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Incidence and predictors of type 2 diabetes mellitus in a population-based cohort study in Abu Dhabi

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Diabetes mellitus (DM) is a global health burden. Monitoring its determinants and incidence trends is important for identifying risk factors and projecting future health service needs. The Abu Dhabi Risk Study (ADRS) is a retrospective cohort study of 8699 participants in Abu Dhabi, United Arab Emirates (UAE), with an average follow-up period of 9.2 years. This study reports the prevalence of diabetes in this cohort, as well as the incidence of diabetes among the 6,772 participants who were diabetes-free at the start of the follow-up period in 2011–2013. Cox regression was used to develop a prediction model and identify significant determinants. Over the 12-year follow-up period, 643 individuals developed new diabetes, with an overall incidence of 7.4%. The prevalence of diabetes DM increased to 28.5%. Reaching 25.3% in females and 31.9% among males. Significant risk factors for developing new diabetes were a higher level of HbA1C, current smoking status at screening, and a higher level of eGFR. The model developed showed good performance in predicting new diabetes with a c-statistic of 0.837 (0.818–0.856), a sensitivity of 75.1%, and a specificity of 78.1%. Determinants of developing pre-DM included higher Diastolic Blood Pressure (DBP), total cholesterol, Random Blood Sugar (RBS), Body Mass Index (BMI), age, and lower High-Density Lipoprotein (HDL) levels. Gender and smoking status were not significant determinants for the diagnosis of prediabetes. The cumulative prevalence of prediabetes and diabetes is increasing steadily, with a plateau reached at 40 in the case of pre-DM and 60 with DM, and a decline with increasing age. The prevalence of diabetes in Abu Dhabi remains high. The Derived model is valuable for informing clinical practice and preventing diabetes.

Keywords Diabetes, Incidence, Prediction Model, Cohort study, Risk factors

The prevalence of type 2 diabetes among United Arab Emirates nationals is among the highest in the world¹. The latest reported prevalence was 21% among males and 23% among females, with a similarly high prevalence of its main risk factors, such as obesity^{2,3}. Assessing the burden of diabetes and its risk factors is important due to their significant contribution to mortality, quality of life, and healthcare utilization^{1,4,5}. Additionally, control of this increasing burden requires high-quality studies to inform healthcare decision-makers and patient care. An important area in such studies is the regional variation⁶ that may be influenced by factors such as healthcare system preparedness and responses toward prevention and management, aging, urbanization, culture, and physical inactivity across different countries and ethnicities⁷.

Cohort studies are particularly important in diabetes epidemiology, especially in the areas of prevention and treatment, as well as in understanding the differences among various populations. With accumulating evidence that diabetes mellitus can be prevented or delayed, the contributions of different preventive and management strategies to outcomes can only be shown in these types of studies. For example, healthier Lifestyles and the use of pharmacological interventions such as metformin were found to reduce the rate of progression to type 2 diabetes in people with impaired glucose tolerance, with lifestyle interventions being as effective as pharmacological treatment. Such interventions target multiple risk factors, but once stopped, the effects are not sustained⁸. Risk

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assessment to identify individuals with a higher risk of diabetes and tailoring strategies for the initiation of suitable and effective interventions requires large cohorts and diverse populations to increase the precision of interventions. Risk scores developed from research-based prediction models are key in assessing and identifying such patients^{9,10}. They as well guide policy decisions in diabetes surveillance and prevention to decrease the progression of diabetes to complications, disability, and mortality.

The prevalence of diabetes is highest in the Gulf Cooperation Council (GCC) countries at 25.45%, compared to non-GCC countries, which have a lower prevalence of 12.69%¹¹. Incidence studies of diabetes in Abu Dhabi and the surrounding region are rare, even though diabetes research in the country is relatively robust. Therefore, assessing regional variations within the UAE or the surrounding areas is challenging. The few available studies have limitations, including small sample sizes, short follow-up durations, and a lack of community-based aspects^{12,13}.

The United Arab Emirates is a rapidly developing country with a well-resourced healthcare system¹⁴. Strategies for the early detection and management of chronic diseases on a large scale have been implemented for many years. For example, the cardiovascular screening program, Weqaya, which started in 2008, could have one of the best screening coverages in the world and was designed to assess cardiovascular risk factors among the Abu Dhabi population. This study is part of a large retrospective cohort study, which includes a sample of the Weqaya screening participants from 2011 to 2013. Diabetes-free Abu Dhabi cardiovascular screening program participants were retrospectively evaluated for the incidence of diabetes, prediabetes, and risk factors studied.

