where available: authors, year of publication, number of study participants, the location, mean age and/or age range of study participants, sample size, predictor variables (age, body mass index (BMI), waist circumference, waist to height ratio), diabetes risk assessment tools used, accuracy level of the tools and/or risk of developing diabetes, and tool validation.

The article selection process is presented in the PRISMA flow chart (Figure 1). For synthesis of results, qualitative description of data was performed using area under the receiver

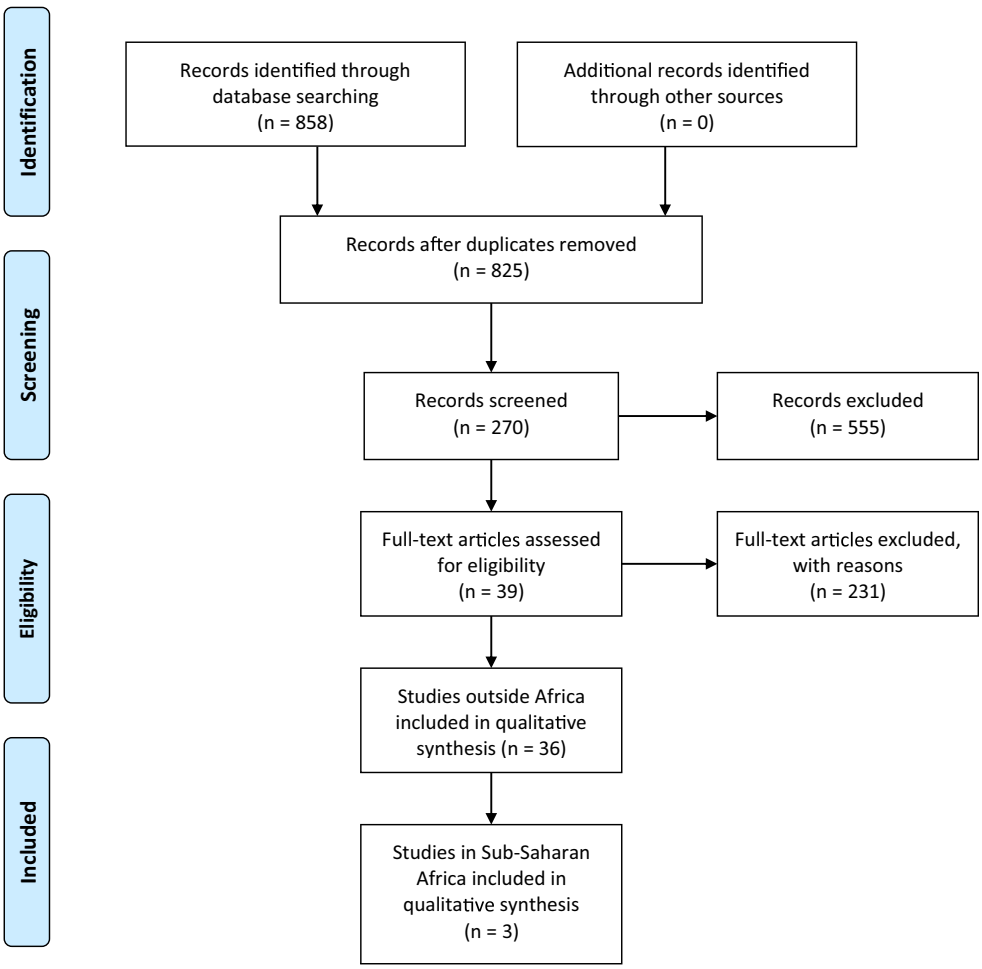

Fig. 1 Flow chart of the article selection process. Of the 42 studies that met the inclusion criteria, only three were from sub-Saharan Africa

operating curve (AUC), sensitivity, specificity, positive predictive value, negative predictive value, and odds ratios.

Inclusion and exclusion criteria

Eligible articles for inclusion were those that reported on the following: individuals 15 years and older; quantitative scores of predictive models; diabetes risk assessment tools developed and used in an African population; validated tools for assessing risk factors for diabetes in an African population; and on specific tools developed for assessing diabetes risk factors in an African population.

