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Review Article

Identifying individuals at risk of type 2 diabetes using risk assessment tools: an overview

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ABSTRACT

Diabetes is a chronic disorder that arises mainly due to unhealthy lifestyles in genetically susceptible individuals and has affected over 460 million people worldwide. Hence, alternative ways of identifying individuals at risk for developing diabetes are needed. Risk assessment tools can be useful for identifying and segmenting those at higher risk. The goal of this article is to assess various diabetes risk models that have been established in general populations to predict future diabetes, and to compare the technology behind their development and validation. PubMed, Google Scholar and Scopus were searched from inception to 10th November 2021. Studies that reported the use of risk assessment tools to identify individuals at risk of diabetes were included. Of the 9045 articles identified, 28 were included. This study includes six diabetes risk assessment tools, all of which were developed using logistic regression analysis. The most commonly included variables were age and a family history of diabetes. All six tools were subjected to external validation. The risk scores exhibited an overall strong predictive capacity for the population it was developed. However, the external populations had a lower discriminatory performance, implying that risk scores may need to be verified within the group in which they are meant to be utilised. Further, developing the risk tools using modifiable diabetes risk factors and biochemical tests can be more useful for predicting future diabetes.

Keywords: Diabetes, Health risk assessment, Risk model, Risk score, Validation

INTRODUCTION

Diabetes is a chronic medical disorder characterised by hyperglycaemia caused by insulin secretion, insulin action, or both. It arises when the pancreas fails to produce enough insulin or when the body's insulin is ineffectively used. Insulin is required by the body to convert sugar, carbohydrates, and other nutrients into energy. When the insulin secretion and action are impaired in the body, resulting in unusually high glucose levels in the blood, a disease known as diabetes. According to the International Diabetes Federation Atlas Ninth edition 2019, around 463 million individuals globally are anticipated to have diabetes and that figure is expected to rise to 578 million by 2030 and 700 million by 2045.[1-4]

Reduced physical activity and eating unhealthy foods in bigger portion sizes in genetically vulnerable persons are the major causes of T2DM's rising prevalence. Lifestyle modification is already proven to be better and more cost-effective therapy than pharmaceuticals for the prevention and treatment of diabetes and its complications.[5-7]

The persistent hyperglycemia of diabetes is linked to long-term organ malfunction, damage, and failure, particularly in the eyes, kidneys, nerves, heart, and blood vessels. Undiagnosed type 2 diabetes puts people at a higher risk of stroke, coronary heart disease, and peripheral vascular disease than people who aren't diabetic. They are also more likely to suffer from dyslipidemia, hypertension and obesity. Hence diabetes screening may be beneficial in certain cases since early detection and treatment can lessen the burden of diabetes and its complications.[8,9]

A health risk assessment (HRA), often called a health risk appraisal, is a questionnaire that examines an individual's lifestyle habits and health risks. An HRA includes questions about nutrition, fitness, stress, sleep, mental health, and physiological data like blood pressure and cholesterol. An HRA will aid the population and health professionals in identifying chronic disease risk factors such as heart disease, diabetes, cancer, and obesity. The origin of health risk assessment may be traced all the way back to the late 1940s when Dr Lewis C. Robbins began documenting patients' health risks in order to not only treat but also prevent sickness. Dr Don Hall developed the first computerized health risk appraisal in the United States in 1979, and the Centers for Disease Control and Prevention published HRA software with a self-administered survey to quantify adult health risk in 1980. As a result, health evaluations are now widely used by health professionals and in the workplace.[10-12]