Methods

The Abu Dhabi Risk Study (ADRS) is a retrospective cohort study of 8699 participants in Abu Dhabi, United Arab Emirates (UAE), with an average follow-up period of 9.2 years. This study reports the prevalence, incidence, and risk factors of diabetes in this cohort, as well as the derivation of a prediction model for the risk of diabetes development over a 9.2-year follow-up period. The study methodology was described in detail in a related publication¹⁵. The participants were from Weqaya, a national screening program in Abu Dhabi³. This study cohort included 8699 United Arab Emirates nationals, nearly 2% of the total Abu Dhabi United Arab Emirates population in 2011. It was sampled from individuals who participated in the first Abu Dhabi population-wide cardiovascular screening program for adults aged 18 and older, Weqaya (prevention), between 2010 and 2013. From 12,752 with no missing values for the main variables, 8699 were randomly selected to have their charts reviewed 2023.

Data collected at baseline included demographic data, self-reported health indicators, including smoking status, physical activity, preexisting CVD (angina, heart attack, transient ischemic attack, stroke, other circulatory disorder), family history of premature cardiovascular disease (a first-degree relative with a heart attack or stroke before the age of 50 years), history of cardiovascular risk factors for diabetes, hypertension, and dyslipidemia and whether participants were taking medication for these conditions. Anthropometric measures included waist and hip circumference, body mass index (BMI in kg/m²), and a single arterial blood pressure reading. A digital automatic blood pressure monitor measured blood pressure from the left arm with the patient relaxed and seated. Hematological parameters included non-fasting glucose (mmol/L), total cholesterol, high-density lipoprotein (HDL) cholesterol (mmol/L), glycosylated hemoglobin (HbA1C), vitamin D, and creatinine. The inclusion of the non-fasting glucose is a pragmatic approach in screening to improve the completion of the screening by participants. The Mean BP was calculated as (Systolic + 2*Diastolic)/3. Obesity was classified into three classes: I (30–34.9), II (35–39.9), and III (≥ 40)¹⁶. The glomerular filtration rate was calculated using the Chronic Kidney Disease Epidemiology Collaboration (CKD-EPI) equation¹⁷. Medications for diabetes risk factors were collected for hypertension and dyslipidemias. As well as aspirin use. There was no specification of which medications were used; instead, the use of blood pressure-lowering medications, statins, or aspirin. The dates and durations of statin and aspirin use were also collected.

- At baseline, 8699 subjects from the national cardiovascular screening program of 2011–2013, with an average follow-up of 9.2 years (ranging from a minimum of 1 year to a maximum of 12 years), were eligible for enrollment if they were non-diabetic. The pre-diabetic definition was an HbA1C level of 5.7–6.4%. Diabetes was identified as HbA1C of $> 6.4\%$, a documented diabetes diagnosis (entered by the treating physicians in the problem list within the EMR) or ICD code entered when prescribing diabetic medications. Participants were assessed retrospectively in 2023 for health outcomes. Age-adjusted prevalence for age-specific comparisons between countries utilized the population percentage in each 5-year age group in the new WHO World Standard population, based on the expected evolution of the world's population age structure over the first quarter of the 21st century¹⁸. All participants had their eGFR determined. The method to determine the age-specific percentiles for the estimated glomerular filtration rate was the LMS method¹⁹. The resultant age and sex-specific GFR percentiles were derived from this cohort after excluding subjects with comorbidities such as diabetes, hypertension, coronary heart disease, stroke, and cancer. Subjects were classified in appropriate eGFR percentiles according to age, sex, and eGFR.

Statistical analysis

Prediction models for diabetes were developed using Cox proportional hazards regression, with progression to diabetes as the endpoint. Patients were censored at the time of death or at their last HbA1C measurement if it was $< 6.4\%$. Potential predictors included age, RBS, BMI, current smoking status, sex, HbA1C, mean BP, eGFR, HDL, and HTN. (Table 2) Every possible combination of variables was tested, as well as all potential interactions between these variables. For discrimination, the time-dependent area under the receiver operating characteristic (ROC) curve was compared for the resulting prediction models.

SPSS (Statistical Package for the Social Sciences) version 29 was used.