Exclusion criteria included articles that reported on validated tools for assessing risk factors for diseases other than DM; on health topics other than DM; and on invasive diabetes risk assessment tools. In addition to those included, articles were also selected and grouped if they included information on diabetes risk assessment tools developed for non-African populations. The same exclusion criteria were adopted but these articles were considered separately from the African studies, only if they met the inclusion criteria.

Results

Diabetic risk assessment tools in Africa

Thirty-nine articles met the inclusion criteria for a full review. Only three of those articles were from sub-Saharan Africa (37, 39, 40) and involved the use of non-invasive diabetes risk assessment tools in local populations (Table 2). The quality of the data in each of the studies conducted in SSA countries is presented in Table 2.

In the current review, the age range of participants in the studies that included Africans was 18–62 years and the sample size ranged from 136 to 58,657 persons. All the studies were observational. The most common non-invasive predictor variables used in the three studies on the African population were age, body mass index (BMI), waist circumference, family history of diabetes, and activity levels. Others include vegetable consumption, waist-to-height ratio (WHtR), and history of use of antihypertensive agents.

Type of tools and tool accuracy

Five different tools were used in the selected studies including the Finish Medical Association DM risk tool, WHO STEPS instrument, General Practice Physical Activity Questionnaire (GPPAQ), Rapid Eating and Activity Assessment for Patients (REAP), and an anthropometric tool. The accuracy of disease assessment tools was measured in terms of sensitivity, specificity, or as the area under the receiver operating curve (AUC). Among residents in Nigeria, one study (40) reported that the predictor WHtR has the highest AUC for predicting two or more cardiometabolic syndrome (CMS) in women (0.70); BMI has the highest AUC for predicting two or more CMS in men, and another (37) measured the risk of developing DM in 10 years using logistic regression and found a mean risk score of 5.60 ± 3.90 for developing DM for their sample population. Among Ghanaians, Gudjinu and Sarfo (39) found total cholesterol greater than 6.3, REAP score greater than 51, BMI greater than 35 kg/m^2, GPPAQ score for inactivity, serving of fruit per meal less than one, and middle socio-economic status (SES) to be predictors with the highest odds ratios for developing DM. None of the studies reported validation of the tools used for the study population.

Diabetic risk assessment tools outside Africa

Given the few studies done in Africa, in addition, we reviewed the 36 articles that met our criteria but were outside of SSA. This was done to broaden the understanding and the depth of interpretation of the African tools since the tools used in the African studies have been used previously in non-African populations. The continents covered include North America, South America, Europe, Asia, and Australia and two studies from the Middle East Region (55, 56). The age range of subjects was between 15 and 85 years with a sample size ranging from 44 to 15,768 participants. The most used predictor variables common to all studies were anthropometric variables including BMI, WHtR, and waist circumference (WC), as well as age and family history. Other less commonly used variables were visceral adiposity index (VAI), body adiposity index (BAI), triglyceride (TG) level, smoking, ethnicity, sedentary lifestyle, and hypertension.

Type of tools and accuracy

Twenty different tools were used in seven studies but the anthropometric and Finnish diabetes risk assessment tools accounted for about 40% of all tools. Others used locally adapted questionnaires and compared accuracy results with published diabetic risk tools (18, 22, 50, 52, 55, 60, 67). Most (69.2%) of the articles reviewed use AUC to report the accuracy of the tools with values ranging from 0.60 to 0.88, while others used sensitivity and specificity for performance validation of the risk assessment tools (51.3%). Validation of tools was recorded in 77.1% of the studies using methods such as internal, external, measurement, and split-sample validation.

