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Development and validation of a novel 10-year cardiovascular risk prediction nomogram for the United Arab Emirates national population

Saif Al-Shamsi

Department of Internal Medicine, United Arab Emirates University College of Medicine and Health Sciences, Al Ain, Abu Dhabi, UAE

Correspondence to
Dr Saif Al-Shamsi;
salshamsi@uaeu.ac.ae

ABSTRACT

Objectives Atherosclerotic cardiovascular disease (ASCVD) is the leading cause of morbidity and mortality among United Arab Emirates (UAE) nationals. Recent studies have shown that current tools are poor in predicting the risk of incident ASCVD in Emiratis. To improve ASCVD risk prediction in this high-risk population, this study sought to develop and validate a novel and practical 10-year ASCVD risk nomogram using risk factors known to be significant in UAE nationals.

Design A 10-year retrospective cohort study.

Setting Outpatient clinics at a large public tertiary care hospital in Al-Ain, UAE.

Participants Emiratis aged ≥18 years without prior cardiovascular disease (CVD) who had presented to Tawam Hospital's clinics between 1 April 2008 and 31 December 2008, were included. Patients' data were collected retrospectively until 31 January 2020.

Exposure Cox proportional hazards models were developed to estimate the 10-year ASCVD risk.

Primary outcome measure Model discrimination and calibration were assessed using the Harrell C-statistic and the Greenwood-Nam-D'Agostino (GND) χ^2 test, respectively. Receiver operating characteristic curve analysis was used to determine the optimal cut-off point of the nomogram for elevated ASCVD risk.

Results The study included 1245 patients, of whom 117 developed ASCVD within 10 years. The ASCVD risk nomogram comprised age, sex, family history of CVD, hypertension treatment, systolic blood pressure, total cholesterol, glycosylated haemoglobin A1c and estimated glomerular filtration rate. The Harrell C-statistic was 0.826 and the GND χ^2 was 2.83 (p=0.830), which indicated good discrimination and calibration of the nomogram model, respectively. The optimal cut-off point was determined to be 10% (sensitivity=79%; specificity=77%). The nomogram can be freely accessed as an online calculator at (https://ascvdriskuae.shinyapps.io/ASCVDrisk/).

Conclusions The developed nomogram provides an accurate prognostic tool for 10-year ASCVD risk prediction in UAE nationals. These findings may help guide future research on CVD prevention in this high-risk population.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ A relatively large patient cohort representing approximately 1% of the adult United Arab Emirates national population in Al-Ain city was used for model development and validation.

⇒ This is the first cardiovascular disease risk assessment tool that has been empirically developed and validated using 10-year follow-up data from a predominantly Arab population.

⇒ The study cohort may not represent the general United Arab Emirates population because the study participants were recruited from the outpatient clinics of a single large medical centre. Therefore, the generalisability of the nomogram is inconclusive.

⇒ The nomogram's predictive performance was evaluated thoroughly internally, however, external validation using different sources of data is necessary.

Arab Emirates (UAE), where approximately one of every three deaths annually is due to vascular disease.[1] The high prevalence of traditional CVD risk factors, such as diabetes, hypertension (HTN) and obesity, among UAE nationals contributes significantly to this increased CVD risk.[2–4] Furthermore, chronic renal failure has also been shown to be an independent risk factor for CVD among UAE nationals.[5]

The burden of CVD can be reduced by early risk assessment and stratification; therefore, primary prevention is a top priority for health policymakers.[6 7] To achieve this goal, CVD risk assessment tools have been developed and extensively used to ensure that high-risk patients are correctly identified for interventions aimed at primary disease prevention.[8] Currently, in the UAE, several different CVD risk assessment calculators are being used for primary prevention of CVD[8 9]; however, a recent study revealed that the tools to predict risk derived from the Framingham and pooled cohort equation (PCE) studies offer poor predictions of incident CVD in

INTRODUCTION

Cardiovascular disease (CVD) is a serious and rising global concern, especially in the United

UAE nationals.[10] This may be because these externally validated models excluded young patients. Several studies conducted in the Middle East have reported a high prevalence of CVD in younger Arab patients.[11 12] Therefore, a substantial proportion of the local population is not being appropriately screened for CVD by these prediction tools. Furthermore, these models do not include non-traditional CVD risk factors that are considered significant in UAE nationals, such as low estimated glomerular filtration rate (eGFR).[5]

Therefore, this study aimed to develop and validate models for 10-year risk prediction of atherosclerotic CVD (ASCVD) using data from a UAE national cohort. Three models were developed: the first model included variables chosen from the original PCE risk score study, the second model contained all relevant risk factors and the third model included a reduced number of variables that were considered significant. After internally validating all three models, the model with the best overall predictive performance was selected to construct a simple-to-use nomogram to screen for ASCVD among UAE nationals.

