Machine learning and translational approaches to personalised care for women with high-risk pregnancies

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

Trinity Term 2026

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Abstract

This thesis examines how machine learning and translational approaches may support more personalised care for women with high-risk pregnancies, with a particular focus on gestational diabetes (GDM), long-term prevention of type 2 diabetes (T2DM), and the use of digital tools to improve continuity of care and frontline maternal healthcare.

First, I conducted a systematic review to assess the methodological quality and clinical readiness of prediction models for adverse outcomes following GDM. This review found that most published models were at high risk of bias and rarely externally validated. Second, I externally validated an existing prognostic model for T2DM complications using a UK cohort of 167,798 women. The model showed moderate discrimination in the validation cohort but poor calibration and overestimation of risk, limiting transportability to a new setting.

In two further studies, I examined postpartum prevention pathways in primary care. This work showed that automated search tools in primary care could improve identification of women eligible for referral to the NHS Diabetes Prevention Programme. However, this translational work also revealed substantial coding gaps between hospital and primary care records, with many women with hospital-recorded GDM lacking a corresponding primary care code. These missing cases were socially patterned and associated with greater future risk of T2DM.

Finally, I explored the development and evaluation of SMART*health* GPT (SHP GPT), a large language model (LLM)-based support tool for community health workers in India. This work showed that LLM-based tools may support frontline maternal healthcare when developed through participatory design, grounded in trusted guidelines, and iteratively refined through expert and user feedback.

Taken together, the studies in this thesis suggest that personalised care in high-risk pregnancy depends not only on improved computational methods, but also on validating them rigorously, engaging intended users throughout development and evaluation, and integrating them into routine care pathways.

Declaration of Originality

This thesis is the result of my own work. Any work done in collaboration has been indicated and my role has been specified. All literature referenced in the process of writing has been cited where relevant.

Declaration of AI use

During the preparation of this thesis, I used ChatGPT only to improve the readability, cohesiveness, and language of my work, as well as to find errors in my code. AI was never used in the analysis or interpretation of data. Following the use of this tool, I always formally reviewed the content for its accuracy and edited it as necessary. All AI use in this thesis complies with university, divisional and departmental guidance. I take full responsibility for all the content of this thesis.

Declaration of Length

This thesis does not exceed the prescribed word limit (50,000 words) set by the Medical Sciences Division. The word count abstract, tables, appendices, and reference list.

Word Count: 42,209

Declaration of Funding

I am grateful to have been funded for my PhD program through the MRC iCase Doctoral Training Program. The funder had no role in developing this research.

Acknowledgements

I would first like thank my supervisors, Dr Jane Hirst , Dr Nerys Astbury, Dr Huiqi Lu, and Dr Lucy Mackillop. Thank you for challenging me to think more critically, for helping me shape this work, and for supporting me through the inevitable uncertainty that comes with research. Jane and the Global Women's Health Team, thank you for your generosity, belief in me, and constant support throughout this PhD.

I am also grateful to the SMART*health* GPT team: Uday Adavi, Ankita Sharma, Neelanjana Das, Dr Huiqi Lu, Zara Small, Sreya Majumdar, Bhaskar Kumar, Renu John, Sridevi Gara, Sudhir Thout Raj, Anne Ferrey, Varun Arora, Dr Devarsetty Praveen, and Dr Jane Hirst. The development of SHP GPT was truly an interdisciplinary effort, and I am grateful to have

learnt from each of you. I would especially like to thank Ankita Sharma, who has been my teammate since my very first day at Oxford. Working alongside you has been one of the greatest gifts of this project, and I am so lucky to call you my friend.

I would also like to acknowledge my industrial supervision team for teaching me the intricacies of industry, for broadening how I think about translation and implementation, and for helping me see the real-world application aspect of research. My thanks also go to Dr Ugochinyere Ukah for her support with the external validation work and for sharing expertise that strengthened this thesis.

And above all, I am grateful for my big Al Ghadban-Nasr family who have believed in me since before I could speak and have always helped me find my voice. Mama, thank you for being the best role model for what a good scientist should be. Baba, thank you for pushing me to reach places you may not always understand, but still encourage me to pursue. Yara and Sama, thank you for always making me laugh and for being proud of me even when you have no idea what I actually do. To my friends, those in Beirut, London, Philly, NYC, Cairo, Oslo and all the other pockets of the world, thank you for carrying me through this journey in ways both big and small. Sukanya, thank you so many for being by my side through it all.

Finally, I want to acknowledge the Arab women who inspired me to focus on women's health. This thesis is, in many ways, shaped by your experiences, your strength, and the inequities that continue to define so much of women's healthcare. I am also mindful that this research is still far from reaching many of the women who most need it. I hope this work is only a small step towards more equitable, responsive, and person-centred care for all.

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List of Abbreviations

AI – Artificial Intelligence
AIRS – Artificial Immune Recognition System
ANOVA – Analysis of Variance
ASHA – Accredited Social Health Activist
AUC – Area Under the Curve
AUROC – Area Under the Receiver Operating Characteristic Curve
BMI – Body Mass Index
CART – Classification and Regression Trees
CDSS – Clinical Decision Support Systems
CENTRAL – Cochrane Central Register of Controlled Trials
CHARMS – Checklist for critical Appraisal and data extraction for systematic Reviews of prediction Modelling Studies
CINAHL – Cumulated Index to Nursing and Allied Health Literature
C-index – Concordance Index
CITL – Calibration-in-the-Large
CPRD – Clinical Practice Research Datalink
C-section – Caesarean Section
CVD – Cardiovascular disease
DCA – Decision Curve Analysis
DPP – Diabetes Prevention Programme
EHR – Electronic Health Records
EMBASE – Excerpta Medica Database
EMMOI – English Maternal Morbidity Outcome Indicator
EPV – Events Per Variable
FAQs – Frequently Asked Questions
FIGO – International Federation of Gynaecology and Obstetrics
FPG – Fasting Plasma Glucose
GDM – Gestational Diabetes Mellitus
GP – General Practitioner
GWAS – Genome-Wide Association Studies
HbA1c – Haemoglobin A1c
HDP – Hypertensive Disorders of Pregnancy

HELLP – Haemolysis, Elevated Liver enzymes, and Low Platelets

HES – Hospital Episode Statistics

HL – Hosmer–Lemeshow

HSD – Tukey's Honest Significant Difference

IADPSG – International Association of Diabetes and Pregnancy Study Groups

IFA – Iron-Folic Acid

IFG – Impaired Fasting Glucose

IGR – Impaired Glucose Regulation

IGT – Impaired Glucose Tolerance

IMD – Index of Multiple Deprivation

LASSO – Least Absolute Shrinkage and Selection Operator

LGA – Large for Gestational Age

LLM – Large Language Model

LP – Linear Predictor

LR – Likelihood Ratio

MEDLINE – Medical Literature Analysis and Retrieval System Online

MICE – Multiple Imputation by Chained Equation

MHRA – Medicines and Healthcare products Regulatory Agency

ML – Machine Learning

MMR – Maximal Marginal Relevance

MODY – Maturity-Onset Diabetes of the Young

NDH – Non-Diabetic Hyperglycaemia

NHS – National Health Service

NICE – National Institute for Health and Care Excellence

NICU – Neonatal Intensive Care Unit

NI – No Information

NIHR – National Institute for Health Research

NLP – Natural Language Processing

NR – Not Reported

OGTT – Oral Glucose Tolerance Test

ONS – Office for National Statistics

OPLS-DA – Orthogonal Partial Least Squares Discriminant Analysis

OPCS-4 – Office of Population Censuses and Surveys Classification of Interventions and Procedures

PCOS – Polycystic Ovary Syndrome

PCPNDT Act – Pre-Conception and Pre-Natal Diagnostic Techniques Act

PCR – Primary Care Records

PI – Prognostic Index

PICOTS – Population, Intervention, Comparator, Outcomes, Timing, Setting

PRISMA – PICPreferred Reporting Items for Systematic reviews and Meta-Analyses

PROBAST – Prediction model Risk Of Bias ASsessment Tool

PROSPERO – International Prospective Register of Systematic Reviews

RAG – Retrieval-Augmented Generation

RCS – Restricted Cubic Splines

RECPAM – REcursive Partition and Amalgamation

ROC – Receiver Operating Characteristic

SES – Socioeconomic Status

SGA – Small for Gestational Age

SHP – SMARThealth Pregnancy

SHP GPT – SMARThealth GPT

SMD – Standardised Mean Difference

SMM – Severe Maternal Morbidity

T1DM – Type 1 Diabetes Mellitus

T2DM – Type 2 Diabetes Mellitus

TRIPOD – Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis

WHO – World Health Organisation

CHAPTER 1

Introduction

1. CHAPTER 1: Introduction

1.1. Maternal health and inequities in pregnancy

Pregnancy is a critical period in the life course of both mother and child. It is characterised by rapid biological, physiological, and psychological change in the mother, while also being a highly sensitive developmental window for the fetus. Complications during pregnancy can affect birth outcomes but also influence longer-term maternal and child health trajectory (1). At the same time, pregnancy provides an opportunity for prevention and risk reduction, as women may be particularly receptive to health promotion during this period (2,3).

Marked inequities in maternal health persist across and within countries. The burden of maternal morbidity and mortality is distributed unequally across the globe, with sub-Saharan Africa and South Asia bearing a disproportionate share of the global burden. A multi-country prospective cohort study including 278,186 pregnancies across 11 study sites found that the maternal mortality ratios (MMR) were 351 per 100,000 livebirths and 336 per 100,000 livebirths in sub-Saharan Africa and south Asia, respectively (4). In comparison, most high-income countries have MMRs between 3 to 12 per 100,000 livebirths (5). Morbidity is similarly unequally distributed (5,6).

Inequalities are also evident within countries. For example, in the UK, persistent disparities in both maternal mortality and severe maternal morbidity (SMM) are seen by ethnicity and deprivation. Women of Black ethnicity are at significantly increased risk of maternal mortality compared to women of white ethnicity, with the greatest risk being for women of Caribbean descent (7). Additionally, when compared with women in the least deprived quantile, women in the most deprived quintile have a 13% higher odds of SMM (8).

1.2. High-risk pregnancies and their impact on maternal and fetal health

High risk pregnancies are a heterogeneous group of conditions that increase the risk of adverse maternal and fetal outcomes relative to the general obstetric population. There are several factors that can make a pregnancy high risk. Risk may arise from existing health conditions, such as hypertension (9), diabetes (10), renal disease (11) and polycystic ovary syndrome (PCOS) (12). Demographic factors may also contribute such as advanced maternal age, which has been associated with higher risks of pregnancy-related disorders including

gestational diabetes mellitus (GDM), gestational hypertension, pregnancy loss and delivery complications (13). In addition, lifestyle factors, such as alcohol, tobacco or drug use, can affect placental function, fetal growth and pregnancy outcomes (14–16). Finally, conditions of pregnancy, such as preeclampsia (17) or GDM (18), can make a pregnancy high-risk. Among these conditions, GDM is a focus of this thesis and is examined across several chapters.

1.2.1. GDM definition

GDM is glucose intolerance with first onset or recognition during pregnancy in women who did not have overt diabetes prior to conception. It is one of the most common disorders of pregnancy, with a global prevalence of 14.0%. However, prevalence differs significantly between regions ranging from 7.1% in North America and the Caribbean to 27.6% in the Middle East and North Africa (MENA) (19). With increasing obesity and maternal age worldwide, the incidence of GDM is likely to increase, causing a strain on health systems (20).

GDM is typically defined by elevated blood glucose on an oral glucose tolerance test (OGTT) using pregnancy-specific thresholds. In the UK, National Institute for Health and Care Excellence (NICE) guidance recommends targeted testing of women with risk factors (e.g., obesity, previous GDM, family history) using a 75 g OGTT typically at 24–28 weeks' gestation. Under current NICE criteria, GDM is diagnosed if fasting plasma glucose (FPG) is ≥ 5.6 mmol/L and/or the 2-hour value is ≥ 7.8 mmol/L on this 75 g OGTT (21). Hyperglycaemia first detected on an OGTT during pregnancy may not always represent true GDM but may instead reflect previously undiagnosed overt T2DM. NICE recommends measuring Haemoglobin A1c (HbA1c) at the time of GDM diagnosis to help identify women who may actually have pre-existing T2DM (22).

Selective screening based on recognised risk factors may fail to identify some women who develop GDM but are not offered testing. In one observational cohort, selective screening would have missed one-sixth of GDM cases identified through universal screening. Although these missed cases appeared metabolically milder, with lower fasting glucose and less need for insulin, they were still part of the spectrum of pregnancy-related dysglycaemia and would have remained undiagnosed under the NICE criteria (23). Additionally, the narrower

diagnostic criteria may exclude women who have meaningful hyperglycaemia and adverse pregnancy risk. In an analysis comparing NICE criteria with IADPSG (International Association of Diabetes in Pregnancy Study Group), 59.1% of women identified as having GDM by IADPSG criteria would not have been classified as GDM using NICE criteria (24). Yet, these women still showed evidence of persistent hyperglycaemia and similar rates of pregnancy complications. This highlights how the screening strategy and diagnostic thresholds used can influence which women are classified as having GDM.

1.2.2. Pathophysiology of GDM

GDM develops when the normal insulin resistance of pregnancy is not matched by a sufficient increase in insulin secretion. In late pregnancy, placental hormones and maternal weight gain make the mother's tissues (muscle, liver, fat) less responsive to insulin, which is normally offset by expansion and heightened activity of pancreatic β-cells to keep blood glucose normal. In GDM, this adaptive β-cell response is inadequate, so maternal blood glucose rises. Women who develop GDM may already have chronic, progressive β-cell dysfunction and insulin resistance before pregnancy, but the metabolic stress of gestation unmasks this problem (25–27).

At the molecular level, several interconnected pathways worsen insulin resistance and impair β-cell function. Proinflammatory cytokines such as TNF-α and IL-6 disrupt insulin signalling in muscle and adipose tissue, while chronic low-grade inflammation and oxidative stress damage mitochondria, promoting insulin resistance and β-cell dysfunction. Adipokine imbalances, including low adiponectin and altered leptin, reduce insulin sensitivity and interfere with glucose uptake in skeletal muscle and liver. Placental hormones (such as human placental lactogen) promote lipolysis, increasing circulating free fatty acids that further impair insulin action, and the placenta itself behaves as an immunoendocrine organ, producing mediators that reinforce inflammation and metabolic stress. Genetic and epigenetic variations, as well as altered noncoding RNAs, modulate these pathways and help explain why some women cannot mount an adequate β-cell response to the insulin-resistant state of pregnancy (25–27).

1.2.3. Complications of GDM

Short-term maternal and neonatal complications of GDM

GDM can have adverse short-term consequences on both the mother and the fetus. A meta-analysis of 156 studies with 7,506,061 pregnancies found that women with GDM were at a higher risk of experiencing pregnancy complications and adverse neonatal outcomes (18). In particular, the odds of having a caesarean section (C-section), preterm delivery, macrosomia, large for gestational age babies, neonatal respiratory distress syndrome, neonatal jaundice and admission to a neonatal intensive care unit (NICU) were higher in women with GDM than in women with normoglycemic pregnancies.

Long-term maternal and neonatal complications of GDM

Although most women who are diagnosed with GDM return to normoglycemia after birth, GDM may lead to long-term consequences for both the mother and the child. The odds of developing type 2 diabetes mellitus (T2DM) are significantly higher for women with GDM than without (28–30). A meta-analysis of 20 studies found that women with GDM were 7.4 times as likely to develop T2DM than women with normoglycemic pregnancies (29). Women with GDM are at a significantly higher risk of hypertension, obesity, and cardiovascular morbidity and premature mortality (30–32). Additionally, children exposed to GDM also have a higher risk of obesity, cardiovascular morbidity and glucose intolerance compared to unexposed children (33–37).

1.2.4. Diagnosis and management of GDM

The guidelines developed by NICE in the UK highlight the need for increased antenatal surveillance for women with GDM and recommend clinical review at least every two weeks as well as post-natal follow-up (21). The International Federation of Gynaecology and Obstetrics (FIGO) also recommends long-term follow up (including history and physical examination, blood pressure measurements and screening for diabetes) for all women with GDM starting 6–12 weeks after birth, and periodically thereafter (38).

There are interventions that have the potential to mitigate many GDM-related complications, such as diet advice, lifestyle modification and medications (39–41). However, proper detection, treatment, and follow-up programs are resource-intensive and often face challenges

with poor compliance. With increasing obesity and maternal age, GDM prevalence is likely to increase and continue to pose substantial burden on healthcare systems (20). As such, there is a need to develop effective strategies for risk stratification, resource allocation and personalised management.

1.3. Personalised obstetric care and the role of machine learning

The heterogeneity of pregnancy conditions highlights the limitations of a uniform approach to obstetric care. Traditional clinical pathways do not fully account for the fact that women with the same diagnosis do not all face the same level of risk, nor do they all benefit equally from the same interventions. As a result, one-size-fits-all approaches can lead to an underestimation of risk which may delay intervention or an overestimation of risk which may contribute to unnecessary surveillance, anxiety, and resource use.

Therefore, personalised care emerges as an important goal in obstetric management to improve both care and efficiency (42). Personalised medicine refers to tailoring surveillance, prevention and treatment to the individual woman based on her clinical characteristics, risk profile, and likely response to intervention, rather than relying on uniform thresholds (43). Machine learning has the potential to support this shift in several ways. First, in imaging, AI-enabled systems can automate fetal biometry and anomaly detection with reliability comparable to that of experts. For example, one study found that an AI-assisted model estimated fetal biometrics with an accuracy comparable to that of sonographers (44). Second, in risk stratification, machine-learning models can integrate large volumes of clinical, imaging and biochemical data to generate more individualised estimates of risk (43). Third, these predictions can be translated into clinical decision support systems (CDSS) that embed risk estimates into routine care. A systematic review of maternity CDSS found that their use was associated with improved outcomes overall, despite heterogeneity in CDSS types and outcomes (45). Additionally, two different meta-analyses found that decisions aids for pregnancy reduced decisional conflict and are effective in facilitating shared decision making in clinical practice (46,47). CDSS are not replacements for clinical judgements, but they can augment decision-making by providing more individualised risk estimates.

However, the promise of personalised medicine lies not only in a tool's computational precision but also in its ability to be integrated into real healthcare settings and to

demonstrate clinical utility. This thesis focuses on prediction models, automated searches and large language models (LLMs) as approaches with potential to support personalised obstetric care for high-risk pregnancies.

1.3.1. Clinical prediction models

Clinical prediction models have seen an increased focus in the medical field, including in obstetrics, as tools for estimating the probability of clinically relevant outcomes in individual patients. According to the TRIPOD framework, a multivariable prediction model combines multiple predictors and assigns relative weights to them to estimate a risk (48). Prediction models can be divided into diagnostic and prognostic models (48). Diagnostic prediction models are used to assess the presence or absence of a condition in an individual. They estimate the likelihood that an individual already has a particular condition. Prognostic prediction models are used to calculate an individual's risk of developing an outcome of interest over a specific time. They estimate the risk of an outcome occurring in the future.