Discussion

This study found that the diabetes risk factors pertinent to SSA included waist circumference to height ratio, age, BMI, waist

Table 2 Characteristics of studies included in the review

Author	Age (years)	*N*	Predictors	Tools	Tool accuracy	Validation
Studies conducted in sub-Saharan Africa						
Alebiosu et al. 2013 (37)	25–54	58,657	Age, BMI, waist circumference below ribs, exercise, vegetable consumption, use of anti-hypertensives, previous record of high blood sugar level, family history	Finnish Medical Association DM risk tool	5.05 % of study sample had DM. Mean risk score 5.60 ± 3.90. 5.05% had high risk of developing DM in 10 years. 15% of study population had moderate to very high risk of developing DM in 10 years	No
Gudjinu et al. 2017 (41) 45	35–62	136	Rapid eating and activity level, weight, height, waist circumference, fasting venous blood, fasting lipids	WHO STEPS instrument, GPPAQ and REAP	Risk factors with the highest risk scores of developing DM: Total cholest > 6.3 = 10.67; REAP score > 51 = 7.34; BMI > 35 = 6.06 GPPAQ score for inactivity = 7.3; serving per eating < 1 = 5.76; middle SES = 5.03	No
Oguoma et al. 2016 (40)	18–59	422	Hyperglycemia, HTN, hypertriglyceridemia, LDL-HDL	Anthropometric tools	WHtR highest AUC for predicting ≥ 2 CMS in women (0.701); BMI highest AUC for predicting ≥ 2 CMS in men (value)	No
Studies conducted outside of sub-Saharan Africa						
Skogberg et al. 2017 (42)	30–64	917	BMI, WHtR, WC, and WHR	Anthropometric	0.81 AUC	No
Agarwal et al. 2019 (43)	36–69	200		Finnish Diabetes Risk Score (FINDRISC), Canadian diabetes risk questionnaire (CANRISK), Indian Diabetes Risk Score (IDRS), American Diabetes Association (ADA) risk score, undiagnosed diabetes mellitus, Filipino	Filipino tool: highest specificity (0.73); IDRS and undiagnosed DM highest NPV (0.96); highest AUC (FINDRISK, CANRISK) 0.8; overall FINDRISK more effective with sensitivity of 0.96	Yes
Elizalde-Barrera et al. 2019 (44)	47.14	280	BMI, WHtR, VAI, BAI, and TG	Anthropometric	The measurements with the highest area under the curve were TG (0.631, 95% confidence interval [CI] 0.566–0.697), VAI (0.628, 95% CI 0.563–0.693), and WHtR (0.622, 95% CI 0.557–0.688), and in the adjusted binary logistic regression model, were found to be independently associated with impaired fasting glucose (IFG), odds ratio of 2.665, (95% CI 1.567–4.533) 2.567 (95% CI 1.527–4.317) and 2.171 (95% CI 1.102–4.276)	No
McGrath et al. 2018 (45)	65.3 ± 10.5	278		HARP		No
Rauh et al. 2018 (46)	28–85	3544	Age, BMI, waist circumference, use of anti-hypertensives, smoking, family history of myocardial infarction/ stroke, and family history of diabetes	Anthropometric	AUC of 0.78 (95% CI 0.75–0.81) in men and 0.78 (95% CI 0.74–0.81) in women. Calibration was poor (HL statistic: p <0.001) but improved considerably after intercept recalibration. Examination of individual outcomes showed that in men, AUC was highest for CKD (0.85 [95% CI 0.78–0.91]) and lowest for T2D (0.69	Yes

Table 2 (continued)