Health risk assessments can help identify and segment individuals who are at greater risk for chronic disease and predict their risks before they occur. Health risk assessments can also help policymakers collect crucial data that can help them improve the effectiveness of their intervention initiatives. Furthermore, completing health risk assessments encourages people to make healthier lifestyle choices by prompting them to consider the dangers they face and what they can do to improve their habits. This shift in thinking leads to a change in behavior, which lowers the amount of money spent on healthcare needs over time. Some health risk assessments provide feedback and recommendations for health education, which can assist employees to make good lifestyle changes because persons who eat nutritious foods and exercise regularly have superior job performance and are less absent from work, this enhances production and minimizes absenteeism. Diabetes risk assessment tools assist you in determining your personal diabetes and metabolic syndrome risk. It also includes information on diabetes risk factors as well as suggestions for how to reduce them.[10,13,14]

Cardiovascular disease risk models and scores were the first to emerge, and they are now widely utilized in clinical and public health practice. In the United Kingdom, for example, all electronic patient record systems in general practice offer the ability to calculate the Framingham score, which indicates a patient's risk of a cardiovascular incident within the next ten years. This risk score is used in many guidelines and decision-making processes, and general practitioners are paid to calculate it. Even though several models and scores for diabetes risk have been established, we found little evidence that they should be used as part of a formal health strategy, guideline, or incentive plan for practitioners in any country. This is probably surprising, considering that cardiovascular disease-related morbidity and mortality have been declining in many countries since the 1970s, whereas diabetes-related morbidity and mortality have been rising.[15-17]

A diabetes risk assessment score is an example of a prognostic model. Such scores should ideally be created by taking a large, age-defined cohort of people without diabetes, evaluating baseline risk variables, and tracking the cohort for a long enough time to see who gets diabetes. Although prospective longitudinal designs in specifically constructed cohorts are costly, complicated, and time-consuming to implement, cross-sectional designs that quantify risk factors in a population of people with and without diabetes are methodologically inferior. Researchers usually use one of two approaches: they either investigate a cohort of patients without diabetes who have gathered years ago with relevant baseline measures for some other reason, or they analyze routinely available data, such as computerized patient records. Both of which have a high chance of bias.[16,18,19]

Risk assessments for diabetes can serve various objectives. Individuals would need to be accurately ranked according to their absolute risk for the risk score to be accurate. Risk scores in many cases will be required to give predictive information as well as an accurate estimate of the expected benefit from an intervention. Furthermore, presenting information about the projected benefit of an intervention program may impact an individual's decision to enroll in the program. Again, precise information on absolute risk is required, but it should be based mostly on modifiable risk factors.[20,21]

In this review, we wanted to find and evaluate diabetes risk models and scores that have been developed or tested in general populations to predict future diabetes and explore the methodology surrounding the development, validation, and comparison of risk scores. As a result, we were especially interested in identifying the qualities of a risk score that would make it appropriate for use in various scenarios and locations.

REVIEW OF LITERATURE

A literature search was performed for studies on diabetes risk assessment tools using computerized bibliographic databases, PubMed, Google Scholar and Scopus until 10th November 2021. Search terms included the following Medical Subject Headings: type 2 diabetes, risk assessment/score/prediction and specific names of different known risk assessment tools. We also went through the reference lists of the publications found through the initial electronic search.

Eligible studies included those that reported on the following: derived or validated in prospective cohort studies, studies with adults 15 years and older, evaluated for individuals without diabetes at baseline, and indicated the risk score for predicting incident diabetes. Articles that developed or validated tools for measuring risk factors for diseases other than diabetes, as well as invasive diabetes risk assessment tools, were excluded.

The title search was done individually by all three authors, followed by the abstract and full paper searches. On various occasions, PubMed, Google scholar, and Scopus were searched. The authors utilized the same predetermined search terms as previously specified. The search results were then manually evaluated for relevance and gathered for further screening using established inclusion and exclusion criteria. Tables and figures, as well as the text of manuscripts, were used to compile data. Data were extracted from all of the papers chosen by the reviewers. Disagreements over the extracted models were resolved through discussion (Figure 1).