	B	P value	HR	95.0% CI for HR	
Age (years)	0.03	<0.001	1.03	1.024	1.037
Random Blood Glucose (mmol/L)	0.185	<0.001	1.204	1.139	1.272
BMI (kg/m ²)	0.016	0.013	1.017	1.003	1.03
Current Smoker at screening	0.354	0.007	1.425	1.1	1.846
Sex (1 female 2 male)	-0.185	0.048	0.831	0.691	0.999
HbA1C (%)	1.923	<0.001	6.841	5.326	8.788
Mean Blood Pressure	0.009	0.024	1.009	1.001	1.017
eGFR Percentile 3rd		0.03			
Percentile 10th	-0.308	0.02	0.735	0.567	0.952
Percentile 25th	-0.281	0.049	0.755	0.57	0.999
Percentile 50th	-0.034	0.764	0.966	0.771	1.21
Percentile 75th	0.075	0.343	1.078	0.923	1.258
Percentile 90th	0.084	0.37	1.087	0.905	1.306
Percentile 95th	0.146	0.481	1.157	0.772	1.735
Percentile 97th	0.321	0.016	1.379	1.063	1.789
HDL (mmol/L)	-0.91	<0.001	0.403	0.304	0.534
Hypertension at baseline	0.199	0.069	1.22	0.984	1.513

Table 2. Determinants of progression to DM using Cox regression. HbA1C: Haemoglobin A1c, HDL: High Density Lipoprotein, eGFR: estimated Glomerular Filtration Rate, BMI: Body Mass Index.

Results

The prevalence of DM at baseline was 22.2%, with 18.5% in females and 25.8% in males. The HbA1C was ordered based on routine care as per the physician's decision and the patient's agreement. Among the 6,772 diabetes-free subjects (3,537 females and 3,235 males), 643 developed new diabetes over the follow-up years, resulting in an overall incidence of 9.5%, with 317 (9.0%) females and 326 (10.0%) males over the 12-year follow-up period. The incidence of DM fluctuated throughout the years of follow-up (Appendix 1), with an increasing incidence from the 6th to the 9th year, peaking at 14.8% in the 7th year of follow-up.

During the follow-up years, the prevalence increased to 28.5%, with 25.3% in females and 31.9% among males. The overall age-standardized prevalence rose from 18 to 23.7%.

The participant's demographics at baseline are shown in Table 1. Smoking was less common (0.7%) among females than among males (20.9%). 65.5% of females had an HDL of more than 1.29 compared to 28.5% of males. Concerning cardiovascular health, 6.5% of males and 4.9% of females were under lipid-lowering therapy, whereas 38.4% of males and 33.6% of females had cholesterol levels more than 5.2. There were 36.0% and 28.8% of males with optimum and normal blood pressure, respectively, compared to 66.8% and 18.0% of females. Hypertension had been diagnosed in 11.3% of males compared to 6.7% of females. Obesity was slightly more prevalent among females, with 20.8% having class I (30–34.9) obesity, 9.5% having class II (35–39.9), and 5.3% being class III (≥ 40), compared to 20.2%, 6.6%, and 3.7%, respectively, among males.

HbA1C is the main determinant of new DM, with a nearly seven-fold increase in risk for each one-unit rise in HbA1C. A one-unit increase in Random glucose RBS had a 1.2% increase in the risk of DM, while the hazard of developing DM decreased by 0.403 for each one-unit rise in HDL. From multivariate Cox regression, for each one-year increase in age, the risk of developing DM increases by 1.03%, adjusted for other risk factors. Appendix 2.

Different percentiles of eGFR have varying effects, with the 3rd percentile showing a significant risk of developing DM. Interestingly, higher eGFR was found to be a significant risk factor for developing diabetes. An eGFR in the 97th percentile increased the risk of diabetes by 37.9%, with a hazard ratio of 1.379 (1.063–1.789) and a p-value of 0.016.

Smokers have a 1.425% increased risk, and obesity is a significant risk factor, with a 1.017% increase in risk with each one-unit increase in BMI. Mean blood pressure (BP) is another significant risk factor, with a 1.009% increase in risk for each one-unit mmHg increase in Mean BP. However, the hypertension was not statistically significant.