Author	Age (years)	*N*	Predictors	Tools	Tool accuracy	Validation
					[95% CI 0.65–0.74]). In women, AUC was highest for CVD (0.88 [95% CI 0.83–0.94]) and lowest for T2D (0.71 [95% CI 0.66–0.75]).	
Zhang et al. 2017 (47)	< 30–60	15768	Drinking tea frequently, body mass index ≥28.0 kg/m^2, waist to height ratio ≥ 0.5, triglycerides level 1.70 to 2.25 and ≥2.26 mmol/L, and fasting plasma glucose 5.6 to 6.0 and ≥6.1 mmol/L	Cox proportional hazard score	The sensitivity, specificity, and AUC (95% confidence interval) for this full model were 69.63%, 75.56%, and 0.791 (0.783–0.799), respectively.	Yes
Bould et al. 2017 (48)	> 45	1035		FINDRISC		No
Liu et al. 2016 (49)	≥ 55	1857	Impaired FPG, poor self-assessment of health, overweight, obesity, and reduced physical activity	Anthropometric;	AUC was 0.76 (95% confidence interval: 0.72–0.80), and the optimism-corrected AUC was 0.78 (95% confidence interval: 0.69–0.87)	Yes
Khunti et al. 2016 (50)	40–75	577		Leicester Practice Computer Risk Score (LPCRS); Leicester Self-Assessment Score (LSAS)		No
Dugee et al. 2015 (31)	15–64	1018		FINDRISK; Rotterdam risk score	AUC for FINDRISK= 61, Rotterdam = 64; adapted risk score = 77 (95% CI: 71–88%).	No
Robinson et al. 2011 (51)	40–74	6223		CANRISK; FINDRISK	AUC CANRISK = 0.75; FINDRISK = 0.69	Yes
Xie et al. 2010 (52)	35–74	15540		Self-administered tool	Sensitivity of 0.61 (95% CI 0.55 to 0.67), a specificity of 0.71 (95% CI 0.70 to 0.73) in women, and a DRL of 3 or greater predicted type 2 diabetes status with a sensitivity of 0.59 (95% CI 0.52 to 0.65) and a specificity of 0.63 (95% CI 0.62 to 0.65) in men.	Yes
Chen et al. 2010 (25)	≥ 25	6,060		AUSDRISK	The AUROC of the diabetes risk tool was 0.78 (95% CI, 0.76–0.81) and HL chi^2 statistic was 4.1 (p = 0.85). Using a score > or = 12 (maximum, 35), the sensitivity, specificity, and positive predictive value for identifying incident diabetes were 74.0%, 67.7%, and 12.7%, respectively. The AROC and HL chi^2 statistic in the two independent validation cohorts were 0.66 (95% CI, 0.60–0.71) and 9.2 (p = 0.32), and 0.79 (95% CI, 0.72–0.86) and 29.4 (p < 0.001), respectively.	Yes
Otero et al. 2011 (53)	30–74	44	BMI, WC, physical exercise, consumption of fruits, and vegetables, HTN, hx of high blood sugar, smoking	CANRISK	CANRISK tool identified 11·4% of the sample to be at high risk, 9·1 at moderate risk, and 43·2% at slightly elevated risk for developing DM.	Yes
Guo et al. 2018 (54)	35–74	194	Height, weight, and Waist circumference	CHINARISK (adapted CANRISK) FINDRISK	AUC 0.705 (95% CI 0.632, 0.778), demonstrating moderate diagnostic value at a cut-off score of 30. The sensitivity was 73%,	Yes

Table 2 (continued)