1.3.2. Automated searches

Automated searches in this thesis refer to structured queries of routinely collected electronic health record (EHR) data to identify patients who meet predefined criteria for follow-up, referral, or intervention. By using coded diagnoses, laboratory results, and demographic information these searches can support proactive population health management and reduce reliance on opportunistic identification. Evidence from a systematic review suggests that EHR can improve population surveillance and preventive care (49). A study evaluating an embedded EHR notification system in primary care found the system to be an efficient alternative to manual chart review (50).

1.3.3. Large language models

LLMs are a more recent form of artificial intelligence designed to generate, summarise, and interpret natural language. LLMs are trained on large corpora of text and can process unstructured language-based information. In health care, this enables them to perform tasks such as answering questions, summarising clinical information, translating complex medical concepts into lay language and supporting communication between patients and clinicians.

1.4. Rationale for the Research

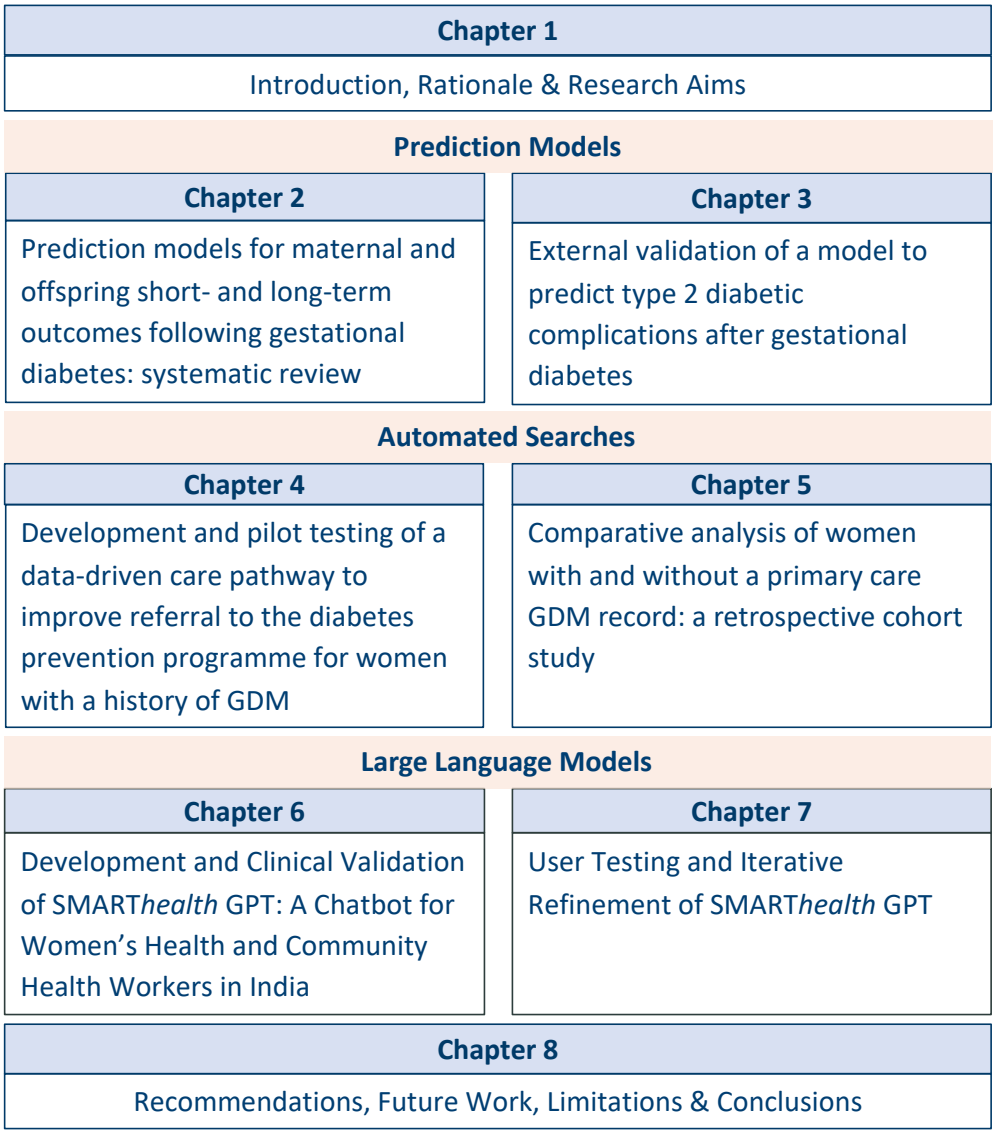
Although personalised care is increasingly recognised as an important goal in obstetrics, the evidence and systems required to support its implementation remain underdeveloped. This thesis addresses these methodological and translational gaps, and investigates how prediction models, data-driven tools and LLMs can contribute to improved care for women with high-risk pregnancies.

1.5. Research Aims and Objectives

The overall aim of this thesis was to investigate how machine learning and translational approaches can be used to support more personalised care for women with high-risk pregnancies. Specifically, the thesis seeks to examine both the methodological foundations and the practical implementation of data-driven tools for risk stratification, clinical referral, and decision support across different healthcare settings.

To address this aim, the thesis had four main objectives. The relationship between the four research objectives and the empirical chapters of the thesis is summarised in Figure 1.1. First, it aimed to systematically evaluate the existing literature on prediction models for short- and long-term maternal and offspring outcomes following GDM, to assess their methodological quality and readiness for clinical use (Chapter 2). Second, it aimed to externally validate an existing prognostic model for long-term diabetes-related complications after GDM using routinely collected UK clinical data, and to assess the model's transportability to a different healthcare system (Chapter 3). Third, it aimed to identify and address translational barriers within postnatal care pathways, including coding and referral gaps, and to explore how data-driven approaches could be used to improve referral to preventive services (Chapters 4 & 5). Fourth, it aimed to develop and clinically evaluate an LLM-based maternal health support tool, and to assess its performance in real-world settings through iterative development and pilot testing (Chapters 6 & 7).

Figure 1.1. Overview of the thesis structure, objectives and methodological components



These objectives were designed to address different stages in the pathway from prediction to implementation: understanding the existing evidence for prediction models, testing the performance of prediction models, translating risk identification into actionable referral systems, and exploring how conversational artificial intelligence (AI) tools might extend evidence-based support at the point of care. In doing so, this thesis seeks to bridge the gap between computational innovation and clinically meaningful, patient-centred application in maternal health.

CHAPTER 2

Prediction models for maternal and offspring short- and long-term outcomes following gestational diabetes: systematic review

2. CHAPTER 2: Prediction models for maternal and offspring short- and long-term outcomes following gestational diabetes: systematic review

2.1. Chapter Overview

This chapter presents a systematic review of prediction models for short- and long-term maternal and offspring outcomes following GDM. Specifically, it outlines the clinical rationale for prognostic modelling in GDM and describes the methods used to identify, appraise and synthesise published prediction model studies. It summarises the characteristics, performance, risk of bias and applicability of existing models. It also examines the methodological limitations in the current literature and considers the implications of these findings for future model development, validation and clinical implementation.

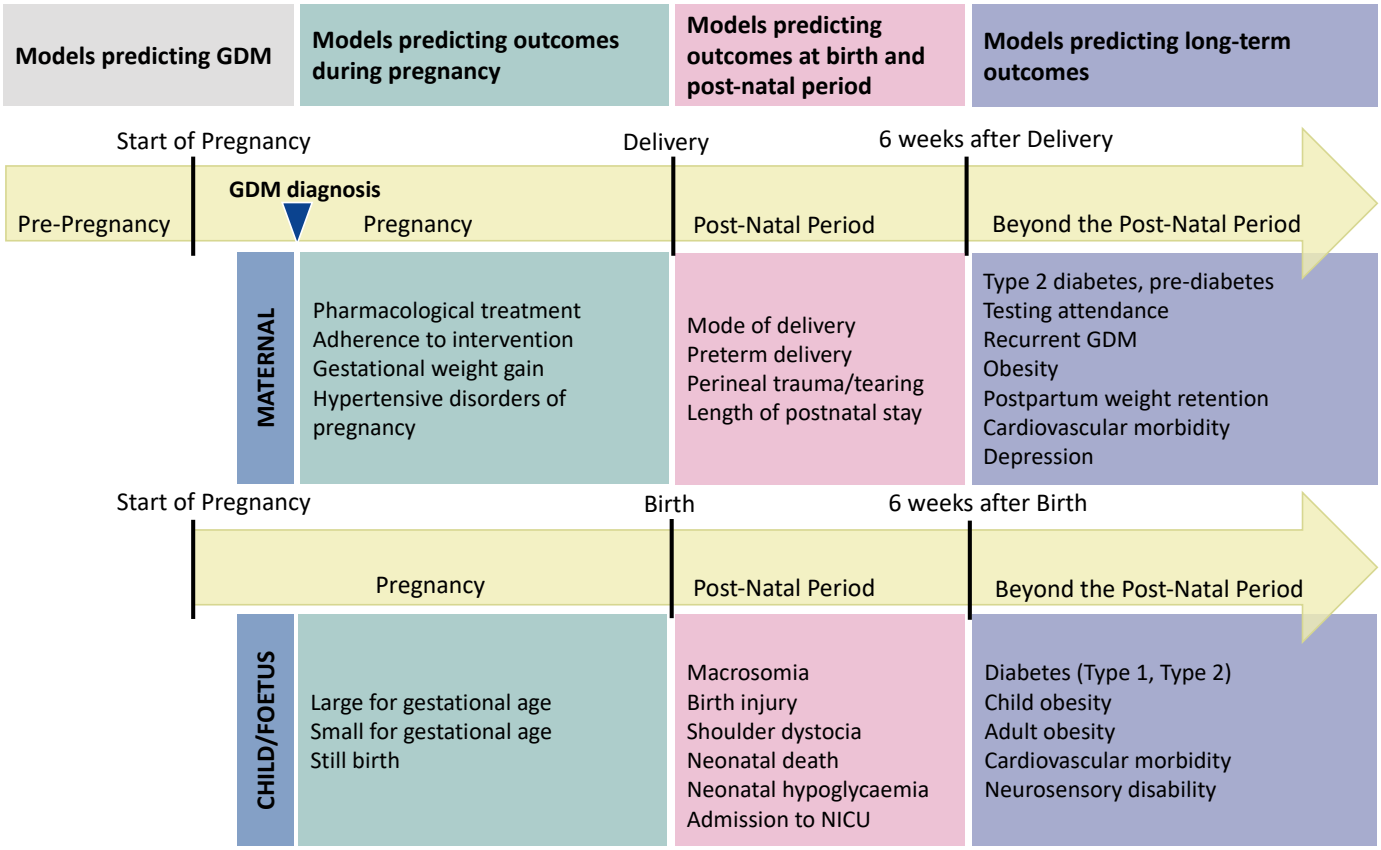
2.2. Background and Rationale

In recent years, researchers have increasingly turned to data-driven prediction models combining various factors to estimate an individual's likelihood of developing a specific outcome. Prognostic models can be used at different time points (pre-conception, during pregnancy, at birth and in the post-natal period, and long-term) to predict the risk of developing GDM or the risk of pregnancy, birth and long-term outcomes associated with GDM (Figure 2.1).

Two recent reviews have studied and compared prognostic models for predicting the risk of GDM (51,52). Both found that several published models achieve acceptable discrimination and calibration but vary in quality. Additionally, there has been a systematic review published of five prognostic prediction models for GDM pregnancy and birth outcomes. This review found that the published prediction models for pregnancy outcomes were all at high risk of bias in their development and lacked external validation, thus limiting their clinical utility (53). However, given the fast development in this field, there has been further work since this review was conducted: an initial literature search identified at least five additional papers to be included (54–58). As such, I believe an updated review was justified to include more recent work. To my knowledge, no review has also studied prediction models of long-term GDM outcomes. Therefore, an updated systematic review was needed to investigate existing prognostic models of maternal and child GDM outcomes (short- and long-term) and

inform the future development of prediction models for use in risk stratification and clinical decision making.

Figure 2.1. The use of prediction models at different stages of pregnancy: pre-conception, during pregnancy, at birth and in the post-natal period (6 weeks after delivery), and long-term.



Grey-shaded sections represent models predicting GDM itself; these models were excluded from this systematic review, which focused on models predicting outcomes after GDM.

Note. This figure has been reprinted from Al Ghadban et al., 2025, Figure 1. The use of prediction models at different stages of pregnancy: preconception, during pregnancy, at birth and in the postnatal period, and long-term (59).

2.3. Aims of this Systematic Review

The aim of this systematic review was to critically evaluate published prognostic models for the prediction of short- and long-term outcomes associated with GDM, considering outcomes for both the woman and offspring. This included prognosis model studies without external validation, prognosis model studies with external validation in independent dataset and external model validation studies with or without model updating. This synthesis will inform

whether further testing of existing models is justifiable, or the development of new models is needed before predictive models will make a measurable impact on clinical outcomes.

2.4. Methods

The systematic review was registered on PROSPERO, the International Prospective Register of Systematic Reviews (CRD42023396697) and follows the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement. The completed PRISMA checklist is presented in Appendix 2 (Appendix 2. Supplementary Material for Chapter 2 Supplementary Table 10.1).

2.4.1. PICOTS Framework

The review question and eligibility criteria were formulated with the PICOTS (Population, Intervention, Comparator, Outcomes, Timing, Setting) framework provided by the Checklist for critical Appraisal and data extraction for systematic Reviews of prediction Modelling Studies (CHARMS) (Table 2.1) (28).

Table 2.1. Framing the review aim with PICOTS

PICOTS	
Type of Model	The aim is to review models that predict future events: prognostic models for GDM pregnancy, birth, and long-term outcomes: 1. Prognosis model studies without external validation 2. Prognosis model studies with external validation in independent dataset 3. External model validation studies with or without model updating
Population	Target population in which the prediction models will be used: women with GDM as defined in the included studies.
Intervention (model)	Any prognostic model developed to predict maternal and child GDM outcomes
Comparator	Models were divided based on whether they predict pregnancy, birth, or long-term outcomes; and which specific outcomes. Models in each category are compared to one another when appropriate (such as similar populations and reported performance metrics).
Outcome	Maternal and child outcomes were selected based on outcomes studied in the literature (60) and a core outcome set developed for GDM (61). Due to variations in outcome definitions, outcomes were collected as reported and defined in the included studies.
Timing	Given that some women are diagnosed with GDM early in their pregnancy whereas others are diagnosed later, the timespan of prediction may vary. In general, models predicting pregnancy or birth outcomes evaluated endpoints during the rest of pregnancy, at birth or in the post-natal period. In other words, these models are to be used in the period between diagnosis with GDM until the end of the postnatal period (6 weeks after delivery). On the other hand, models predicting long-term outcomes evaluated endpoints at defined months or years after delivery.
Setting	The intended use of prognostic models is to perform risk stratification in the assessment of pregnant women to inform healthcare professionals' decision making and resource allocation. As such, the models are designed for use in clinical settings.

Note. This table has been reprinted from Al Ghadban et al., 2025, Table 1. Framing the review eligibility criteria with PICOTS (59).

2.4.2. Search strategy

The search strategy was guided by the PICOTS framework and CHARMS with the goal of identifying all prognostic models for the target population, outcomes and setting outlined above. The literature search was conducted using the Excerpta Medica Database (EMBASE),

the Medical Literature Analysis and Retrieval System Online (MEDLINE), Web of Science (core collections), the Cumulated Index to Nursing and Allied Health Literature (CINAHL), and the Cochrane Central Register of Controlled Trials (CENTRAL) databases with key terms related to GDM and predictive models. No restrictions based on language or publication date was included in the strategy. All databases were last searched on September 8th, 2023.

The search strategy was developed with the guidance of a librarian. Additionally, the search filters used were developed based on previously validated search filters (18,62,63). The full search strategies have been published (64–68) and presented in Supplementary File 10.1 (Appendix 2). Forward and backward searching were performed for the studies included to improve the yield of the search strategies. To investigate the potential of publication bias, grey literature (conference abstracts, theses, dissertations, trial registers) were also identified by searching grey literature databases.

2.4.3. Selection criteria

Model development studies with or without validation and external model validation studies with or without model updating were included if they were predicting at least one outcome of interest, as a single endpoint or composite, as defined in the specific studies (Figure 2.1).

I excluded studies reporting models with a single predictor, studies investigating overall prognosis or prognostic factors without model development or validation, studies that included only pre-gestational diabetes or only twin pregnancies and non-original and non-peer-reviewed studies. Studies with both GDM and pre-gestational diabetes women were included only if the models/outcomes are reported separately for women with GDM. There were no restrictions on the type of data used, study design, timing or setting of data collection.

2.4.4. Selection process

The results of the literature search were imported into Covidence, a systematic review management software, for deduplication and screening (69). Title/abstract screening and full

text screening were performed by two independent reviewers (YAG and AS), with a third reviewer (JEH) referred to for conflicts.

2.4.5. Data extraction and critical appraisal

Data extraction was informed by CHARMS (70), and critical appraisal and assessment of applicability was done using the Prediction model Risk Of Bias ASsessment Tool (PROBAST) (71). A template for data extraction and risk of bias assessment in systematic reviews of predictive models informed by CHARMS and PROBAST was used (72).

Specifically, for model development I extracted the following items: study design; outcome definition and measurement; candidate predictors definition, measurement, method of selection; included predictors; sample size; number of events; handling and reporting of missing data; type of model; methods and metrics used for model evaluation. For studies reporting validation, I extracted similar items but also extracted differences between the model development and validation regarding definition and measurement of predictors and outcomes, handling of continuous predictors and methods used to handle missing data.

Data extraction and critical appraisal were performed once for each development and validation of each distinct prediction model in a publication. In a deviation to the published protocol, data extraction and critical appraisal was completed by the lead reviewer (YAG) and verified by a second reviewer (AK, BO, TYL) for all models. Uncertainties were discussed between reviewers and referred to a third (JEH) when an agreement could not be reached.

2.4.6. Data synthesis

A meta-analysis was not applicable given the heterogeneity of studies included and the lack of external validation studies available for any one model. Instead, data was synthesized qualitatively as reported in the protocol, using generated tables from the template of CHARMS and PROBAST (72).