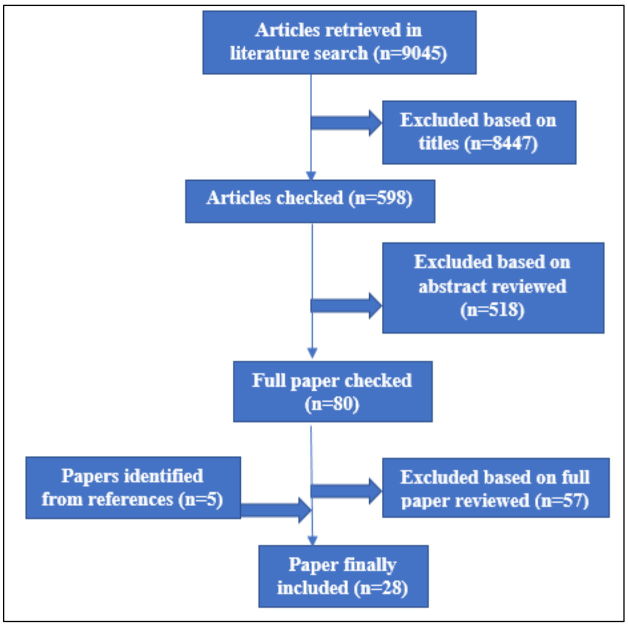

Figure 1: Identification of studies included in the review.

Australian Type 2 Diabetes Risk Assessment Tool (AUSDRISK)

The AUSDRISK was developed in 2008 by the National Australian Diabetes Obesity and Lifestyle Study (AusDiab). It has a short series of questions that enables both health professionals and individuals to assess the risk of getting type 2 diabetes in the following 5 years.

This tool was developed based on nine risk factors- age, sex, ethnicity, parental history of diabetes, history of high blood glucose level, use of antihypertensive medications, smoking, physical inactivity and waist circumference that is either known or easily assessed.

The AUSDRISK score ranged from 0 to 35, with a value of 5 or less indicating a low risk of diabetes, 6-11 indicating an intermediate risk, and 12 or more indicating a high risk of T2DM in the following 5 years.[22]

Risk test by American Diabetes Association

The American Diabetes Association (ADA) introduced its initial risk test in 1993, and it was in 2009 that the ADA developed its current version of the risk test for prediabetes screening. A published study altered the exam, which was then verified using data from the Centres for Disease Control and Prevention.

The ADA diabetes risk test calculates a risk score based on seven factors, including the individual's age, gender, family history of diabetes, history of gestational diabetes in women, history of hypertension, physical activity, and BMI. The risk test has a score range of 0 to 10. A high score on the online risk test (five or above) indicates that a person is at a high risk of developing undiagnosed prediabetes or type 2 diabetes.[23-25]

Finnish Diabetes Risk Score (FINDRISC)

The Finnish Diabetes Risk Score (FINDRISC) was developed by Dr. Jaana Lindström and Dr. Jaakko Tuomilehto of the National Institute for Health and Welfare in Helsinki, Finland, to identify people who are at high risk of developing T2DM. The FINDRISC is also used in the International Diabetes Federation's online diabetes chance assessment tool, which seeks to forecast an individual's risk of having type 2 diabetes within the following ten years. FINDRISC comprises six simple questions and two anthropometrical measurements which are age, BMI, waist circumference, physical activity, daily consumption of fruits, berries, or vegetables, history of antihypertensive drug treatment, history of high blood glucose and family history of T2DM.

The FINRISC is used to identify undiagnosed T2DM, impaired glucose tolerance and metabolic syndrome as well as to estimate the risk of acquiring T2DM in the next ten years. A score of less than 7 suggests low risk, 7-11 indicates slightly elevated risk, 12-14 indicates moderate risk, 15-20 indicates high risk, and more than 20 indicates a very high probability of having T2DM within ten years.[26,27]

The Simple Chinese Diabetes Risk Score (NCDRS)

In the year 2010, the simple Chinese risk score was created to give a consistent DM risk measurement in the Chinese population. Age, waist circumference and family history of diabetes are among the parameters.