Author	Age (years)	*N*	Predictors	Tools	Tool accuracy	Validation
					with a positive predictive value of 57% and negative predictive value of 78%.	
Carrillo-Larco 2019 (34)	42–50	711–6995	Age, waist circumference, and family history of diabetes, and only one study used oral glucose tolerance test as the outcome	FINDRISK, simplified FINDRISK, Latin America FINDRISK, Peruvian Risk score	AUC 66–72	9 models were validated
Al-Lawati and Tuomilheto, 2007 (55)	≥ 20	4881 and 1432	Strongest predictors (age > 60years, +ve family history of diabetes); moderate predictors (WC, BMI, current hypertension status)	Developed the model for diabetes risk assessment of Oman using two existing data sets	Sensitivity = 78.6%, Specificity = 73.4%; AUC = 83% (for cohort 1); 62.8%; 78.2%; 76% (for cohort 2)	Yes
Al-Khalaf et al. 2010 (56)	36.2 ± 8.9	562	Age ≥ 35 years (3.72), WC ≥ 100 cm (6.89), BP med (2.66), +ve Fam Hx (2.66)	Blood glucose, anthropometric, self-administered questionnaire	AUC = 0.82; NPV = 99%	No
de Leon et al. 2008 (57)	18–75	6237	Age, waist/height ratio, +ve family history of diabetes, systolic blood pressure	Blood glucose, anthropometric, self-administered questionnaire	AUC = 0.837 (M), 0.874 (F), sensitivity = 84.2%, specificity = 39.8%; PPV = 17.2% (M), 15.3% (F)	Yes
Gao et al. 2010 (18)	20–74	1986/4336	Age, WC, +ve FHx	Lifestyle questionnaire with validation and anthropometric measurement	AUC = 62.4 (M), 63.2 (F); sensitivity = 72.5%; specificity = 60.1%; PPV = 17%; NPV = 95.1%	Yes
Mohan et al. 2005 (22)	>30	2600	Age, abdominal obesity, +ve FHx, physical activity	OGTT, lifestyle questionnaire, anthropometric measurement	AUC = 69.8%, 61.3%; sensitivity = 72%; specificity = 56%; PPV = 6.5%; NPV = 98%	Yes
Bang et al. 2009 (17)	≥ 20	5258	Age, sex, + FHx, HTN, obesity, physical activity	National Health and Nutrition Examination Survey	AUC = 0.83	Yes
Bindraban et al. 2008 (58)	35–60	336, 593, 486 respec-tively	Age, BMI, WC, resting HRt, + FHx, HTN, Hx of CVD, ethnicity	National Health and Nutrition Examination Survey	Sensitivity = 76%; specificity = 72%	No
Glumer et al. 2004 (59)	30–60	6784	Age, sex, BMI, HTN, physical activity, + FHx	Diabetic symptoms and risk factors questionnaire with validation and OGTT	AUC = 0.804; sensitivity = 81%; specificity = 45%	Yes
Gray et al. 2010 (20)	40–75	6390	Age, sex, ethnicity, + FHx, WC, BMI, HTN, BP drugs	UK screening study, OGTT	AUC = 0.72; sensitivity = 77%; specificity = 72%; PPV = 11.3%; NPV = 98.2%; PLR = 2.76, NLR = 0.32	Yes
Griffin et al. 2000 (60)	40–64	1077	Age, sex, BMI, steroids medication, BP drugs, + FHx, Smoking Hx	Demographic data and medical records form general practices, lifestyle questionnaire, OGTT, anthropometric measures	AUC = 0.80; sensitivity = 88% (DM), 75% (pre-DM); specificity = 75% (DM), 65% (pre-DM); PPV = 14% (M), 49% (pre-DM); NPV = 99.3% (DM), 85% (pre-DM)	Yes
Heikes et al. 2008 (61)	≥ 20		Age, WC, gest DM, ht, ethnicity, HTN, + FHx, exercise	National Health and Nutrition Examination Survey	AUC = 0.85 (DM), 0.75 (pre-DM)	Yes
Li et al. 2009 (62)		771	Age, BMI, Hx Bld glc	FINDRISC	AUC = 0.88 (95% CI = 0.85–0.92) for continuous predictors, 0.86 (95% CI = 0.82–0.90) for categorical predictors; sensitivity = 78.5%; specificity = 62.5%; PPV = 18.3%; NPV = 96.4%	Yes

Table 2 (continued)