METHODS

Study design and setting

This cohort study included patients who had presented to the outpatient clinics at Tawam Hospital between 1 April 2008 and 31 December 2008. Tawam Hospital is a government tertiary care centre situated in Al-Ain city and is one of the largest hospitals in the UAE. The hospital has over 80 specialist clinics, serving approximately 120 000 adult UAE nationals in Al-Ain. Baseline sociodemographic, biomedical and follow-up data were extracted retrospectively from ambulatory electronic medical records of patients until 31 January 2020.

Study cohort

UAE nationals aged ≥18 years were included in the study. Patients with a documented history of CVD at recruitment were excluded. History of CVD was characterised as a prior documented diagnosis of peripheral arterial disease, heart failure, angina, myocardial infarction, coronary angioplasty, coronary artery surgery, stroke or a transient ischaemic attack. In addition, patients who were lost to follow-up and those with missing outcome data were excluded. The final sample comprised 1245 patients for analysis (figure 1).

Outcome data

During the follow-up, the definition of ASCVD was used from the PCE model to define the primary outcome measure, which included acute myocardial infarction, coronary death and fatal and non-fatal stroke.[8] If a patient had more than one endpoint recorded, the first event's occurrence was used to determine the onset of the outcome event. Outcome measures were determined by a panel of clinical experts who assessed the electronic medical records and death certificates of each patient.

Figure 1 Flow diagram of the study cohort. CVD, cardiovascular disease; UAE, United Arab Emirates

The duration between study entry and ASCVD event or study end date (31 January 2020), whichever occurred first, was used to calculate the follow-up time.

Predictor variables

Potential predictors were chosen according to known risk factors, clinical significance and availability in daily clinical practice[5] and included age, sex, smoking (characterised as current smoker or prior smoking history), family history of CVD (defined as a first-degree relative with a history of documented coronary artery disease, cerebrovascular disease, peripheral arterial disease or heart failure), use of lipid-lowering medications, blood pressure-lowering drugs, glucose-lowering medications, systolic blood pressure (SBP), diastolic blood pressure (DBP), body mass index (BMI; calculated by dividing weight in kg by height in m^2), serum high-density lipoprotein-cholesterol (HDL-C), serum triglyceride (TG), serum total cholesterol (TC), serum glycosylated haemoglobin A1c (HbA1c) and eGFR. The 2021 Chronic Kidney Disease Epidemiology Collaboration equation, determined by serum creatinine, was used to calculate eGFR.[13] History of diabetes was defined as a serum HbA1c level of ≥6.5% or use of glucose-lowering medications.

Sample size

The minimum sample size required for this study was calculated using methods proposed by Riley *et al* for multivariable time-to-event predictive models,[14 15] which suggests three criteria to be considered when deriving sample sizes for predictive models with binary and time-to-event outcomes. First, to avoid overfitting, a heuristic shrinkage factor ≥0.9 is required. Second, the difference between the apparent and adjusted Nagelkerke's R^2 should be ≤0.05 (an additional measure to avoid overfitting), and third, the estimate of overall risk must be precise.

Assuming a CVD event rate of approximately 0.0127,[5] a conservative R^2 estimate of 0.15 based on existing CVD risk prediction models,[16] and the assumption that up to 20 parameters would be selected to develop the prediction model, a minimum of 1097 patients would be required to

fulfil all three criteria. Thus, the final sample size for this study of 1245 patients was determined to be adequate for model development.