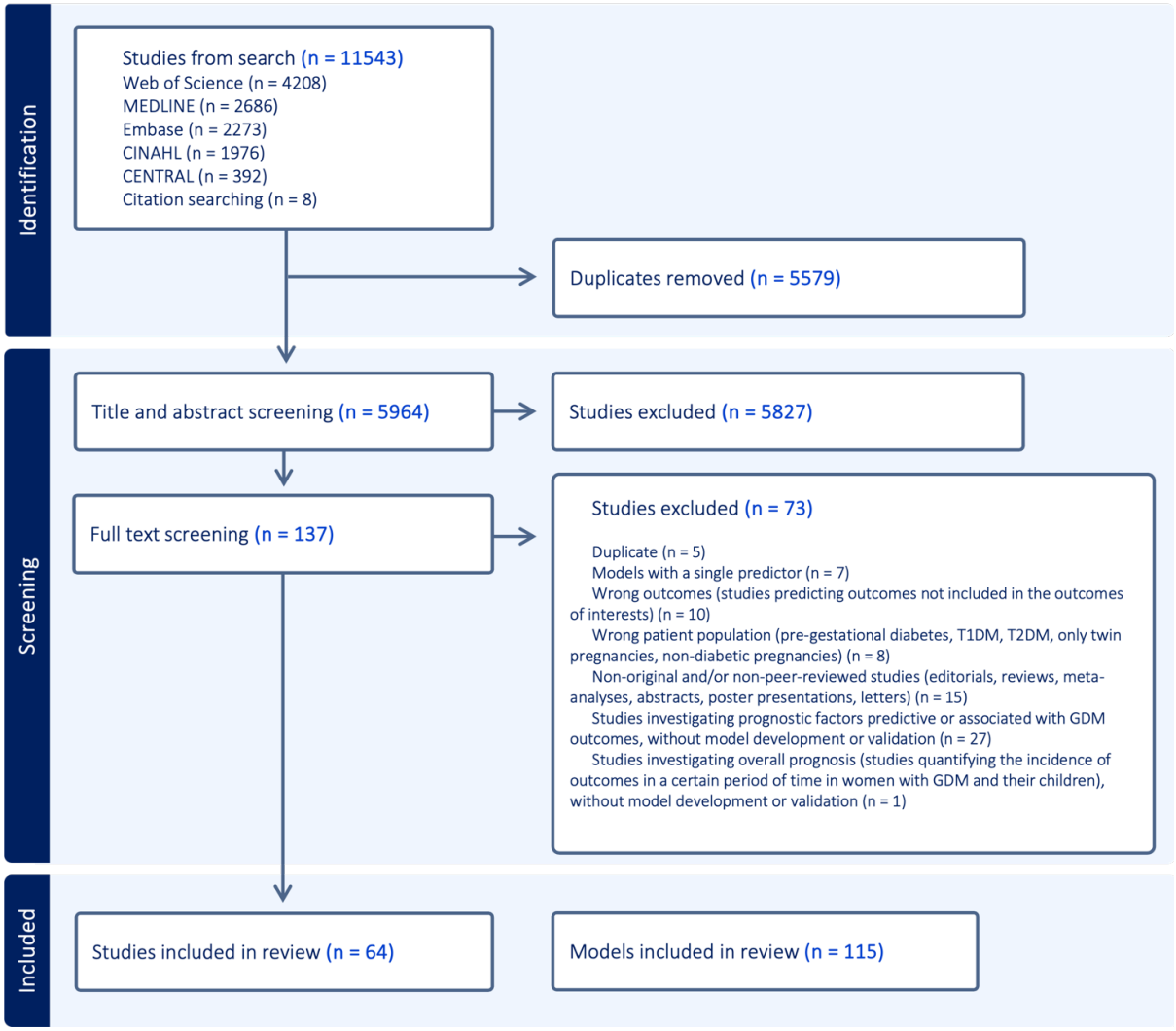
2.5. Results

2.5.1. Study selection

Database searches identified 11,543 records. After deduplication, 5,964 studies were screened by title and abstract, and 137 studies were screened by full text screening. Sixty-four studies, describing 115 models (103 model development and 12 external validation), were included in this review (

Figure 2.2).

Figure 2.2. PRISMA flow diagram of study selection



Note. This figure has been reprinted from Al Ghadban et al., 2025, Figure 2. PRISMA flow diagram of study selection (59).

2.5.2. Included study characteristics

Of the 64 included studies, most were retrospective cohort studies (39/64; 61%), 16 (25%) were prospective cohort studies, four (6%) were nested case-control studies and two (3%) were randomized trials. Forty-one (64%) studies were single centre studies.

Studies were from 24 different countries, with most represented countries (17/24, 71%) were high-income countries according to the World Bank 2023 classification (73). Nearly half of the studies (30/64; 47%) were based in Europe and North America and the Caribbean. A significant proportion of studies (25/64; 39%) originated from the Western Pacific region while fewer than 10% of studies represented South America, Africa, the MENA region, or Southeast Asia. Diagnostic criteria for GDM varied across studies and regions, with the most common being the Carpenter & Coustan criteria (74) and the IADPSG criteria (75).

The overwhelming majority of studies (56/64; 88%) were model development studies without external validation. Seven studies (11%) reported both model development and external validation and only one (2%) study described an external validation study without model development. The validation only article included several authors who were also on the paper that developed the model being evaluated. Thirty-nine (61%) studies reported one model while the remaining 25 (39%) studies reported multiple models. Studies reported more than one model for a range of reasons: external validation, use of different predictors or populations, prediction of different outcomes or time of outcome ascertainment.

Long-term outcomes were most common, representing just under half of all studies (29/64; 45%). Among maternal cardiometabolic complications, outcomes predicted included T2DM in 19 studies (30%), glucose metabolism complications (postpartum glucose intolerance, pre-diabetes, and abnormal glucose tolerance) in eight studies (13%) and lipid metabolism issues in one study (2%). Long-term outcome studies exclusively focused on maternal outcomes with no model predicting long-term child outcomes. Birth outcomes were predicted in 20 studies (31%) with macrosomia predicted in 10 studies. Finally, pregnancy outcomes were predicted in 15 studies (23%) with 14 studies predicting treatment modality. Almost all studies reported single outcomes, with only three studies predicting composite outcomes.

Reporting of participant characteristics varied by study. Around half of the studies reported the number of nulliparous women (35/64; 55%) and the population's ethnic composition (32/64; 50%). Additionally, excluding studies that aimed to predict GDM treatment modality, 29/47 studies (62%) reported GDM treatment. One study included only women on glyburide (76), three studies did not include women receiving any pharmacological treatment (77–79), and in one study, women received no treatment for GDM (including medical nutrition therapy) as both clinicians and patients were blinded to the OGTT results (80).

The full details of included studies are available in Table 2.1.

Table 2.2. Characteristics of the studies included in the systematic review (n=64)

Author, Year	Source of data (sample size)	Enrolment period	Study setting	GDM Diagnosis Criteria	Participant Characteristic[a]			Number of Models (reasons for multiple models)	Outcome(s)
					Ethnicity	Nulliparous	Pharmacological Treatment		
Pregnancy Outcomes									
Phaloprakarn, 2009 (81)	Retrospective cohort (n=813)	Jan 2003 - Feb 2008	Single center; Bangkok, Thailand	Universal screening; Carpenter & Coustan	92% Thai; 8% Southeast Asians	40.0%	34.1%	1	Preeclampsia
Badr, 2022 (82)	Retrospective cohort (n=1,298)	Jan 2018 - Dec 2018	Single center; Brussels, Belgium	IADPSG	85.0% Europe, North Africa, Middle East; 12.0% Sub-Saharan Africa; 2.9% South or East Asia	27.3%	NR	4 (2 different screening used and external validation)	Treatment Modality
Barnes, 2016 (83)	Retrospective cohort (n=4,015)	1992 - 2015	Single center; New South Wales, Australia	Universal screening; ADIPS 1998	33.7% East and South-East Asian; 27.0% Middle Eastern; 22.5% European; 11.5% South Asian; 5.3% African or Pacific Islander	33.0%	32.4%	2 (external validation)	Treatment Modality
Du, 2021 (84)	Retrospective cohort (n=626)	May 2016 - Dec 2019	Single center; Shengjing Hospital, China	IADPSG	100% Chinese	81.5%	30.0%	1	Treatment Modality
Eleftheriades, 2021 (85)	Prospective cohort (n=775)	2010 - 2018	Single center; Athens, Greece	Universal screening; IADPSG	NR	NR	16.8%	2 (external validation)	Treatment Modality
Ford, 2022 (86)	Retrospective cohort (n=2,048)	Jan 2016 - Dec 2017	Single center; Melbourne, Australia	Universal screening; IADPSG	NR	29.5%	31.6%	1	Treatment Modality
Harper, 2016 (76)	Retrospective cohort (n=220)	Jan 2007 - Dec 2013	Single center; Alabama, USA	Universal screening; Carpenter & Coustan	51.4% Black; 12.3% White; 28.6% Hispanic; 41.8% Other	27.7%	100.0%	1	Treatment Modality

Author, Year	Source of data (sample size)	Enrolment period	Study setting	GDM Diagnosis Criteria	Participant Characteristic[a]			Number of Models (reasons for multiple models)	Outcome(s)
					Ethnicity	Nulliparous	Pharmacological Treatment		
Koefoed, 2023 (87)	Retrospective cohort (n=1,104)	2012 - 2017	Single center; Denmark	Selective screening; Danish Guidelines	86.9% Caucasian; 12.1% Afro-Caribbean; 1.1% Other	44.4%	25.5%	1	Treatment Modality
Liao, 2022 (58)	Retrospective cohort (n=27,240)	Jan 2007 - Dec 2016	Multicenter; California, USA	Universal screening; Carpenter & Coustan	22.7% White; 28.1% Hispanic; 4.3% African American; 40.3% Asian/Pacific Islander; 4.6% Other	40.8%	37.8%	8 (different predictors and external validation)	Treatment Modality
Mendez-Figueroa, 2014(88)	Retrospective cohort (n=367)	Jun 2006 - Dec 2011	Single center; Rhode Island, USA	Carpenter & Coustan	23.5% White; 13.7% African American; 15.0% Asian; 39.0% Hispanic; 8.7% Other	18.3%	38.9%	1	Treatment Modality
Much, 2015 (89)	Retrospective cohort (n=856)	1998 - 2010	Single center; Munich, Germany	IADPSG	NR	NR	21.4%	1	Treatment Modality
Souza, 2018 (90)	Retrospective cohort (n=408)	2012 - 2015	Single center; Sao Paulo, Brazil	IADPSG	NR	NR	33.1%	1	Treatment Modality
Velardo, 2021 (91)	Retrospective cohort (1,543)	2014 - 2019	Multicenter; NHS Trusts, UK	Varies by center	NR	NR	NR	1	Treatment Modality
Yerlikaya, 2018 (92)	Retrospective cohort (n=203)	May 2015 - Jan 2017	Single center; Vienna, Austria	Universal screening; IADPSG	NR	27.6%	46.8%	3 (different predictors)	Treatment Modality
Zaccara, 2023 (93)	Retrospective cohort (n=869)	Jan 2012 - Mar 2020	Single center; Sao Paulo, Brazil	Universal screening; IADPSG	NR	NR	16.7%	1	Treatment Modality
Birth Outcomes									

Author, Year	Source of data (sample size)	Enrolment period	Study setting	GDM Diagnosis Criteria	Participant Characteristic[a]			Number of Models (reasons for multiple models)	Outcome(s)
					Ethnicity	Nulliparous	Pharmacological Treatment		
Pintaudi, 2018 (94)	Retrospective cohort (n=2,736)	Jan 2012 - May 2015	Multicenter; Italy	Selective screening; IADPSG	Caucasian 44.8%	45.3%	41.3%	1	Adverse outcomes composite
Cooray, 2022 (54)	Retrospective cohort (n=1,747)	Jul 2017 - Jun 2018	Multicenter; Melbourne, Australia	Universal screening; IADPSG	19.6% Caucasian; 35.3% Southern and Central Asian; 13.8% East Asian; 5.2% African; 3.3% Oceanian not Australian; Other 22.9%	38.2%	36.6%	2 (external validation)	Adverse outcomes composite
Park, 2015 (95)	Retrospective cohort (n=802)	Mar 2001 - Apr 2013	Single center; Seoul, South Korea	Carpenter & Coustan	NR	NR	NR	1	Adverse outcomes composite
Lu, 2022 (56)	Randomized trial (n=155)	Sept 2013 - Jun 2015	Single center; Oxford, UK	IADPSG	NR	NR	NR	2 (different predictors)	Caesarean Delivery
Phaloprakarn, 2020 (81)	Retrospective cohort (n=385)	Jan 2011 - Dec 2014	Single center; Bangkok, Thailand	Universal screening; Carpenter & Coustan	NR	41.6%	12.2%	2 (external validation)	Caesarean Delivery
Ramos, 2023 (96)	Retrospective cohort (n=3570)	Jan 2022 – Mar 2013	Single center; USA	Carpenter & Coustan	62.4% White; 7.2% Black; 5.9% Asian; 24.5 % Other	55.2%	24.9%	1	Caesarean Delivery
Kim, 2022 (97)	Retrospective cohort (n=660)	2006 - 2013	Multicenter; South Korea	Carpenter & Coustan	NR	NR	NR	1	Large for Gestational Age
Kang, 2019 (98)	Retrospective cohort (n=1,891)	Jan 2010 - Dec 2017	Single center; Nantong, China	NR	NR	NR	NR	2 (different predictors)	Macrosomia
Odinokova, 2019 (99)	Prospective cohort (n=220)	2017–2018	Moscow, Russia	IADPSG	100% Caucasian	NR	NR	1	Macrosomia

Author, Year	Source of data (sample size)	Enrolment period	Study setting	GDM Diagnosis Criteria	Participant Characteristic[a]			Number of Models (reasons for multiple models)	Outcome(s)
					Ethnicity	Nulliparous	Pharmacological Treatment		
Sun, 2020 (100)	Prospective cohort (n=64)	Jun 2017 - Apr 2018	Single center; Hangzhou, China	IADPSG	100% Chinese Han	76.4%	NR	1	Macrosomia
Sun, 2023 (101)	Retrospective cohort (n=991)	Nov 2020 – Feb 2022	Single center; Shanxi, China	IADPSG	NR	NR	9.3%	1	Macrosomia
Tomlinson, 2018 (102)	Retrospective cohort (n=275)	Mar 2010 - May 2012	Massachussets, USA	Carpenter & Coustan	82.0% White; 5.0% Black; 12.0% Other	51.0%	NR	1	Macrosomia
Tomlinson, 2021 (103)	Retrospective cohort (n=477)	Jan 2015 - Jun 2018	Perinatal database, St Louis, USA	Carpenter & Coustan	54.0% White; 40.0% Black; 6.0% Other	30.0%	NR	1	Macrosomia
Yuan, 2022 (104)	Unclear (n=40)	Jul 2019 - Jun 2021	Multicenter; Jiangsu, China	IADPSG	NR	NR	NR	1	Macrosomia
Yuan, 2023 (78)	Retrospective cohort (n=88)	Jan 2020 - Jun 2020	Single center; Nanjing, China	IADPSG	100% Han Chinese	70.5%	0%	1	Macrosomia
Zhang, 2023 (79)	Retrospective cohort (n=322)	Oct 2020 - Oct 2021	Single center; Shantou City, China	Universal screening; IADPSG	NR	NR	0%	1	Macrosomia
Zou, 2021 (105)	Retrospective cohort (n=783)	Oct 2019 - Oct 2020	Single center; Qingdao, China	IADPSG	NR	NR	NR	1	Macrosomia
Huang, 2023 (55)	Retrospective cohort (n=564)	Jan 2017 - Jan 2020	Single center; Wehzhou, China	IADPSG	NR	63.5%	10.5%	2 (external validation)	Preterm delivery
Mukherjee, 2023 (106)	Retrospective cohort (n=627)	2015 - 2016	UK	Selective screening; IADPSG	NR	NR	33.2%	7 (different outcomes)	Preterm birth, Hypoglycaemia, Hyperbilirubinemia, NICU,

Author, Year	Source of data (sample size)	Enrolment period	Study setting	GDM Diagnosis Criteria	Participant Characteristic[a]			Number of Models (reasons for multiple models)	Outcome(s)
					Ethnicity	Nulliparous	Pharmacological Treatment		
									Macrosomia, Shoulder dystocia, Composite
McIntyre, 2018 (80)	Prospective cohort (n=1,248)	Jul 2000 - Apr 2006	Single center; South Brisbane, Australia	ADIPS 1991; IADPSG; Carpenter & Coustan; NICE 2015	100% Caucasian	54.5%	NR	6 (different outcomes)	Caesarean delivery, Birth injury, LGA, Adiposity, Hyperinsulinaemia, Hypoglycaemia
Long-term Outcomes									
Jotic, 2023 (77)	Prospective cohort (n=147)	Jan 2017 - Dec 2021	Single center; Serbia	IADPSG	NR	NR	0%	1	Dyslypidemia
Hahn, 2023 (107)	Retrospective cohort (n=159)	Jan 2014 - Sept 2020	Single center; Germany	IADPSG	NR	NR	59.7%	1	GDM Recurrence
Schwartz, 2016 (108)	Retrospective cohort (n=788)	1991 - 2012	Single center;, Israel	Universal screening; Carpenter & Coustan or NDDG	52.8% Jews; 47.2% Arabs	48.5%	34.1%	1	GDM recurrence
Bengtson, 2022 (109)	Prospective cohort (n=203)	Jan 2017 - Jul 2018	Single center; Rhode Island, USA	Carpenter & Coustan	48.3% White; 10.3% Non-Hispanic black; 30.5% Hispanic; 10.8% Other	NR	57.1%	1	Postpartum glucose intolerance
Kondo, 2018 (110)	Retrospective cohort (n=123)	Apr 2012 - Apr 2017	Single center; Yamaguchi-City, Japan	Universal screening; IADPSG	NR	NR	22.0%	3 (different predictors)	Postpartum glucose intolerance
Bartakova, 2021 (111)	Retrospective cohort (n=244)	2011 - 2013	Single center; Czech Republic	Unclear	100% Caucasian	44.3%	37.3%	1	Postpartum glucose intolerance

Author, Year	Source of data (sample size)	Enrolment period	Study setting	GDM Diagnosis Criteria	Participant Characteristic[a]			Number of Models (reasons for multiple models)	Outcome(s)
					Ethnicity	Nulliparous	Pharmacological Treatment		
Pei, 2023 (112)	Prospective cohort (n=133)	Jan 2018 – Dec 2020	NR	IADPSG	NR	NR	NR	1	Impaired glucose tolerance remission
Muche, 2020 (113)	Prospective cohort (n=112)	Mar 2018 - Mar 2019	Multicenter; Gonda, Ethiopia	Universal screening; IADPSG	NR	NR	6.2%	1	Postpartum pre-diabetes
Periyathambi, 2022 (114)	Retrospective cohort (n=607)	Jan 2016 - Dec 2019	Single center; Nuneaton, UK	Selective screening; NICE 2015	79.2% White European ; South Asian 11.1%; Other 9.7%	43.9%	NR	1	Return for testing
Ingram, 2017 (115)	Retrospective cohort (n=165)	Jan 2007 - Jun 2009	Single center; Tasmania	Universal screening; ADIPS 1998	86.6% Caucasian; 4.8% Aboriginal and Torres Strait; 8.5% Other	NR	60.6%	3 (different outcome)	Return for testing, Abnormal glucose tolerance
Barden, 2013 (116)	Prospective cohort (n=150)	1998 - 2001	Multicenter; Perth, Western Australia	ADIPS 1998	74.7% Caucasian; 25.3% Asian/aboriginal/middle-eastern	18.7%	NR	1	Type 2 Diabetes
Lin, 2011 (117)	Retrospective cohort (n=607)	NR	Single center; Taipei, Taiwan	Universal screening; NDDG	NR	NR	NR	1	Type 2 Diabetes
Man, 2021 (118)	Randomized trial (n=317)	1996 - 2001	Multicenter; USA	NR	59.3% Caucasian; 19.9% African American; 17.0% Hispanic; 3.8% Other	NR	33.1%	1	Type 2 Diabetes
Ignell, 2016 (119)	Prospective cohort (n=362)	2003-2005	Multicenter; Skane, Southern Sweden	Universal screening; Modification to WHO 1999	16.0% non-European	NR	9.1%	2 (different population)	Type 2 Diabetes
Allalou, 2016 (120)	Nested case-control (n=244)	Sep 2008 - Dec 2011	Multicenter; California, USA	Carpenter & Coustan	17.2% White; 30.7% Asian; 11.1% Black; 39.3% Hispanic; 1.6% Other	35.2%	46.3%	3 (different predictors)	Type 2 Diabetes
Joglekar, 2021 (121)	Prospective cohort (n=82)	Jun 2003 - Dec 2005	Single center; Australia	ADIPS 1998	NR	NR	48.1%	2 (different predictors)	Type 2 Diabetes

