Subscription Agency
Exploring and Distributing Knowledge Globally

Pharmaceutical Sciences
Volume 3 Issue 2, 2023
eISSN No.: 2582-8371

A Systematic Review on Risk Assessment Tools for Identifying Individuals at Risk of Developing prediabetes and Type 2 Diabetes

Amirah Farhana Nazri[a], May Khin Soe[b], Nurul Nadiah Ashara[a]
[a]Final Year of Pharmacy Students, Kulliyyah of Pharmacy, International Islamic University Malaysia (IIUM), Jalan Sultan Ahmad Shah, 25200 Kuantan, Pahang, Malaysia
[b] Supervisor, Assistant Professor, Department of Basic Medical Sciences, Kulliyyah of Pharmacy, International Islamic University Malaysia (IIUM), 25200 Kuantan, Pahang, Malaysia

****Corresponding Author***
Email ID: may_soe@iium.edu.my

ABSTRACT

Introduction: *Type 2 diabetes mellitus (T2DM) is a common metabolic disease that leads to various complications and financial distress. T2DM is influenced by a complex interplay of genetic, metabolic, and environmental risk factors. Moreover, the rapid increase of prediabetes and type 2 diabetes world-wide have the effect of gaining attention to predict it since early age. However, early detection and appropriate treatments can successfully prevent or delay the development of T2DM and its complication. Thus, identifying high risk persons should be done using self-assessment questionnaires, tools and scoring method. It is crucial to choose the right diabetes risk assessment tools in places with diverse populations.*
Objectives: *To systematically review all recent research on the risk assessment tool used for identifying people at risk of developing T2DM.*
Methods: *A comprehensive systematic literature review was performed using multiple electronic databases like PubMed, Scopus, and ScienceDirect. Selection criteria included adult aged 18 years and older and taking diabetes risk assessments. Data from included studies were extracted using a predesigned data extraction tool. Joanna Briggs Institute Critical Appraisal checklists were used as the main tool for critical appraisal.*
Results: *Fifteen published studies between 2012 to 2022 were finally included out of 271 articles obtained from databases. Some had been removed due to incomplete criteria. Nine of the included studies uses one risk assessment tools and six of them uses multiple tools. The included diabetes risk assessment tools are FINDRISC, IDRS, RAPID, QDiabetes score, ADA, QDRS and CANRISK.*
Conclusion: *The chance of developing prediabetes and T2DM and is increased by a variety of modifiable risk factors. It is possible to identify individuals with high-risk group by using a simple, practical, non-invasive and affordable diabetes risk score.*
Keywords: *Systematic Review, Type 2 Diabetes Mellitus, Prediabetes, Diabetes Risk Assessment Tools, Diabetes Risk Score.*

INTRODUCTION

Type 2 diabetes mellitus (T2DM) is a significant global health problem and is prevalent in healthcare situations (Oo et al., 2020). It is a severe metabolic disease that leads to a great deal of complications, death, and financial distress (Riaz et al., 2012). The International Diabetes Federation (IDF) reported, diabetes caused 4.2 million deaths worldwide and 463 million individuals between the ages of 20 and 79 had diabetes in 2019; that figure is predicted to reach 700 million by the year 2045 (Basit et al., 2021; Galicia-Garcia et al.,

Pharmaceutical Sciences
Volume 3 Issue 2, 2023
eISSN No.: 2582-8371

2020; Sun et al., 2019). The occurrence of T2DM is influenced by a complex interplay of environmental risk factors, genetics and metabolism. Ethnicity and genetic predisposition or family history, which are non-modifiable risk factors for T2DM, have a strong foundation in T2DM development (Galicia-Garcia et al., 2020). However, early treatments can successfully prevent or delay T2DM, as demonstrated by numerous studies (Kengne et al., 2014) by stressing on the major modifiable risk variables like low physical activity, obesity, and an unhealthy diet (Galicia-Garcia et al., 2020; Khan et al., 2020; Sezer et al., 2021). Physical activity reduces body weight, controls blood pressure, and improves insulin sensitivity, demonstrating how altering modifiable risk variables can reduce the likelihood of developing T2DM (Nagarathna et al., 2020). Furthermore, early detection of patients with undiagnosed T2DM can greatly reduce the consequences it causes; thus, lowering the burden of the disease (Lotfaliany et al., 2019).

Risk Assessment Tools

The diagnosis of T2DM can be made through measures of glycated haemoglobin (HbA1c), fasting plasma glucose (FPG), or the level of glucose at two hours following an oral glucose tolerance test (OGTT) (Akter & Qureshi, 2020; Mavrogianni et al., 2019). However, these procedures are intrusive, costly, and time-consuming, making them unsuitable for mass screening.

Additionally, since they only offer data by measuring glucose level, it would be more decisive to detect those who are at high risk of T2DM even while they are in a normoglycemic condition. This would allow for the effective implementation of therapies to avoid prediabetes and overt T2DM (Mavrogianni et al., 2019). Recently released recommendations by the National Institute for Health and Care Excellence (NICE) help determine who is high-risk of getting T2DM. According to these recommendations, identifying high risk people should be done using self-assessment questionnaires or tools that have undergone rigorous validation.

The recommendations also advise utilising validated risk assessments, such as the Cambridge Risk Score (CRS), or the QDiabetes® risk calculator that account for regularly gathered data in primary care. Besides, validated self-assessment questionnaires, such as the most popular and validated version, the Finnish Diabetes Risk Score (FINDRISC), or the Leicester Risk Assessment (LRA), may be utilized to identify those at high risk (Gray et al., 2015, 2016). It is crucial to choose the right diabetes risk assessment tools in places with diverse populations as it may affect the result. For instances, Asian countries with multicultural citizens should use risk assessment tools derived from Asian countries to ensure results' authenticity since there are differences in Asian and European diet consumption (Fernandez & Frost, 2013). The American Diabetes Association (ADA) encourages testing for people at high-risk of T2DM who are 40 years or older, obese, physically inactive, or have dyslipidaemia.