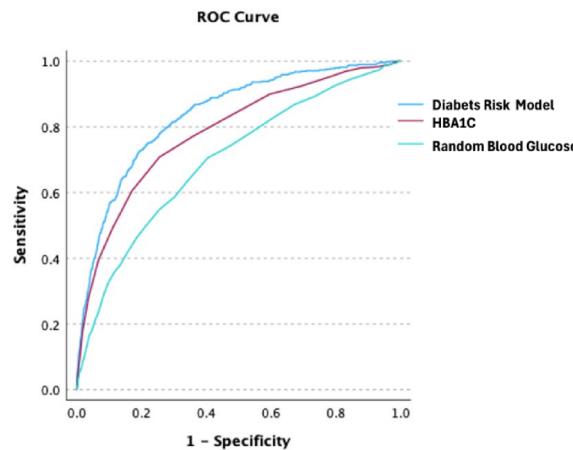
The DM hazard ratio steadily increases with increasing HbA1C. At the pre-DM cutoff level of 5.7, the HR is 10, doubles at 6, and triples at 6.5, the chosen cutoff point for DM, as shown in Appendix 3. Finally, although higher BMI was associated with a higher risk of progression to DM, as per Appendix 4, subjects with normal BMI and overweight also have high levels of HbA1C.

The model developed showed good performance with a c-statistic of 0.837 (0.818–0.856). The ROC is shown in Fig. 1 with a cutoff point identified for the hazard ratio of 2.06; it has a sensitivity of 75.1% and a specificity of 78.1%. HbA1C alone as a predictor of DM performance was lower than the model but close to it, with a c-statistic of 0.784 (0.761–0.807), Fig. 1. The hazard ratio's cutoff for HbA1C, identified by the model, is 5.650, with a sensitivity of 68.6% and a specificity of 73.2%. In comparison, the c-statistics for using only random blood sugar as a predictor was 0.698 (0.672–0.723). Figure 1.

Characteristic	Male		Female		
	No.	%	No.	%	
Age (years)*	< 30	1325	30.4%	1483	34.2%
	30–39	1028	23.6%	1153	26.6%
	40–49	712	16.3%	809	18.7%
	50–59	636	14.6%	540	12.5%
	60–69	466	10.7%	249	5.7%
	70–79	181	4.2%	87	2%
	>=80	12	0.3%	16	0.4%
	Total	4360	50.1%	4337	49.9%
Education Level*	Illiterate	477	11.1%	816	18.9%
	Primary	449	10.4%	411	9.5%
	Intermediate	1650	38.3%	1290	29.9%
	Secondary	557	12.9%	354	8.2%
	University	1070	24.8%	1382	32.1%
	Post Grad	106	2.5%	58	1.3%
	Total	4309	49.99%	4311	50.01%
Smoking Status at baseline*	Yes	945	21.7%	16	0.4%
	No	3374	78.3%	4295	99.6%
HDL (mmol/L) *	< 0.9	625	14.3%	143	3.3%
	0.91–1.14	1998	45.8%	928	21.4%
	1.16–1.29	564	12.9%	577	13.3%
	>=1.29	1174	26.9%	2690	62%
	Total	4361	50.1%	4338	49.9%
High Cholesterol level (mmol/L) *	< 4.14	1290	29.6%	1105	25.5%
	4.14–5.2	1563	35.9%	1789	41.3%
	5.2–6.2	1027	23.6%	1043	24.1%
	6.2–7.2	380	8.7%	313	7.2%
	>=7.2	99	2.3%	85	2%
	Total	4359	50.1%	4335	49.9%
High cholesterol on treatment*	Yes	744	17.7%	588	13.7%
Chronic Kidney Diseases (CKD) (eGFR < 60)	Yes	84	1.9%	61	1.4%
	No	4277	98.1%	4277	98.6%
	Total	4361	50.1%	4338	49.9%
Hypertension*	Yes	743	17.2%	543	12.5%
	No	3565	82.8%	3795	87.5%
Blood pressure categorize*	No	4277	98.1%	4277	98.6%
	Normal	1196	27.4%	819	18.9%
	High normal	974	22.3%	465	10.7%
	Stage 1	649	14.9%	365	8.4%
	Stage 2	132	3%	52	1.2%
	Hypertension crisis	16	0.4%	7	0.2%
	Total	4361	50.1%	4338	49.9%
Obesity (BMI classes) *	Underweight (< 18.5 kg/m ²)	94	2.2%	166	3.8%
	Normal (18.5 kg/m ² -24.9 kg/m ²)	1094	25.1%	1115	25.7%
	Overweight (25 kg/m ² -29.9 kg/m ²)	1696	39%	1275	29.5%
	Class I obesity (30 kg/m ² -34.9 kg/m ²)	980	22.5%	1039	24%
	Class II obesity (35 kg/m ² -39.9 kg/m ²)	309	7.1%	469	10.8%
	Class III obesity (> = 40 kg/m ²)	180	4.1%	271	6.3%
	Total	4353	50.1%	4335	49.9%

Table 1. Subjects' characteristics distributed by sex. *P value < 0.001.