Author, Year	Source of data (sample size)	Enrolment period	Study setting	GDM Diagnosis Criteria	Participant Characteristic[a]			Number of Models (reasons for multiple models)	Outcome(s)
					Ethnicity	Nulliparous	Pharmacological Treatment		
Khan, 2019 (122)	Nested case-control (n=140)	Sept 2008 - Dec 2011	Multicenter; California, USA	Carpenter & Coustan	64.3% Hispanic; 35.7% Asian	23.6%	42.2%	1	Type 2 Diabetes
Kwak, 2013 (123)	Prospective cohort (n=395)	Jan 1996 - Feb 2003	Single center; Seoul, South Korea	Universal screening; NDDG	NR	NR	28.4%	4 (different predictors)	Type 2 Diabetes
Lai, 2020 (124)	Nested case-control (n=337)	Sept 2008 - Dec 2011	Multicenter; California, USA	Carpenter & Coustan	17.9% White; 29.8% Asian; 11.7% Black; 39.4% Hispanic; 1.2% Other	35.2%	46.3%	1	Type 2 Diabetes
Lappas, 2015 (125)	Prospective cohort (n=104)	Jun 2003 - Dec 2005	Single center; Australia	ADIPS 1998	NR	NR	48.1%	3 (different predictors)	Type 2 Diabetes
Lappas, 2016 (126)	Prospective cohort (n=95)	Jun 2003 - Dec 2005	Single center; Australia	ADIPS 1998	NR	NR	51.0%	3 (different predictors)	Type 2 diabetes
Lappas, 2018 (127)	Prospective cohort (n=98)	Jun 2003 - Dec 2005	Single center; Australia	ADIPS 1998	NR	NR	49.5%	3 (different predictors)	Type 2 Diabetes
Zhang, 2021 (128)	Nested case-control (n=216)	Sept 2008 - Dec 2011	Multicenter; California, USA	Carpenter & Coustan	16.2% White; 31.5% Asian; 8.3% Black; 43.1% Hispanic; 0.9% Other	NR	42.6%	1	Type 2 Diabetes
Li, 2018 (129)	Retrospective cohort (n=1,263)	2005 - 2009	Single center; Tianjin, China	Universal screening; WHO 1999	100% Chinese	NR	NR	2 (different time for outcomes)	Type 2 Diabetes
Elnour, 2006 (130)	Unclear (n=165)	Dec 2001 - Jun 2002	Single center; UAE	Universal screening; Carpenter & Coustan	NR	NR	NR	1	Type 2 Diabetes
Kohler, 2016 (131)	Prospective cohort (n=304)	1989 - 1999	Multicenter; Germany	German Diabetes Association	NR	NR	33.5%	1	Type 2 Diabetes

Author, Year	Source of data (sample size)	Enrolment period	Study setting	GDM Diagnosis Criteria	Participant Characteristic[a]			Number of Models (reasons for multiple models)	Outcome(s)
					Ethnicity	Nulliparous	Pharmacological Treatment		
Marozas, 2018 (132)	NR (n=151)	NR	NR	NR	NR	NR	14.4%	2 (different outcomes)	Type 2 Diabetes and Impaired metabolism
Cormier, 2014 (133)	Retrospective cohort (n=214)	Oct 2009 - Aug 2012	Quebec City, Canada	NR	93.6% White	NR	NR	2 (different outcomes)	Type 2 Diabetes and Pre-diabetes
Ukah, 2022 (134)	Retrospective cohort (n=90,143)	Apr 1989 - Mar 2016	Multicenter; Quebec, Canada	Varies by center	NR	60.3%	NR	2 (different time for outcomes)	Type 2 Diabetes complications

[a]When possible, in studies that reported patient characteristics for each sub-group, data was converted to get a value for the complete sample.

Abbreviations: Not Reported (NR); International Association of Diabetes in Pregnancy Study Groups (IADPSG); Australasian Diabetes in Pregnancy Society (ADIPS); National Data Diabetes Group (NDDG); National Institute for Health and Care Excellence (NICE); World Health Organisation (WHO); Oral Glucose Tolerance Test (OGTT); Neonatal Intensive Care Unit (NICU); Large for Gestational Age (LGA)

Note. This figure has been reprinted from Al Ghadban et al., 2025, Table 2. Characteristics of the studies included in the systematic review (n=64) (59).

2.5.3. Sample size

In 93 of 103 developed models (90%), data on the number of events and candidate predictors allowed event-per-variable (EPV) calculations, which ranged from 0.7 to 151.3 with a median of 5.5. Fewer than half (45/93; 48%) of these models met an EPV ≥ 10, and only a third (32/93; 34%) met an EPV ≥ 20. For the 12 validated models, four included fewer than 100 participants with the outcome.

2.5.4. Missing data

An overwhelming majority did not report the number of missing data (93/115; 81%) or the handling of missing data (49/115; 43%). Of the models that reported how missing data was handled, over half (39/66; 59%) used complete-case analysis, 18/66 (27%) used multiple imputation and 5/66 (8%) used single imputation.

2.5.5. Model development

The included studies described 103 developed models with varying model development methods (Table 2.2). The sample size used to develop the prediction models ranged from 40 to 90,143 with a median of 322, and the number of events ranged from 4 to 10289 with a median of 78. Most models used logistic regression (74/103; 72%) and 15 (15/103, 15%) used machine-learning methods. Among the 15 machine learning models, tree-based models were the most common, with six models employing techniques such as decision trees, CART (Classification and Regression Trees), random forest, and RECPAM (REcursive Partition and AMalgamation). One study used a probabilistic model, specifically the Naive Bayes classifier. Two models were ensemble models, utilising a voting meta-algorithm to combine top-performing classifiers. Neural networks were used in two models, applying deep learning techniques to capture complex relationships in GDM-related data. Lastly, specialized methods were used in four studies, including cluster analysis, a filtered classifier, AIRS (Artificial Immune Recognition System), and OPLS-DA (Orthogonal Partial Least Squares Discriminant Analysis) for classification tasks. From the 45 models predicting outcomes determined after months or years of follow up, only 7/45 (16%) models used Cox regression, a survival analysis method which can account for loss to follow up. In the 84 models that used regression-based methods, only nine models (11%) applied shrinkage techniques to alleviate overfitting. Additionally, less than half (35/84; 42%) reported regression

coefficients, and only 20/84 (24%) reported the full model equation including the intercept or baseline survival.

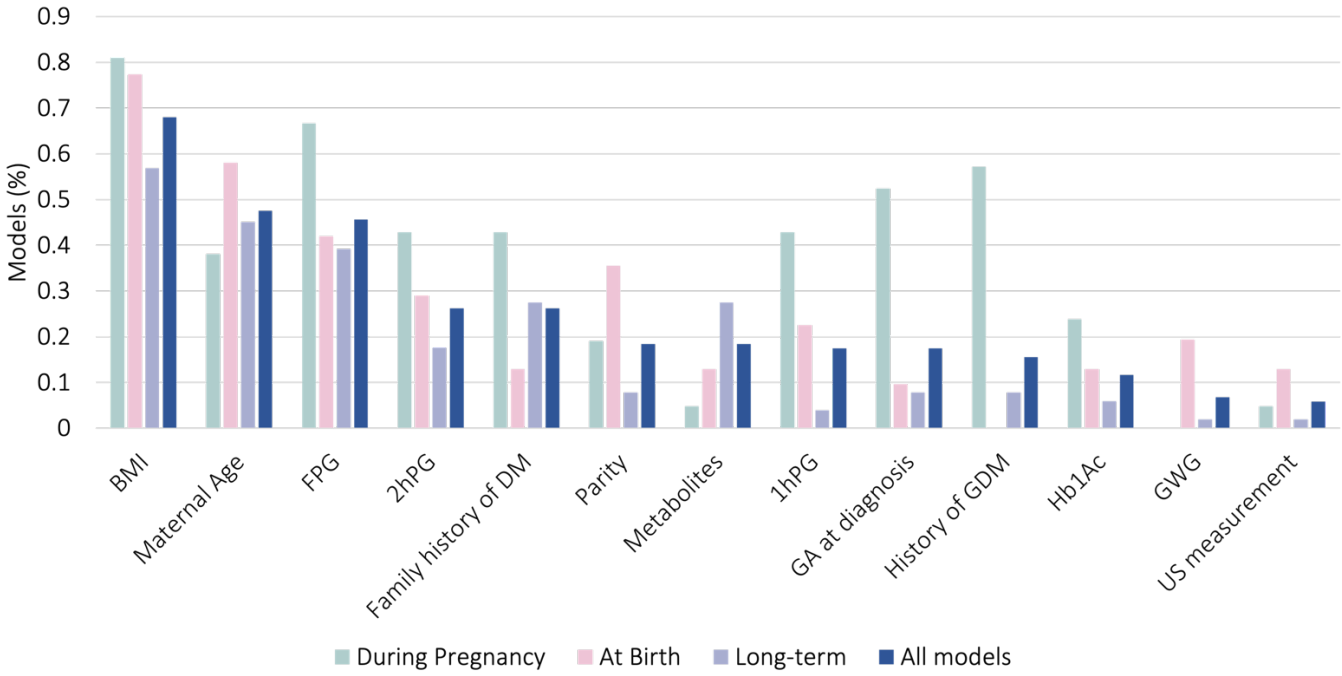
2.5.6. Predictors

In model development, 47/103 (46%) models selected candidate predictors based on univariable associations, while 28/103 (27%) selected candidate predictors based on existing knowledge.

The number of predictors in the model ranged from 2 to 20, with a median of 5. A variety of candidate predictors were selected across models (Figure 2.3). Clinical factors routinely available from standard electronic health records (BMI, age, ethnicity, parity, medical history), and blood glucose measures recorded at or around the time of GDM diagnosis (Hb1Ac, OGTT results) were the most used. However, 29 (28.2%) models also used predictors not typically available in clinical practice, such as omics (proteomics, metabolomics, transcriptomics), genetic factors or digital daily blood glucose readings. The single most commonly used predictor was BMI (body mass index), included in 70 models (68%) followed by maternal age included in 49 models (48%), and FPG included in 47 models (46%) (Figure 2.3).

Studies typically reported the mean, standard deviation, or interquartile range of continuous predictors. Only 10 models (10/103; 10%) reported the range of any continuous predictors. Additionally, only half of models (51/103; 50%) handled continuous variables without categorisation. In 21/27 (78%) of models that reported categorising continuous variables, cut points were chosen by selecting the thresholds that result in the highest predictive performance, rather than by pre-defining thresholds.

Figure 2.3. Bar graph showing the most common predictors included in the development of the models (n=103) by type of model



Abbreviations: Body Mass Index (BMI); Fasting Plasma Glucose (FPG); 2-hour Plasma Glucose (2hPG); 1-hour Plasma Glucose (1hPG); Gestational Age (GA); Gestational Weight Gain (GWG); Ultrasound (US)

Note. This figure has been reprinted from Al Ghadban et al., 2025, Figure 3. Bar graph showing the most common predictors included in the development of the models (n=103) by type of model (59).

2.5.7. Performance metrics

Calibration metrics were reported in 30 models (26%). Among these, 9 models (30%) employed the Hosmer-Lemeshow goodness of fit test. Only one model reported the calibration slope, while 20 included a calibration plot. R^2 values were reported in three models. Discrimination, measured through the C-statistic (area under the ROC curve), was reported in 108 models (94%). Additionally, 60% of models (69/115) presented the receiver operating characteristic (ROC) curve, but only 16% (11/69) labelled cut-off points to determine sensitivity and specificity, while 51% (59/115) reported these metrics. Clinical utility, which assesses the actual usefulness in decision-making, was examined for 10/115 (9%) models using decision curve analysis (DCA), a novel method to calculate the net-benefit of a model in comparison to default strategies such as treating all or none.

2.5.8. Model presentation

Thirty-five models (35/103; 34%) presented an alternative model presentation. Seventeen models (17/103; 16%) were presented as a score system, a simplified format where predictor coefficients are converted to integers and summed together. Eleven models (11/103; 11%) presented their model using a nomogram, a graphical representation which displays the associations between predictors and response in a multivariable model and enables users to estimate the outcome probability for each patient. The remaining models were presented using an online calculator or regression trees. Only 5/35 (14%) models presented both the full model equation and the simplified model.

2.5.9. Model validation

Most models lacked internal or external validation. Of the 103 developed models, 43 (42%) included one form of internal validation. Nine of these used random sample splitting between development and validation, while 34 applied cross-validation or bootstrap methods. External validation was reported in 12 models (12%). Clinical utility was evaluated in 10 models (9%), with DCA applied to assess net benefit.

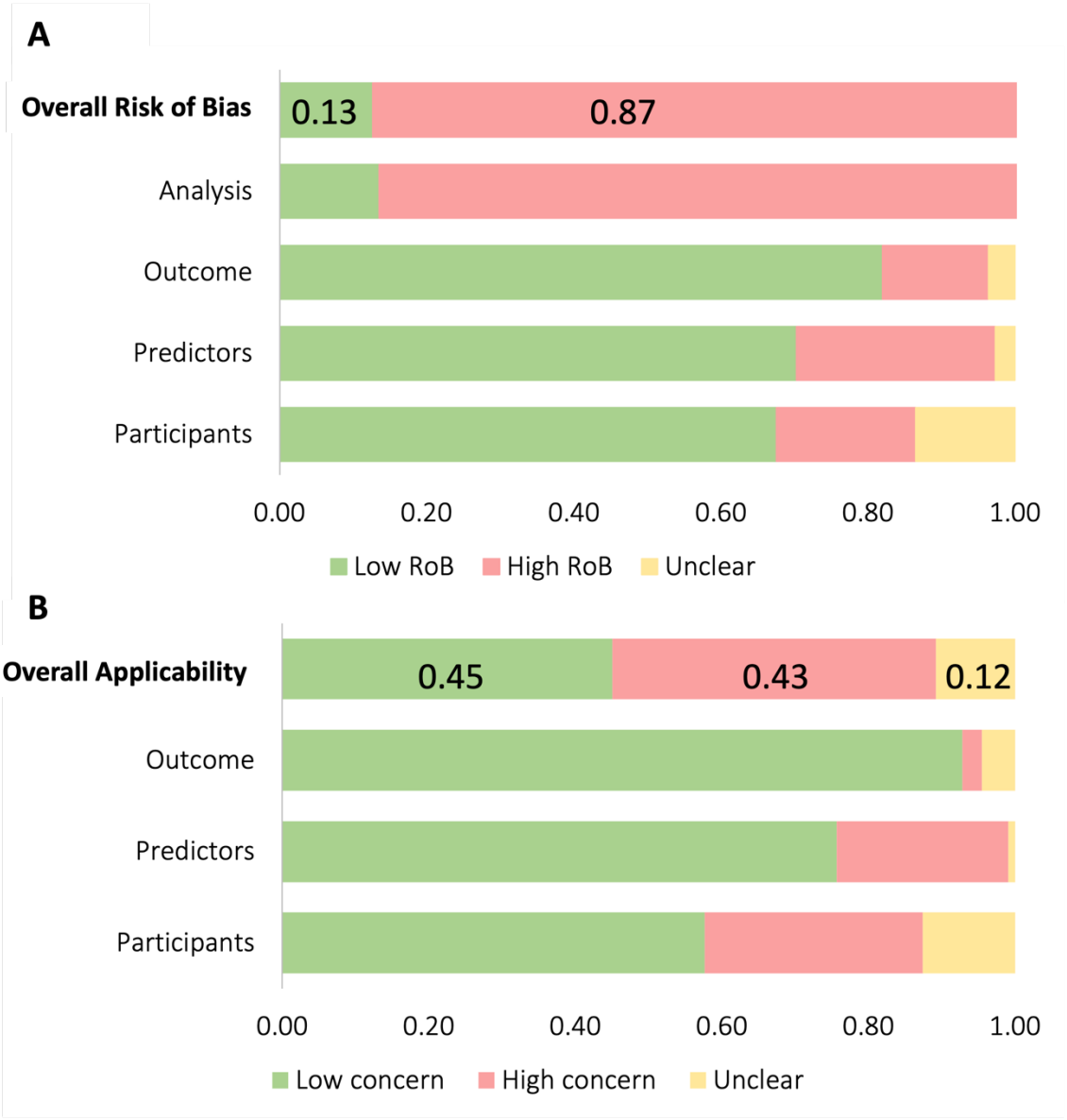
Of the 12 externally validated models, seven had an alternative presentation but it was unclear whether the full model or the alternative model was validated. Nine of these models (9/12; 75%) used temporal validation, evaluating their model in data from the same centre but from a different time-period. Only three models (25%) were validated in an independent sample, and none were validated by independent researchers. All studies reported the sample size used to validate the model (range: 168 to 3234; median: 716) but two studies did not report the number of events. For validation studies that reported the number of events, the median number of events was 368 (range 628 to 1,528). For 10/12 models, the characteristics of both the development and validation cohorts were reported, allowing a comparison of case-mix between the two.

2.5.10. Risk of bias and applicability

Most models (100/115; 87%) had an overall high risk of bias (

Figure 2.4). Low risk of bias was observed across the outcome, predictors, and participants domains; however, 99 models exhibited high risk of bias in how the analysis was performed. Less than half of models (52/115; 45%) were applicable to the research question (Figure 2.4). Supplementary Table 10.3 includes individual PROBAST domain ratings across all development and external validation analyses.

Figure 2.4. Summary of Risk of Bias (A) and Applicability (B) Assessment



Note. This figure has been reprinted from Al Ghadban et al., 2025, Figure 4. Summary of Risk of Bias (A) and Applicability (B) Assessment (59).

2.5.11. Grey literature

I identified 13 conference abstracts relevant to this review (135–147). The findings of six of these abstracts were subsequently published in peer-reviewed articles included in this review (54,83,96,97,118,121). The limited information available in the abstracts hindered my ability to conduct adequate data extraction and critical appraisal. However, with the information available, I found similar methodological issues similar to those in the included models such as inadequate evaluation of calibration, lack of internal validation and small sample sizes.