The possibility of the existence or potential onset of a health problem is objectively assessed in the first act of identification of T2DM case which is by using diabetes risk assessment tools. Next, an OGTT or HbA1c test may be conducted in the second step among individuals who were identified as high-risk in the first act (Savić et al., 2020).

OBJECTIVES

1) To systematically review all recent research on the diabetes risk assessment tools used for identifying individuals at risk of developing prediabetes and T2DM.

2) To measure the effectiveness of diabetes risk assessment tools for the identification of T2DM high-risk individuals.

METHODOLOGY

Several databases were used as search engines to find articles of interest. They were PubMed, Scopus and Science Direct. The search strategy based on the keywords of the study by using the PICO (Population, Interest, Comparison, Outcome) method shown in **Table 1**.

Table 1: The search strategy for literature selection

PICOS	Description (Key words)
Population	Individuals aged 18 years and older
Interest	Diabetes risk assessment tools
Comparison	Comparison of different diabetes risk assessment tools
Outcome	Effectiveness of diabetes risk assessment tools

Eligibility Criteria

In this systematic review, criteria made for the selection of articles was that they were published between 2012 and 2022. The language use was limited to English only with full-text articles. Additionally, studies were required to utilise any form of self-assessment or risk assessment tools. This review focused on the age group of young adults, adults, and the elderly. Studies with the children population were excluded. Summarized inclusion and exclusion criteria were listed in Table 2.

Table 2: Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
From January 2012 onwards	Before January 2012
English language	Other than English
All study designs	Systematic Reviews, Meta-Analysis, Reviews
Young adults, adults, and elderly	Children
Any form of self-assessment or risk assessment tools	No self-assessment or risk assessment tools
High risk individuals of developing T2DM	T2DM, Gestational Diabetes
Recognized and validated risk assessment tools	Developing risk assessment tools

Study Records

The Mendeley reference manager's library is used to store each database from distinct folders. All the selected articles were collected in a folder for duplicate checking. After that, they were imported to “Rayyan.com” for the selection process. Duplicates were removed, titles and abstracts of the identified studies were screened by using “Rayyan” based on the inclusion and exclusion criteria. Then, reviewers screened all the articles.

Any kind of disagreement was solved through discussion. The selection flow of research was documented and recorded using the “Preferred Reporting Items for Systematic Reviews and Meta-Analyses” (PRISMA) flow diagram. The information related to the data extraction needed from included articles were listed in Table 3.

Pharmaceutical Sciences
Volume 3 Issue 2, 2023
eISSN No.: 2582-8371

Table 3: Information extracted from eligible studies

Study details	Methods	Results
Authors Year of publication Location Aims/objectives Study population	Predictor variables (age, BMI, waist circumference, waist-to-hip ratio)	Diabetes risk assessment tools Tool accuracy Tool validation Conclusion

JBI critical appraisal checklists were used in this study. After, two independent reviewers meticulously evaluated each article for inclusion criteria in this systematic review. The outcomes of this evaluation were used to assist in the synthesis and interpretation of the data from this review (Munn et al., 2020). Since, this study uses synthesis without the meta-analysis (SWiM) reporting guideline. The SWiM guideline was created to direct full disclosure in intervention reviews (Campbell et al., 2020). Qualitative description of data was collected, and it focused on sensitivity, positive and negative predictive value, area under the receiver operating curve (AUC), and specificity.

RESULTS

The identified records from databases yielded 271 articles, which include 137 articles from Scopus, 40 articles from PubMed and lastly 94 articles from ScienceDirect. The article search was done by following the PRISMA guideline. After thoroughly checking the duplicates, full text availability and the research inclusion criteria (done according to the JBI critical appraisal checklist), only 15 articles were found eligible and were included in this systematic review.

Data Analysis of Review

All 15 articles included in this study were publish between 2013 until 2021. The articles included were from the following countries: three from United Kingdom, two from Pakistan, one each from Malaysia, Philippines, Turkey, Australia, Belgium, China, Bosnia and Iran. The included articles have different study designs: six of them are cross-sectional studies, three of them are randomized-controlled trial (RCT), five of them are cohort studies and one case-control study. The included articles use different types of risk assessments tools: nine of them only use one risk assessment tool in their studies, six of them uses multiple risk assessment tools in their studies , nine of them uses FINDRISC , two of them uses the “Indian Diabetes Risk Score” (IDRS) (Dudeja et al., 2017; Nagarathna et al., 2020), two of them uses Risk assessment of Pakistani individuals for diabetes (RAPID) three of them uses QDiabetes score, two of them uses LRA, three of them uses CRS, two of them uses Australian type 2 diabetes risk assessment tool (AUSDRISK, two of them uses American Diabetes Association risk score (ADA), one of them uses Qingdao Risk Score (QRS) (Sun et al., 2019) and one of them uses Canadian Diabetes Risk Questionnaire (CANRISK) (Agarwal et al., 2019).