Statistical analyses

Missing data

Multiple imputation was used to replace missing values for family history of CVD (21.1% missing), TC (0.16% missing), HDL-C (0.16% missing), TG (3.0% missing), HbA1c (4.7% missing), creatinine (0.9% missing), SBP (0.08% missing), DBP (0.08% missing), height (0.3% missing) and weight (0.16% missing). All missing values occurred at random. Five imputations were carried out using the predictive mean matching technique for variables with missing data. The generated imputed datasets were then used for subsequent analysis. The results across the imputed datasets were combined using Rubin's rules.[17]

Categorical variables are presented as proportions. Continuous variables with a normal distribution are presented as means and SDs, whereas continuous variables that were not normally distributed are presented as medians and percentiles.

Model selection

The Cox proportional hazards models were used to determine the 10-year ASCVD risk. Three models were developed: the first model (recalibrated PCE model) used predictors included in the PCE risk score (ie, age, sex, history of diabetes, smoking, SBP, blood pressure-lowering medications, TC and HDL-C)[18]; the second (full) model included all variables, such as age, sex, smoking, family history of CVD, use of lipid-lowering medications, blood pressure-lowering drugs, glucose-lowering medications, SBP, DBP, BMI, HbA1c, HDL-C, TG, TC and eGFR; the third model (stepwise model) was constructed using backward-stepwise selection with a stopping rule of a p≤0.20 for the variable selection. All three models were applied to the study cohort and their predictive performance was compared with the original PCE risk score. For the PCE risk score, 'white' was used to describe the variable of ethnicity in the study cohort.

The relative risk for each model were estimated by calculating the HRs and 95% CIs. The proportional hazards assumption was tested by examining plots of the scaled Schoenfeld residuals against time failure for the predictors. The variance inflation factor was used to test for multicollinearity.

Model validation

The three models' clinical performance for predicting 10-year ASCVD risk was assessed according to their discrimination ability, calibration and clinical usefulness. Model discrimination was assessed using the Harrell C-statistic,[19] and model calibration was visually examined by plotting Kaplan-Meier estimates to assess the observed incidence of ASCVD events compared with the predicted risk of each model. In addition, the Greenwood-Nam-D'Agostino

(GND) χ^2 goodness-of-fit test was used to assess calibration, where good calibration was indicated by a nonsignificant χ^2 (p>0.05).[20] A total of 1000 bootstrap samples was used for internal validation.

The Brier score, which is an additional measure of accuracy, was also obtained by calculating the mean squared difference between the predicted and observed risk. A score closer to 0 indicated greater accuracy. The Akaike information criterion (AIC) and the Bayes information criterion (BIC) were used to assess model fit.

Decision curve analysis was conducted to assess the net benefit of the three risk prediction models.[21] This method compares the benefits of accurately classifying patients who will develop ASCVD within 10 years against the harms of an incorrect positive categorisation, which may result in unnecessary intervention. The three models' net

Table 1 Characteristics of the study cohort at baseline and outcome events

Characteristic	Total (n=1245)
Baseline	
Age (years), mean±SD	48.2±15.5
Men, n (%)	651 (52.3)
Women, n (%)	594 (47.7)
Smoking history, n (%)	237 (19.0)
Diabetes mellitus, n (%)	484 (38.9)
Family history of CVD, n (%)	111 (8.9)
Lipid-lowering medication, n (%)	553 (44.4)
Blood pressure-lowering medication, n (%)	612 (49.2)
Glucose-lowering medications, n (%)	403 (32.4)
Systolic blood pressure (mm Hg), mean±SD	129.9±17.8
Diastolic blood pressure (mm Hg), mean±SD	77.1±11.4
Body mass index (kg/m^2), median (25th, 75th percentile)	29.3 (25.8, 33.3)
Total cholesterol (mmol/L), mean±SD	5.0±1.1
HDL-C (mmol/L), median (25th, 75th percentile)	1.1 (0.9, 1.3)
Triglycerides (mmol/L), median (25th, 75th percentile)	1.1 (0.8, 1.6)
HbA1c (%), median (25th, 75th percentile)	5.9 (5.5, 6.8)
eGFR (mL/min.1.73 m^2), median (25th, 75th percentile)	106.0 (93.0, 118.0)
10 years PCE predicted risk (%), median (25th, 75th percentile)	4.0 (1.0, 14.0)
Follow-up	
Follow-up (years), median (25th, 75th percentile)	10.2 (8.0, 11.0)
Observed ASCVD events, n (%)	117 (9.4)

ASCVD, atherosclerotic CVD; CVD, cardiovascular disease; eGFR, estimated glomerular filtration rate; HbA1c, glycosylated haemoglobin A1c; HDL-C, high-density lipoprotein-cholesterol; PCE, pooled cohort equation.