2.6. Discussion

2.6.1. Summary of findings

This systematic review is the largest review to date of prognostic models which aim to determine the risk of adverse outcomes in women affected by GDM and her offspring. I included 64 studies, describing 115 models. The most common outcomes predicted were: (i) the longer-term risk of developing diabetes for the woman, (ii) birth outcomes, with a focus on macrosomia, and (iii) GDM treatment modality during pregnancy (lifestyle modification or medication).

The regional distribution of studies revealed a concentration in Europe, North America, and the Western Pacific, where GDM prevalence is 7.2%, 7.8%, and 14.7% (19). However, other regions with some of the highest reported GDM incidence rates—such as the MENA region (27.6%) and Southeast Asia (20.8%)—are underrepresented in the literature, with fewer than 10% of studies originating from these areas (19). This imbalance may limit the generalisability of prediction models and underscores the need for more research in regions with a high GDM burden to ensure broader applicability and relevance across diverse populations.

Additionally, a significant gap was identified for models addressing long-term health outcomes both for children born to mothers with GDM and for maternal cardiovascular risks. Children exposed to GDM are at higher risk for obesity, metabolic syndrome, and T2DM (33–35), yet few models address these intergenerational risks, reducing opportunities for early intervention that could improve long-term health outcomes. This likely reflects the greater methodological difficulty of developing such models, as long-term child outcomes

require prolonged follow-up, and linked mother-child datasets. Similarly, models that predict long-term cardiovascular outcomes for women with GDM are limited, despite the known association between GDM and increased risks of hypertension and cardiovascular disease (30,32). These outcomes often emerge years after pregnancy and require large longitudinal cohorts with sufficient event rates for robust model development. Developing models that incorporate these risks could support preventive strategies for both mother and child, ultimately enhancing lifetime care through targeted interventions and comprehensive management of long-term health risks associated with GDM.

Together, these gaps in regional representation, long-term offspring outcome modelling, and models of cardiovascular outcomes highlight important limitations in the current body of GDM prediction research. Addressing these areas in future studies will be essential to develop more comprehensive and clinically useful models that support individualised care across diverse settings and patient populations.

2.6.2. Bias and Methodological Limitations

Overall, I found that most models are not suitable for clinical use in their current form due to major methodological limitations. Of the 115 models, 8 unique models were found to be at low risk of bias. These models predicted treatment modality (58), a composite of adverse outcomes (54), T2DM complications (134) and primary C-section (96,148). External validation in different populations is needed to determine real-world performance and impact.

These methodological challenges are consistent with findings in GDM research (53,149) and other fields, such as of psychiatry, tuberculosis, and asthma (150–152), where prediction models frequently exhibit high risk of bias and inadequate calibration. The key methodological issues identified were related to sample size, missing data, predictor selection and model evaluation.

Sample Size

Many models were developed with a low EPV, with fewer than half meeting the EPV ≥ 10 criterion, and even fewer reaching the recommended EPV ≥ 20. These limitations raise concerns about overfitting, which can lead to overly optimistic model performance that fails to generalise to broader populations. To enhance the reliability of future models, studies

should move beyond a one-size-fits-all EPV threshold. Instead, sample size requirements should be calculated based on the specific complexity of each model and the expected predictive accuracy (153,154). Adopting these tailored sample size calculations will help produce more robust and clinically applicable models across diverse patient populations.

Handling of Missing Data

The reporting and handling of missing data was frequently insufficient, with over half of the models relying on complete-case analysis. This approach can introduce significant bias by selectively excluding certain patients, resulting in a non-random subset of the study population. This can lead to skewed predictor-outcome associations and biased model performance. Multiple imputation is regarded as the most appropriate method for handling missing data in prediction model development and validation (155–157). It minimises bias by estimating the missing values based on other observed data, thereby preserving the overall structure of the dataset and providing more accurate estimates of model performance, including correct standard errors and p-values.

However, authors should also consider how missing predictor values will be handled when the model is deployed in practice because routine clinical datasets often contain missing data. Models developed only on complete cases may be difficult to apply or may systematically exclude some patients from risk estimation. As missing data is expected at the point of deployment, authors should pre-specify a compatible strategy for real-time handling of missing predictors. Future studies should prioritise rigorous approaches for handling missing data such as multiple imputation or joint modelling imputation, as these methods provide better precision and less bias (158). They should also evaluate how the model performs under realistic missingness patterns that are likely to occur in routine care. Additionally, it is crucial for authors to transparently report how missing data were handled and to provide comparisons between included and excluded participants to assess potential bias.

Predictor Selection

In this review, many models relied on univariable analysis to select candidate predictors, an approach that selects predictors based solely on their individual statistical significance without considering how they interact with other variables. This method can result in omitting relevant predictors that may only show importance when adjusted for other factors

or, conversely, including predictors based on accidental associations. Such selection practices increase the risk of both underfitting and overfitting, compromising the model's performance in new datasets. A more reliable approach to predictor selection emphasises the use of nonstatistical methods grounded in established knowledge, clinical credibility, and practical considerations relevant to the model's intended setting. Predictors known to be significant in prior research should be retained, regardless of their statistical significance in a specific dataset, ensuring that the model incorporates clinically meaningful variables. Methods like backward selection or penalized regression can also help refine predictor sets in a multivariable context without relying on preliminary univariable testing, preserving predictor integrity while minimising overfitting (159). Additionally, using internal validation techniques to assess overfitting and optimise model performance is crucial when refining predictor sets (159). Adopting these predictor selection strategies can improve model stability and enhance generalisability, ultimately producing models that are both simpler and more clinically relevant without compromising predictive power.

Model Evaluation

Our review identified calibration as a frequently neglected aspect in model evaluation, with many studies relying solely on the Hosmer-Lemeshow test. This test is limited in statistical power, especially with large datasets, and can be overly sensitive to sample size, often leading to misleading assessments of calibration quality. Calibration plots and calibration slopes are more informative alternatives, as they visualize and quantify the alignment between predicted and observed outcomes across the risk spectrum, offering a more nuanced understanding of model performance (160,161). In addition, cut-off points on ROC curves were often overlooked. Without these measures, the interpretation of discrimination—the model's ability to differentiate between individuals with and without the outcome—remains incomplete. Reporting only the area under the ROC curve (AUROC) can obscure important calibration issues, as a model with high discrimination may still miscalibrate, predicting risks inaccurately in certain subgroups. To improve future models, a more comprehensive approach to evaluating calibration and discrimination is needed. Calibration slopes, plots, and recalibration techniques should be used alongside discrimination metrics to provide a balanced assessment of a model's predictive accuracy.

2.6.3. Implications for research and clinical practice

The increasing availability of 'big data' from EHR records, glucose sensors and other sources (such as 'omics studies) has led to the development of a large number of prognostic models for GDM outcomes. Unfortunately, the lack of external validation of these models results in considerable research waste and limits the uptake of models in practice. Instead of continually developing new models, it is imperative to focus on the evaluation of existing models in new datasets. Poor performance in external validation does not necessarily indicate the need for an entirely new model. Updating or recalibrating the existing model based on both development and validation data can improve its performance, stability, and generalisability.

When the development of a new model is warranted, rigorous methodology should be followed using existing guidelines for prognosis research. Methodological guidance is available for all aspects of model development including sample size calculation, selection of predictors, shrinkage techniques, model evaluation, internal and external validation (153,162,159,163). Models should be reported adequately using the TRIPOD guidelines to ensure transparency and reproducibility (164).

Finally, impact studies are critical to understanding a model's true clinical value. By evaluating how a model affects clinical decision-making, patient outcomes, resource utilisation, and cost-effectiveness, impact studies provide insight into the practical benefits of these tools (165). Such studies are crucial for determining whether a model delivers measurable improvements in care, guiding the integration of prognostic models into practice confidently. These approaches collectively support the translation of GDM prognostic models into tools that can reliably enhance patient care and clinical efficiency.

2.6.4. Strengths and limitations

This review demonstrates several notable strengths, including a prospective protocol registration, an extensive search across multiple databases without limitations on language or publication date and data extraction and critical appraisal using specialised tools such as CHARMS (70) and PROBAST (71). Additionally, while non-exhaustive, the grey literature search increased the review's comprehensiveness and reduced potential publication bias. However, I was unable to assess for reporting bias as only one included study followed a

prospectively published protocol. This further drives the point of the need for more transparent reporting in predictive modelling studies. An important limitation is that I was unable to compare prediction models quantitatively due to the heterogeneity of studies included. For example, GDM was diagnosed using eight different criteria and management protocols differed by centre. Focusing on external validation can support future head-to-head comparisons of prognostic models.

2.6.5. Conclusions

In conclusion, this systematic review provides a comprehensive summary of current prediction models for GDM outcomes and establishes a benchmark for future model development. By identifying key methodological best practices and emphasising the need for improved geographic representation, this review highlights critical areas for enhancement in the field. Adopting these practices—such as rigorous validation, tailored sample size calculations, and broader regional applicability—will be essential for improving the reliability, generalisability, and clinical utility of future models, ultimately supporting more effective, patient-centred care in diverse global settings.

CHAPTER 3

External validation of a model to predict type 2 diabetes and type 2 diabetic complications after gestational diabetes

3. CHAPTER 3: External validation of a model to predict type 2 diabetes and type 2 diabetic complications after gestational diabetes

3.1. Chapter Overview

This chapter presents the external validation of a previously published prediction model for T2DM complications following GDM. Specifically, it describes the rationale for the validation of an existing prognostic model in a UK population and the construction of a retrospective cohort using linked CPRD Aurum, Hospital Episode Statistics (HES), and Office of National Statistics (ONS) data. This chapter also presents the methods used to assess model performance. It also compares the characteristics and outcome patterns of the development and validation cohorts and evaluates whether the model retains adequate transportability for use in routine clinical practice in England.

3.2. Background and Rationale

3.2.1. Type 2 Diabetes after GDM

T2DM is a chronic metabolic disorder characterised by hyperglycaemia due to insulin resistance and dysfunction of pancreatic β-cells. Women diagnosed with GDM have a significantly elevated lifetime risk of progressing to T2DM. A systematic review published in 2002, including 28 studies of varied populations and diagnostic criteria, identified a cumulative incidence of T2DM after GDM ranging from 2.6% to over 70% during follow-up periods spanning six weeks to 28 years postpartum (166). The highest conversion rates from GDM to T2DM were observed within the first five years postpartum (166). Additionally, a large meta-analysis of 20 studies including more than 675,000 women reported a sevenfold increased risk of developing T2DM among those with previous GDM compared with women without GDM (29). A more recent meta-analysis, which included 134 studies and over 1.3 million participants, found that the overall relative risk for T2DM was 9.5 times higher in women with previous GDM than in healthy controls (167). The transition from GDM to T2DM is recognised as multifactorial, reflecting the interplay of genetic predisposition, metabolic dysfunction, lifestyle behaviours, and sociodemographic influences.

3.2.2. Risk factors for developing T2DM after GDM

Genetic and Physiological Determinants

Physiologically, pregnancy induces increased insulin resistance to ensure adequate glucose supply for the fetus. This adaptation is primarily mediated by hormonal changes, including elevated human placental lactogen, oestrogen, and prolactin levels. In most women, pancreatic β-cells compensate for this physiological insulin resistance by increasing insulin secretion. However, in women predisposed to GDM, this compensatory mechanism is insufficient, resulting in maternal hyperglycaemia during pregnancy (168). The β-cell dysfunction and insulin resistance that emerge during pregnancy may not fully resolve after delivery, leaving a residual metabolic impairment that predisposes these women to the development of T2DM. Genetically, GDM and T2DM share multiple susceptibility loci identified through genome-wide association studies (GWAS) and meta-analyses, such as MTNR1B, TCF7L2, CDKAL1, IGF2BP2, and GCK (169,170). Additionally, family history of diabetes increases risk of T2DM after GDM (171–174), highlighting the importance of genetic predisposition.

Demographic and Lifestyle Factors

Demographic factors, such as BMI, ethnicity, socioeconomic status, can also impact the risk of developing T2DM after GDM. A meta-analysis including nearly 200,000 women reported that a higher pre-pregnancy BMI was associated with an almost threefold increase in the risk of developing T2DM following GDM (171). Elevated postpartum BMI conferred an even greater risk, with a more than fourfold increase in the likelihood of T2DM (171). Similarly, another large meta-analysis found that women with higher BMI had approximately twice the risk of developing T2DM in the future. The likelihood of progression to T2DM was further elevated among those classified as overweight or obese, with increasing BMI thresholds corresponding to progressively greater risk (172). Additionally, the incidence of T2DM following GDM increases with greater socioeconomic deprivation (175).

Advanced maternal age has also been identified as a significant demographic risk factor across different populations, with women who are older at the time of pregnancy having a higher likelihood of progressing to T2DM (171–174). Additionally, multiple meta-analyses have found that ethnicity is a significant modifier of the risk of developing T2DM following GDM (171,172,174,176). In one meta-analysis including 39 studies and 95,750 women, non-

white ethnicity was associated with a 49% higher risk of progression to T2DM after GDM compared to white ethnicity (172).

Lifestyle factors such as physical inactivity, poor diet, and smoking also contribute to risk. For example, a prospective cohort study demonstrated that women with optimal levels of five modifiable risk factors (normal BMI, high-quality diet, regular physical activity, moderate alcohol consumption, and no current smoking) had over 90% lower risk of T2DM compared to those with none, and this protective effect persisted even among women with high genetic susceptibility or overweight/obesity (177).

Pregnancy-related factors

Women with recurrent GDM, defined as a GDM diagnosis in more than one pregnancy, were almost three times more likely to develop T2DM than women with non-recurrent GDM (171). The use of insulin during pregnancy, which can indicate more severe GDM, is associated with a markedly increased risk of future T2DM. Two large meta-analyses found that women who required insulin therapy during pregnancy were approximately four times more likely to develop T2DM later in life compared with those whose GDM was managed without insulin (171,172). Laboratory measures during pregnancy can also be predictive, though their predictive strength has varied across studies due to heterogeneity in diagnostic criteria, measurement timing, study populations and length of follow-up. In a meta-analysis published in 2016, HbA1c was identified as a high-risk factor for T2DM, while fasting glucose, 1-hour, and 2-hour post-OGTT glucose were classified as moderate-risk factors (172). However, a more recent meta-analysis found that elevated fasting glucose, increased HbA1c, and higher 1-hour, 2-hour, and 3-hour post-OGTT glucose values all increase the risk of T2DM by 3-4 fold (171).

3.2.3. Impact of progression to T2DM

T2DM causes a wide range of serious health complications that increase illness and premature death worldwide. These complications are typically divided into microvascular conditions, affecting the kidneys, eyes, and nervous system, and macrovascular conditions such as cardiovascular disease (CVD). Around half of people with T2DM develop microvascular complications and over a quarter experience macrovascular complications (178). Compared with individuals without diabetes, those with T2DM have up to 10–20 times

greater risk of microvascular disease and two to four times greater risk of macrovascular disease (179). In the UK, the National Diabetes Audit 2017-18 found that while people with diabetes make up about one in twenty adults, they account for approximately a quarter to a third of hospital admissions for cardiovascular disease (180). The audit also highlights that people with diagnosed diabetes account for over 40% of bed days for hospitalisations related to amputations and renal replacement therapy. Additionally, the mortality data show that the risk of death for people with diabetes is 50% higher than in the general population (180).

Women who develop T2DM following GDM also experience increased health complications. A large population-based cohort study conducted in Ontario, Canada examined over 1.5 million women with live births between 1994 and 2014 to assess how the development of T2DM after GDM influences microvascular and macrovascular outcomes (181). The study found that microvascular complications, such as retinal disease, renal failure, and diabetic foot infections, were significantly increased only among women who developed T2DM after GDM. Specifically, women with T2DM after GDM had over seven times the risk of requiring renal dialysis**,** four times the likelihood of undergoing vitrectomy or laser photocoagulation for eye disease, and over four times the risk of hospitalisation for foot infections. In contrast, women with a history of GDM who did not develop T2DM showed no significant increase in these microvascular outcomes compared with those without any history of diabetes, indicating that diabetes progression is the primary driver of such complications (181).

For macrovascular outcomes, the same study found that women with a history of GDM had about a 30% higher risk of developing heart disease even if they did not go on to develop T2DM (181). However, women who progressed to T2DM after GDM exhibited an approximately three times higher risk of cardiovascular disease, compared to women with no history of diabetes. Similarly, the likelihood of developing coronary artery disease was about 40% higher in women with GDM alone and more than three and a half times higher in those who later developed T2DM (181). These findings indicate that while GDM alone carries a modest long-term cardiovascular risk, the combination of GDM followed by T2DM confers a significantly greater health burden.

These health consequences translate into a considerable financial burden for healthcare systems. A study investigating the economic burden of diabetes in the UK found that in

2010/11, the total cost of T2DM was approximately £21.8 billion, comprising around £8.8 billion in direct healthcare costs and £13 billion in indirect societal and productivity losses due to sickness absence, early retirement, and premature mortality. The direct costs were driven largely by managing diabetes-related complications, including cardiovascular disease, renal failure, neuropathy, and visual impairment, rather than by routine diabetes care itself. The study projected that by 2035/36, the total cost of T2DM would rise to approximately £35.6 billion (182).

Similarly, a longitudinal Swedish case–control study followed women up to 14 years after delivery and found that those who developed diabetes after GDM used healthcare resources 14 times more frequently than women without diabetes, with an average 101% increase in annual costs. In contrast, women with previous GDM who did not develop diabetes had healthcare utilisation comparable to women with no GDM history, indicating that nearly all excess resource use is attributable to diabetes progression rather than GDM itself (183).

In summary, the clinical progression from GDM to T2DM amplifies health risks and substantially increases healthcare resource use and long-term financial costs. Preventing or delaying the onset of T2DM in women with previous GDM could therefore play a crucial role in reducing both microvascular and macrovascular complications later in life, as well as the economic burden of the disease.

3.2.4. T2DM after GDM model description (134)

Although women with GDM are at increased risk of subsequent T2DM and related adverse outcomes, not all will go on to develop these complications. Prediction models offer a practical means of identifying women at highest risk of progression from GDM to T2DM and its complications, enabling targeted prevention and follow-up. The model described below was selected following the systematic review in Chapter 2, considering methodological quality, clinical relevance, and feasibility of implementation using routinely collected healthcare data.

Cohort description

The model was developed using a retrospective population-based cohort of 90,143 women aged 18–45 who delivered in Quebec, Canada, between 1989 and 2016 and had at

least one pregnancy affected by GDM. Women with pre-existing diabetes or related complications were excluded. The median follow-up time was 6.2 years, during which 1,025 events (hospitalisations for T2DM complications) occurred, corresponding to 283 women.

Outcome definition

The primary outcome was hospitalisation for T2DM complications within 10 years after the first GDM-affected delivery. Complications included diabetic coma, acidosis, renal, ophthalmic, neurological, circulatory, and other diabetes-related complications, identified using validated ICD-9 and ICD-10 codes.