Nine studies that uses only one diabetes risk assessment tool were as follows. According to the test results of a Malaysian research, less than 40% has low risk and more than 59% of participants had a moderate to high risk of developing T2DM in the following ten years with 36.2% has moderate risk and 23.2% has high (Oo et al., 2020). Next, in a Turkish study, 13.9% has high risk of developing T2DM, 16.67% has moderate risk and 69.35% has low risk. These number were expected because of their Mediterranean diet (Sezer et al., 2021). Furthermore, a study in Belgium stated that 12% has moderate, 17% has high risk and 5.5%

Pharmaceutical Sciences
Volume 3 Issue 2, 2023
eISSN No.: 2582-8371

has very high risk of getting T2DM. For a cut-off value of 12, the sensitivity and specificity for diagnosing T2DM were 100% and 84.1%, respectively, while for a cut-off value of 15, they were 80% and 95.9% (Vandersmissen & Godderis, 2015). Additionally, a Bosnian study stated that 23.6% has a high risk and 9.3% has a very high risk of developing T2DM (Savić et al., 2020). Other than that, an Indian study showed that 40.9% has a high risk and 29.7% has moderate risk of developing T2DM. Area under the ROC curve was 0.763, the sensitivity of 78.05 and specificity of 62.68 was observed (Nagarathna et al., 2020). Another study also conducted in India has a sensitivity of 95.12% and specificity of 28.9% when the score is 60 and above. It also has an area under the curve (AUC) of 0.651 (Dudeja et al., 2017). Besides that, there are two Pakistani studies, one of them has an AUC for the receiver operator curve (ROC) of 0.658, the positive predictive value was 54.5% while negative predictive value was 70.1% (Riaz et al., 2012). Another one has found that 25.9% of the population was at risk of having T2DM, and an OGTT revealed that 18.1% of those individuals had diabetes and 74.1% who were not at risk of T2DM, only 7.6% had developed it by OGTT (Basit et al., 2021). Lastly, from the study conducted in China, 47.9% was found high risk of getting T2DM by using QDRS (Sun et al., 2019).

Six studies that uses multiple diabetes risk assessments tools were as follows: two studies conducted in United Kingdom, QDiabetes, LRA, FINDRISC and CRS were used. The first study in 2015, the CRS (13.6%), FINDRISC (6.6%), QDiabetes (6.1%) and LRA (3.1%) of high-risk individuals of getting T2DM. However, it was reported that a high number of males were identified as high risk by using CRS (25.4%), QDiabetes (9.8%), LRA (4.8%) and FINDRISC (4.9%). Meanwhile, FINDRISC identified 7.8% of females which is higher compared to other tools like QDiabetes (3.3%) and LRA (1.8%) (Gray et al., 2015). Then, in the next year, 2016, by using FINDRISC, 5.3% of females has high risk of developing T2DM, but by using LRA, 15% of females has high risk of developing T2DM while for the males, by using FINDRISC, 6.6% has high risk but by using CRS, 13.1% has high risk (Gray et al., 2016). A Philippine's study that uses ADA, CANRISK, FINDRISC and IDRS stated, FINDRISC has the highest sensitivity, which is 0.96 and the highest AUC, 0.8. IDRS has the highest negative predictive values, 0.96. CANRISK has the specificity of 0.54 and sensitivity of 0.86 (Agarwal et al., 2019).Next, a study in Australia that used AUSDRISK and IDRS reported that 28% of people who were deemed to be at low risk by AUSDRISK were categorised by IDRS as being at moderate risk, while 35% of people who were deemed to be at moderate risk by AUSDRISK were categorised as being at high risk (Fernandez & Frost, 2013). Lastly, a study in Iran that used FINDRISC, AUSDRISK and ADA showed that AUSDRISK had the highest discrimination power with AUC of 0.77 as compared to FINDRISC with AUC of 0.75 and ADA with AUC of 0.73 (Lotfaliany et al., 2019). Data was summarized in Table 4 regarding types of risk assessment tools and its accuracy and validation.

Table 4: Characteristics of different studies included in this review

Type of Study	Country	Age (year)	Sample Size	Predictors	Tools	Tool accuracy	Validation
Cohort	Malaysia	18 years & above	591	Age, gender, use of antihypertension drug, family history of diabetes, waist circumference, BMI, daily consumption of	Modified FINDRISC score	In the following ten years, diabetes was 40.6% less likely to develop. In the following ten years, 36.2% and 23.2% of them had a moderate or high risk of developing diabetes, respectively.	Yes

				soft drinks and physical activity.			
Cohort	United Kingdom	44 – 54 years	651	Age, height, weight, waist circumference, blood pressure, BMI, family history of diabetes, daily consumption of vegetables, physical activity, smoking status and use of antihypertensive medications	QDiabetes, LRA, FINDRISC and CRS	Predicted risk of developing T2DM. Females: 5.3% (FINDRISC) and 15.0% (Leicester Risk Assessment). Males: 6.6% (FINDRISC) 13.1% (Cambridge Risk Score). High-risk median HbA1c. Females: 39mmol mol^{-1} (5.7%) (FINDRISC and Cambridge Risk Score) and 41mmol mol^{-1} (5.8%) (QDiabetes and Leicester Risk Assessment). Males: 39mmol mol^{-1} (5.7%) (Cambridge Risk Score), 40mmol mol^{-1} (5.8%) (QDiabetes, Leicester Risk Assessment) or 42mmol mol^{-1} (6.0%) (FINDRISC).	Yes
Case Control	Philippines	40 years and above	200; 50 with diagnosed diabetes and 150 without diabetes	Age, ethnicity, weight, height, waist circumference, BMI, blood pressure, physical activity at home/work, family history of diabetes, daily consumption of vegetables, and use of antihypertensive medications	ADA, CANRISK, FINDRIC and IDRS	FINDRISC: highest sensitivity (0.96) and highest AUC (0.8). IDRS: highest negative predictive values (0.96). CANRISK: specificity (0.54) and sensitivity (0.86)	Yes
Cross-sectional	Turkey	20 – 64 years	744	Age, gender, use of antihypertension drug, family history of diabetes, waist circumference, BMI, daily consumption of vegetables and physical activity	FINDRISC	104 participants (13.9%) had a FINDRISC score of at least 15. The mean FINDRISC: 8.72± 4.95.	
Cross-sectional	India	35 years and above	155	Age, ethnicity, weight, height, waist circumference, BMI, blood pressure, physical activity at home/work, family history of diabetes	IDRS	Sensitivity: 95.12%, Specificity: 28.95%	Yes
Cross-sectional	Pakistan	25 years and above	First study: 1264. Second study: 856	Age, weight, BMI, gender, waist circumference, family history of diabetes, smoking status, and history of hypertension.	RAPID	The ROC's AUC was 0.658, and for two validation sets, it was 0.758 and 0.7. In the second set of data, the AROC is 0.7 with a sensitivity of 44% and a specificity of 89%, compared to a cut point of 4 with a sensitivity of 47.0% and 88%. Positive predictive value: 54.5% for cross-sectional data	Yes

