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PREVALENCE, RISK DETERMINANTS, AND COMPLICATION BURDEN OF TYPE 2 DIABETES MELLITUS AMONG ADULTS IN SAUDI ARABIA: A SYSTEMATIC REVIEW AND MULTILEVEL META-ANALYSIS

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Abstract

Background: Saudi Arabia is among the countries with the highest burden of type 2 diabetes mellitus (T2DM), yet national estimates are fragmented, derived from heterogeneous sampling frames, and rarely stratified by complication status or by region. Objective: To synthesise the prevalence of T2DM, prediabetes, and undiagnosed diabetes among Saudi adults, quantify the association of modifiable and non-modifiable risk factors, and estimate the burden of microvascular and macrovascular complications. Methods: Following PRISMA 2020 and MOOSE guidance, we will search MEDLINE, Embase, Scopus, Web of Science, and regional databases for population-based and registry-based studies published between 2000 and 2024. Risk of bias will be appraised with the Hoy tool and certainty of evidence with GRADE. Pooled proportions will be derived using random-effects models with Freeman-Tukey double-arcsine transformation, and heterogeneity will be quantified using I^2 and 95% prediction intervals. Meta-regression will examine study year, sex, region, diagnostic criteria, and sampling method. Results: [Insert number of studies, pooled prevalence, and pooled odds ratios after analysis.] Conclusions: By integrating a multilevel determinant framework with complication-stratified estimation and a pre-specified quantification of between-study heterogeneity, this review aims to provide the first methodologically harmonised national benchmark for T2DM in the Kingdom, informing screening policy and resource allocation under Saudi Vision 2030.

Keywords: *Type 2 diabetes mellitus; prevalence; risk factors; diabetic complications; Saudi Arabia; meta-analysis*

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Introduction

Background and context

Diabetes is among the fastest-growing chronic conditions worldwide. The International Diabetes Federation estimated that diabetes affected roughly one in ten adults globally in 2021, with the Middle East and North Africa region projected to experience the steepest proportional increase by 2045 (Sun et al., 2022). The Global Burden of Disease 2021 analysis projects continued growth in prevalence to 2050, driven predominantly by T2DM (Ong et al., 2023). Saudi Arabia exemplifies this trajectory. Rapid economic transition over the past five decades has been accompanied by reduced physical activity, energy-dense diets, and high rates of obesity

(Althumiri et al., 2021; Memish et al., 2014). These factors act on a population with a high background of consanguinity and a plausible genetic susceptibility.

Early national surveys reported that nearly a quarter of adults aged 30–70 years had diabetes (Al-Nozha et al., 2004), and the later SAUDI-DM study reported comparable or higher figures (Al-Rubeaan et al., 2015a). Subsequent smaller studies have produced estimates that vary widely, reflecting differences in diagnostic criteria, age ranges, and sampling strategies (Aldossari et al., 2018; Alotaibi et al., 2017).

Research gap

Three limitations constrain the existing evidence:

1. **Methodological heterogeneity is described but rarely quantified.** Earlier reviews (Al Dawish et al., 2016; Alotaibi et al., 2017; Meo, 2016) are largely narrative and do not pool estimates or partition heterogeneity attributable to diagnostic criteria (fasting glucose versus HbA1c versus self-report).
2. **Complications are analysed in isolation.** Registry-based reports describe retinopathy, nephropathy, and foot disease separately (Al-Rubeaan et al., 2014; Al-Rubeaan et al., 2015b; Al-Rubeaan et al., 2015c), without a unified, complication-stratified synthesis or attention to diabetes duration as a confounder.
3. **Risk factors are treated as a flat list.** Few studies place determinants within an explicit multilevel framework that separates individual, behavioural, and structural drivers.

Objectives and research questions

Objective: To produce a harmonised national synthesis of T2DM epidemiology in Saudi Arabia.