Selection of predictors

Candidate predictors were chosen based on prior evidence linking them to T2DM risk and availability in administrative data. Variables considered included maternal age, socioeconomic deprivation, substance abuse, morbid obesity, parity, gestational age at delivery, and pregnancy complications such as hypertensive disorders of pregnancy (HDP), SMM, and prior obstetric complications. Predictors were refined using LASSO regression after addressing collinearity and low-frequency variables. The final model included seven predictors: maternal age, socioeconomic deprivation, substance abuse disorder, gestational age at delivery, SMM, previous pregnancy complications, and HDP.

Modelling method

A Cox proportional hazards (Cox PH) regression model was used to estimate the risk of developing T2DM complications within 10 years after GDM. Continuous variables such as maternal age and gestational age were modelled using restricted cubic splines (RCS) to account for non-linear associations.

Model performance

Internal validation was performed using bootstrapping with 200 iterations**,** with a mean optimism of 0.0077, indicating minimal overfitting. The model demonstrated good discrimination with an AUROC of 0.72 (95% CI 0.69–0.74) and excellent calibration (slope = 0.99, intercept = −0.31). Risk stratification showed a clear gradient across risk categories,

with a positive likelihood ratio of 8.68 in the highest risk group, indicating a moderate ability to identify women at highest risk of diabetic complications.

3.3. Aims of this Research

Building on the systematic review presented in Chapter 2, which identified substantial heterogeneity in the performance, validation, and transportability of prognostic models for outcomes following GDM, the aim of this research was to externally validate and assess the transportability of a previously published prediction model for long-term T2DM complications after GDM.

3.4. Methods

This study is reported in accordance with the TRIPOD statement for prediction model validation studies. The TRIPOD checklist is presented in Appendix 3 (Supplementary Table 10.4). All analyses were performed using R, version 4.5.2 (184). All codes used for the analysis are available at https://github.com/yasminaalghadban/dphil.git.

3.4.1. CPRD Dataset

Overall description

The Clinical Practice Research Datalink (CPRD) is a large UK primary care database supported by the Medicines and Healthcare products Regulatory Agency (MHRA) and the National Institute for Health Research (NIHR). It contains routinely collected patient data from over 2,400 general practices that have consented to support public health research (185). Specifically, the database captures anonymised electronics health records from over 65 million patients in the UK. It includes coded information on demographics, diagnoses, prescriptions, test results, referrals, immunisations, and lifestyle factors recorded by primary care staff. To date, over 3,600 peer-reviewed publications have used CPRD data in a wide range of epidemiological studies to inform clinical practice.

The CPRD database comprises two datasets, CPRD Aurum (186) and CPRD GOLD (187), which differ in the GP software systems from which their data are derived. CPRD GOLD captures data from practices using the Vision® clinical system, while CPRD Aurum captures data from practices using EMIS Web®. Both datasets provide longitudinal primary care

records from 1995 to the present, but they differ in size, geographical distribution, and population coverage. As of the June 2025 release, CPRD GOLD contained records for 21,602,574 patients, with currently registered patients representing 3.7% of the UK population, and its current contributing practices being concentrated primarily in Scotland and Wales (188). In contrast, CPRD Aurum contains records for 50,973,960 patients, with currently registered patients accounting for 24.8% of the UK population, and its current contributing practices being located only in England (189). The projects described in this thesis have used the CPRD Aurum dataset as it has a significantly larger sample size.

Linkage to other health datasets

The CPRD dataset can be linked to a wide range of external health data sources such as HES, death registrations, cancer registries, and small-area deprivation indices, allowing for longitudinal follow-up and outcome ascertainment across multiple care settings. Through this linkage, managed by the Trusted Third-Party National Health Service (NHS) England, primary care records are complemented with secondary care events, cause and date of death, cancer incidence and staging data, and contextual socioeconomic information by area, enabling more complete capture of disease onset, progression, complications, and mortality.

These linkages include:

- HES Admitted Patient Care (APC) data, which provide records on inpatient hospital admissions
- HES Outpatient data, which provide records on outpatient hospital visits
- HES Accident and Emergency data, which provide records on Accident and Emergency department visits
- HES Diagnostic Imaging Dataset, which provide records on imaging procedures conducted within the NHS
- ONS Death Registration data, which provide records on date and cause of death
- National Cancer Registration and Analysis Service (NCRAS) cancer datasets, which provide records on cancer diagnoses, staging, and treatment.
- Small-area level data, such as indices of multiple deprivation, which allow the incorporation of socioeconomic context into analyses

For this project, I used the linked primary care data to the HES APC data, the ONS death registration data and the small-area level data.

Data approval and access

Access to CPRD data for this study was obtained through approval of the protocol *Risk prediction modelling for gestational diabetes* (protocol ID 22_002383) by the CPRD Research Data Governance process. The protocol, approved on 07/07/2023, specified the study design, study population, outcomes, covariates, sample size calculations and data analysis.

Following approval of the protocol, two types of linkage requests were submitted and granted. A Type 1 linkage request (ID 3185) was used to define the study population using HES APC records of deliveries. For this purpose, the following variables were requested:

- *patid* (the pseudonymised patient identifier)
- *sex*
- *epitype* (episode type to identify the deliveries)
- *admidate* (admission date)
- *numbaby* (number of babies delivered).

Subsequently, a Type 2 linkage request (ID 3587) was approved to provide the linked datasets for the defined study population. As the study population was larger than 600K patients, CPRD required us to minimise the data by restricting the variables to only those needed. The protocol, linkage requests and a description of the data structure (including tables and variables) can be found in Appendix 3 (Supplementary File 10.3, Supplementary Table 10.5).

3.4.2. Study population

The study population included women registered at a CPRD practice for at least one year, with an admission date in HES APC from 01/01/2010 onwards, and with a recorded singleton delivery, identified using epitype=2 and numbaby=1. Twins and other multiple births were excluded because multiple pregnancies have substantially different risk profiles (higher rates of preterm birth, pre-eclampsia, and caesarean delivery) that could confound the study's

findings if mixed with singleton pregnancies (190). Using these criteria, a total of 2,902,285 eligible patients were identified as the study population.

3.4.3. Study cohort definition

I derived the study cohort from the study population by applying additional inclusion and exclusion criteria to identify women with pregnancies affected by GDM.

Inclusion criteria

Women in the study population were eligible for inclusion in the study cohort if they had a diagnosis of GDM associated with one or more of these pregnancies. GDM was identified using a triangulation approach: either the presence of a relevant MedCodeID in primary care records or an ICD-10 code for GDM (O24.4) in HES at any time. A complete code list can be found in Appendix 3 (Supplementary Table 10.6). The choice to include all women with a GDM code at any time was made in line with previous studies investigating GDM using similar datasets (175,191), as well as the National GDM Audit (192).

I treated the woman, rather than the pregnancy, as the unit of analysis. The cohort entry point (t_0) was defined as the first (index) pregnancy affected by GDM. For women with multiple eligible deliveries, the earliest GDM-affected pregnancy in the study window, which was not necessarily the first lifetime pregnancy, was designated as the index pregnancy. This decision was made for several reasons. As this study constitutes an external validation of a previously developed prediction model, it was important to define the cohort in the same way as the development cohort (134), to ensure that the validation was methodologically consistent with, and comparable to, the original model development. Second, the primary outcome of interest, T2DM, is a property of the woman rather than of any individual pregnancy, since it is diagnosed once and persists thereafter, making the woman the more appropriate unit for analysis. Third, defining the cohort at the level of the pregnancy would have meant that women with multiple GDM-affected pregnancies contributed multiple, non-independent observations, violating the assumption of independence required for standard survival and regression methods. Finally, anchoring the analysis to the woman allowed a single, unambiguous follow-up period to be defined for each individual beginning at the index pregnancy.

Exclusion criteria

Women with a GDM diagnosis recorded before 01/01/2010 were excluded, reflecting the introduction of updated diagnostic thresholds and screening recommendations for GDM (75). Records prior to 2010 were retained in the dataset to identify previous obstetric events, medical comorbidities, and parity.

In line with methods used in the development cohort, women younger than 18 or older than 45 were excluded. Additionally, women who experienced maternal mortality in the index pregnancy were excluded. Maternal mortality was ascertained using the registered date of death in the ONS record and defined as death during pregnancy or within 42 days of the end of pregnancy (193).

Women with any form of pre-existing diabetes prior to the study start date were excluded. Pre-existing diabetes was identified using code lists for T2DM and type 1 diabetes (T1DM) recorded in either CPRD or HES prior to the GDM event date. These exclusions ensured that only women with incident GDM were included in the analytic cohort.

Delivery and GDM diagnosis dates

Delivery dates were identified from multiple HES sources to ensure comprehensive coverage and to validate the link between each GDM diagnosis and its corresponding pregnancy. Specifically, delivery-related information was extracted from three sources: the HES maternity table, which contains detailed maternity episode data (including delivery and discharge dates); the HES procedures table, using OPCS-4 procedure codes that indicate labour and delivery procedures (e.g. C-section, induction of labour, vaginal delivery); and the HES diagnoses table, using ICD-10 diagnosis codes associated with delivery or obstetric outcomes.

These datasets were cleaned, with date formats standardised and combined to identify a single delivery date for each index pregnancy. When the GDM diagnosis was recorded between 240 days and 30 days before a delivery date, the GDM diagnosis date was linked to that delivery episode. This interval was chosen to reflect the typical gestational window between diagnosis (usually at 24–28 weeks of gestation) and delivery (around 40 weeks), while allowing for variation in gestation length and timing of GDM screening.

However, if the diagnosis date was not consistent with the delivery date (outside of the 240-30 days before delivery), I estimated the date of GDM diagnosis based on the HES delivery date. In these cases, it was assumed that GDM had been diagnosed at 26 weeks of gestation (14 weeks prior to delivery), in line with NICE guidance recommending GDM screening between 24 and 28 weeks of pregnancy (21). This approach ensured that pregnancies with incomplete or inconsistent coding were retained while maintaining a biologically plausible diagnosis-to-delivery interval.

3.4.4. Outcome assessment

I defined two primary outcomes for validation:

- Any T2DM representing the first recorded diagnosis of T2DM following a pregnancy affected by GDM, irrespective of complications.
- T2DM with complications representing T2DM accompanied by at least one predefined diabetes-related complication. This encompassed a clinically relevant and predefined set of complications consistent with the development study, including:
    - diabetic coma
    - diabetic acidosis
    - renal complications (such as diabetic nephropathy)
    - ophthalmic complications (such as retinopathy)
    - neurological complications (such as neuropathy)
    - circulatory complications (such as peripheral vascular disease)
    - other or unspecified complications
    - multiple complications when more than one category was present

Both outcomes were ascertained using diagnostic codes (ICD-10 in HES and ONS; MedCodeIDs in CPRD Aurum) (194) and a complete code list can be found in Appendix 3 (Supplementary Table 10.7). Outcome ascertainment in the validation cohort drew on the three linked data sources: CPRD Aurum for primary care records, HES for secondary care/hospitalisation records, and ONS mortality data. This contrasts with the development study by Ukah et al., which ascertained T2DM complications using hospitalisation records alone.

In this validation study, the second primary outcome was defined to mirror that used by Ukah et al., namely, the development of T2DM complications following a pregnancy affected by GDM. In the development cohort, the outcome was ascertained using ICD-10 and ICD-9 codes for T2DM complications within 10 years of the index GDM delivery, identified using administrative hospital data. To maintain comparability, I replicated this outcome definition as closely as possible using the linked CPRD Aurum**,** HES, and ONS datasets, which together provide longitudinal coverage of clinical, hospital, and mortality records in England.

This choice was driven by the structure of the data sources available for this validation and to maximize outcome ascertainment. Relying on HES alone risks underestimating outcome incidence and skewing the captured cases toward more severe presentations. Using linked CPRD Aurum, HES, and ONS data instead provides fuller coverage of the diagnostic pathway, capturing diagnoses recorded in general practice as well as those identified in secondary care or contributing to death. Because Ukah et al.'s model was built on a hospitalisation-only T2DM complications, it was implicitly developed to predict a more clinically severe subset of T2DM complications, cases that led to hospitalisations, whereas the outcome ascertained here is broader and may include milder, primary-care-managed cases that would not have met the development study's outcome definition. As a result, some discordance in case ascertainment between the two studies can be expected, and this should be kept in mind when interpreting the validation results.

To assess the practical scale of this discordance in the validation cohort, I conducted a sensitivity analysis comparing case identification of diabetic complications across the three sources. In practice, every woman with a recorded complication in CPRD Aurum was also identified via HES, and no cases were ascertained from ONS mortality records alone. HES identified 266 women with T2DM complications, of whom 78 (29.3%) were also captured in CPRD Aurum. No women were identified by CPRD Aurum who were not also captured by HES. The anticipated discordance between a primary-care-inclusive outcome and a hospital-only outcome therefore did not materialise to any meaningful degree in this cohort, supporting the comparability of outcome definitions between the validation and development studies. All three sources were nonetheless retained in the final outcome algorithm, both to align with recommended CPRD multi-source linkage practice and as a safeguard against source-specific under-ascertainment that could arise in other subgroups or in future applications of this algorithm.

Women were followed from the date of delivery of the index GDM-affected pregnancy until the earliest of the following events: (i) outcome development, (ii) death, (iii) the end of CPRD data collection, or (iv) ten years after delivery. Only events occurring after the index delivery were counted as incident outcomes. This approach ensured that the validation assessed new-onset diabetes and its complications within the same ten-year follow-up horizon used by Ukah et al., while also allowing women to be censored earlier if death, loss to follow-up, or data cut-off occurred sooner.

3.4.5. Covariates definition

Predictors in this external validation study were defined to correspond as closely as possible to those used by Ukah et al. in their development of the model to predict T2DM complications following GDM.

Maternal age

Maternal age was calculated as the difference between the woman's year of delivery and her year of birth, extracted from the CPRD Aurum Patient table. Maternal age was modelled using RCS to reflect the non-linear associations used in the original Ukah et al. model. The exact knot locations were not reported in the development paper, but upon request, the authors provided them. As such, spline knots were placed at the same quantiles as in the development paper: at the 4th, 45th, and 96th percentiles. The same number of spline terms as in the original model was retained to preserve functional form.

Socioeconomic status (SES)

In the development study, Ukah et al. derived a composite index of neighbourhood-level deprivation from income, education, and employment data available in the Quebec administrative databases (195). To reflect this construct in the UK context, I used the Index of Multiple Deprivation (IMD), a small-area measure of relative deprivation derived from census indicators and national statistics. Each woman was assigned an IMD quantile based on her residential postcode. Socioeconomic status was represented both as a categorical variable and as a binary socioeconomic deprivation variable, to replicate the dichotomisation of

socioeconomic deprivation used by Ukah et al. For the binary variable, deprivation was categorised as “yes” for quantile 5 (most deprived 20%) and “no” for quantiles 1 to 4.

Smoking status

Smoking exposure was derived from both CPRD primary care records using MedCodeIDs and linked HES diagnoses using ICD-10 codes (196,197). All smoking-related codes dated before the delivery date were identified from either source. For each patient, the most recent smoking code before delivery was used to assign smoking status. Smoking status was treated as a categorical variable with three categories: current smoker, former smoker and never smoker. If no codes were present from either source, smoking status was assigned as NA.

Alcohol status

Alcohol exposure was derived analogously (196,198). All smoking-related codes dated before the delivery date were identified from either source. For each patient, the most recent alcohol code before delivery was used to assign alcohol status. Alcohol status was treated as a categorical variable with three categories: current drinker, former drinker and never drinker. If no codes were present from either source, alcohol status was assigned as NA.

Substance use disorder

While smoking status and alcohol status were not included in the model, Ukah et al. included substance use disorder (tobacco, alcohol, or drug-related) as a binary variable, based on administrative health records. I replicated this by identifying any record of substance misuse (tobacco, alcohol, opioids, stimulants, or other drugs) using both primary and secondary care data (199). A woman was coded as having substance use disorder (“yes”) if a relevant code was present in either dataset before the delivery date.

Gestational age

Gestational age at delivery was derived from HES maternity records. Implausible gestational ages (< 24 or > 50 weeks) were excluded and coded as missing. As in the original Ukah et al. model, gestational age was modelled using RCS with knots located at the 3rd, 10th, and 75th percentiles. The same number of spline terms as in the original model was retained to preserve functional form.

Birthweight

Birthweight, treated as a continuous variable, was extracted from the HES maternity records. Implausible birthweight values (<1000g or >6000g) were excluded.

Parity

Parity was defined as a binary variable: primiparous if no previous pregnancies were recorded, and multiparous otherwise. For women missing the number of previous pregnancies in maternity records, parity was estimated from prior delivery records in HES data. Any delivery recorded for the same woman more than 294 days before the index delivery date was taken as evidence of a previous birth, and the woman was classified as multiparous. This approach was used to reduce missing data.

Delivery method

Delivery method was defined as a binary variable, with women classified as having either a spontaneous or instrumental delivery. It was derived using a hierarchical approach based on linked HES maternity data, procedure, and diagnosis records. The primary source was the HES maternity delivery method field. For women with missing delivery method data in the HES maternity dataset, delivery method was backfilled using HES procedure records and diagnoses records. OPCS-4 procedure codes and ICD-10 diagnosis codes indicating spontaneous or instrumental delivery were searched within 7 days of the index delivery date. This 7-day window was chosen to allow for small discrepancies in timing between linked routine data sources and is consistent with approaches used in the UK pregnancy register (200). When both spontaneous and instrumental codes were present, instrumental delivery was prioritised. If delivery method could not be determined, the woman was classified as having a missing delivery method.

Severe maternal morbidity (SMM)

Ukah et al. defined SMM using the Canadian Perinatal Surveillance System (CPSS) list of maternal morbidity conditions (201). To align this with the UK context, I used the English Maternal Morbidity Outcome Indicator (EMMOI), a composite indicator on based on conditions associated with maternal morbidity and mortality in the UK as well as by the

quality of the routine hospital data. It encompasses 26 conditions and procedures indicative of SMM or mortality (202). These conditions include life-threatening maternal complications such as organ failure, severe haemorrhage, sepsis, or emergency obstetric interventions. Using ICD-10 and OPCS-4 codes from HES, SMM was defined as a binary variable. Women were classified as having SMM in the index pregnancy if one or more EMMOI-defined diagnoses or procedures were recorded during pregnancy or the postnatal period (from 294 days before the delivery date to 42 days after the delivery date).

Previous pregnancy complications

In Ukah et al., previous pregnancy complications were defined based on adverse obstetric history, including stillbirth, preterm birth, or neonatal death. In this study, I used HES maternity and diagnostic data to identify equivalent events. Previous pregnancy complications were identified from records occurring before 294 days prior to the delivery date of the index pregnancy. A woman was classified as having a previous pregnancy complication if she had any record of preterm delivery (<37 weeks), low birthweight (<2500 g), neonatal intensive care admission, or a diagnosis indicating supervision for high-risk pregnancy. Previous pregnancy complications were represented as a three-level categorical variable: primiparous, multiparous with previous pregnancy complications, and multiparous without previous pregnancy complications.