						and 59.6% and 39% for validation data. Negative predictive value: cross-sectional data was 70.1%, 82.7% and 91.3% for validation data.	
RCT	India	20 years and above	240, 000	Age, ethnicity, weight, height, waist circumference, BMI, blood pressure, physical activity at home/work, family history of diabetes	IDRS	Statistical significance was determined to be p 0.0001 and the ROC was found to be 0.763 at a 95% CI of 0.761-0.765. Youden index displayed sensitivity of 78.05% and specificity of 62.68% at >50 cut off.	Yes
Cohort	United Kingdom	25 years & above	27 779 and 12 403 diagnosed diabetes	Age, gender, use of antihypertension drug, family history of diabetes, blood pressure, waist circumference, BMI, daily consumption of vegetables, smoking status, use of antihypertensive medication and physical activity	AUSDRISK, CRS, FINDRISC and QDiabetes	The overall C statistics varied from 0.76 (95% CI 0.72 - 0.80) to 0.81 (0.77-0.84), whereas the C statistics for men and women were respectively 0.73 (0.70-0.76) and 0.79 (0.74-0.83). One model overstated risk by 40% (28-52%) for Cambridge.	Yes
Cross-sectional	Australia	18 - 77	136	Age, ethnicity, weight, height, waist circumference, BMI, blood pressure, physical activity at home/work, family history of diabetes, daily consumption of vegetables, smoking status and use of antihypertensive medications	IDRS and AUSDRISK	Mean risk score. IDRS: 48; AUSDRISK: 13. AUC. IDRS: 0.72 (0.56 – 0.88): AUSDRISK: 0.75 (0.60 – 0.90) (p=0.61).	Yes
Cross-sectional	Belgium	35 years & above	275	Age, gender, use of antihypertension drug, family history of diabetes, waist circumference, BMI, daily consumption of vegetables and physical activity	FINDRISC	For a cut-off value of 12, the sensitivity and specificity for diagnosing dysglycaemia were 100% and 84.1%, respectively, and 80% and 95.9% for a cut-off value of 15.	Yes
Cohort	United Kingdom	40 years & above	676	Age, gender, family history of diabetes, use of antihypertension medication, waist circumference, BMI, physical	CRS, FINDRISC, LRA, and QDiabetes	High risk. CRS: 13.6%, FINDRISC: 6.6%, QDiabetes: 6.1%, LRA: 3.1% After analysis by sex, Males. CRS: 25.4%, QDiabetes: 9.8%, LRA: 4.8%, FINDRISC: 4.9%; Females. FINDRISC: 7.8% QDiabetes: 3.3%, LRA: 1.8%,	Yes

				activity and daily consumption of vegetables and fruits			
RCT	China	35-74	3033	Age, height, waist and hip circumference, BMI, gender, occupation, history of hypertension, smoking status and blood pressure	QDRS	In comparison to people with a QDRS 14, those with a QDRS 14 had a considerably increased chance of developing diabetes (hazard ratio (HR): 2.37 vs. 1.49; 95% CI 1.35-4.15 vs. 1.09-2.04). Furthermore, being overweight or obese and having a QDRS of less than 14 together had an additive impact on the risk of developing diabetes in urban areas (RERI = 1.59, S = 2.34, AP = 42.06%). Rural areas, however, showed a negative interaction (RERI = 0.07, S = 0.89, AP = 4.55%).	Yes
Cohort	Bosnia	18 - 70	520	Age, gender, use of antihypertension drug, family history of diabetes, waist circumference, BMI, daily consumption of vegetables and physical activity	FINDRISC	Using FINDRISC, it was discovered that among 520 respondents, 12.4% of women and 11.2% of men had a high risk of developing T2DM in the following 10 years, while 5.6% of women and 3.7% of men had a very high risk.	Yes
RCT	Pakistan	20 years & above	4904	Age, gender, weight, BMI, waist circumference, smoking status, family history of diabetes, and history of hypertension.	RAPID	25.9% positive for risk of developing diabetes.	Yes
Cohort	Iran	30 years & above	3467	Age, gender, ethnicity, family history of diabetes, blood pressure, waist circumference, BMI, physical activity, daily consumption of vegetables, smoking status and use of antihypertensive medications	FINDRISC, AUSDRISK , and ADA	AUSDRISK AUC: 0.77, FINDRISC AUC: 0.75, ADA AUC: 0.73	Yes

Risk of Bias and Quality Assessment

The JBI critical appraisal checklists were used to assess the quality of all articles included for this systematic review (Munn et al., 2020). Since the articles collected has different kinds of study designs, different JBI checklist were used according to their study design. In short, the quality of all articles can be considered as moderate and high quality as all studies have scores higher than 60%, except for one study with 38.46% score.