With regard to pre-DM, among non-diabetic patients, 804 did not do the HbA1C after screening, or it is not documented (17.7%), 803 in the non-pre-DM group. Based on the latest test, the mean HbA1C in the pre-DM group was 5.9, SD 0.2 (min 4.9 max 6.4), and in the non-pre-DM range group, it was 5.2, SD = 0.21 (min 2.8 max 5.7) among those with no pre-DM at screening, 14.45%. Interestingly, almost half, 44.1%, of those with pre-DM at screening reverted to normal values. Determinants of developing pre-DM were higher screening DBP, total



	Area Under the ROC Curve	95% Confidence Interval		Cutoff	Sensitivity	Specificity
Diabetes Risk Model	0.837	0.818	0.856	2.06	75.1	78.1
Random Blood Glucose	0.698	0.672	0.723	5.55	55	73.3
HbA1C	0.784	0.761	0.807	5.65	68.6	73.2

Fig. 1. Area Under the Curve of the model developed to predict the development of new diabetes compared to using HbA1C only or RBS only.

	B	P value	OR	95% C.I.
DBP (mmHg)	0.01	0.002	1.01	1.004 1.016
Total Cholesterol (mmol/L)	0.203	<0.001	1.225	1.149 1.305
Random Blood Sugar (mmol/L)	0.246	<0.001	1.278	1.186 1.377
HDL (mmol/L)	-0.203	0.03	0.816	0.68 0.981
BMI (kg/m ²)	0.02	<0.001	1.02	1.01 1.031
Age (years)	0.036	<0.001	1.037	1.032 1.043

Table 3. Baseline characteristics with significant association with changing the status of participants to pre-diabetes. Participants with no diabetes or pre-diabetes are included. Logistic regression was used to identify baseline characteristics associated with the development of pre-diabetes as the outcome variable.

cholesterol, RBS, BMI, and age, as well as lower levels of HDL Table 3. Gender and smoking status were not significant determinants for the diagnosis of prediabetes during follow-up.

Figure 2 is a scatter plot showing the cumulative prevalence of prediabetes and diabetes with age. It is increasing steadily, with a plateau reached at 40 years of age in the case of pre-DM and 60 with DM. After the plateau, there is a decline with increasing age.

Discussion

This study is the first longitudinal population-representative examination of diabetes incidence in an area considered among the highest in prevalence. Our estimate of prevalence for 2011 is close to the International Diabetes Federation's (IDF) estimate of 18.8% in 2011 for the UAE²⁰. With an increase in age-standardized prevalence from 18.8 to 23.7%, the problem of DM is worsening, underscoring the urgent need for comprehensive public health interventions in the region. The incidence is close to previously reported study in Abu Dhabi¹². By taking proactive steps to address the underlying determinants of diabetes, it will be possible to mitigate its impact on population health and improve outcomes for individuals living with or at risk of developing the disease. These study results can inform the screening programs and the development of interventions for patients identified as being at high risk. Possible effective interventions could be targeted smoking cessation programs, lifestyle interventions focusing on weight management and diet, and earlier screening for individuals with high HbA1c, in this high-risk population. All programs must be supported by training for healthcare professionals and community awareness.

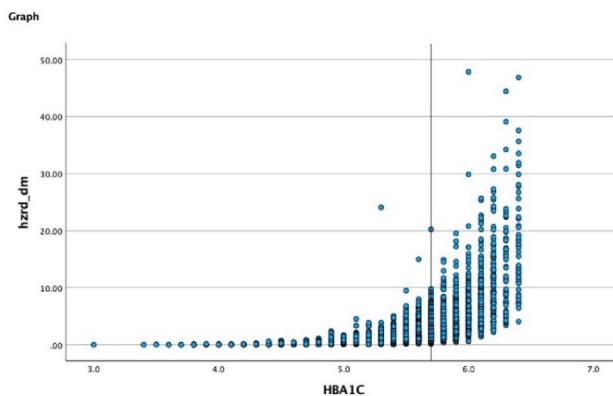


Fig. 2. Scatter plot showing the cumulative prevalence of prediabetes and diabetes with age.