Table 2 Adjusted HR from COX proportional hazard models

Predictor	Recalibrated PCE model Adjusted HR (95% CI)	Full model Adjusted HR (95% CI)	Nomogram (stepwise) model Adjusted HR (95% CI)
Age (years)	1.05 (1.04 to 1.07)**	1.04 (1.02 to 1.06)**	1.04 (1.02 to 1.06)**
Sex	1.47 (0.96 to 2.26)	1.21 (0.77 to 1.92)	1.25 (0.85 to 1.86)
Smoking history	1.29 (0.82 to 2.04)	1.17 (0.74 to 1.85)	
Diabetes mellitus	1.78 (1.16 to 2.73)*		
Family history of CVD		2.47 (1.52 to 4.03)**	2.49 (1.54 to 4.02)**
Lipid-lowering medication		1.00 (0.63 to 1.59)	
Blood pressure-lowering medication	0.76 (0.47 to 1.24)	0.70 (0.42 to 1.18)	0.68 (0.42 to 1.10)
Glucose-lowering medications		1.12 (0.67 to 1.87)	
Systolic blood pressure (mm Hg)	1.03 (1.02 to 1.04)**	1.03 (1.02 to 1.04)**	1.02 (1.01 to 1.03)**
Diastolic blood pressure (mm Hg)		0.98 (0.96 to 1.00)	
Body mass index (kg/m^2)		0.98 (0.95 to 1.01)	
Total cholesterol (mmol/L)	1.14 (0.97 to 1.35)	1.09 (0.91 to 1.30)	1.13 (0.96 to 1.32)
HDL-C (mmol/L)	0.74 (0.37 to 1.45)	1.24 (0.60 to 2.58)	
Triglycerides (mmol/L)		1.13 (0.96 to 1.34)	
HbA1c (%)		1.18 (1.07 to 1.30)*	1.21 (1.12 to 1.31)**
eGFR (mL/min.1.73 m^2)		0.98 (0.98 to 0.99)**	0.98 (0.97 to 0.99)**

*p<0.05, **p<0.01.
CVD, cardiovascular disease; eGFR, estimated glomerular filtration rate; HbA1c, glycosylated haemoglobin A1c; HDL-C, high-density lipoprotein-cholesterol; PCE, pooled cohort equation.

benefit was assessed by plotting the expected net benefit relative to 'intervention for none' and comparing it to 'intervention for all' across a range of probability thresholds. The model with the highest net benefit at any given probability threshold was considered to have the highest clinical value.

Finally, a nomogram was developed using the risk model that demonstrated the best overall predictive performance. The closest top left point method to the receiver operating characteristic (ROC) curve was applied to obtain the optimal elevated-risk threshold for the nomogram model.[22] A time-dependent ROC curve was then used to determine the sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) at the optimal elevated-risk threshold and compared with those of the recommended 7.5% PCE elevated-risk threshold.[8]

In this study, statistical significance was defined as a two-tailed p≤0.05. All statistical analyses were conducted using R software V.4.1.2 (The R Foundation, Vienna, Austria) and IBM SPSS software V.28 (IBM). The Transparent Reporting of a multivariable prediction model

Table 3 Comparison of predictive performance and model fit between the new 10-year ASCVD risk models and the original PCE risk score

Statistic	Model PCE risk score	Recalibrated PCE model	Full model	Nomogram (stepwise) model
C-statistic (95% CI)*	0.777 (0.737 to 0.816)	0.790 (0.750 to 0.830)	0.830 (0.792 to 0.868)	0.826 (0.787 to 0.865)
Difference of *C*-statistic (p value)	Reference	0.013 (0.126)	0.053 (<0.001)	0.049 (<0.001)
GND χ^2 (p value)	40.40 (<0.001)	4.08 (0.665)	5.67 (0.461)	2.83 (0.830)
Brier score†	0.045	0.044	0.042	0.042
AIC‡	1518	1490	1457	1449
BIC‡	1521	1512	1499	1471

*Higher scores indicate better discrimination.
†Lower scores indicate better performance.
‡Lower values indicate better fit.
.AIC, Akaike information criterion; ASCVD, atherosclerotic cardiovascular disease; BIC, Bayes information criterion; GND, Greenwood-Nam-D'Agostino; PCE, pooled cohort equation.

for Individual Prognosis Or Diagnosis statement was followed.[23]

Patient and public involvement

There was no patient or public involvement in the design and conduct of the study.