Pharmaceutical Sciences
Volume 3 Issue 2, 2023
eISSN No.: 2582-8371

It is considered as high risk of bias and was excluded from this systematic review. Data on risk of bias and quality assessment for each article were summarized in Table 5, Table 6, Table 7, Table 8.

Table 5: Summary of quality assessments (Cross-Sectional) using JBI appraisal checklist

Authors	Items on Joanna Briggs Institute checklist								Raw Score and %	Risk
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8		
(Oo et al., 2020)	1	1	U	1	NA	NA	1	1	5/8 = 62.5%	Moderate
(Fernandez & Frost, 2013)	1	1	1	1	NA	NA	1	1	6/8 = 75%	Low
(Vandersmissen & Godderis, 2015)	1	1	1	1	0	0	1	1	6/8 = 75%	Low
(Sezer et al., 2021)	1	1	1	1	U	U	1	1	6/8 = 75%	Low
(Riaz et al., 2012)	1	1	1	1	U	U	1	1	6/8 = 75%	Low
(Dudeja et al., 2017)	U	1	1	1	0	0	1	1	5/8 = 62.5%	Moderate

Table 6: Summary of quality assessments (Randomised Controlled Trial) using JBI appraisal checklist

Authors	Items on Joanna Briggs Institute checklist													Raw Score and %	Risk
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13		
(Nagarathna et al., 2020)	1	U	1	0	0	0	1	U	1	1	1	1	1	8/13 = 61.54%	Moderate
(García-Alcalá et al., 2012)	0	0	U	0	0	0	U	1	0	1	1	1	U	5/13 = 38.46%	High
(Sun et al., 2019)	1	U	1	0	0	0	1	1	1	1	1	1	1	9/13 = 69.23%	Moderate
(Basit et al., 2021)	1	1	U	0	0	0	1	U	1	1	1	1	1	8/13 = 61.54%	Moderate

Table 7: Summary of quality assessments (Cohort) using JBI appraisal checklist

Authors	Items on Joanna Briggs Institute checklist											Raw Score and %	Risk
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11		
(Kengne et al., 2014)	1	1	1	1	U	1	1	U	U	0	1	7/11 = 63.64%	Moderate
(Gray et al., 2015)	1	1	1	1	U	1	1	0	0	0	1	7/11 = 63.64%	Moderate
(Savić et al., 2020)	1	1	1	0	NA	1	1	NA	NA	NA	1	6/11 = 54.55%	Moderate
(Gray et al., 2016)	1	1	1	1	1	1	1	1	NA	NA	1	9/11 = 81.82%	Low
(Lotfaliany et al., 2019)	1	1	1	1	1	NA	1	1	1	0	1	9/11 = 81.82%	Low

Table 8: Summary of quality assessments (Case control) using JBI appraisal checklist

Authors	Items on Joanna Briggs Institute checklist										Raw Score and %	Risk
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10		
(Agarwal et al., 2019)	1	1	1	1	1	NA	NA	NA	1	1	7/10 = 70%	Low

DISCUSSION

From this review, the age range of participants for included studies is 18 – 77 years and the sample size range from 136 – 240,000 participants. The most used predictor variables in all

Pharmaceutical Sciences
Volume 3 Issue 2, 2023
eISSN No.: 2582-8371

the included studies age, gender, height, weight, waist circumference, body mass index (BMI), family history of diabetes, physical activity, history of hypertension and use of hypertension medications. Other than that, some diabetes risk assessments tools have daily soft drinks consumption, daily vegetables consumption, smoking status, and ethnicity.
One of the diabetes risk assessment tools used is FINDRISC, the dietary fibre was proven to be slowing the progression of T2DM development (San Oo et al., 2021). Furthermore, According to Malaysian research, 34% and 25.5% of participants, respectively, were overweight or obese. Modifiable risk factors like BMI and waist circumference were found to be significantly associated with a greater risk score. Although most research participants were under 40, there were a significant number of overweight and obese individuals (Oo et al., 2020). The findings were like another study conducted in Malaysia, despite engaging in moderate physical exercise, 51.2% of participants were overweight or obese (Chan et al., 2017). It concluded that readily available junk food, drinks with a high sugar and trans-fat content, and a sedentary lifestyle are what promote overweight and obesity (Chan et al., 2017; Oo et al., 2020).

Besides, smoking status was one of the questions asked in these risk assessments tools: RAPID and AUSDRISK. In a study conducted in Iran by using AUSDRISK, 13.6% of participants who are smokers are at high risk of developing T2DM (Lotfaliany et al., 2019). It was discovered that a smoker has a 1.6 times higher risk of developing T2DM than a non-smoker. Results indicate that ex-smokers had a 17–60% higher risk of developing type 2 diabetes (Ismail et al., 2021). The authors estimated that smoking was responsible for developing T2DM cases for men is 18.8% while T2DM cases for women is 5.4%. Despite the association between smoking cigarettes and a higher risk of developing T2DM, a cause-and-effect relationship between smoking and the disease cannot be determined because of additional risk factors like age, physical activity, diet, and waist circumference also play a part (Campagna et al., 2019).

