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Development and validation of a Jordan-specific risk score for type 2 diabetes mellitus

Asalah Alareeki ,[1] Susanne F Awad ,[1,2] Julia A Critchley ,[3] Kamel M Ajlouni ,[4] Yousef Khader ,[5] Laith J Abu-Raddad [1,2,6,7]

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For numbered affiliations see end of article.

Correspondence to
Dr Laith J Abu-Raddad; lja2002@qatar-med.cornell.edu

AA and SFA are joint first authors.

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ABSTRACT

Background Jordan has a high prevalence of type 2 diabetes mellitus (T2DM), but it is estimated that nearly half of all cases in the Middle East and North Africa region remain undiagnosed. This study aimed to develop, validate and assess the diagnostic performance of a diabetes risk score to identify Jordanians at high risk of T2DM.

Methods Random samples of 5000 Jordanians aged 20–79 years were simulated at different time points using an existing mathematical model describing T2DM epidemiology in Jordan. The risk score was derived through logistic regression applied to the simulated samples, using age, sex, obesity, smoking and physical inactivity as predictive variables. Cut-off values were determined based on the maximum sum of sensitivity and specificity.

Results In 2020, the estimated area under the curve (AUC), sensitivity and specificity of the derived Jordan Diabetes Risk Score were 0.79 (95% CI: 0.77 to 0.80), 78.7% (95% CI: 77.5 to 79.8%) and 64.2% (95% CI: 62.9 to 65.6%), respectively. The positive and negative predictive values were 29.7% (95% CI: 28.4 to 31.0%) and 94.0% (95% CI: 93.3 to 94.7%), with 42.7% of Jordanians at high risk for diabetes. Similar diagnostic metrics were observed for the 2030 and 2050 risk scores, with AUCs of 0.78 (95% CI: 0.77 to 0.80) and 0.77 (95% CI: 0.76 to 0.79), respectively. The performance of the derived model-based score was comparable to a survey-based score and demonstrated better performance within the Jordanian population compared with existing regional and international scores.

Conclusions The Jordan Diabetes Risk Score demonstrated strong diagnostic performance, offering an effective, non-invasive and accessible tool for diabetes screening. This tool can facilitate early detection, timely intervention and increased awareness, ultimately aiming to reduce the burden of T2DM and its complications in Jordan.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Globally, type 2 diabetes mellitus poses a significant public health burden, disproportionately impacting the Middle East and North Africa (MENA) region. In this region, nearly half of the diabetes cases remain undiagnosed, further exacerbating the problem. Jordan, a MENA country, faces a concerning scenario with high and rising diabetes prevalence, associated risk factors and escalating healthcare costs. Effective tools for screening and risk assessment are critical to identify individuals at high risk of diabetes. Diabetes risk scores offer a highly cost-effective approach for population-based screening. However, Jordan currently lacks a risk score tailored to its specific population characteristics.

INTRODUCTION

The diabetes pandemic presents a global public health challenge, particularly pronounced in the Middle East and North Africa (MENA) region, where it ranks among the world's fastest-growing epidemics.[1] As of 2021, an estimated 73 million adults aged 20–79 years (1 in 6) in MENA were living with diabetes, with projections indicating this number could rise to 136 million (1 in 5 adults) by 2045.[1] Alarmingly, approximately 45% (1 in 2 adults) of type 2 diabetes mellitus (T2DM) cases in MENA remain undiagnosed.[1]

Jordan, situated within this region, had an estimated T2DM prevalence of 16.0% in 2020, along with concerning rates of obesity (38.0%), as well as substantial rates of smoking (27.2%) and physical inactivity (18.2%).[2] Further, in 2020, 21.1% of Jordan's total health expenditure was spent on treatment of people with T2DM.[2] Given these high and escalating rates of diabetes, associated risk factors and healthcare costs in Jordan and across MENA, there is a need to develop effective screening and risk assessment tools tailored to the population's specific health needs.[1 2]

T2DM often manifests without noticeable symptoms, increasing the risk of cardiovascular complications, disability and premature mortality due to prolonged elevated blood glucose levels.[1 3] Therefore, early detection is essential for preventing diabetes-related complications and mitigating the burden and costs on individuals and healthcare systems.[3] Given the evidence supporting the

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> **WHAT THIS STUDY ADDS**
>
> ⇒ This study developed and validated a diabetes risk score specific to the population of Jordan that involves a few easy-to-capture and implement questions. The resulting 'Jordan Diabetes Risk Score' demonstrated strong performance, with an area under the curve of 0.79, a sensitivity of 79%, a specificity of 64%, a positive predictive value of 30% and a negative predictive value of 94%. The score outperformed existing regional and international scores when applied to the Jordanian population, identifying a high proportion of adults (about 40%) with scores above the cut-off value, indicating a high risk for diabetes and the need for regular blood sugar testing. The score also indicated that any Jordanian over 50 years old or anyone over 40 years with obesity should be considered high risk for undiagnosed diabetes and undergo regular testing.
>
> **HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY**
>
> ⇒ Exemplified by Jordan, the study demonstrated an effective mathematical modelling method for deriving diabetes risk scores in countries where survey data may be inconsistent or conflicting. This approach can be extended to other countries lacking specific diabetes risk scores for their populations. The Jordan Diabetes Risk Score could provide significant public health benefits, such as the early identification of individuals at high risk for diabetes, enabling healthcare and public health professionals to implement timely interventions that can delay or prevent diabetes onset. This simple, non-invasive and accessible risk score supports effective screening campaigns, raises awareness about diabetes and its risk factors within communities and empowers individuals to make informed lifestyle choices and take proactive steps towards managing their health, ultimately reducing the burden of diabetes and its complications.

effectiveness of lifestyle interventions in diabetes prevention,[4–6] identifying individuals currently with diabetes or those at high risk of developing diabetes in the future becomes paramount for curbing the epidemic's progression.