RESULTS

Baseline characteristics

Of the 1245 patients, 117 (9.4%) developed ASCVD within 10 years (event rate: 10.9; 95% CI 9.1 to 13.1 events per 1000 person-years). The numbers and incidence rates of ASCVD subtypes were as follows: fatal and non-fatal coronary heart disease (84 patients (7.7; 95% CI 6.2 to 9.5 events per 1000 person-years)) and fatal and non-fatal stroke (38 patients (3.5; 95% CI 2.5 to 4.7 events per 1000 person-years)).

Table 1 summarises patients' characteristics at baseline. The average age of the study cohort was 48 years, and almost half of the patients were women (48%). More than one-third of patients had diabetes, approximately half were taking antihypertensive medications, 19% had a history of smoking and 9% had a family history of CVD. Mean SBP was 130 mm Hg, the median BMI was 29 kg/m^2, the median eGFR was 106 mL/min.1.73m^2 and mean serum TC level was 5 mmol/L.

Multivariable model

Table 2 shows the HRs for ASCVD events associated with the predictors in the recalibrated PCE, full and stepwise models. In the stepwise model, age, family history of CVD, SBP, HbA1c and eGFR were found to be statistically significant predictors associated with 10-year ASCVD risk. Antihypertensive medication use, serum TC levels and sex were included in the stepwise selection, although they were not significantly associated with ASCVD risk.

For the Cox regression analysis, the variance inflation factor ranged from 1.04 to 2.00, which indicated an absence of multicollinearity, and the proportional hazards assumption was satisfied.

Model validation

The predictive performance of the three new models are described in table 3, with comparisons with the original PCE risk score. The Harrell C-statistic of all four models was ≥0.75, which indicated good discrimination. Compared with the PCE risk score (C-statistic: 0.777), the full and stepwise models had superior discriminative ability. When compared with each other, the full and stepwise models had similar discrimination ability (p=0.336), whereas both models had better discrimination ability when each model was compared with the recalibrated PCE model (p<0.001). Of the three new models, the stepwise model had the lowest AIC and BIC, which indicated that it had the best-fit model.

None of the p values of the GND χ^2 statistic of the three new models were statistically significant, which indicated
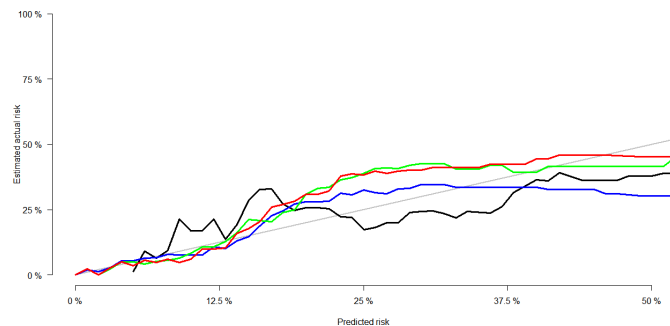

Figure 2 Calibration plots of the observed and predicted 10-year ASCVD risk using the PCE risk score (black), recalibrated PCE (blue), full (green) and stepwise (red) risk prediction models in adult UAE nationals. ASCVD, atherosclerotic cardiovascular disease; PCE, pooled cohort equation; UAE, United Arab Emirates.

good calibration. In contrast, the PCE risk score exhibited poor calibration (p<0.001). The calibration plots comparing the observed and predicted risk of the full and stepwise models were similar; however, all three new models slightly underestimated the risk at approximately 20%–30% of the predicted risk (figure 2). Brier scores of the full and stepwise models were similar, although they were both lower than that of the recalibrated PCE model and the PCE risk score, indicating superior predictive accuracy of the full and stepwise models (table 3).