It was developed after conducting two consecutive population-based diabetes surveys and standard 2 h 75 g oral glucose tolerance tests (OGTTs) were performed to diagnose diabetes in both surveys. The simple Chinese risk Score ranges from 3 to 32, with 14 being the suggested cut-off point for undiagnosed T2DM.[28]

Cambridge diabetes risk score

It was created by Simon J. Griffin in 2000 to identify people at high risk of having undiagnosed diabetes, predict who will develop diabetes and cardiovascular disease, and experience premature mortality. Age, gender, body mass index, steroid and antihypertensive medication, family and smoking history are all factors that were considered for the development of this tool. The CRS was calculated as the probability (ranging from 0 to 1).[29]

Indian diabetes risk score

The Madras Diabetes Research Foundation (MDRF) developed IDRS to detect persons with undiagnosed Type 2 diabetes. This score is based on CURES, an extraordinarily large population-based diabetes study in India (Chennai Urban Rural Epidemiology Study). IDRS considers two modifiable (waist circumference and physical inactivity) and two non-modifiable (age and family history of diabetes) risk variables. The scale runs from 0 to 100, with a score of more than 60 suggesting a higher risk of undiagnosed diabetes.[30,31]

DISCUSSION

Australian type 2 diabetes risk assessment tool (AUSDRISK)

For validation of the AUSDRISK, in 2008, 6,060 people from throughout Australia were examined twice, five years apart. Multiple logistic regression models were used to build models for predicting the onset of diabetes. Around 362 persons got diabetes among the adults studied. The diabetes risk tool has an AROC of 0.78, with a Hosmer-Lemeshow Chi-square value of 4.1 (p=0.85). The sensitivity, specificity, and positive predictive value for detecting incident diabetes with a score ≥12 was 74.0%, 67.7%, and 12.7%, respectively. In the two separate validation cohorts, the AROC and HL chi-square statistics 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. According to this tool, people of southern European, Asian, Aboriginal and Torres Strait Islander and Pacific Islander were combined into a single, high-risk ethnic group. When compared to other risk tools, this one is unique in that it includes ethnicity as well as ethnic- and sex-specific waist circumference cut-points.[22]

Risk test by American Diabetes Association

From 1999 to 2004, the National Health and Nutrition Examination Survey was used to build the model, and a combined cohort of two community studies, the ARIC (Atherosclerosis Risk in Communities) Study and the CHS (Cardiovascular Health Study), was used to validate the ADART. Logistic regression was used to figure out which participant characteristics were linked to undiagnosed diabetes. The risk tool exhibited a sensitivity of 79%, specificity of 67%, and a positive predictive value of 10% at a cut-off point of >5. The area under the curve was 0.72.

According to this tool, African Americans, Hispanic/Latino Americans, American Indian/Alaska Natives, Asian Americans, and Pacific Islanders have a higher risk of prediabetes and type 2 diabetes. And also, Asian Americans are at increased risk for type 2 diabetes at a lower body weight.[24,32,33]

Finnish Diabetes Risk Score

Validation of Finnish Diabetes Risk Score (FINDRISC) was done using a prospective cohort of people aged 35 to 64 years with no antidiabetic drug treatment at baseline from 1987 to 1992 and was followed for 10 years. Logistic regression was used to compute β-coefficients for known risk factors for diabetes. 196 of the 4,746 non-diabetic patients in the 1987 study acquired drug-treated diabetes over the 10-year follow-up period. The risk rose as the patient's age, BMI, and waist circumference increased. Furthermore, elevated blood pressure was linked to a greater rate of drug-treated diabetes. With a sensitivity of 78% and specificity of 77% in the 1987 cohort and a sensitivity of 81% and specificity of 76% in the 1992 cohort, the Diabetes Risk Score value 7 was chosen as the cut point for increased risk of drug-treated diabetes. For the 1987 cohort (10-year follow-up), the positive predictive value was 13%, and for the 1992 cohort, it was 5% (5-year follow-up). Because of the shorter follow-up time, the overall incidence was lower in the 1992 cohort.[26]