A T2DM risk score is a recommended and highly cost-effective tool for population-based screening of T2DM.[3 7] It aids in assessing an individual's likelihood of having undiagnosed T2DM or developing it in the future.[8–10] The score serves as an early detection and intervention tool, facilitating timely lifestyle recommendations and medical care to manage and potentially prevent progression to T2DM and its complications.[10 11] It is based on objective factors that are easy to collect, such as age, anthropometry (body mass index (BMI) or waist circumference), smoking status, physical activity level and family history of diabetes.[3]

In a recent advancement, we introduced a novel methodology for T2DM risk score development that uses mathematical modelling and applied it to Qatar.[12] While this approach has its own limitations, it addresses key challenges of conventional methods—such as constraints in data availability and potential biases in survey data—which commonly affect risk scores derived from regression analyses of cross-sectional or prospective datasets.[8–10 12] This methodology is not intended to replace existing approaches, but rather to complement them by providing a viable alternative in settings where conventional methods may be less reliable or infeasible.

This novel alternative approach offers key advantages, notably its ability to incorporate population dynamics and adapt to the evolving patterns of the T2DM epidemic and its associated risk factors.[12] It is particularly valuable for countries such as Jordan, where available survey data may be inconsistent or conflicting.[12–18] Jordan has conducted several population-based surveys; however, integrating these data presents challenges due to variations in survey quality, timing, design, geographic coverage, methods of T2DM assessment and risk factor ascertainment, as well as differences in outcome definitions and response rates.[13–18] Mathematical modelling addresses these complexities by optimising model fitting to best align with available data.[12] This process incorporates all survey data, adjusts for data discrepancies and assigns weights based on survey confidence levels, thereby enhancing the reliability of derived T2DM risk scores despite data limitations and inconsistencies.[12]

To predict past, current and future trends in T2DM prevalence and incidence in Jordan from 1990 to 2050, we recently developed the Jordan T2DM Model, a population-level, age-structured, dynamic mathematical model.[2] This model incorporates the interplay between T2DM natural history, established T2DM risk factors and demographics.[2] The model leveraged existing evidence on T2DM and its risk factors in Jordan, using data from six population-based surveys for model calibration.[2 13–18]

Building on this model, the present study aims to derive a T2DM risk score tailored to the Jordanian population by applying our novel risk score development methodology.[12] This score is designed not only for current application but also to be adaptable for use in future years. Its primary purpose is to serve as a practical tool for healthcare and public health professionals, facilitating early detection, timely intervention and improved health outcomes for individuals at risk of developing T2DM, thereby helping to reduce the overall burden of the disease and its complications.

METHODS

Mathematical model to project past, current and future T2DM trends

The Jordan T2DM Model,[2] previously described in detail,[2] was used to project T2DM incidence and prevalence in the population of Jordan. The Jordanian population was stratified based on sex (male and female), age groups (spanning 20 5-year intervals from 0 years to 99 years old), key T2DM risk factors (obesity, smoking and physical inactivity) and T2DM status (with and without T2DM).[2] The model accounted for overlapping risk factors, such as individuals categorised as both obese and smokers, through further model compartmentalisation.[2]

The model's calibration was based on representative epidemiological and demographic data specific to

Jordan.[2 13–18] This ensured that the model's predictions accurately reflect the T2DM epidemiology of the Jordanian population. Sex-specific and age-specific prevalence data for T2DM, obesity, smoking and physical inactivity among Jordanians were obtained from population-based surveys conducted in 1994,[15] 2004,[13 16] 2007,[14] 2009[17] and 2017.[18] The model-fitting process involved point estimates of 323 prevalence measures weighted during fitting by survey response rate and stratified by sex.[2]

In addition to prevalence data, the model was calibrated to Jordan's age-specific and total population size, using estimates from the United Nations Department of Economic and Social Affairs.[19] Estimates of the relative risks of developing T2DM for each major risk factor were obtained from large, high-quality prospective studies.[20–22] Through a fitting process, the model parameters were derived to produce curves that best fit the data. Further details on this type of model structure, parameterisation, fitting process and robustness assessment can be found in previous publications.[2 23–26] All modelling analyses were conducted using MATLAB 2019a.