Online supplemental figure S1 describes the net benefit curves of all models. All four models offered higher net benefit than methods that consider either no or all patients for intervention across a range of threshold probabilities. Both the full and stepwise models had higher net benefit than the recalibrated PCE model, and all three new models had higher net benefit than the original PCE risk score. Both the full and stepwise models showed relevance at threshold probabilities of approximately 2%–40%.

Nomogram

The stepwise model was selected to construct the nomogram. The regression coefficients from the stepwise model, which determined age, sex, family history of CVD, treatment for HTN, SBP, TC, HbA1c and eGFR as predictors of developing ASCVD, were used to create the nomogram for predicting ASCVD events within 10 years (figure 3). To use the nomogram, points are obtained for each predictor by drawing a vertical line from the predictor's value up to the points' axis. The total points are then summed. From the total points' axis, a vertical line is then drawn to the 10-year ASCVD Risk axis, which yields a patient's overall 10-year ASCVD risk.

This simple nomogram can be used in clinical practice. For example, a 40-year-old female patient with a family history of CVD, who is undergoing HTN treatment and has an SBP of 140 mm Hg, TC of 4 mmol/L, HbA1c of 6% and eGFR of 80 mL/min/1.73 m^2, would receive 33 points for age, 0 points for sex, 26 points for family history of CVD, 0 points for HTN treatment, 38 points for SBP,
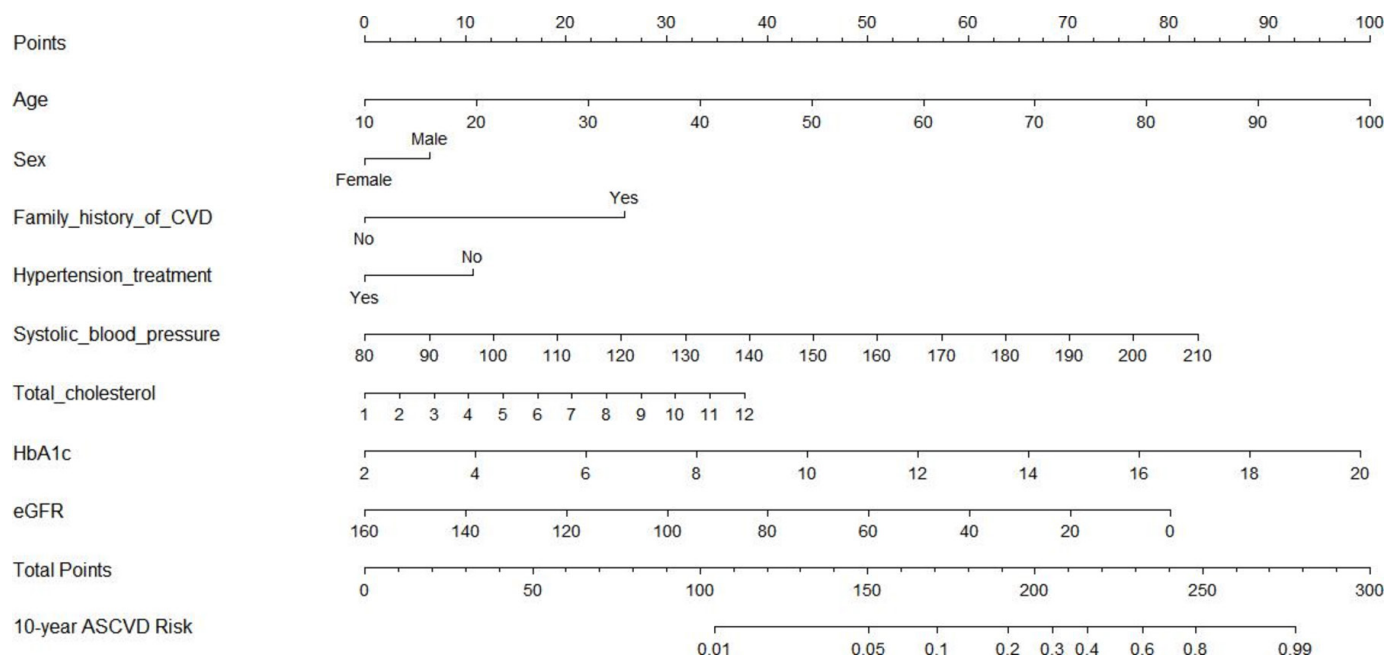
Figure 3 Nomogram to predict the risk of ASCVD within 10 years in adult UAE nationals. ASCVD, atherosclerotic CVD; CVD, cardiovascular disease; eGFR, estimated glomerular filtration rate; HbA1c, glycosylated haemoglobin A1c; HTN, hypertension; SBP, systolic blood pressure; UAE, United Arab Emirates.