Apart from that, ADA and AUSDRISK has ethnicity as one of the questions asked. However, it is unclear why people of a certain ethnicity have an increased risk of developing T2DM than others. It might be because of the ethnicity dependent relationship with gene and body fat deposition. For a similar amount of body fat, Asians, on average, have a 3–4 kg/m2 lower BMI than Caucasians. As well as insulin sensitivity based on ethnicity because Asians, Aficans, and Mexican-Americans, according to studies, are less insulin sensitive than non-Hispanic whites (Chen et al., 2010; Ismail et al., 2021). AUSDRISK was created with the help of 6,000 adult participants in the Australian diabetes, obesity, and lifestyle study. Age, ethnicity, gender, family diabetes history, waist circumference, history of high blood glucose, physical activity, use of antihypertensive drugs are the risk factors used to predict a five-year chance of developing T2DM (Lotfaliany et al., 2019). This tool is distinctive which it includes ethnicity that reflects the diversity in T2DM risk brought on by racial and ethnic differences (Chen et al., 2010).

Furthermore, studies that focused on multiple diabetes risk assessment tools mostly has different results when using different tools. Accordingly, care should be taken when using these risk assessment tools to identify high risk individuals and they must be validated first with the community (Akter et al., 2020). This was proven by a study conducted in United Kingdom, the risk of an individual to develop T2DM depend on what kind of diabetes risk assessment tools that they used. When the CRS was used, it was found that more than 25% of males were anticipated to fall into the highest-risk quintile. In comparison to the LRA and FINDRISC, this value was five times higher, and more than twice as many people were

Pharmaceutical Sciences
Volume 3 Issue 2, 2023
eISSN No.: 2582-8371

classified as high risk using the QDiabetes. On the other hand, when comparing the Leicester Risk Assessment to the QDiabetes tool, twice as many people in females were once more classified as high risk. But the FINDRISC model anticipated that 7.8% of females would be at high risk (Gray et al., 2015).

It should be noted that, non-invasive risk assessments tools might be applied as a cornerstone of the public health strategy for preventing T2DM. Most trials for T2DM prevention have relied on a high-risk status determined by blood testing. Therefore, several studies used diabetes risk assessments tools and found that the results have positive effects on risk factor levels. For instance, participants that answered FINDRISC showed that a moderate weight loss significantly reduced T2DM risk after a year of intervention (Kengne et al., 2014). Currently available guidelines for diabetes screening that rely on blood tests are seldom followed; leaving many people without a diagnosis. The questionnaire approach aids people in determining if they need to see a doctor for a diabetes test (Basit et al., 2021).

As the limitation of this review, it was observed that some studies only mentioned the percentage of high-risk individual identified by using diabetes risk assessment tools but, other studies elaborate more on AUC, sensitivity, specificity, and negative and positive values. These differences making it hard to compare the efficiency of these tools. Moreover, Herath et al., (2017) reported that gestational diabetes women had a 10 times increased chance of developing T2DM over a 10-year follow-up period rather than those without gestational diabetes., none of the included tools mentioned about gestational diabetes. Nevertheless, this review successfully serves as a foundation for determining the most suitable tool to be incorporated within the community, so that the findings may be utilised as future reference.

CONCLUSION

Early identification and evaluation of those who exhibit these risk characteristics is important and they should be monitored closely. It is possible to identify people who are at high risk for developing prediabetes and diabetes using a simple diabetes risk score, enabling prompt intervention. However, these tools are useful only in identifying high risk individuals because it does not provide any diagnostic confirmation. These tools are non-invasive, more practical, and more affordable than models that rely on blood testing. Such tools may be incorporated into the recommendations for authorities as a best practise for diabetes screening at the population level. Trained healthcare professionals may use these tools during routine screening not only to identify people at risk for diabetes but also to detect the prediabetes patients early so that healthcare professionals can initiate the actions for further life style modification and other potential management.

ACKNOWLEDGEMENTS

This work was done under the Final Year Research Project for final year student funded by Kuliyyah of Pharmacy, International Islamic University Malaysia.

REFERENCES

1) Agarwal, G., Guingona, M. M., Gaber, J., Angeles, R., Rao, S., & Cristobal, F. (2019). Choosing the most appropriate existing type 2 diabetes risk assessment tool for use in the Philippines: A case-control study with an urban Filipino population. *BMC Public Health*, *19*(1). https://doi.org/10.1186/s12889-019-7402-0