Derivation of the Jordan Diabetes Risk Score

To represent the Jordanian population of adults aged 20–79 years, a Monte Carlo sampling method was employed to randomly select 5000 individuals from this adult simulated population generated by the Jordan T2DM Model. This sampling process was conducted at four distinct time points: 2017 (the year of the most recent survey data used for model calibration, included for validation purposes), 2020, 2030 and 2050. Individual-level data for each sampled person included sex, age, obesity status (defined by a BMI ≥30 kg/m^2), smoking status (defined as current daily tobacco use) and physical inactivity (defined as less than 150 min of moderate-intensity activity, less than 75 min of vigorous-intensity activity or less than 600 metabolic equivalent-minutes per week).[2 27 28]

To derive a T2DM risk score for each time point, a multivariable logistic regression was conducted with each covariate assigned a score based on the β-coefficients derived from the regression model, following an established methodology.[29] For ease of use, the β-coefficients were multiplied by 10 and rounded to the nearest integer. The cumulative risk score for each individual in the sample was then determined by summing these scores. Interaction terms between covariates were intentionally excluded to maintain the simplicity of the risk score for practical use in clinical and community-based settings.[3 11 30]

Assessment of the Jordan Diabetes Risk Score performance

At each time point, the performance of the risk score was assessed using several metrics. The area under the receiver operating characteristic curve (AUC) was calculated to evaluate the score's overall discrimination ability. Additionally, sensitivity (the probability of correctly diagnosing someone with T2DM), specificity (the probability of correctly identifying someone without T2DM), positive predictive value (PPV; the proportion of individuals truly having T2DM among those identified as high risk by the score) and negative predictive value (NPV; the proportion of individuals truly without T2DM among those identified as low risk by the score) were determined.

To identify the optimal threshold for risk stratification, the cut-off score was chosen to maximise the sum of sensitivity and specificity, representing the trade-off between correctly identifying individuals with and without T2DM. This approach also allowed for the identification of the proportion of individuals exceeding this cut-off score, a population segment who were recommended for further biochemical (glycaemia) testing to confirm T2DM diagnosis.

To explore the impact of prioritising either high specificity or high sensitivity, two additional analyses were conducted for the 2020 sample. The first analysis prioritised reducing false positives by setting a score cut-off that achieved a specificity of 90%. This approach is effective for identifying individuals with no T2DM, thereby reducing glycaemia testing costs. Conversely, the second analysis aimed to maximise true positives by setting a score cut-off that achieved a sensitivity of 90%. This approach prioritises identifying as many individuals with T2DM as possible using the risk score, but at the expense of a higher number of false positives requiring further glycaemia testing.

Validation of the model-based Jordan Diabetes Risk Score

To validate the performance of the model-based Jordan Diabetes Risk Score, its performance was compared with a survey-based risk score that was derived directly from the 2017 survey data[18] using the same method described above. The model-based score for 2017 was applied to the survey data from the same year, and its performance was assessed against the survey-based score derived from that same dataset.

Comparison with regional and international diabetes risk scores

The performance of the developed Jordan Diabetes Risk Score was compared with other published regional and international risk scores that use similar variables. Regional risk scores included those from Oman,[29] Qatar,[12] Saudi Arabia[31] and the United Arab Emirates.[32] International comparisons were made with Denmark,[33] Finland,[11] the Netherlands[30] and Thailand.[34]

Only variables that overlapped between the Jordan risk score and each compared score were included in this analysis. To ensure equitable comparison, each regional and international risk score was recalibrated for the Jordanian population by choosing a cut-off score that maximises the sum of sensitivity and specificity.

Statistical analyses were conducted using STATA/SE V.18.0.

Table 1 Univariable and multivariable logistic regression analysis of risk factors for type 2 diabetes mellitus at three different time points: (A) 2020, (B) 2030 and (C) 2050, to derive the Jordan Diabetes Risk Score

		OR (95% CI)	aOR* (95% CI)	β†	Risk score‡
A) 2020§					
Age group (years)	20–24	1.00	–	–	0
	25–29	1.70 (1.02 to 2.85)	1.67 (0.99 to 2.80)	0.51	5
	30–34	2.90 (1.80 to 4.69)	2.44 (1.50 to 3.97)	0.89	9
	35–39	4.48 (2.83 to 7.09)	3.67 (2.30 to 5.84)	1.30	13
	40–44	6.35 (4.02 to 10.04)	4.99 (3.13 to 7.95)	1.61	16
	45–49	7.71 (4.88 to 12.19)	5.63 (3.53 to 8.96)	1.73	17
	50–54	16.14 (10.33 to 25.23)	11.94 (7.57 to 18.83)	2.48	25
	55–59	16.63 (10.54 to 26.24)	12.63 (7.92 to 20.13)	2.54	25
	60–64	22.53 (14.09 to 36.03)	15.91 (9.82 to 25.77)	2.77	28
	65–69	18.76 (11.39 to 30.89)	14.34 (8.61 to 23.89)	2.66	27
	70–74	22.89 (13.13 to 39.9)	18.16 (10.23 to 32.22)	2.90	29
	75–79	18.96 (9.93 to 36.19)	16.14 (8.28 to 31.45)	2.78	28
Sex	Women	1.00	–	–	0
	Men	1.34 (1.15 to 1.56)	1.63 (1.36 to 1.96)	0.49	5
Obesity¶	Non-obese	1.00	–	–	0
	Obese	3.42 (2.92 to 4.00)	2.62 (2.20 to 3.13)	0.96	10
Smoking**	Non-smoker	1.00	–	–	0
	Smoker	1.12 (0.95 to 1.33)	1.36 (1.12 to 1.66)	0.31	3
Physical inactivity††	Physically active	1.00	–	–	0
	Physically inactive	1.76 (1.47 to 2.10)	1.38 (1.13 to 1.68)	0.32	3
B) 2030‡‡					
Age group (years)	20–24	1.00	–	–	0
	25–29	1.60 (0.98 to 2.63)	1.57 (0.95 to 2.58)	0.45	5
	30–34	2.65 (1.67 to 4.21)	2.37 (1.49 to 3.79)	0.86	9
	35–39	3.84 (2.44 to 6.05)	3.43 (2.17 to 5.43)	1.23	12
	40–44	6.45 (4.18 to 9.95)	5.16 (3.32 to 8.03)	1.64	16
	45–49	6.56 (4.20 to 10.25)	4.77 (3.03 to 7.52)	1.56	16
	50–54	12.42 (8.02 to 19.24)	9.89 (6.33 to 15.45)	2.29	23
	55–59	13.40 (8.66 to 20.73)	10.64 (6.81 to 16.63)	2.37	24
	60–64	21.99 (13.94 to 34.67)	15.71 (9.85 to 25.05)	2.75	28
	65–69	20.69 (12.92 to 33.14)	16.85 (10.40 to 27.3)	2.82	28
	70–74	22.05 (13.37 to 36.39)	17.17 (10.25 to 28.75)	2.84	28
	75–79	16.48 (9.27 to 29.30)	13.09 (7.22 to 23.74)	2.57	26
Sex	Women	1.00	–	–	0
	Men	1.36 (1.17 to 1.57)	1.68 (1.41 to 2.00)	0.52	5
Obesity§	Non-obese	1.00	–	–	0
	Obese	3.14 (2.70 to 3.64)	2.56 (2.17 to 3.02)	0.94	9
Smoking¶	Non-smoker	1.00	–	–	0
	Smoker	1.04 (0.88 to 1.22)	1.24 (1.02 to 1.51)	0.22	2
Physical inactivity**	Physically active	1.00	–	–	0
	Physically inactive	2.10 (1.79 to 2.48)	1.63 (1.36 to 1.96)	0.49	5
C) 2050§§					
Age group (years)	20–24	1.00	–	–	0
	25–29	1.37 (0.80 to 2.33)	1.25 (0.73 to 2.14)	0.23	2