10 points for TC, 22 points for HbA1c and 40 points for the eGFR (total=169 points). Consequently, the patient's likelihood of developing ASCVD at 10 years would be approximately 10%.

Sensitivity and specificity

Table 4 provides the time-dependent sensitivity, specificity, PPV and NPV of the elevated-risk threshold of 7.5% recommended by the American College of Cardiology (ACC)/American Heart Association (AHA) for 10-year ASCVD risk[8] and the 10% optimal cut-off point selected by the ROC curve analysis. Sensitivity and specificity at the 7.5% risk threshold were 82% and 63%, respectively, whereas at the 10% optimal cut-off point, they were 79% and 77%, respectively.

Sensitivity analysis

The constructed nomogram's predictive accuracy and clinical utility were assessed separately for men and women (online supplemental table S1). The nomogram showed good discrimination ability and calibration for predicting 10-year ASCVD risk in both sexes (online supplemental tables S2, S3 and figure S2). Clinical relevance was

demonstrated at threshold probabilities of approximately 2%–40% in men and 2%–30% in women (online supplemental figure S3). Among the men, the sensitivity and specificity of the 10% optimal cut-off point were 78% and 77%, respectively, whereas in women, they were 83% and 79%, respectively (online supplemental table S4).

In addition to the nomogram, a user-friendly online calculator based on the nomogram model to assess the 10-year ASCVD risk was developed. The purpose of both the nomogram and online application was to engage local healthcare providers to determine their patients' risk and guide decision-making in the primary prevention of ASCVD. The web-based calculator is freely accessible at (https://ascvdriskuae.shinyapps.io/ASCVDrisk/).

DISCUSSION

This is the first study to develop and validate several novel models to predict 10-year ASCVD risk using data from a predominantly Arab population. Both the full and stepwise models performed better than both the original and recalibrated PCE models. The relatively poor predictive

Table 4 Sensitivity and specificity of cut-off thresholds for the prediction of 10-year ASCVD risk using the nomogram (stepwise model)

Cut-off threshold, %	Sensitivity, % (95% CI)	Specificity, % (95% CI)	PPV, % (95% CI)	NPV, % (95% CI)
≥7.5	81.8 (74.3 to 89.2)	63.3 (59.4 to 67.2)	19.7 (15.8 to 23.5)	96.9 (95.5 to 98.3)
≥10*	79.0 (71.2 to 86.9)	76.7 (73.4 to 80.1)	27.2 (21.9 to 32.5)	97.1 (95.9 to 98.3)

*Optimal cut-off point determined by the ROC curve analysis.
ASCVD, atherosclerotic cardiovascular disease; NPV, negative predictive value; PPV, positive predictive value; ROC, receiver operating characteristic.

performance of the original PCE risk score observed in this study may be attributed to its applicability to patients aged 40–79 years. However, a recent study demonstrated that even among this age group, the PCE risk score performed poorly among UAE nationals in predicting the 10-year ASCVD risk.[10]

Because the stepwise model included fewer variables yet performed similarly to the full model in predicting ASCVD risk, it was thus selected for constructing the nomogram. This simple-to-use nomogram comprised five clinical variables (ie, age, sex, family history of CVD in a first-degree relative, treatment for HTN and SBP) and three routine laboratory measurements (serum TC, serum HbA1c and eGFR), which would enable local healthcare providers to efficiently assess the 10-year ASCVD risk in adult UAE nationals. Furthermore, the inclusion of novel risk factors, such as renal failure, will contribute to a more accurate risk level assessment in this specific population. This will aid in the development of more effective monitoring programmes for CVD in the region.