Author	Age (years)	*N*	Predictors	Tools	Tool accuracy	Validation
Pires da Sousa et al. 2009 (63)	≥ 35	1224	Age, BMI, abdominal circumf, HTN, Tot Chol, LDL, TG	Anthropometric measures	AUC = 77%; sensitivity = 66%; specificity = 70%; PPV = 31%; NPV = 39%	Yes
Saaristo et al. 2005(64)	45–74	4622	Undiagnosed DM2, AGT, metabolic syndrome, and CV risk factors	FINDRISC	AUC = 72% (M), 73% (F); sensitivity = 73%; specificity = 56%; PLR = 1.6	No
Chaturvedi et al. 2008 (65)	35–64	4044	Age, WC, BP, +FHx,	Lifestyle questionnaire with validation; anthropometric measures,	Sensitivity = 83.3%; specificity = 65.5%; PPV = 12.83%; NPV = 98.53%	Yes
Dong et al. 2011 (66)	35–74	5348	Age, BMI, WtHR, syst/diast BP, HRt, +Fhx	OGTT and lifestyle questionnaire with validation	Sensitivity = 96.8%; specificity = 24%; PPV = 17.8%; NPV = 97.8%	Yes
Keesukphan et al. 2007 (67)	48.4 ± 10.9	429	Age, BMI, HTN	Lifestyle questionnaire with validation	Sensitivity = 81%; specificity = 54%; PPV = 6%; PLR = 1.8	No
Lee et al. 2012 (68)	≥ 20	9602	Age, +FHx, HTN, WC, smoking, alcohol	Korean National Health and Nutrition Examination Survey, anthropometric measurements	AUC = 73%	Yes
Pongchaiyakul et al. 2011 (69)	15–85	4314	Age, sec, BMI, Sys BP	Anthropometric measurement and lifestyle questionnaire with validation	AUC = 75%; sensitivity = 76.6%; specificity = 59.9%; PPV = 9.4%; NPV = 97.9%	Yes
Ramachandran et al. 2005 (70)	≥ 20	4993	Age, BMI,WC, +FHx, sedentary lifestyle	Lifestyle questionnaire with validation and OGTT	Sensitivity = 59% (M), 61% (F); specificity = 63% (M), 71% (F); PPV = 11 % (M), 14% (F); NPV = 95% (M), 96% (F); PLR = 1.61 (M). 2.16 (F); NLR =	Yes

Included studies that used populations that were not Africans. *BMI*, body mass index; *DM*, diabetes mellitus; *WHO STEPS*, World Health Organization STEPS Instrument for Chronic Disease Risk Factor Surveillance; *GPPAQ*, General Practice Physical Activity Questionnaire; *REAP*, Rapid Eating and Activity Assessment for Patients; *SES*, socio-economic status; *HTN*, hypertension; *L-HDL*, low- and high-density lipoprotein; *WHtR*, waist-to height ratio; *CMS*, cardiometabolic syndrome; *AUC*, area under the curve; *WC*, waist circumference; *NPV*, negative predictive value; *VAI*, visceral adiposity index: *BAI*, blood adiposity index; *TG*, triglycerides; *HARP*, Hospital Admission Risk Program; *NA*, not available. *PLP*, positive likelihood rate; *NLP*, negative likelihood rate; *M*, male; *F*, female

circumference below the ribs, exercise, vegetable consumption, use of anti-hypertensives, previous history of hyperglycemia, positive family history of diabetes, rapid eating, fasting venous blood glucose, and fasting lipids. Different diabetes risk assessment tools have been used in different populations in SSA, but none was developed and/or validated for use in the SSA populations. The findings provide insights and guidelines in a first phase for developing a more population-based diabetes risk assessment tool for SSA based on the reported risk factors in the available studies, and in a second phase for devising and building new risk assessment methods based upon the data collected from the tool design project. The study also reviewed evidence from non-African populations to ensure results are applicable to a wider population. By reviewing both African and non-African studies, this study provides the basis for the selection of the most relevant risk score to be implemented within the population.

It is typical to validate a newly developed tool for use in a population, or adapt a tool previously validated for use in another population. Studies (42) have indicated that available diabetes risk assessment tools perform differently for different populations. This underscores the need to validate a tool prior to its use in a population that is different from its original design. Differences in lifestyle, diet, and other sociodemographic characteristics could account for this variability warranting the need for validation of the tool. In this review, we found that the studies used various validation methods including split-sample cross-validation (51, 71), validation with another external population (18, 46, 62, 72), and bootstrapping (31, 49).