- **RQ1:** What is the pooled prevalence of diagnosed T2DM, undiagnosed diabetes, and prediabetes among Saudi adults, and how has it changed since 2000?
- **RQ2:** Which risk factors are most strongly associated with T2DM, and does their effect differ by sex and region?
- **RQ3:** What is the pooled prevalence of microvascular and macrovascular complications among adults with T2DM?
- **RQ4:** How much between-study heterogeneity is explained by diagnostic criteria, sampling frame, and calendar period?

Significance

The review will provide policymakers with a methodologically transparent estimate, identify under-studied regions and populations, and supply parameters for health-economic models, an area where cost estimates already exist but rest on uncertain prevalence inputs (Alhowaish, 2013).

Literature Review

Prevalence Studies

Population-based surveys form the backbone of the evidence. The Saudi Arabian national survey reported a diabetes prevalence of 23.7% among those aged 30–70 years, with higher rates in urban settings (Al-Nozha et al., 2004). The SAUDI-DM study later documented abnormal glucose metabolism across a large national sample (Al-Rubeaan et al., 2015a), and the Saudi Health Interview Survey characterised diabetes and related risks in the 2010s (El Bcheraoui et al., 2014). Male-focused work reported both diabetes and prediabetes burdens (Aldossari et al., 2018).

Critical appraisal. These studies differ in age bands (30–70 years versus 15 years and above), in whether prediabetes was defined by fasting glucose, 2-hour glucose, or HbA1c, and in whether estimates are age-standardised. Direct comparison is therefore unsafe, and apparent secular trends may partly reflect measurement artefact. Modelling studies (Al-Quwaidhi et al., 2014a; 2014b) offer projections but depend on the quality of the underlying inputs.

Risk factors

Obesity is consistently identified as the leading modifiable factor (Althumiri et al., 2021; Memish

et al., 2014), alongside hypertension (El Bcheraoui et al., 2014b), physical inactivity, and age. Regional reviews of the Gulf Cooperation Council highlight shared drivers and shared data limitations (Aljulifi, 2021). Global syntheses emphasise gene-environment interplay (Zheng et al., 2018).

Critical appraisal. Most Saudi studies report crude or minimally adjusted associations. Dietary pattern, sleep, socioeconomic position, and family history are inconsistently measured, limiting causal interpretation.

Complications

Registry analyses from the Saudi National Diabetes Registry quantify retinopathy (Al-Rubeaan et al., 2015b), nephropathy (Al-Rubeaan et al., 2014), and foot complications (Al-Rubeaan et al., 2015c) and associate them with duration, glycaemic control, and hypertension.

Critical appraisal. Registry populations are drawn from care-seeking patients and may over-represent severe or long-standing disease. Absence of screening-programme denominators prevents estimation of true population-level complication rates.

Methodological and theoretical advances

Prevalence meta-analysis has matured considerably. Guidance on reviews of prevalence data (Munn et al., 2015), double-arcsine and logit approaches (Barendregt et al., 2013), prediction intervals (IntHout et al., 2014), and the Hoy risk-of-bias tool (Hoy et al., 2012) now permit rigorous synthesis. Concurrently, data-driven subphenotyping has shown that adult-onset diabetes is not a single entity (Ahlqvist et al., 2018), and precision-medicine consensus calls for population-specific evidence (Tobias et al., 2023).

How this study advances the field

This review contributes by (i) pooling rather than narratively listing estimates, (ii) partitioning heterogeneity by diagnostic criterion, (iii) jointly synthesising complications with duration-adjusted meta-regression, and (iv) organising determinants within a multilevel framework (Section 5.2).

Methodology

Design and justification

A systematic review and meta-analysis of observational studies is the most defensible design for resolving discordant estimates across heterogeneous sources. It follows PRISMA 2020 (Page et al., 2021) and MOOSE (Stroup et al., 2000), and the protocol will be registered on PROSPERO.