Continued

Table 1 Continued

		OR (95% CI)	aOR* (95% CI)	β†	Risk score‡
	30–34	2.33 (1.42 to 3.83)	1.96 (1.18 to 3.23)	0.67	7
	35–39	3.75 (2.33 to 6.02)	3.07 (1.90 to 4.96)	1.12	11
	40–44	4.96 (3.12 to 7.88)	3.56 (2.22 to 5.70)	1.27	13
	45–49	6.41 (4.05 to 10.16)	4.40 (2.75 to 7.04)	1.48	15
	50–54	9.16 (5.81 to 14.43)	6.55 (4.12 to 10.42)	1.88	19
	55–59	14.46 (9.19 to 22.76)	10.15 (6.38 to 16.13)	2.32	23
	60–64	17.08 (10.75 to 27.13)	12.23 (7.63 to 19.61)	2.50	25
	65–69	14.94 (9.35 to 23.87)	11.33 (7.02 to 18.3)	2.43	24
	70–74	20.34 (12.56 to 32.92)	15.03 (9.17 to 24.63)	2.71	27
	75–79	14.20 (8.54 to 23.61)	11.45 (6.76 to 19.41)	2.44	24
Sex	Women	1.00	–	–	0
	Men	1.26 (1.10 to 1.45)	1.65 (1.40 to 1.95)	0.50	5
Obesity§	Non-obese	1.00	–	–	0
	Obese	3.21 (2.78 to 3.72)	2.77 (2.35 to 3.26)	1.02	10
Smoking¶	Non-smoker	1.00	–	–	0
	Smoker	0.89 (0.76 to 1.05)	1.10 (0.91 to 1.33)	0.09	1
Physical inactivity**	Physically active	1.00	–	–	0
	Physically inactive	1.72 (1.47 to 2.02)	1.23 (1.03 to 1.47)	0.21	2

*ORs are adjusted for age, sex, obesity, smoking and physical inactivity.
†β-coefficients are based on the multivariable analysis.
‡The maximum risk score for any individual is 50 for 2020, 49 for 2030 and 45 for 2050.
§The variance explained by the multivariable logistic regression model (adjusted R^2) was 16.8%.
¶Defined as a body mass index ≥30 kg/m^2.
**Defined as current daily tobacco use.
††Defined as <150 min of moderate-intensity activity or <75 min of vigorous-intensity activity or <600 metabolic equivalent-minutes per week.[27 28]
‡‡The McFadden's pseudo R^2 for the multivariable logistic regression model was 17.0%.
§§The McFadden's pseudo R^2 for the multivariable logistic regression model was 15.7%.
aOR, adjusted OR.

RESULTS

Characteristics of simulated samples

Among the 5000 adults sampled from the simulated 2020 population of Jordan, the prevalence rates of T2DM, obesity, smoking and physical inactivity were 16.1%, 38.5%, 26.6% and 17.7%, respectively (online supplemental table S1). In 2030, the prevalence rates were projected to be 18.2%, 39.3%, 25.3% and 19.5%, respectively, while in 2050, they were projected to be 19.7%, 41.8%, 25.3% and 21.5%, respectively.