- The model of prediction of progression from non-DM to DM derived from this study was excellent and would support the identification of high-risk patients as a tool for risk stratification, thereby facilitating personalized preventive strategies. The high c-statistic value suggests that our model has excellent discriminatory power in distinguishing between individuals who will develop diabetes mellitus (DM) and those who will not. This level of accuracy is particularly significant in the context of diabetes, where early identification of individuals at risk is crucial for targeting preventive measures. Compared to the commonly used diabetes prediction model, the American Diabetes Association's Diabetes Risk Score, this study-derived model performed close to it with an AUC of 0.837, compared to the ADA Risk Score of 0.85–0.87²¹. Worth noting that the ADA tools were validated recently in Indonesia and Iran, and the AUC was 0.71 and 0.737, respectively^{22,23}. Another example is the Canadian Diabetes Risk Assessment Questionnaire (CANRISK), which has an AUC of 0.75²⁴. Additionally, there are increasing reports of the use of Machine learning in improving the performance of diabetes prediction tools, which could be a future opportunity for advances in this area^{25,26}.
- This study model's ability to identify a broader range of significant risk factors compared to previous studies may enhance its utility in clinical practice^{27,28}. Notably, it should facilitate a holistic approach to tailor interventions and preventive strategies based on each patient's risk factors. Such a multidimensional approach not only enhances the accuracy of diabetes prediction but also provides valuable insights into the complex interplay of factors contributing to disease development.
- Not surprisingly, advancing age emerged as a significant predictor of diabetes progression, with a 5.1% increase in risk for each one-year increase. Among potentially modifiable risk factors, higher levels of HbA1C, lower levels of HDL, higher BMI, higher DBP, and higher RBS were also associated with increased diabetes risk. These identified risk factors could be targeted through early intervention, focusing on lifestyle choices, including physical activity and dietary choices^{29,30}. Recent studies have suggested that high HDL levels decrease insulin resistance¹⁶. In addition, HDL is known to have anti-inflammatory properties, which may reduce chronic inflammation, which is often thought to lead to insulin resistance³¹.

The high predictive value of HbA1C alone highlights the extent to which DM constitutes a chronic progressive disorder. It also highlights how to monitor this progression, as measuring HbA1C is a valid, simple test with minimal day-to-day fluctuation. It obviates a requirement for prior fasting and has superior predictive value compared to random blood glucose (RBG)^{32,33}.

Another risk factor is random blood glucose (RBG). A single RBG ≥ 100 mg/dL was suggested as more strongly associated with undiagnosed diabetes, similar to this study. In fact, the cutoff value for the best sensitivity and specificity to detect DM in this study was 98, similar to their result, supporting the use of abnormal RBG values as a risk factor for diabetes that should be considered in screening guidelines³⁴.

In this study, we found that high DBP carries a much higher risk of developing diabetes compared to high SBP. Other studies have linked both SBP and DBP to the progression of DM³⁵. Nevertheless, other studies reported that insulin resistance (IR) is a risk factor for prehypertension and hypertension, and since IR is a state preceding diabetes, DBP could be a result of IR and not a risk factor for diabetes³⁶. Insulin has a peripheral vasodilator, has an anti-natriuretic action in the distal renal tubules, and increases the activation of the renin–angiotensin–aldosterone system. These actions result in increased vasoconstriction and increased total circulating plasma volume, both of which play crucial roles in the pathophysiology of hypertension. This relationship requires further investigation to assess if DBP is a risk factor or an outcome of IR, which was not among the baseline variables in this study. This knowledge is important and will contribute to other research investigating whether the risk of diabetes can be modified by altering the identified risk factors.

Smoking increases the risk of DM by altering the body composition, insulin sensitivity, and pancreatic β -cell function³⁷. This should add another item to the long list of arguments for healthcare professionals to address smoking prevention and cessation in their patients. Furthermore, the onset at a younger age was found to be associated with increased risk of worse cardiovascular outcomes³⁸. This should urge healthcare professionals to focus on the younger age group for prevention and management options, as effective strategies already exist.