Conceptual framework

Determinants are organised using the **Dahlgren-Whitehead "rainbow" model** (Dahlgren & Whitehead, 1991), extended to four tiers:

Tier	Examples extracted
Individual (non-modifiable)	Age, sex, family history, consanguinity
Behavioural	Physical inactivity, diet, smoking, sleep
Clinical/metabolic	BMI, waist circumference, hypertension, dyslipidaemia
Structural	Region, urban/rural residence, education, income, healthcare access

This structure lets us test whether associations are attenuated after adjustment for upstream factors, and it echoes Rothman's sufficient-component-cause view in which diabetes arises from multiple interacting causes (Rothman, 1976).

Eligibility (PECOS)

- **Population:** Adults (≥18 years) resident in Saudi Arabia
- **Exposure/outcome:** T2DM, prediabetes, undiagnosed diabetes, or complications
- **Comparator:** Adults without diabetes (for risk-factor analyses)
- **Study types:** Population-based cross-sectional surveys, cohort studies, and registry

analyses

- **Exclusions:** Hospital convenience samples under 300 participants, type 1 or gestational diabetes only, non-Saudi expatriate-only samples, duplicate publications

Search strategy

MEDLINE, Embase, Scopus, Web of Science, and Saudi Digital Library/regional indexes, from January 2000 to December 2024. Example MEDLINE string: *("diabetes mellitus, type 2"[MeSH] OR "diabet*"[tiab]) AND (prevalence OR incidence OR "risk factors" OR complications) AND ("Saudi Arabia"[MeSH] OR Saudi[tiab])*. Reference lists will be hand-searched.

Screening and extraction

Two reviewers will independently screen and extract data, with disagreements resolved by a third. Extracted variables: sampling frame, sample size, age range, diagnostic criterion (ADA, 2024), diabetes duration, region, and adjusted effect estimates.

Quality and certainty assessment

Risk of bias will be rated using the Hoy tool (Hoy et al., 2012). Certainty of evidence for each outcome will be graded using GRADE.

Statistical analysis

Analyses will use R (*metafor*; Viechtbauer, 2010).

Pooled prevalence. For study *i* with x_i cases among n_i, the Freeman-Tukey double-arcsine transform is:

$$y_i = \arcsin\left(\sqrt{\frac{x_i}{n_i + 1}}\right) + \arcsin\left(\sqrt{\frac{x_i + 1}{n_i + 1}}\right)$$

with variance approximately $1/(n_i + 0.5)$. Under a random-effects model:

$$y_i = \mu + u_i + \varepsilon_i,\ u_i \sim N(0, \tau^2),\ \varepsilon_i \sim N(0, v_i)$$

Pooled values are back-transformed (Barendregt et al., 2013). Between-study variance τ^2 is estimated by restricted maximum likelihood with Hartung-Knapp adjustment (IntHout et al., 2014).

Heterogeneity. Quantified with:

$$I^2 = \max(0, (Q - (k - 1)) / Q) \times 100\%$$

(Higgins & Thompson, 2002; Higgins et al., 2003), and reported alongside the 95% prediction interval, which describes the expected range of true prevalence in a new setting.

Meta-Regression

$$\text{logit}(p_i) = \beta 0 + \beta 1 \cdot \text{Year}_i + \beta 2 \cdot \text{Criterion}_i + \beta 3 \cdot \text{Region}_i + \beta 4 \cdot \text{Sex}_i + \beta 5 \cdot \text{MeanAge}_i + \ldots$$

Risk-factor synthesis. Adjusted odds ratios will be pooled on the log scale using inverse-variance random-effects, with separate pooling of crude and adjusted estimates.

Complications. Pooled with duration-adjusted meta-regression to address the confounding of complication prevalence by disease duration.

Publication bias and sensitivity. Funnel plots and Egger's test (Egger et al., 1997) when $k \geq 10$, leave-one-out analysis, and restriction to low-risk-of-bias studies.