Derivation of the Jordan Diabetes Risk Score

Table 1 presents the results of univariable and multivariable logistic regression analyses on the samples for 2020, 2030 and 2050, along with the corresponding risk score for each covariate (variable). Virtually all examined variables were significantly associated with T2DM in both the univariable and multivariable analyses across the three time points. Age and obesity were the strongest predictors of T2DM, contributing the most to the risk score across all time points. The risk of T2DM increased sharply with age, particularly among individuals aged 50 years or older. Notably, the β-coefficients—and consequently the risk scores, which were calculated by multiplying the β-coefficients by 10 and rounding to the nearest integer—for age declined over calendar time. In contrast, the β-coefficients and risk scores for sex, obesity, smoking and physical inactivity remained relatively stable. Figure 1 provides a visual representation of the equation for each of the 2020, 2030 and 2050 Jordan Diabetes Risk Scores.

Performance of the Jordan Diabetes Risk Score

In 2020, the risk score demonstrated good discrimination ability with an AUC of 0.79 (95% CI: 0.77 to 0.80) (table 2 and figure 2). The optimal cut-off score for risk stratification was 24, balancing sensitivity (78.7%, 95% CI: 77.5 to 79.8%) and specificity (64.2%, 95% CI: 62.9 to 65.6%). This resulted in a PPV of 29.7% (95% CI: 28.4 to 31.0%) and an NPV of 94.0% (95% CI: 93.3 to 94.7%). Importantly, 42.7% of Jordanians aged 20–79 years scored above this threshold, indicating a high-risk group for undiagnosed T2DM who would benefit from glycaemia testing.

In 2030, the risk score maintained good discrimination ability with an AUC of 0.78 (95% CI: 0.77 to 0.80) (table 2

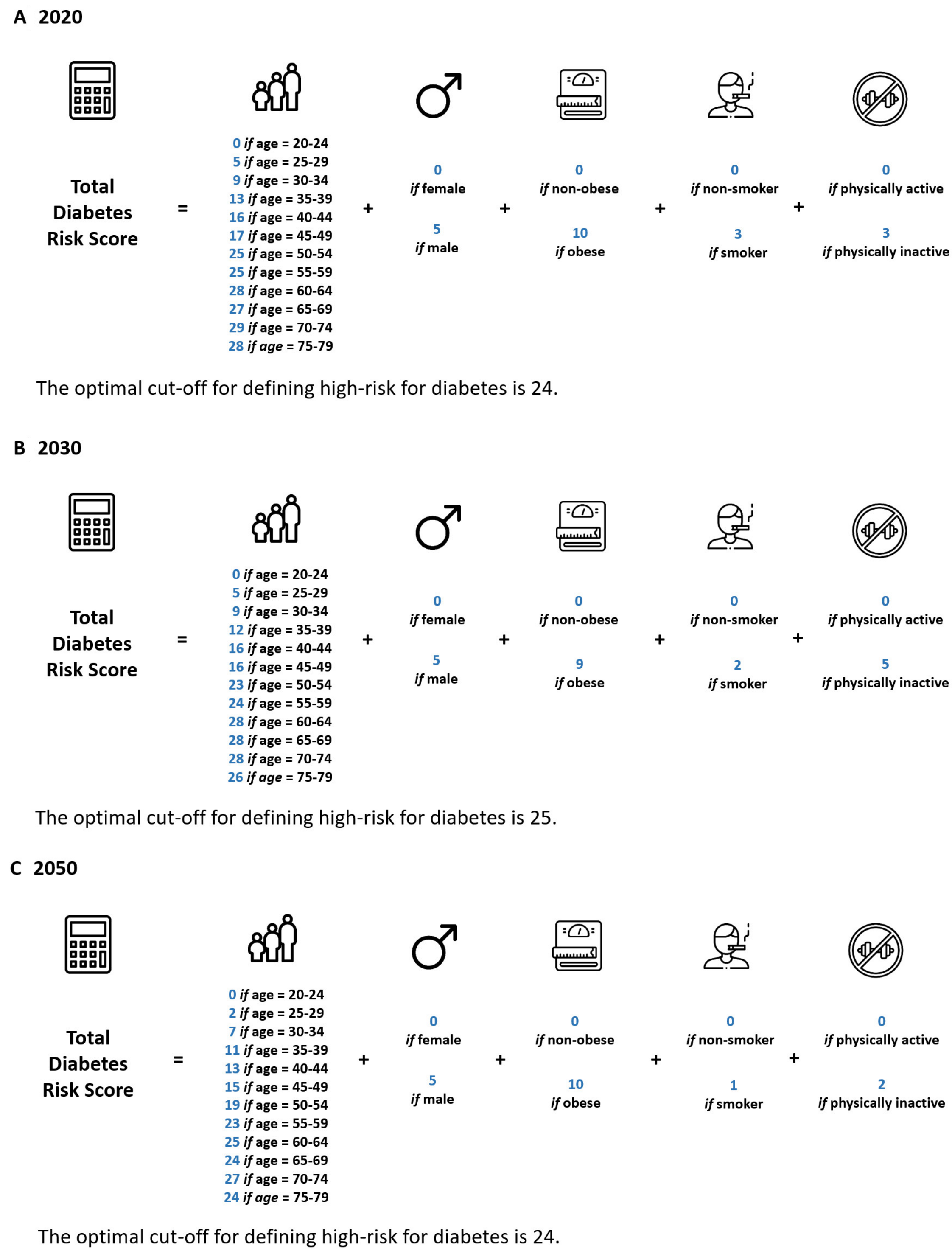

Figure 1 Equation for each of the (A) 2020, (B) 2030 and (C) 2050 Jordan Diabetes Risk Scores.

and figure 2). The optimal cut-off score for risk stratification was 25, achieving a balance between sensitivity (76.1%, 95% CI: 74.9 to 77.3%) and specificity (68.4%, 95% CI: 67.1 to 69.6%). This resulted in a PPV of 34.9% (95% CI: 33.6 to 36.2%) and NPV of 92.8% (95% CI: 92.0 to 93.5%). An estimated 39.8% of Jordanians aged 20–79 years scored above this cut-off, indicating a high-risk group for undiagnosed T2DM who would benefit from glycaemia testing.