Studies conducted in sub-Saharan Africa

This review study did not identify a diabetic risk assessment tool specifically designed and validated for the population of SSA and that reported tool accuracy metrics like AUCs, sensitivity and specificity, and positive and negative predictive values. The implication is that clinicians may have to depend on tools developed for other populations to screen for diabetes in the sub-region. Given the vast variation in social, economic, nutritional, demographic, and genetic factors between different populations, and how these factors interplay in the aetiology of diabetes, the accuracies of these external diabetic risk assessment tools may be in question. This claim seems to have empirical support from the study done by Skogberg et al. who demonstrated higher accuracy levels among Finns compared to Russian, Somali, and Kudish immigrants when the variables WC and WHtR were used to predict DM. With the prevalence of DM in SSA expected to grow significantly, the need for accurate early detection is imperative. Our study argues strongly in favor of developing such tools.

We found some issues with three studies (56, 60, 67) identified in this review. Paramount among them was the fact that tools developed for other populations were used in some local SSA populations without validating them for the local populations. The study by Alebiosu et al. (56) provides one such example. They used the Finnish Medical Association diabetes risk assessment (FINDRISK) tool, without validating the tool in the local SSA population. Although they reported a significant correlation between total risk score and fasting blood sugar, they did not report any of the standard measures of tool accuracy like the AUC, sensitivity and specificity, and negative and positive predictive values. Without accurate results, it is not clear if the tool could accurately screen for DM particularly at the early stages in the population they studied.

The WHO STEPS instrument, GPPAQ, and REAP were used in Ghana by another study (52) to assess the risk factors for type 2 DM but did not predict DM directly. Although the tools have utility in associating DM risk factors to scores, robust predictive values were not reported and as with the study by Alebiosu et al. (56), the tools were not validated for the local population. One study (60) reported accuracy levels using the area under the receiver operating characteristics curve (AUC). Anthropometric variables were not used to predict DM directly but of cardiometabolic syndrome (CME), a syndrome which comprises hyperglycemia, hypertension, and hypertriglyceridemia. Although they demonstrated similar AUCs for female and male anthropometric variables like WHtR and BMI, the tool was designed specifically to predict CMS; therefore, its predictive utility for DM remains unclear.

An accurate DM risk assessment tool validated for local SSA populations does not seem to exist yet. However, the few related studies we reviewed showed pertinent anthropometric risk factors for DM that could be used to develop and validate a DM tool in SSA. These anthropometric factors include waist circumference to height ratio, age, BMI, waist circumference below the ribs, exercise, vegetable consumption, use of anti-hypertensives, previous history of hyperglycemia, positive family history of diabetes, and rapid eating. The cut-off values of the anthropometric variables used in the reviewed studies are presupposed normative values for populations outside Africa and could lower the predictive value of the tools in the African population. Perhaps a non-invasive tool that uses normative values for WC, WHtR, BMI, dietary intake, exercise regimen, etc., which are pertinent to the local population, could give higher overall accuracy including sensitivity and specificity values. These findings therefore provide insights and guidelines in a first phase for developing a more population-based diabetes risk assessment tool for SSA based on the reported risk factors identified for local populations. A second phase will involve devising and building new risk assessment methods based on the data collected from the tool design project.

Studies conducted outside sub-Saharan Africa

Regarding the studies conducted outside of SSA, a total of 36 articles on diabetes risk assessment tools were reviewed. In general, the tools were developed in Europe, Asia, the USA, and the Middle East. However, none of the tools was developed or validated for the African population (58). A similar lack of validated risk assessment tools found in SSA has been noted among some Latin American populations with the study recommending that the health authorities prioritize the development, validation, and implementation of a risk assessment tool (59). Considering the high prevalence of diabetes and undiagnosed diabetes in the SSA region (10), the health authorities in the various countries should take similar actions by prioritizing the development and validation of a tailored diabetes risk assessment tool. Such tool should ideally be non-invasive, easy to use, free, and easily available to clinicians, public health workers, researchers, and individuals to assess their level of risk for developing diabetes. As with other Western countries, making the tool available on Ministry of Health websites will enable screening and early diagnosis of diabetes to reduce the rate of complications related to undiagnosed diabetes.