Reporting. Observational reporting follows STROBE principles (von Elm et al., 2007).

Optional extension: risk-prediction model

If individual-participant data become available, a prediction model can be developed, with sample size justified per Riley et al. (2020) and reported per TRIPOD+AI (Collins et al., 2024). Comparison against established tools such as the Finnish Diabetes Risk Score (Lindström & Tuomilehto, 2003) is suggested.

Results (framework to populate)

No data are reported here because the analysis has not been run. Replace brackets with your own output.

Study selection. [N records identified; N after de-duplication; N full texts assessed; N included.] Present a PRISMA flow diagram (Figure 1).

Study characteristics (Table 1).

First author, year	Region	Design	n	Age range	Diagnostic criterion	Risk of bias
[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

Pooled prevalence (Table 2).

Outcome	k	Pooled % (95% CI)	I^2	95% prediction interval
T2DM (diagnosed)	[ ]	[ ]	[ ]	[ ]
Undiagnosed diabetes	[ ]	[ ]	[ ]	[ ]
Prediabetes	[ ]	[ ]	[ ]	[ ]

Meta-regression (Table 3). [Report β, 95% CI, and R^2 for year, criterion, region, sex, mean age.] A forest plot (Figure 2) and a regional prevalence map (Figure 3) are recommended.

Risk factors (Table 4). [Pooled crude and adjusted OR for obesity, hypertension, inactivity, family history, consanguinity, smoking, education, urban residence.]

Complications (Table 5). [Pooled prevalence of retinopathy, nephropathy, neuropathy, foot ulcer/amputation, ischaemic heart disease, stroke, with duration-adjusted estimates.]

Sensitivity and bias. [Funnel plot, Egger's p, leave-one-out results, GRADE summary of findings.]

Discussion

Structure to follow once results are available; the prompts below indicate the critical arguments to develop.

Interpretation. Compare the pooled estimate with the early national figure (Al-Nozha et al., 2004) and SAUDI-DM (Al-Rubeaan et al., 2015a). Determine whether apparent secular change survives adjustment for diagnostic criterion. If criterion explains a large share of heterogeneity, argue that previous trend narratives were partly methodological artefacts.

Comparison with literature. Position findings against global and regional estimates (Sun et al., 2022; Ong et al., 2023; NCD Risk Factor Collaboration, 2016) and GCC data (Aljulifi, 2021).

Risk determinants. Discuss whether the effect of obesity is attenuated by structural variables, and whether sex differences are consistent with reported male and female surveys (Aldossari et al., 2018).

Complications. Interpret duration-adjusted estimates and discuss registry selection bias (Al-Rubeaan et al., 2014; 2015b; 2015c). Consider implications for screening intervals.

Implications

- *Policy:* A standardised national surveillance instrument using HbA1c-anchored criteria.
- *Clinical:* Risk-stratified screening, including for undiagnosed diabetes.
- *Research:* Alignment with precision-medicine agendas (Tobias et al., 2023) and exploration of phenotypic clusters (Ahlqvist et al., 2018) in Saudi cohorts.

8. Conclusion

Key findings: [Summarise pooled prevalence, leading risk factors, and complication burden.]

Contributions: This work provides a harmonised, heterogeneity-aware national benchmark, integrates complications within a single synthesis, and embeds determinants in a multilevel framework.

Limitations: Findings are bounded by the quality of primary studies, likely high between-study heterogeneity, limited data for some regions, reliance on aggregate rather than individual data, and potential publication bias.

Future directions: (1) A nationally representative, longitudinal cohort with standardised HbA1c-based diagnosis; (2) genetic and gene-environment studies in a high-consanguinity population; (3) data-driven subphenotyping; (4) validated, locally calibrated risk-prediction tools reported per TRIPOD+AI; and (5) evaluation of Vision 2030 prevention programmes using quasi-experimental designs.

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