2) Akter, N., Diabetes, N. Q.-S. L. J. of, & 2020, undefined. (2020). Comparison of IDRS, ADA and FINDRISC diabetes risk assessment tools: a cross-sectional analysis in a tertiary care hospital. *Researchgate.Net*. https://doi.org/10.4038/sjdem.v10i2.7415
3) Akter, N., & Qureshi, N. K. (2020). Comparison of IDRS, ADA and FINDRISC Diabetes Risk Assessment Tools: A Cross-Sectional Analysis in a Tertiary Care Hospital. *Sri Lanka Journal of Diabetes Endocrinology and Metabolism*, *10*(2), 10. https://doi.org/10.4038/sjdem.v10i2.7415
4) Basit, K. A., Fawwad, A., Riaz, M., Tahir, B., Khalid, M., & Basit, A. (2021). Ndsp 09: Risk assessment of pakistani individual for diabetes (rapid) – findings from second national diabetes survey of Pakistan (ndsp) 2016–2017. *Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy*, *14*, 257–263. https://doi.org/10.2147/DMSO.S277998
5) Campagna, D., Alamo, A., di Pino, A., Russo, C., Calogero, A. E., Purrello, F., & Polosa, R. (2019). Smoking and diabetes: dangerous liaisons and confusing relationships. *Diabetology & Metabolic Syndrome 2019 11:1*, *11*(1), 1–12. https://doi.org/10.1186/S13098-019-0482-2
6) Campbell, M., McKenzie, J. E., Sowden, A., Katikireddi, S. V., Brennan, S. E., Ellis, S., Hartmann-Boyce, J., Ryan, R., Shepperd, S., Thomas, J., Welch, V., & Thomson, H. (2020). Synthesis without meta-analysis (SWiM) in systematic reviews: reporting guideline. *BMJ*, *368*. https://doi.org/10.1136/BMJ.L6890
7) Chan, Y. Y., Lim, K. K., Lim, K. H., Teh, C. H., Kee, C. C., Cheong, S. M., Khoo, Y. Y., Baharudin, A., Ling, M. Y., Omar, M. A., & Ahmad, N. A. (2017). Physical activity and overweight/obesity among Malaysian adults: Findings from the 2015 National Health and morbidity survey (NHMS). *BMC Public Health*, *17*(1), 1–12. https://doi.org/10.1186/S12889-017-4772-Z/TABLES/4
8) Chen, L., Magliano, D. J., Balkau, B., Colagiuri, S., Zimmet, P. Z., Tonkin, A. M., Mitchell, P., Phillips, P. J., & Shaw, J. E. (2010). AUSDRISK: an Australian Type 2 Diabetes Risk Assessment Tool based on demographic, lifestyle, and simple anthropometric measures. *The Medical Journal of Australia*, *192*(4), 197–202. https://doi.org/10.5694/J.1326-5377.2010.TB03478.X
9) Dudeja, P., Singh, G., Gadekar, T., & Mukherji, S. (2017). Performance of Indian diabetes risk score (IDRS) as screening tool for diabetes in an urban slum. *Medical Journal Armed Forces India*, *73*(2), 123–128. https://doi.org/10.1016/j.mjafi.2016.08.007
10) Fernandez, R., & Frost, S. (2013). Congruence between the Indian Diabetes Risk Score and Australian Type 2 Diabetes Risk Assessment tool screening in Asian-Indians. *Nurse Researcher*, *21*(2), 36–39. www.pc.gov.au/research/commission/
11) Galicia-Garcia, U., Benito-Vicente, A., Jebari, S., Larrea-Sebal, A., Siddiqi, H., Uribe, K. B., Ostolaza, H., & Martín, C. (2020). Pathophysiology of type 2 diabetes mellitus. In *International Journal of Molecular Sciences* (Vol. 21, Issue 17, pp. 1–34). MDPI AG. https://doi.org/10.3390/ijms21176275
12) García-Alcalá, H., Nathalie, C., Genestier-Tamborero, Hirales-Tamez, O., Salinas-Palma, J., & Soto-Vega, E. (2012). Frequency of diabetes, impaired fasting glucose, and glucose intolerance in high-risk groups identified by a FINDRISC survey in Puebla city, Mexico. *Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy*, *5*, 403–406. https://doi.org/10.2147/DMSO.S35545
13) Gray, B. J., Bracken, R. M., Turner, D., Morgan, K., Thomas, M., Williams, S. P., Williams, M., Rice, S., & Stephens, J. W. (2015). Different type 2 diabetes risk assessments predict dissimilar numbers at 'high risk': A retrospective analysis of diabetes risk-assessment tools. *British Journal of General Practice*, *65*(641), e852–e860. https://doi.org/10.3399/bjgp15X687661

14) Gray, B. J., Bracken, R. M., Turner, D., Morgan, K., Thomas, M., Williams, S. P., Williams, M., Rice, S., Stephens, J. W., Cottrell, C., Davies, V., Newbury-Davies, L., di Battista, E. M., Street, L., Judd, F., Evans, C., James, J., Jones, C., Williams, C., … Williams, R. (2016). Examining the relationship between HbA1c and diabetes risk models in a European population indicates a lower threshold to identify 'high risk' is required. *Diabetes and Vascular Disease Research*, *13*(3), 228–235. https://doi.org/10.1177/1479164116629351

15) Herath, H., Herath, R., & Wickremasinghe, R. (2017). Gestational diabetes mellitus and risk of type 2 diabetes 10 years after the index pregnancy in Sri Lankan women—A community based retrospective cohort study. *PLoS ONE*, *12*(6). https://doi.org/10.1371/JOURNAL.PONE.0179647

16) Ismail, L., Materwala, H., & al Kaabi, J. (2021). Association of risk factors with type 2 diabetes: A systematic review. In *Computational and Structural Biotechnology Journal* (Vol. 19, pp. 1759–1785). Elsevier B.V. https://doi.org/10.1016/j.csbj.2021.03.003

17) Kengne, A. P., Beulens, J. W. J., Peelen, L. M., Moons, K. G. M., van der Schouw, Y. T., Schulze, M. B., Spijkerman, A. M. W., Griffin, S. J., Grobbee, D. E., Palla, L., Tormo, M. J., Arriola, L., Barengo, N. C., Barricarte, A., Boeing, H., Bonet, C., Clavel-Chapelon, F., Dartois, L., Fagherazzi, G., … Wareham, N. J. (2014). Non-invasive risk scores for prediction of type 2 diabetes (EPIC-InterAct): A validation of existing models. *The Lancet Diabetes and Endocrinology*, *2*(1), 19–29. https://doi.org/10.1016/S2213-8587(13)70103-7

18) Khan, M. A. B., Hashim, M. J., King, J. K., Govender, R. D., Mustafa, H., & Kaabi, J. al. (2020). Epidemiology of Type 2 Diabetes – Global Burden of Disease and Forecasted Trends. *Journal of Epidemiology and Global Health*, *10*(1), 107. https://doi.org/10.2991/JEGH.K.191028.001

19) Lotfaliany, M., Hadaegh, F., Asgari, S., Mohammad, ;, Mansournia, A., Azizi, F., Oldenburg, B., & Khalili, D. (2019). Non-invasive Risk Prediction Models in Identifying Undiagnosed Type 2 Diabetes or Predicting Future Incident Cases in the Iranian Population IRANIAN MEDICINE. In *Arch Iran Med* (Vol. 22, Issue 3). www.aimjournal.ir