In 2050, the risk score showed similar discrimination ability with an AUC of 0.77 (95% CI: 0.76 to 0.79) (table 2 and figure 2). The optimal cut-off score for risk stratification in 2050 was 24. This cut-off achieved a balance between sensitivity (74.2%, 95% CI: 73.0 to 75.4%) and specificity (65.6%, 95% CI: 64.2 to 66.9%). The PPV was 34.6% (95% CI: 33.3 to 36.0%) and the NPV was 91.2% (95% CI: 90.4 to 92.0%). An estimated 42.3% of Jordanians aged 20–79 years scored above

Table 2 Diagnostic performance of the Jordan Diabetes Risk Score at three different time points: 2020, 2030 and 2050

Year	AUC (95% CI)	Sensitivity (%) (95% CI)	Specificity (%) (95% CI)	PPV (%) (95% CI)	NPV (%) (95% CI)	Risk score cut-off*	Proportion needed testing† (%)
2020	0.79 (0.77 to 0.80)	78.7 (77.5 to 79.8)	64.2 (62.9 to 65.6)	29.7 (28.4 to 31.0)	94.0 (93.3 to 94.7)	24	42.7
2030	0.78 (0.77 to 0.80)	76.1 (74.9 to 77.3)	68.4 (67.1 to 69.6)	34.9 (33.6 to 36.2)	92.8 (92.0 to 93.5)	25	39.8
2050	0.77 (0.76 to 0.79)	74.2 (73.0 to 75.4)	65.6 (64.2 to 66.9)	34.6 (33.3 to 36.0)	91.2 (90.4 to 92.0)	24	42.3

*The risk score cut-offs were chosen based on the maximum the sum of sensitivity and specificity values for each score.
†Proportion of individuals who had a risk score greater than or equal to the cut-off value and therefore require glycaemia testing.
AUC, area under the curve; NPV, negative predictive value; PPV, positive predictive value.

this cut-off, indicating a high-risk group for undiagnosed T2DM who would benefit from glycaemia testing.

Additional analyses were performed to evaluate the trade-off between specificity and sensitivity of the risk score. Using a cut-off of 36, chosen to target 90% specificity, only 12.4% of Jordanians aged 20–79 years in 2020 would be identified as high risk for undiagnosed T2DM and requiring glycaemia testing. However, this approach missed 65.9% of existing T2DM cases. Conversely, a cut-off of 17, selected to target 90% sensitivity, missed only 10.0% of T2DM cases, but identified a much larger proportion (60.3%) of the population as high risk and requiring glycaemia testing.

Validation of the derived model-based Jordan Diabetes Risk Score

Online supplemental table S2 shows the derivation of the survey-based risk score using the 2017 survey data.[18] Online supplemental table S3 presents the derivation of the model-based risk score based on the model estimates for 2017. Table 3 compares the performance of these two risk scores when applied to the 2017 survey data.[18] The AUC for the model-based risk score was 0.77 (95% CI: 0.75 to 0.78), similar to the AUC of the survey-based risk score, which was 0.80 (95% CI: 0.78 to 0.81). Both scores demonstrated overall comparable diagnostic performance in terms of sensitivity, specificity, PPV and NPV.

Comparison with regional and international diabetes risk scores

Table 4 summarises the performance of regional (Oman, Qatar, Saudi Arabia and the United Arab Emirates) and international (Denmark, Finland, the Netherlands and Thailand) risk scores applied to the 2020 Jordan sample. All scores yielded AUCs between 0.69 and 0.77, which were lower than the AUC of the Jordan risk score (0.78). Among the regional scores, the Qatar score achieved the highest AUC (0.77, 95% CI: 0.76 to 0.79) with a sensitivity of 77.0% (95% CI: 75.8 to 78.1%) and a specificity of 63.9% (95% CI: 62.6 to 65.3%). Similarly, the Denmark score exhibited the highest AUC (0.76, 95% CI: 0.75 to 0.78) among international scores, with a sensitivity of 75.2% (95% CI: 74.0 to 76.4%) and a specificity of 67.1% (95% CI: 65.8 to 68.5%).