The number of cases of diabetes used in the derivation model for risk factors in the studies conducted outside of Africa varied from 48 (61) to 207 (63), and for validation, it was between 29 and 582 cases. Compared to studies in SSA populations, these studies reported similar risk factors outside of Africa (63–65) including age, waist circumference, and family history of diabetes. These were the most common predictors of diabetes and in one study oral glucose tolerance test was the outcome. Of five studies that assessed the use of diabetes risk assessment tools in South America (59), one review study found a high discrimination performance (AUC 70%, range: 66–72%) across studies, and the highest metric was always the negative predictive value (61, 64–66). Although discrimination estimates in those studies were largely acceptable, calibration metrics were not reported. For countries such as Brazil (68), Mexico (69), and Peru (66) where risk assessment tools were developed and validated both cross-sectionally and prospectively, there was enough scientific evidence to implement these tools as part of the standard of care for type 2 DM screening at the population level (66). Two studies from the Middle East also reported a high discrimination performance (AUC ranged from 76 to 83%) and only one study reported the tool's accuracy in terms of sensitivity and specificity (44) while another study reported the negative predictive value of the tool (42).

Generally, diabetes risk assessment tools cannot be directly transferred from one demographic group to another, due to the variation in factors such as diet and activity levels in different population groups. This is because the accuracy level of the tool varies with racial demographics (62) and since the three studies conducted in the African population used tools that were neither developed nor validated for the SSA population, it may be problematic to assume that their results can be replicated. In addition, only one of the studies reported an accuracy level for the tools used making it impossible to assess the performance of these tools in the SSA population. These findings indicate the need for the development of an accurate and validated non-invasive diabetes risk assessment tool for the SSA population. This tool should be cost-effective and able to identify persons at high risk of developing type 2 diabetes with reasonably high accuracy levels. Such a tool is important because the projected increase in the prevalence of diabetes in Africa will no doubt exert an enormous cost on the healthcare delivery systems in SSA, which are already chronically underfunded and understaffed (17, 18).

Limitations and strengths

One of the limitations of the current review relates to the fact that there was no standardized format for reporting the outcome variables in the different studies. For example, only one of the three studies in sub-Saharan Africa reported the level of accuracy of the screening tool used. The variation in the different tools used in the studies did not allow for comparison of the performance of the screening tools when used for the African population. Another limitation of this study was the small number of published reports on the diabetes risk assessment tools, leading to the inclusion of studies published in non-African regions to enlarge the scope of the discussion as suggested by a reviewer. Despite these limitations, this is the first study to provide evidence on the diabetes risk assessment tools used in SSA. The study reviewed evidence from non-African populations to ensure results are applicable to a wider population. By reviewing both African and non-African studies, this study provides the basis for the selection of the most relevant risk score to be implemented within the population such that the findings can be used as a reference to developing a tool for use among the African population.

Conclusions

This comprehensive review of the available literature found that no available diabetes risk assessment tool was developed and validated for the SSA population, despite the disproportionately high prevalence of diabetes in this region and the projected increase. This review found only three articles for the SSA region over a 20-year period which demonstrates the limited published research on diabetes risk assessment tools in the region. Although the existing European or American diabetes risk tools cannot be adopted in SSA countries without prior validation in the specific population, the findings of this

study provided useful evidence of the risk factors and diabetes risk scores that could be further studied in different SSA countries. There is need for practical strategies to address the barriers to the implementation of diabetes risk assessment tools including that a low-cost, reliable screening tool for undiagnosed diabetes be developed and internally validated for the SSA population. The potential for cost and morbidity savings could be significant. Development of such tools should take into account the peculiar demographic characteristics of the sub-region identified in this study. Having a validated diabetes risk assessment tool with sufficiently high sensitivity and specificity will help healthcare policy-makers make informed decisions in the prudent allocation of scarce resources. The tool could then be deployed by trained healthcare workers in the screening of those at risk of diabetes for further clinical examination and possible care and it can be adapted by different SSA countries for validation in different communities. As in many developed countries, such tools can be integrated into the guidelines for policy-makers as a standard of practice for diabetes screening at the population level.

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