20) Mavrogianni, C., Lambrinou, C. P., Androutsos, O., Lindström, J., Kivelä, J., Cardon, G., Huys, N., Tsochev, K., Iotova, V., Chakarova, N., Rurik, I., Moreno, L. A., Liatis, S., Makrilakis, K., & Manios, Y. (2019). Evaluation of the Finnish Diabetes Risk Score as a screening tool for undiagnosed type 2 diabetes and dysglycaemia among early middle-aged adults in a large-scale European cohort. The Feel4Diabetes-study. *Diabetes Research and Clinical Practice*, *150*, 99–110. https://doi.org/10.1016/J.DIABRES.2019.02.017

21) Moola, S., Munn, Z., Tufunaru, C., Aromataris, E., Sears, K., Sfectu, R., Currie, M., Qureshi, R., Mattis, P., & Lisy, K. (2020a). *CHECKLIST FOR ANALYTICAL CROSS SECTIONAL STUDIES Critical Appraisal tools for use in JBI Systematic Reviews*.

22) Moola, S., Munn, Z., Tufunaru, C., Aromataris, E., Sears, K., Sfectu, R., Currie, M., Qureshi, R., Mattis, P., & Lisy, K. (2020b). *CHECKLIST FOR CASE CONTROL STUDIES Critical Appraisal tools for use in JBI Systematic Reviews*.

23) Moola, S., Munn, Z., Tufunaru, C., Aromataris, E., Sears, K., Sfectu, R., Currie, M., Qureshi, R., Mattis, P., & Lisy, K. (2020c). *CHECKLIST FOR COHORT STUDIES Critical Appraisal tools for use in JBI Systematic Reviews*. https://synthesismanual.jbi.global/

24) Moola, S., Munn, Z., Tufunaru, C., Aromataris, E., Sears, K., Sfectu, R., Currie, M., Qureshi, R., Mattis, P., & Lisy, K. (2020d). *CHECKLIST FOR RANDOMIZED CONTROLLED TRIALS Critical Appraisal tools for use in JBI Systematic Reviews*.

25) Munn, Z., Barker, T. H., Moola, S., Tufanaru, C., Stern, C., McArthur, A., Stephenson, M., & Aromataris, E. (2020). Methodological quality of case series studies: an introduction to the JBI critical appraisal tool. *JBI Evidence Synthesis*, *18*(10). https://doi.org/10.11124/JBISRIR-D-19-00099
26) Nagarathna, R., Tyagi, R., Battu, P., Singh, A., Anand, A., & Nagendra, H. R. (2020). Assessment of risk of diabetes by using Indian Diabetic risk score (IDRS) in Indian population. *Diabetes Research and Clinical Practice*, *162*. https://doi.org/10.1016/j.diabres.2020.108088
27) Oo, A. M., Ali, A.-A., Al-Abed, A., Lwin, O. M., Kanneppady, S. S., Sim, Y., Mukti, A., Zahariluddin, A. S., & Jaffar, F. (2020). Type 2 Diabetes Mellitus Prediction in Malaysia Using Modified Diabetes Risk Assessment Tool. *Malaysian Journal of Public Health Medicine*, *20*(1), 15–21.
28) Riaz, M., Basit, A., Hydrie, M. Z. I., Shaheen, F., Hussain, A., Hakeem, R., & Shera, A. S. (2012). Risk assessment of Pakistani individuals for diabetes (RAPID). *Primary Care Diabetes*, *6*(4), 297–302. https://doi.org/10.1016/j.pcd.2012.04.002
29) San Oo, S., Moe Thwe Aung, M., Kishor Shetty, C., Salami Ibrahim, M., Nyi Naing, N., Binti Mohd Yusop, Y., Hassan, A., Suhana Munira Mat Azmi, I., & Amaran, S. (2021). Association Between Knowledge, Attitude, And Practice About Dietary Fibre Intake and Type 2 Diabetes Among Rural People in Terengganu, Malaysia. In *Malaysian Journal of Public Health Medicine* (Vol. 21, Issue 2).
30) Savić, S., Stanivuković, S., & Lakić, B. (2020). Ten-year risk assessment for type 2 diabetes mellitus using the finnish diabetes risk score in family medicine. *Medicinski Glasnik*, *17*(2), 510–515. https://doi.org/10.17392/1189-20
31) Sezer, Ö., Lafçi, N. Ö., Korkmaz, S., & Dağdeviren, H. N. (2021). Prediction of a 10-year risk of type 2 diabetes mellitus in the Turkish population A cross-sectional study. *Medicine (United States)*, *100*(44). https://doi.org/10.1097/MD.0000000000027721
32) Sun, J., Bao, G., Cui, J., Yasmeen, N., Aslam, B., Xin, H., Shanshan, L., Fu, P., & Baloch, Z. (2019). The association of diabetes risk score and body mass index with incidence of diabetes among urban and rural adult communities in Qingdao, China Abbreviations AP attributable proportion due to interaction CNY Chinese Yuan CI confidence intervals DBP diastolic blood pressure DRS diabetes risk score. *International Journal of Diabetes in Developing Countries*, *39*(4), 730–738. https://doi.org/10.1007/s13410-019-00740-3/Published
33) Vandersmissen, G. J. M., & Godderis, L. (2015). Evaluation of the finnish diabetes risk score (FINDRISC) for diabetes screening in occupational health care. *International Journal of Occupational Medicine and Environmental Health*, *28*(3), 587–591. https://doi.org/10.13075/ijomeh.1896.00407