The Simple Chinese Diabetes Risk Score

After conducting two population-based diabetes surveys among Chinese individuals aged 20-74 years in 2002 (n=1986) and 2006 (n=4336), the simple Chinese diabetes risk score was developed. Based on data from the 2002 survey, the risk assessment approach was constructed utilizing beta coefficients found by logistic regression analysis. The algorithm's performance was tested on a sample population from the 2006 survey. The sensitivity and specificity of the risk score was 84.2% and 39.8%, respectively, at a cut-off point of 14. The area under the receiver operating characteristic curve for the score was 67.3% (95% CI: 64.9-69.7%). It was discovered to be a useful diabetes screening tool for health promotion and population-based screening programs for the general public.[28]

Cambridge Diabetes Risk Score

A total of 1077 people without diabetes, aged 40 to 64 years, were gathered from a single general practice area. 41 practices in Southern England provided clinical data of newly diagnosed type 2 diabetes patients aged 40 to 64 years in a separate 12-month trial. To create a national population, half of each dataset was randomly picked and pooled. The data was combined into a regression model to produce a formula that predicts the risk of diabetes. The performance of this risk score in diagnosing diabetes was investigated using a randomly selected population-based sample. In the test population, the CRS had 72% specificity, 77% sensitivity, and a likelihood ratio of 2.76. The area under the receiver operating characteristic curve for the score was 80%.[29,34]

Indian Diabetes Risk Score

The IDRS was created using data from the Chennai Urban Rural Epidemiology study and the findings of multiple logistic regression analysis. To calculate the risk scores, a regression analysis was performed with newly diagnosed diabetes as the dependent variable and numerous risk factors as independent variables. Each parameter was given a score based on the beta coefficients. For diagnosing undiagnosed diabetes, the IDRS has a sensitivity of 72.5%, specificity of 60.1%, a positive predictive value of 17.0%, a negative predictive value of 95.1%, and an accuracy of 61.3% for a score of 60 during screening in the Indian population. In comparison to other risk factor scoring systems, IDRS just requires a single waist measurement and three basic questions, making it a quick, cost-effective, and easy-to-use tool. Hence after brief training, community health professionals such as Auxiliary Nurse Midwife (ANMs), Multipurpose Workers Male (MPWs), Accredited Social Health Activists (ASHAs), and Anganwadi workers can utilize it (Table 1).[35,36]

Table 1: Diabetes risk scores and their validation in an external population.

First author, Year	Population, Country	Variables	Sensitivity (%)	Specificity (%)	AROC
Australian type 2 diabetes risk assessment tool (AUSDRISK)					
Chen et al, 2010.[22]	Australia	Age, sex, ethnicity, family history, history of high blood glucose, use of antihypertensive medications, smoking, physical inactivity and waist circumference.	74	67.7	0.78
Fleming et al, 2021.[37]	New South Wales		76	61	0.72
Lotfaliany et al, 2019.[38]	Iran		Not reported	Not reported	0.77
American Diabetes Association Risk Test					
Bang et al, 2009.[33]	United States	Age, sex, family history, history of gestational diabetes in women, history of BP, physical activity and BMI.	79	67	0.72
Woo et al, 2017.[32]	Hong Kong		80	56.7	0.72
Asgari et al, 2020.[39]	Iran		51.6	82.4	0.73
Finnish Diabetes Risk Score (FINDRISC)					
Lindstrom et al, 2003.[26]	Finland	Age, BMI, waist circumference, physical activity, consumption of fruits or vegetables, history of BP, history of high blood glucose and family history.	78	81	0.87
Alssema et al, 2008.[40]	Netherland		Not reported	Not reported	0.71
Omech et al, 2016.[41]	Botswana		48	73	0.63
Cameron et al, 2008.[40]	Australia		62.3	70.5	0.72
The Simple Chinese Diabetes Risk Score					
Gao et al, 2010.[28]	China	Age, waist circumference and family history of diabetes	84.2	39.8	0.67
Shao et al, 2020.[42]	China	Age, gender, ethnic group, hypertension record, smoking history, alcohol use, waist circumference, BMI	74.1	71.16	0.78
Shao et al, 2020.[42]	China	Insulin, HbA1c, glucose, TG, TC	73.08	92.25	0.88
Cambridge Diabetes Risk Score					
Griffin et al, 2000.[29]	United Kingdom	Age, gender, BMI, steroid and antihypertensive medication, family and smoking history.	77	72	0.80
Rahman et al, 2008.[43]	United Kingdom (European Prospective Investigation of Cancer-Norfolk)		54.4	80	0.74