A higher level of eGFR is surprisingly a predictor of DM. This may suggest early renal complications of hyperglycemia, causing hyperfiltration³⁹. No study has identified a higher eGFR percentile as a risk factor for diabetes, and this study is the first to demonstrate such a relationship. Although studies have pointed to the pathogenic and prognostic significance of glomerular hyperfiltration in the development and progression of diabetic kidney diseases³⁹, only cross-sectional studies have shown an association between renal hyperfiltration and higher HbA1C levels, with no longitudinal studies investigating possible etiological factors⁴⁰. Adding to the complexity in this area is the lack of consensus on the definition of renal hyperfiltration and its absence from clinical guidelines, despite increasing reports of its prognostic significance for mortality and metabolic and cardiovascular diseases^{41,42}. This contributes to the challenges in determining potential mechanisms and warrants further investigation.

- The high prevalence of pre-diabetes, particularly among younger age groups, is a significant concern, with 1 in 5 individuals aged 18 exhibiting pre-diabetic status. This is higher than the prevalence in the United States, which was 11.1% among adolescents and 15.8% among young adults^{33,43,44}. This underscores the importance of targeted preventive strategies, as early intervention during the pre-diabetic stage can significantly mitigate the risk of progression to diabetes. Over 12 years, approximately half of pre-diabetic individuals maintained their status, similar to Paprott et al., study⁴⁵. Only 14.1% of the study subjects transitioned to pre-diabetes from a normal glycemic state. These findings highlight the dynamic nature of pre-diabetes and the potential for intervention to influence disease trajectories^{46,47}. Additionally, Olson et al., compared HbA1C and oral glucose tolerance tests (OGTT), and the prevalence was underestimated with HbA1C, suggesting a limitation justifying future research³³.

The drop in the prevalence of pre-DM later in life is probably due to progression to DM or reverting to normal glycemia. The former is more likely, as DM prevalence in relation to age has a similar trend. Also, the drop in the prevalence of DM later in life may be due to a higher-risk population getting older, replacing the older population. Older adults live healthier lives, engage in more physical activity, and have healthier diets. Another possibility is increased mortality among diabetics, but this is not confirmed by any study^{47–49}.

The data collected in this study enabled the evaluation of potential risk factors, which had not been previously assessed in such a large cohort over a long duration of follow-up. Nevertheless, several limitations must be acknowledged. Firstly, the study's retrospective design may introduce bias and might limit the generalizability of the findings. Additionally, the reliance on electronic health records for data collection may lead to incomplete or unstandardized information. Moreover, the study's focus on the Emirate of Abu Dhabi, UAE, may limit its relevance for other populations with different demographic and socio-economic profiles. Although this study contributes to filling a knowledge gap on diabetes risk factors in the region, particularly in the UAE, future studies that include other ethnicities, social determinants of health, and a prospective design will add to the understanding of possible understudied risk factors.

Conclusion

This study provides critical insights into the incidence and prediction of diabetes in the Emirate of Abu Dhabi, UAE, highlighting the urgent need for comprehensive public health interventions. By addressing the identified risk factors and leveraging predictive modeling, clinicians and policymakers can work towards mitigating the impact of the diabetes epidemic and enhancing health outcomes in the region. However, further research is needed to validate our findings and investigate additional factors that contribute to diabetes risk and progression.

Data availability

The data that support the findings of this study cannot be shared openly due to restrictions from the institution, Seha Clinics. Data availability is restricted due to institution policies. Latifa Baynouna Alketbi (latifa.moham-mad@gmail.com) to be contacted regarding this request.

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Author contributions

LBK and NN conceptualized and analyzed data. LBK, MS, RK, MD, NA wrote the manuscript; all other co-authors collected data and reviewed the manuscript. All authors have read and approved the final manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Ethical approval and consent to participate

The study was approved by the Al Ain Human Ethics Committee, approval number 13/58, and Ambulatory Healthcare Services IRB 19-2022. All methods were carried out under relevant guidelines and regulations. The authors confirm that the study was conducted in accordance with the Helsinki Declaration.

Informed consent

Informed consent was waived by the the Al Ain Human Ethics Committee and Ambulatory Healthcare Services IRB as the study was designed for retrospective data gathered as part of patient care and anonymized at analysis.

Additional information

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