Hypertensive disorders of pregnancy (HDP)

In the development study, Ukah et al. categorised HDP as no hypertension, pre-existing or unspecified hypertension, gestational hypertension, pre-eclampsia or HELLP syndrome, and superimposed pre-eclampsia. I used ICD-10 codes from HES and MedCodeID codes from CPRD primary care records to derive the same categorical variable. Records occurring within the 294 days preceding delivery were used to capture HDP during the index pregnancy (203). Women were then assigned to one of the mutually exclusive HDP categories based on their most severe recorded condition: pre-existing/unspecified hypertension, gestational hypertension, pre-eclampsia/HELLP syndrome, or superimposed pre-eclampsia. Women without any of these diagnoses were classified as no HDP.

Body mass index (BMI)

Pre-pregnancy BMI was derived from CPRD primary care records by extracting the most recent BMI record dated before 294 days prior to delivery for each woman. Numeric BMI values were used where available. Implausible BMI values (<15 or >60 kg/m²) were assigned NA. Where a numeric BMI value was not available, the most recent BMI centile or the most recent categorical BMI entry was used as an alternative source. BMI was harmonised into a categorical variable with five levels: underweight (<18.5), normal (18.5–24.9), overweight (25–29.9), obese (30–39.9), and morbid obese (≥40). Where numeric BMI and centile conflicted, numeric BMI took precedence; where neither numeric nor centile were available, coded BMI categories from the record were used. In addition, and following Ukah et al., I used the BMI categories to derive a binary indicator of morbid obesity.

Ethnicity

Ethnicity was derived from the HES patient table and harmonised into broad groups relevant to epidemiological analyses: White, Black, Asian, Mixed, Other, with unknown/missing retained as NA. For women with missing ethnicity in HES, CPRD observation records were searched for ethnicity-related MedCodeIDs, which were mapped to the same broad categories. When multiple differing ethnicity entries were present in CPRD, the modal (most frequently recorded) category was assigned.

Treatment method

Treatment method during pregnancy was represented using a three-level categorical variable: insulin-treated, metformin-treated, and lifestyle management only. Using predefined product code IDs for insulin and metformin (194), I determined whether each woman received either medication within the 240 days before delivery. In this interval, women with any insulin prescription were classified as insulin-treated; those with metformin prescriptions but no insulin were classified as metformin-treated; and women without either medication were categorised as receiving lifestyle management only.

3.4.6. Sample size

For validation studies, a common recommendation is to include at least 100 participants with the outcome to minimise the risk of biased estimates of model performance (71,204).

However more recent recommendations encourage moving away from this general rule of thumb and instead calculating the required sample size to achieve the desired precision of performance metrics (154). Following Riley et al.'s recommendation, I calculated the required sample size using a simulation-based framework designed for the external validation of a clinical prediction model with a time-to-event outcome (154).

The original development article did not report individual predicted risks or the empirical distribution of the linear predictor (LP), so I estimated the required sample size using Royston's D and the reported C-index (0.72).

$$D = 5.5(C - 0.5) + 10.26(C - 0.5)^3 = 1.32$$

$$\sigma_{LP} = \frac{D}{\frac{8}{\pi}} = 0.83$$

I therefore assumed that the LP follows a normal distribution, centred at its mean:
$LP \sim N\ (0, 0.83^2)$

The model development article reports that by 10 years about 0.3% of the study population had diabetes complications. This corresponds to a 10-year survival probability of $S(10) = 0.997$. Through simulation, I found that drawing survival times from a conditional exponential distribution with a baseline rate of about 0.003 and a linear predictor effect of 1 lead to $S(10) = 0.996$, $c - index = 0.72$ and $D = 1.34$.

Next, I specified the assumed distribution of censoring times. The development article reports a median follow up time of 6.2 years. I assumed censoring times follow an exponential distribution (constant censoring hazard). Under that assumption the censoring rate λ_c was obtained from the reported median follow-up.

The median follow-up time m satisfies $\mathrm{P}(C \leq m) = 0.5$ hence $0.5 = 1 - e^{-\lambda_c m}$ so

$\lambda_c = \frac{\ln 2}{m} = 0.11.$

Using these distributions, I used an iterative simulation-based procedure to identify the minimum validation sample size that provides sufficiently precise estimates of model performance. For each simulated validation dataset, the calibration slope and C-index were computed. The process was repeated across a range of candidate sample sizes, and the smallest validation sample size that achieved the desired precision in the performance metrics was selected.

A sample size of 35,000 women achieves precise calibration slope and C-index estimates. With this sample size, across 100 simulations, the mean standard error of the calibration slope estimate was 0.047 (range 0.043–0.052) and the mean confidence interval width for the assumed C-index (0.70) was 0.019.

3.4.7. Missing data

Based on informed thresholds, I identified implausible values and replaced them with NA (Table 3.1). Missing data for each variable is summarised in Table 3.2.

Table 3.1. Implausible Data

Variable	Criteria	Implausible data, n (%)
Gestational age	<24 or >50 weeks	1,071 (0.5)
Birthweight	<1000 g or >6000 g	14,710 (7.3)
BMI	<15 or >60 kg/m²	987 (0.5)

Table 3.2. Missing data

Variable	Missing data, n (%)
Gestational age*	29,782 (15.1)
Birthweight	17,219 (8.7)
BMI value	58,102 (29.4)
BMI category	55,047 (27.8)
IMD*	247 (0.1)
Ethnicity	1,782 (0.9)
Delivery method	5,432 (2.7)
Region	1,278 (0.6)
Smoking status	21,611 (10.9)

Alcohol status	102,097 (51.6)
Pregnancy number	52,430 (26.5)

*These variables are included in the multivariate analysis.

Several variables: namely substance use disorder, SMM, previous complications, HDP, and treatment method, have no formally missing values, as these variables were defined using the presence of relevant clinical codes. Absence of a code was interpreted as absence of exposure, which may not reflect true patient behaviour; therefore, the completeness for these variables should be interpreted with caution.

For variables with missing data, no imputation was performed to maintain consistency with the original model development paper, which likewise did not perform or report any imputation procedures. As such, for multivariable analyses, the cohort was further restricted to women with complete data on all covariates required for model development, including maternal age (no missing data), gestational age (15.1% missing data), socioeconomic deprivation (0.1% missing data), substance use (no missing data), SMM (no missing data), previous obstetric complications (no missing data), and HDP (no missing data). To assess potential differences between included and excluded women, baseline characteristics were compared descriptively between groups (Supplementary Table 10.8). A more thorough assessment of potential differences between women with missing data and those without is presented later in the thesis in Chapter 5.

3.4.8. Statistical analysis

Baseline maternal, pregnancy and neonatal characteristics were summarised overall and stratified by 10-year diabetes status. Continuous variables were described using means and standard deviations, and categorical variables using frequencies and percentages. Differences between groups were assessed using chi-square tests for categorical variables and analysis of variance (ANOVA) for continuous variables. Because the very large sample size increases the likelihood that trivial differences are statistically significant, I additionally calculated SMDs for all variables (205). An SMD ≥ 0.20 was considered to represent a potentially meaningful difference between groups, whereas smaller SMDs were interpreted as negligible regardless of p-values.

Incidence rates were calculated as the number of women experiencing a complication divided by the total person-years at risk and expressed per 10,000 person-years. Incidence rates were estimated overall and stratified by baseline characteristics measured at cohort entry, including maternal age, parity, morbid obesity, substance use, socioeconomic deprivation, and HDP. For subgroup analyses, women were grouped according to the relevant baseline characteristic, and person-time and events were summed within each subgroup. All incidence analyses were restricted to a complete-case analytic cohort. The 95% confidence intervals for incidence rates were calculated assuming a Poisson distribution for the number of events, using chi-squared–based limits.

3.4.9. Model Application

Socioeconomic deprivation (defined as IMD quantile 5), substance use disorder, and SMM were modelled as binary variables. Previous pregnancy complications were specified as a three-level categorical variable: primiparous, multiparous with previous complications, and multiparous without previous complications. HDP were entered as a five-level categorical variable comprising no HDP, pre-existing or unspecified hypertension, gestational hypertension, pre-eclampsia/HELLP syndrome, and superimposed pre-eclampsia, with “no HDP” serving as the reference category. Maternal age and gestational age were modelled using RCS.

To replicate the interaction structure of the Ukah et al. model, two interaction terms were included: an interaction between maternal age (RCS terms) and SMM; and an interaction between maternal age (RCS terms) and HDP category. These interactions were retained to ensure the same predictor–outcome relationships as the original model. No additional predictors were added, and no re-estimation or recalibration of coefficients was performed, as the objective was to evaluate the temporal and geographic transportability of the published model coefficients to the CPRD cohort.

Predicted LPs for each woman were generated by multiplying the individual-level covariate values by the corresponding regression coefficients (β) reported by Ukah et al., including spline and interaction terms.

3.4.10. Performance evaluation

To evaluate the prognostic index (PI) in the validation data, I first fitted a Cox PH model with the PI entered as the sole covariate. The regression coefficient from this model represents the calibration slope of the linear predictor, indicating whether the relative effects implied by the PI are appropriately scaled in the validation population. Regression coefficients are reported with 95% confidence intervals and p-values derived from Wald tests.

While the calibration slope assesses whether the relative effects estimated by the original model apply in the validation cohort, this measure does not evaluate whether the absolute risk predictions are accurate. Assessing absolute calibration for Cox models requires the baseline survival function from the original model, which was not available in this analysis (206). As such, absolute calibration, also referred to as calibration-in-the-large, could not be assessed in this study.

Discrimination of the PI was quantified using Harrell's concordance index (C-index), which measures the ability of the PI to correctly rank individuals according to their risk of the outcome.

To evaluate whether re-estimation of individual predictor effects improved model fit compared with use of the PI alone, I refitted a multivariable Cox PH model in the validation cohort that included all original predictors, nonlinear terms, and prespecified interaction effects. Model fit of this refitted model was compared with that of the PI-only model using a likelihood ratio test based on twice the difference in log-partial likelihoods. The resulting chi-squared statistic and corresponding p-value were used to assess whether allowing individual coefficients to be re-estimated provided a statistically significant improvement in model fit. Regression coefficients estimated in the validation cohort were extracted and compared descriptively with the corresponding coefficients from the development cohort. This comparison was undertaken to assess the consistency of the magnitude and direction of individual predictor effects across cohorts.

As an exploratory analysis, I examined whether adding selected predictors not included in the original PI improved model performance in the validation cohort. Based on prior evidence and clinical plausibility, ethnicity, BMI and treatment method were added to a Cox PH that already included the PI (171,172,174,176). The PI and BMI were entered as continuous covariates,

while ethnicity and treatment method were included as categorical variables using the same reference categories as in descriptive analyses.

Model estimates were reported as regression coefficients with 95% confidence intervals and Wald test p-values. Discrimination of the extended model was assessed using Harrell's C-index. This analysis was undertaken for hypothesis-generating purposes only; and any revised model incorporating additional predictors would require independent external validation prior to clinical use.

3.4.11. Risk stratification after exploratory recalibration

As a secondary exploratory analysis, I examined the impact of recalibration on the predicted 10-year risks of T2DM complications. First, I updated the baseline hazard by fitting a Cox PH model in the validation cohort with the PI as an offset term. In this case, the relative effects represented by the original model are preserved, while the baseline hazard function is re-estimated using the validation data. Second, in addition to re-estimating the baseline hazard, the PI was uniformly shrunk using the calibration slope estimated in the validation cohort as the shrinkage factor.

For both analyses, women were grouped into four predicted risk categories based on their individual predicted 10-year risk. These risk categories were defined a priori as <0.006, ≥ 0.006 to <0.008, ≥ 0.008 to <0.03, and ≥ 0.03. The cut-points were selected based on those in development cohort, to enable direct comparison of risk stratification performance.

For each risk category, I calculated the total number and percentage of women, the number and percentage who experienced a T2DM complication within 10 years of delivery, and the number and percentage who did not experience the outcome. Observed event rates were calculated as the proportion of women within each risk group who experienced the outcome during follow-up.

Likelihood ratios (LRs) were calculated for each predicted risk category to quantify the ability of the model to discriminate between women who did and did not experience a complication. For each risk group, the likelihood ratio was defined as the probability of being classified into that risk group among women who experienced the outcome divided by the

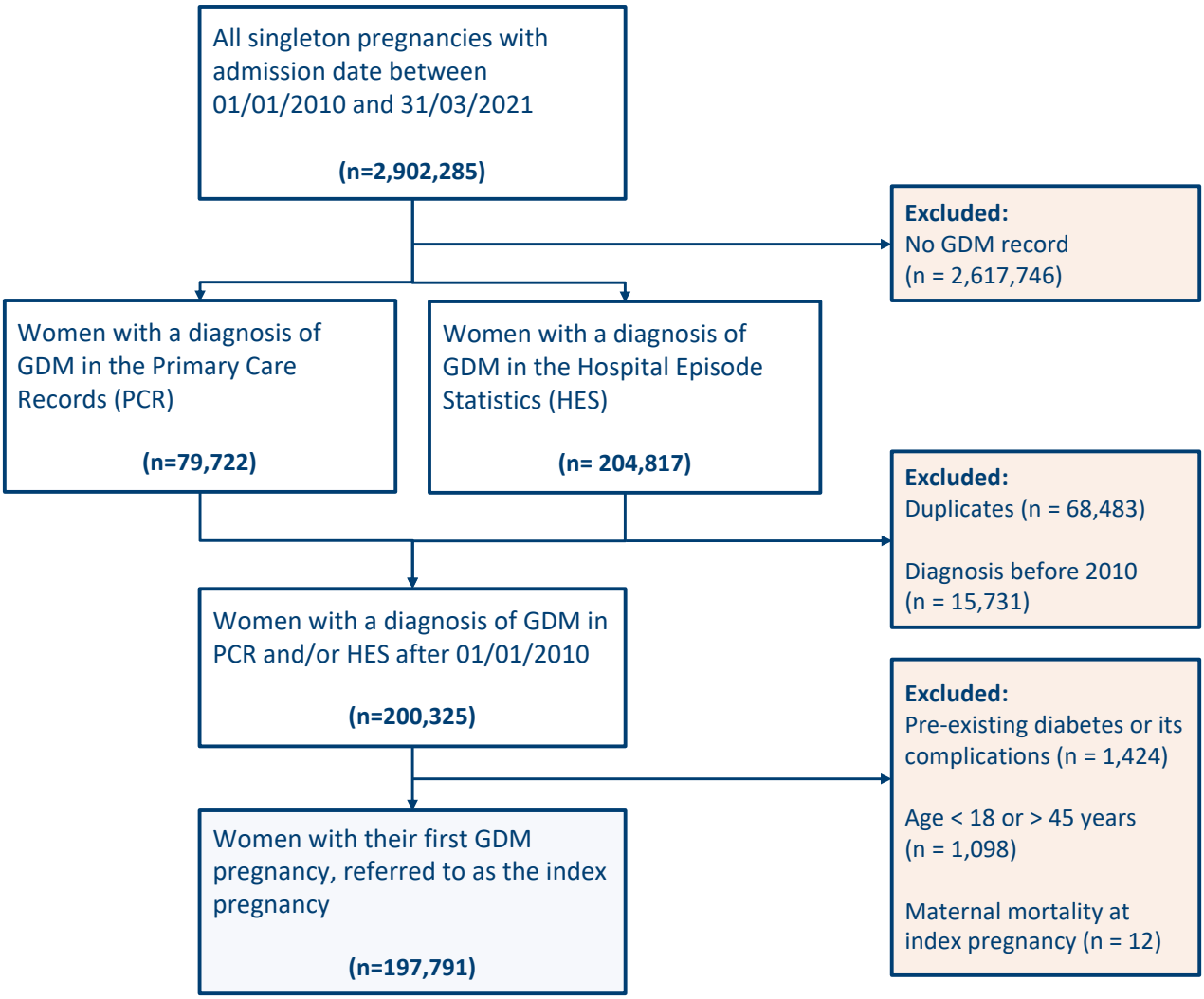
probability of being classified into the same risk group among women who did not experience the outcome. The 95% confidence intervals for LRs were calculated using standard log-transformation methods. Risk stratification results are presented side-by-side for the development and validation cohorts to assess the transportability of the model across populations.

3.5. Results

3.5.1. Study cohort derivation

As shown in Figure 3.1, the cohort was assembled by identifying 2,902,285 singleton deliveries between 2010 and 2021 and then selecting those with a recorded diagnosis of GDM in either PCR or HES. After removing duplicate entries and applying the exclusion criteria (age outside the eligible range, pre-existing diabetes, and maternal mortality), the final study cohort consisted of 197,791 women, from 1475 GP practices, with their first recorded GDM-affected pregnancy. This cohort was used for all subsequent analyses in this chapter.

Figure 3.1. Derivation of the Study Cohort Flowchart



3.5.2. Baseline characteristics of the validation cohort

Baseline characteristics of the cohort overall and stratified by diabetes status within 10 years of delivery are presented in Table 3.3. During follow-up, 5,331 women (2.7%) developed T2DM. The mean follow-up time was 6.9 years (SD 2.5) for the overall cohort but was shorter among women who developed diabetes compared with those who did not (4.3 vs. 6.9 years; SMD 1.10).

Mean maternal age at delivery was similar between groups (32.6 vs. 32.7 years; SMD 0.03). In contrast, differences were observed for BMI between women who developed T2DM and those who did not. Mean BMI was markedly higher among women who developed diabetes (31.3 vs. 27.1 kg/m²; SMD 0.63). Obesity-related categories demonstrated large differences, with higher proportions of obesity (28.4% vs. 17.0%) and morbid obesity (8.3% vs. 3.0%) in

the diabetes group (SMD 0.54). Current smoking was more common among women who developed diabetes (24.9% vs. 20.2%), and these women were less likely to report never smoking (50.0% vs. 58.5%; SMD 0.21). Alcohol use patterns showed smaller differences (SMD 0.07). There were significant differences by ethnicity, with lower proportions of White women (50.4% vs. 60.9%) and higher proportions of Asian (28.0% vs. 22.1%) and Black women (15.1% vs. 8.9%) among those who developed diabetes (SMD 0.28).

Parity did not differ significantly between the two groups but women who developed diabetes had a higher mean number of previous pregnancies (1.81 vs. 1.38; SMD 0.24). Gestational age at delivery was lower among women who developed diabetes (37.5 vs. 38.2 weeks; SMD 0.36), while mean birth weight did not differ materially between groups (SMD 0.01).

Hypertensive disorders of pregnancy were more prevalent among women who developed diabetes. Notably, pre-eclampsia/HELLP syndrome occurred in 6.8% of women who developed diabetes compared with 3.2% of those who did not, and pre-existing hypertension was more than twice as common (3.2% vs. 1.3%; SMD 0.22).

Finally, treatment modality during pregnancy differed significantly. Women who later developed diabetes were less likely to be managed with lifestyle measures alone (72.2% vs. 86.1%) and more likely to require insulin therapy (17.8% vs. 4.9%; SMD 0.42), indicating more severe metabolic disease during pregnancy.