Continued.

First author, Year	Population, Country	Variables	Sensitivity (%)	Specificity (%)	AROC
Katulanda et al, 2016.[44]	Sri Lanka		54.4	59.3	0.66
Ramachandran et al, 2005.[45]	India (National Urban Diabetes Survey)		76.6	59.9	0.73
Indian Diabetes Risk Score					
Mohan et al, 2005.[35]	Chennai Urban Rural Epidemiology Study, India	Waist circumference, physical inactivity, age and family history	72.5	60.1	0.698
Katulanda et al, 2016.[44]	Sri Lanka		66.2	66.1	0.72
Silvanus et al, 2019.[46]	Nepal		84.2	55.24	0.69

According to this table, the predictive efficacy of diabetes risk scores created in people of various ethnic origins varies significantly. The performance of these risk models were described using several statistical methodologies, although they were largely confined to a global measure of discriminating (AROC).

Several risk scores may be used to predict type 2 diabetes based on information that is easily available through questionnaires. Collecting data using these questionnaires are expected to be less expensive and more acceptable than using biochemical tests for screening. However, biochemical measurements especially fasting plasma glucose can significantly improve the performance of any non-invasive model. Other indicators that are generally easy to collect in clinical practice, such as high-density lipoprotein cholesterol, triglycerides, and liver enzymes can also provide a minor boost in the predictive value of any risk models, while less often tested parameters, such as C-reactive protein or adiponectin, have minimal support.[47]

Diabetes risk scores performed well in the research populations from which they were derived. However, its predictive value was typically reduced in foreign populations. As a result, risk prediction models should not be presumed to function similarly well; instead, they should be verified within the population for whom they are designed, especially if ethnicities and nations differ from the derivation cohorts. Furthermore, when models are assessed in an external population, re-estimation of regression coefficients for existing models may result in superior performance. It may also be more beneficial to construct population-specific risk prediction tools rather than attempting to establish a universal risk score that would function across all communities.[26,29,41,44,48,49]

For determining acceptable cut-offs based on cost-benefit considerations, information on sensitivities, specificities, and projected values are required. Some of the prediction models examined in this analysis lacked such data.[38,40]

Although modifiable risk factors may be beneficial to both patients and health care professionals when dealing with non-communicable diseases, non-modifiable parameters such as age, sex, race, and family history dominate the majority of these risk scores. Obesity metrics (BMI, waist circumference) are commonly modifiable risk factors, although smoking and other variables like food and physical exercise are less common.[22,26,33]

CONCLUSION

Using multivariate risk models to calculate diabetes risk is effective for tailoring prevention and treatments to high-risk groups. Moreover, risk scores should not be anticipated to perform comparably well; rather, they should be validated within the population for which they are intended to be used. Also, non-invasive risk assessments can be improved by including widely detected biochemical indicators, particularly glycemic readings. Medical questionnaires should be utilized more frequently to identify individuals or demographic subgroups who can benefit from a more comprehensive risk assessment. Furthermore, regardless of screening and prevention techniques for high-risk patients, population-based methods targeting modifiable diabetes risk factors such as physical activity, food, obesity, and smoking should be supported.

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