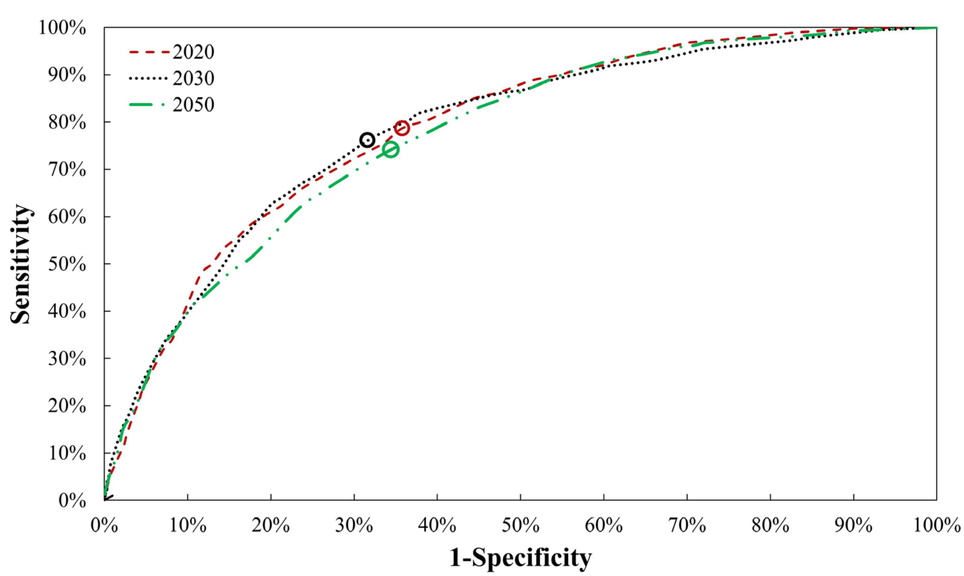

Figure 2 Receiver operating characteristic curves illustrate the performance of the Jordan Diabetes Risk Score in diagnosing type 2 diabetes mellitus at three time points: 2020, 2030 and 2050. The area under the curve was 0.78, 0.77 and 0.79 for the 2020, 2030 and 2050 risk scores, respectively.

Table 3 Validation of the model-based Jordan Diabetes Risk Score. Comparison of the diagnostic performance of the 2017 survey-based risk score and the 2017 model-based risk score, both applied to the 2017 survey data[18]

Diabetes risk score	AUC (95% CI)	Sensitivity (%) (95% CI)	Specificity (%) (95% CI)	PPV (%) (95% CI)	NPV (%) (95% CI)	Risk score cut-off*	Proportion needed testing† (%)
2017 survey-based score	0.80 (0.78 to 0.81)	78.1 (76.8 to 79.4)	68.3 (66.8 to 69.7)	42.7 (41.2 to 44.3)	91.2 (90.3 to 92.0)	35	42.5
2017 model-based score	0.77 (0.75 to 0.78)	69.0 (67.7 to 70.3)	71.1 (69.8 to 72.3)	29.8 (28.5 to 31.0)	92.8 (92.1 to 93.5)	25	35.0

*The risk score cut-offs were chosen based on the maximum the sum of sensitivity and specificity values for each score.
†Proportion of individuals with a risk score greater than or equal to the cut-off value and therefore require glycaemia testing.
AUC, area under the curve; NPV, negative predictive value; PPV, positive predictive value.

DISCUSSION

This study focused on the escalating burden of diabetes in Jordan,[2] where the disease is projected to consume a quarter of the country's total health expenditure in the coming decades.[2] To address the need for cost-effective early detection of undiagnosed T2DM cases, a recently introduced methodology was employed to derive a Jordan-specific T2DM risk score. The score demonstrated strong performance with an AUC of 0.79, a PPV of 30% and an NPV of 94% in 2020. Notably, applying the score to survey data yielded performance comparable to a survey-based risk score, supporting the reliability of this approach for identifying individuals at high risk for T2DM.

The Jordan Diabetes Risk Score offers significant public health benefits. Early detection of individuals at high risk for diabetes is critical for preventative interventions, and this score serves as a useful tool in achieving that goal.[35] Prompt identification allows healthcare and public health professionals to implement timely interventions that can delay or prevent the onset of diabetes altogether. This simple, non-invasive and accessible risk score empowers individuals who may not have adequate access to healthcare or may be hesitant to undergo more invasive testing.[36] By enabling early detection, the score facilitates effective screening campaigns and raises awareness about T2DM and its risk factors within communities. This empowers individuals to make informed lifestyle choices and take proactive steps towards managing their health, ultimately reducing the burden of T2DM and its complications.

Across the three different time points, the results from the Jordan Diabetes Risk Score indicated that a large proportion of the adult Jordanian population (about 40%) has a score at or above the cut-off value, necessitating regular glycaemia testing. The risk score revealed that any Jordanian over the age of 50 years, or any Jordanian over the age of 40 years with obesity (BMI≥30 kg/m²), is at high risk of having undiagnosed T2DM and should undergo regular testing. These results are consistent with the WHO's HEARTS-D guidelines,[37] which recommend testing asymptomatic adults in primary healthcare settings within similar age and BMI categories.