Nomograms are reliable risk prediction tools that are widely used in clinical settings to estimate individualised probabilities of risk by incorporating risk factors tailored for a specific population.[24] The nomogram presented in this study is practical and precise and can be implemented quickly by busy clinicians to prioritise at-risk patients for additional testing and initiation of intensive treatment.

The risk factors included in the nomogram based on the stepwise model are comparable to those described in previous studies. Older age, positive family history of CVD, elevated SBP, increased HbA1c level and low eGFR are all significant predictors of incident ASCVD.[5 25–28] Of these, family history of CVD and eGFR are not included in the original PCE risk score. The 2019 ACC/AHA guidelines on the Primary Prevention of CVD consider a family history of ASCVD and an eGFR of $<60\,mL/min/1.73m^2$ as 'risk-enhancing factors'.[8] A recent meta-analysis of 72 datasets including approximately 9 million adults from various countries determined that the use of chronic kidney disease parameters, such as eGFR, enhanced CVD prediction and that their inclusion in existing prediction models, such as the original PCE risk score, could improve its predictive accuracy.[28] Additionally, newly developed clinical risk scores, such as the NORRISK 2 (based on Norwegian data) and QRISK3 (developed using data from English patients), have incorporated family history into their models to further improve CVD risk estimation in their respective populations.[29 30]

Although the following predictors of sex, antihypertensive treatment and TC levels in the nomogram model were not found to be statistically significant for 10-year ASCVD risk, their inclusion provided a model with the best fit. Interestingly, in the multivariable Cox regression models, the use of antihypertensive medications offered a 'protective' effect. In contrast, for both the Framingham model and the PCE risk score, blood pressure treatment was associated with an increase in CVD risk. A recently published meta-analysis of 48 randomised clinical trials investigating the long-term association between blood pressure-lowering medications and major CVD events reported that regardless of the history of CVD, pharmacological blood pressure reduction decreased the risk of major CVD events, even in patients with normal blood pressure.[31] This is consistent with the findings of the current study.

Surprisingly, smoking was not identified in this study as a significant risk factor for 10-year ASCVD risk. However, smoking may have been masked by the variable of sex because smoking history has been reported to be significantly correlated with men in the UAE.[32] Although smoking is not included in this study's 10-year ASCVD risk prediction nomogram, smoking cessation continues to be an essential component of primary and secondary prevention strategies for CVD.

Strengths and limitations

In this study, a relatively large patient cohort representing approximately 1% of the adult UAE national population in Al-Ain city and high-quality data were used for model development and validation. Although a previous study had developed a CVD risk assessment tool for Omani nationals, their study cohort consisted exclusively of patients with type 2 diabetes and the follow-up period was relatively shorter at 5 years.[33] Therefore, this nomogram is the first 10-year CVD risk assessment tool that has been empirically developed and validated using long-term follow-up data from an Arab population. However, this study has several limitations. First, the study cohort used for the development of the models may not represent the general UAE population because the study participants were recruited from the outpatient clinics of a single large medical centre. Therefore, the generalisability of the nomogram is inconclusive. Nevertheless, the nomogram offers a supplementary evidence-based risk assessment tool that may be used in conjunction with existing CVD risk prediction scores that are currently in use in the UAE. Second, the possibility of selection bias must be considered as a potential limitation owing to the retrospective design of the study. Third, although comprehensive, the models developed did not include other potential clinical risk predictors, such as socioeconomic status, physical activity level and diet, which may be associated with incident ASCVD in Emirati patients.[34 35] Finally, although the nomogram's predictive performance was evaluated thoroughly internally, using different sources of data for external validation is necessary and further investigation is required in the future.

CONCLUSION

Existing externally validated risk prediction tools recommended for use in the UAE have been shown to be inaccurate in predicting CVD risk in UAE nationals.[10] The inclusion of novel yet important risk factors, such as family history of CVD and eGFR, in the models in this study resulted in relatively better accuracy. The established

nomogram demonstrated good discrimination ability, calibration and clinical utility and offers local healthcare providers an additional convenient and practical tool that uses readily available clinical parameters to quickly assess 10-year ASCVD risk in the adult Emirati population. Nevertheless, future prospective studies are warranted to externally validate this nomogram to support its routine use in the general UAE national population.

ORCID iD
Saif Al-Shamsi http://orcid.org/0000-0001-9755-3493

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