The Jordan Diabetes Risk Score exhibited minimal variation in structure, coefficients and the proportion of Jordanians requiring regular testing across the simulated time points that spanned three decades. While the Jordan

Table 4 Diagnostic performance of four regional and four international diabetes risk scores in predicting type 2 diabetes mellitus among Jordanians in 2020, compared with the Jordan Diabetes Risk Score

Diabetes risk scores	AUC (95% CI)	Sensitivity (%) (95% CI)	Specificity (%) (95% CI)	Risk score cut-off*
Jordan	0.79 (0.77 to 0.80)	78.7 (77.5 to 79.8)	64.2 (62.9 to 65.6)	24
Regional risk scores				
Oman	0.75 (0.73 to 0.77)	76.3 (75.1 to 77.5)	63.2 (61.9 to 64.6)	7
Qatar	0.77 (0.76 to 0.79)	77.0 (75.8 to 78.1)	63.9 (62.6 to 65.3)	25
Saudi Arabia	0.75 (0.73 to 0.77)	76.3 (75.1 to 77.5)	63.2 (61.9 to 64.6)	6
The United Arab Emirates	0.73 (0.71 to 0.75)	62.8 (61.4 to 64.1)	74.3 (73.1 to 75.5)	10
International risk scores				
Denmark	0.76 (0.75 to 0.78)	75.2 (74.0 to 76.4)	67.1 (65.8 to 68.5)	17
Finland	0.74 (0.72 to 0.75)	82.3 (81.2 to 83.3)	52.4 (51.0 to 53.8)	2
The Netherlands	0.69 (0.67 to 0.71)	61.3 (59.9 to 62.6)	69.1 (67.8 to 70.4)	8
Thailand	0.73 (0.72 to 0.75)	58.1 (56.7 to 59.4)	78.5 (77.4 to 79.6)	6

*For each risk score, the cut-off was recalculated to maximise the sum of sensitivity and specificity for the 2020 Jordanian sample.
AUC, area under the curve.

score demonstrated the best performance within the Jordanian population compared with existing regional and international scores, these other scores also displayed good accuracy. This suggests universality in the effects of T2DM risk factors, particularly age and obesity, on the global diabetes pandemic. Indeed, the findings related to the temporal evolution of the T2DM epidemic in Jordan, the role of individual risk factors, projected healthcare expenditures and the structure and effect sizes of the risk score components are consistent with results from similar modelling applications in countries such as Qatar, Oman and Turkey.[2 12 23–26 38–40] These similarities underscore the common underlying dynamics of T2DM and its projected trajectory across diverse populations.

This study has limitations. The limitations in the input data and the specific variables included in the original mathematical model have influenced the number of factors that could be incorporated into the risk score. For instance, the risk score did not incorporate family history of diabetes because it was not part of the original mathematical model. However, as more population-based data become available, there may be opportunities to expand the mathematical model and refine the risk score by including additional factors.

Since estimates of the relative risks for the effects of risk factors on T2DM onset and related mortality are not available for Jordan, the model employed relative risks obtained from the global literature, specifically from large, high-quality prospective studies pooled through systematic reviews and meta-analyses.[20–22] Although the direct applicability of these effect sizes to the Jordanian population may be uncertain, they reflect underlying biological effects that are not likely to vary substantially across human populations.

Although the risk score was derived from samples generated directly from the model outcomes, it demonstrated imperfect performance when compared with the model outcomes. By design, a risk score needs to be simple in structure for ease of use; therefore, it cannot fully capture the complex dynamics of T2DM that is modelled in the mathematical model, such as the overlap and interactions of various risk factors.[2 12 23]

We compared our risk score with some regional and international scores. However, comparisons with other scores were not possible due to insufficient overlap in the variables used. The score cut-off value was selected by maximising the sum of sensitivity and specificity. However, other approaches could be employed based on specific programme requirements, such as prioritising sensitivity or specificity, as presented in additional analyses. Maximising specificity is generally more efficient but comes at the cost of missing many individuals with undetected T2DM.

In conclusion, this study focused on the rising burden of diabetes in Jordan, where the disease is projected to consume a quarter of the country's total health expenditure in the coming decades. Using a recently introduced methodology, a Jordan-specific T2DM risk score was developed, demonstrating strong diagnostic performance. The risk score reliably identified individuals at high risk for T2DM, with about 40% of the adult Jordanian population scoring at or above the cut-off value, necessitating regular glycaemia testing. The score indicated that any Jordanian over the age of 50 years or over 40 years with obesity is at high risk for undiagnosed T2DM and should undergo regular testing. This simple, non-invasive and accessible tool empowers individuals to access early detection and timely intervention, facilitating effective screening campaigns and raising awareness about T2DM. Ultimately, the risk score can contribute to reducing the burden of T2DM and its complications in Jordan.

Author affiliations
[1]Infectious Disease Epidemiology Group, Weill Cornell Medicine - Qatar, Cornell University, Qatar Foundation–Education City, Doha, Qatar
[2]Department of Population Health Sciences, Weill Cornell Medicine, Cornell University, New York, New York, USA
[3]Population Health Research Institute, St George's School of Health and Medical Sciences, Tooting Campus, City St George's, University of London, London, UK
[4]The National Centre for Diabetes, Endocrine and Genetics, The University of Jordan, Amman, Jordan
[5]Department of Public Health and Community Medicine, Jordan University of Science and Technology Faculty of Medicine, Irbid, Jordan
[6]Department of Public Health, College of Health Sciences, QU Health, Qatar University, Doha, Qatar
[7]College of Health and Life Sciences, Hamad bin Khalifa University, Doha, Qatar

X Julia A Critchley @NETPHN

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ORCID iDs
Asalah Alareeki http://orcid.org/0000-0001-8555-4878
Susanne F Awad http://orcid.org/0000-0002-5060-7404
Julia A Critchley http://orcid.org/0000-0002-5248-4188
Kamel M Ajlouni http://orcid.org/0000-0001-5569-6306
Yousef Khader http://orcid.org/0000-0002-7830-6857
Laith J Abu-Raddad http://orcid.org/0000-0003-0790-0506

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