Table 3.3. Baseline Characteristics of the cohort overall and by diabetes status 10 years after delivery

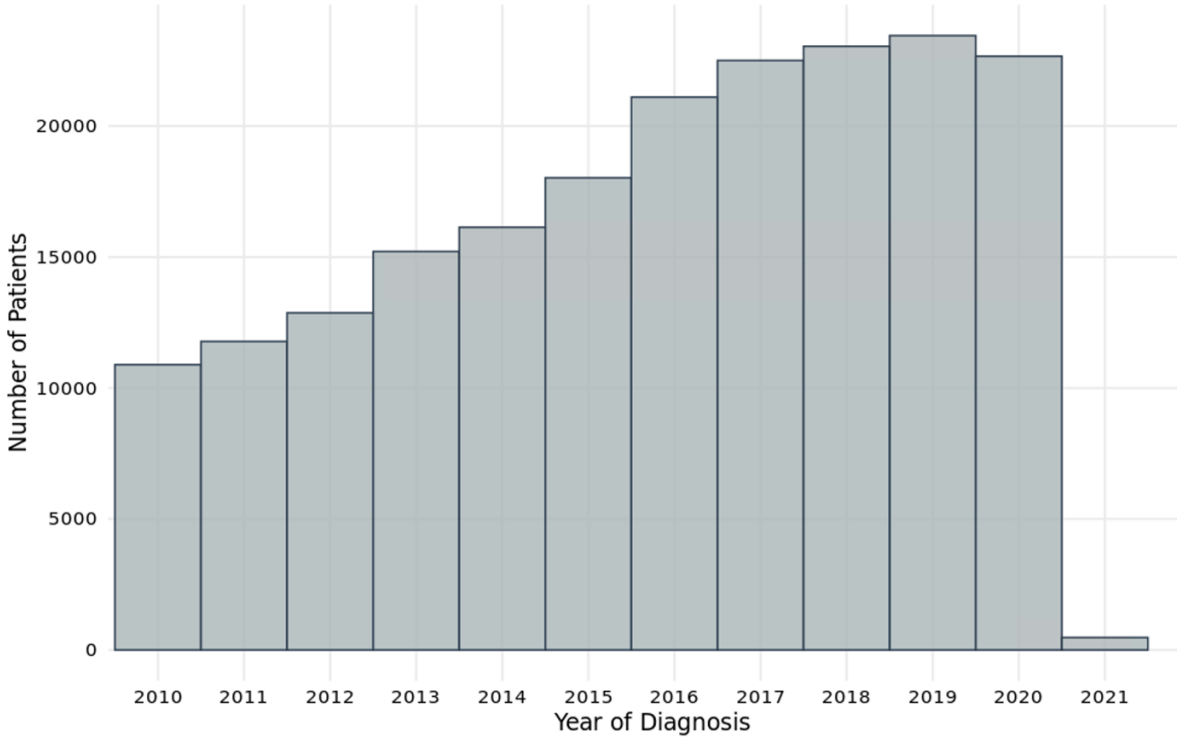
	Overall (N = 197,791)	**No Diabetes (N = 192,460)**	**Diabetes (N = 5,331)**	**SMD (p-value)**
Follow up time, years				
Mean (SD)	6.9 (2.5)	6.9 (2.4)	4.3 (2.5)	1.1 (<0.001)
Maternal age, years				
Mean (SD)	32.5 (5.4)	32.6 (5.3)	32.7 (5.6)	0.03 (0.04)
Maternal age category, n (%)				
< 25	15,893 (8.0)	15,417 (8.0)	476 (8.9)	0.07 (<0.001)
25–29	40,501 (20.5)	39,474 (20.5)	1,027 (19.3)	
30–34	67,632 (34.2)	65,916 (34.2)	1,716 (32.2)	
≥ 35	73,765 (37.3)	71,653 (37.2)	2,112 (39.6)	
BMI, kg/m^2				

	Overall (N = 197,791)	No Diabetes (N = 192,460)	Diabetes (N = 5,331)	SMD (p-value)
Mean (SD)	27.0 (6.5)	27.0 (6.4)	31.3 (7.5)	0.63 (<0.001)
BMI category, n (%)				
Underweight	5,618 (2.8)	5,564 (2.9)	54 (1.0)	
Normal weight	58,086 (29.4)	57,393 (29.8)	693 (13.0)	
Overweight	38,540 (19.5)	37,642 (19.6)	898 (16.8)	0.54 (<0.001)
Obese	34,295 (17.3)	32,780 (17.0)	1,515 (28.4)	
Morbid obesity	6,205 (3.1)	5,760 (3.0)	445 (8.3)	
Gestational age, weeks				
Mean (SD)	38.2 (1.8)	38.2 (1.8)	37.5 (2.0)	0.36 (<0.001)
Birth weight, g				
Mean (SD)	3,302 (543)	3,303 (541)	3,298 (622)	0.01 (0.50)
Number of previous pregnancies				
Mean (SD)	1.39 (1.62)	1.38 (1.61)	1.81 (1.96)	0.24 (<0.001)
Mode of delivery, n (%)				
Instrumental	104,645 (52.9)	101,572 (52.8)	3,073 (57.6)	0.13 (<0.001)
Spontaneous	87,714 (44.3)	85,625 (44.5)	2,089 (39.2)	
SMM, n (%)				
No	195,745 (99.0)	190,513 (99.0)	5,232 (98.1)	0.07 (<0.001)
Yes	2,046 (1.0)	1,947 (1.0)	99 (1.9)	
Previous obstetric complications, n (%)				
Primiparous	78,264 (39.6)	76,310 (39.6)	1,954 (36.7)	
No, multiparous	101,351 (51.2)	98,609 (51.2)	2,742 (51.4)	0.10 (<0.001)
Yes, multiparous	18,176 (9.2)	17,541 (9.1)	635 (11.9)	
Hypertensive disorders, n (%)				
None	188,606 (95.4)	183,812 (95.5)	4,794 (89.9)	
Gestational hypertension	90 (0.0)	87 (0.0)	3 (0.1)	
Preeclampsia/HELLP/ eclampsia	6,486 (3.3)	6,124 (3.2)	362 (6.8)	0.22 (<0.001)
Pre-existing hypertension	2,587 (1.3)	2,415 (1.3)	172 (3.2)	
Superimposed preeclampsia	22 (0.0)	22 (0.0)	0 (0.0)	
Smoking status, n (%)				
Never	115,163 (58.2)	112,498 (58.5)	2,665 (50.0)	0.21 (<0.001)

	Overall (N = 197,791)	No Diabetes (N = 192,460)	Diabetes (N = 5,331)	SMD (p-value)
Former	20,839 (10.5)	20,352 (10.6)	487 (9.1)	
Current	40,178 (20.3)	38,853 (20.2)	1,325 (24.9)	
Alcohol use, n (%)				
Never	22,384 (11.3)	21,730 (11.3)	654 (12.3)	
Former	841 (0.4)	806 (0.4)	35 (0.7)	0.07 (<0.001)
Current	72,469 (36.6)	70,653 (36.7)	1,816 (34.1)	
Ethnicity, n (%)				
White	119,840 (60.6)	117,154 (60.9)	2,686 (50.4)	
Asian	44,024 (22.3)	42,531 (22.1)	1,493 (28.0)	
Black	17,985 (9.1)	17,181 (8.9)	804 (15.1)	0.28 (<0.001)
Mixed	4,448 (2.2)	4,335 (2.3)	113 (2.1)	
Other	9,712 (4.9)	9,488 (4.9)	224 (4.2)	
Treatment method, n (%)				
Lifestyle only	169,490 (85.7)	165,640 (86.1)	3,850 (72.2)	
Metformin	17,937 (9.1)	17,403 (9.0)	534 (10.0)	0.42 (<0.001)
Insulin	10,364 (5.2)	9,417 (4.9)	947 (17.8)	

The temporal distribution of diagnoses included in the study cohort is shown in Figure 3.2. Diagnoses were recorded between 2010 and 2021, with a progressive increase in the number of women entering the cohort over time. Annual counts rose steadily from 2010, peaking between 2017 and 2019, before slightly declining in 2020.

Figure 3.2. Distribution of Diagnosis Years



Geographic distribution of participants is presented in Table 3.4. Women were from all regions of England, with the largest proportion residing in London, followed by the Midlands, the South East, and the North West. Smaller numbers were observed in the East of England, North East and Yorkshire, and Southwest. This wide geographic coverage suggests regional diversity in the study population. Compared with the National GDM Audit and the 2021 Census distribution of all women and girls in England, London was overrepresented in the study cohort whereas the East of England and North Weast and Yorkshire were underrepresented.

Table 3.4. Distribution of GDM cohort by region compared to women in the National GDM Audit, and all women and girls in England

Region	Women with GDM in study cohort n (%)	Women with GDM in National GDM Audit (192) %	All women and girls in England from 2021 Census (207) %
East of England	5966 (3.0)	12.7	11.2
London	64327 (32.5)	19.5	15.6
Midlands	36,060 (18.2)	20.0	19.1
North East & Yorkshire	10,301 (5.2)	14.3	14.4
North West	26554 (13.4)	10.4	13.1
South East	35437 (17.9)	16.1	16.5
Southwest	17868 (9.0)	6.9	10.1
Not recorded	1,278 (0.6)	0.0	0.0

Socioeconomic status, measured using IMD quintiles, is shown in Table 3.5. The cohort included women across the full spectrum of deprivation deciles, with a higher concentration in the more deprived quintiles. Participant counts increased progressively from the least deprived (Q1, 13.5%) to the more deprived quintiles (Q5, 26.3%). This pattern was similar to that observed in the National GDM Audit, where women were also more concentrated in the more deprived quintiles. In contrast, the 2021 Census distribution of all women and girls in England was even across the five quintiles, with each quintile contributing around a fifth of the population.

Table 3.5. Distribution of GDM cohort by IMD quintile compared to women in the National GDM Audit, and all women and girls in England

Deprivation quintile	Women with GDM in study cohort n (%)	Women with GDM in National GDM Audit (192) %	All women and girls in England from 2021 Census (208) %
Q1 - Least deprived	26,773 (13.5)	16.7	19.6
Q2	30,956 (15.7)	17.5	19.8
Q3	36,968 (18.7)	18.9	20.3
Q4	50,794 (25.7)	22.1	20.4
Q5 - Most deprived	52,053 (26.3)	24.7	19.9
Not recorded	247 (0.1)	0	0

The ethnic distribution of participants is presented in Table 3.6. The study cohort included women from a range of ethnic of backgrounds, with the largest proportion identifying as

White, followed by Asian, Black, Other and Mixed. The overall pattern was broadly similar to that observed in the National GDM Audit. However, the 2021 Census distribution of all women and girls in England showed a higher proportion of White women (80.9% vs 60.6%) smaller proportions in the Asian, Black and Other groups. Compared with the general population, ethnic minority groups had a higher proportion in the GDM cohort.

Table 3.6. Distribution of GDM cohort by ethnicity compared to women in the National GDM Audit, and all women and girls in England

Ethnicity	Women with GDM in study cohort n (%)	Women with GDM in National GDM Audit (192) %	All women and girls in England from 2021 Census (209) %
Asian	44,024 (22.3)	25.2	9.6
Black	17,985 (9.1)	6.3	4.4
Mixed	4,448 (2.2)	2.4	3.0
White	119,840 (60.6)	59.0	80.9
Other	9,712 (4.9)	3.2	2.2
Not recorded	1,782 (0.9)	3.9	0.0

3.5.3. Comparison of the original derivation cohort and external validation cohort

After restricting the cohort to women with complete data on all covariates required for model validation, the final analytic validation cohort consisted of 167,798 women (84.8% of the eligible cohort). Individuals excluded due to missing covariates numbered 29,993 (15.2%). Compared with women included in the complete-case analytic cohort, excluded women demonstrated small differences across most baseline characteristics, with SMDs generally below 0.10 (Appendix 3, Supplementary Table 10.8).

Table 3.7 presents the distribution of women across baseline subgroups and the corresponding ten-year incidence of T2DM complications, expressed per 10,000 person-years with 95% confidence intervals, for both the development cohort (N = 90,143) and the external validation cohort (N = 167,798). Overall, the incidence of T2DM was higher in the development cohort, at 3.8 per 10,000 person-years (95% CI 3.4–4.3), compared with 2.3 per 10,000 person-years (95% CI 2.0–2.5) in the validation cohort.

Table 3.7. Ten-year incidence of type 2 diabetic complications in women with GDM, according to characteristics at cohort entry for both the development and validation cohorts

	Development Cohort (134) N = 90,143		**Validation Cohort** N = 167,798			
Characteristics	**Total number of women n (%)**	**Incidence per 10,000 person-years (95% CI)**	**Total number of women n (%)**	**Number of events**	**Person-years**	**Incidence per 10,000 person-years (95% CI)**
Age, years						
<25	10,912 (12.1)	7.1 (5.5–9.0)	13,674 (8.1)	29	99,216	2.9 (2.0–4.2)
25–29	25,703 (28.5)	3.7 (3.0–4.6)	34,380 (20.5)	78	245,346	3.2 (2.5–4.0)
30–34	30,666 (34.0)	3.1 (2.5–3.9)	57,399 (34.2)	80	402,409	2.0 (1.6–2.5)
≥35	22,862 (25.4)	3.1 (2.3–4.0)	62,345 (37.2)	79	430,086	1.8 (1.5–2.3)
Primiparity						
Yes	54,342 (60.3)	3.9 (3.3–4.5)	66,464 (39.6)	90	469,164	1.9 (1.5–2.4)
No	35,801 (39.7)	3.7 (3.0–4.5)	101,334 (60.4)	176	707,892	2.5 (2.1–2.9)
Substance abuse						
Yes	1,684 (1.9)	7.2 (3.3–13.6)	22,683 (13.5)	43	141,160	3.0 (2.2–4.1)
No	88,459 (98.1)	3.8 (3.3–4.2)	145,115 (86.5)	223	1,035,897	2.2 (1.9–2.5)
Socioeconomic deprivation						
Deprived	20,432 (22.7)	7.0 (5.8–8.4)	68,448 (40.8)	152	482,707	3.1 (2.7–3.7)
Not deprived	65,308 (72.4)	2.8 (2.4–3.3)	99,350 (59.2)	114	694,349	1.6 (1.4–2.0)
HDP Type						
No HDP	80,858 (89.7)	3.3 (2.9- 3.8)	159,866 (95.3)	230	1,122,012	2.0 (1.8–2.3)
Pre-existing or unspecified hypertension	3,035 (3.4)	6.2 (3.6–9.9)	2,196 (1.3)	10	14,975	6.7 (3.2–12.3)

	Development Cohort (134) N = 90,143		Validation Cohort N = 167,798			
Characteristics	**Total number of women n (%)**	**Incidence per 10,000 person-years (95% CI)**	**Total number of women n (%)**	**Number of events**	**Person-years**	**Incidence per 10,000 person-years (95% CI)**
Gestational hypertension	2,864 (3.2)	7.5 (4.3–12.2)	78 (0.05)	0	625	0.0 (0.0–59.0)
Pre-eclampsia/HELLP syndrome	3,058 (3.4)	9.6 (6.2–14.3)	5,640 (3.4)	26	39,313	6.6 (4.3–9.7)
Superimposed pre-eclampsia	328 (0.4)	12.4 (2.6–36.3)	18 (0.01)	0	132	0.0 (0.0–279.8)
			Total			
Total	90,143	3.8 (3.4–4.3)	167,798	266	1,177,056	2.3 (2.0–2.5)

Note: After restricting the cohort to women with complete data on all covariates required for model validation, the final analytic validation cohort consisted of 167,798 women (84.8% of the eligible cohort).

In both cohorts, incidence was higher among women with morbid obesity, substance abuse, socioeconomic deprivation, and hypertensive disorders of pregnancy, although absolute incidence rates were lower in the validation cohort. For example, in the development cohort, women with morbid obesity had an incidence of 13.6 per 10,000 person-years (95% CI 9.4–19.1), compared with 3.5 per 10,000 person-years (95% CI 3.1–3.9) among those without morbid obesity. In the validation cohort, the corresponding incidence rates were lower, at 2.8 per 10,000 person-years (95% CI 1.3–5.1) among women with morbid obesity and 2.1 per 10,000 person-years (95% CI 1.8–2.4) among those without morbid obesity.

In both cohorts, women without HDP had the lowest incidence rates, at 3.3 per 10,000 person-years (95% CI 2.9–3.8) in the development cohort and 2.0 per 10,000 person-years (95% CI 1.8–2.3) in the validation cohort. Higher incidence rates were observed among women with pre-existing or unspecified hypertension, with rates of 6.2 (95% CI 3.6–9.9) and 6.7 (95% CI 3.2–12.3) per 10,000 person-years in the development and validation cohorts, respectively. Similarly, women with pre-eclampsia or HELLP syndrome had elevated incidence rates in both cohorts, at 9.6 (95% CI 6.2–14.3) in the development cohort and 6.6 (95% CI 4.3–9.7) in the validation cohort. Estimates for gestational hypertension and superimposed pre-eclampsia in the validation cohort were associated with wide confidence intervals, due to small numbers of events, reflecting limited precision.

Parity showed modest differences in incidence between cohorts. In the development cohort, primiparous women experienced an incidence of 3.9 per 10,000 person-years (95% CI 3.3–4.5), compared with 3.7 per 10,000 person-years (95% CI 3.0–4.5) among multiparous women. In the validation cohort, incidence was lower among primiparous women (1.9, 95% CI 1.5–2.4) than among multiparous women (2.5, 95% CI 2.1–2.9).

Overall, across most baseline characteristics, incidence rates of T2DM complications were consistently higher in the development cohort than in the external validation cohort, although the relative ordering of risk across subgroups was broadly similar.

Table 3.8. Incidence rates of type 2 diabetic complications among women with GDM, within 10 years of delivery, for both the development and validation cohorts

	Development Cohort (134)		**Validation Cohort**	
	N = 90,143		**N = 167,798**	
Complication type	**Number of women**	**Incidence per 10,000 person-years (95% CI)**	**Number of women**	**Incidence per 10,000 person-years (95% CI)**
Any diabetic complication	283	3.8 (3.4–4.3)	266	2.3 (2.0–2.5)
Coma	21	0.3 (0.2–0.4)	8	0.1 (0.0–0.1)
Acidosis	69	0.9 (0.7–1.2)	104	0.9 (0.7–1.1)
Renal	63	0.8 (0.7–1.1)	33	0.3 (0.2–0.4)
Ophthalmic	60	0.8 (0.6–1.0)	54	0.5 (0.3–0.6)
Neurological	61	0.8 (0.6–1.1)	17	0.1 (0.1–0.2)
Circulatory	52	0.7 (0.5–0.9)	8	0.1 (0.0–0.1)
Other/Multiple	200	2.7 (2.3–3.1)	65	0.6 (0.4–0.7)

Note: After restricting the cohort to women with complete data on all covariates required for model validation, the final analytic validation cohort consisted of 167,798 women (84.8% of the eligible cohort).
The total person-years used for the calculation of all incidence rates in the validation cohort is 1,177,056 person-years. This figure is constant across all complication types because women were followed from delivery to a single shared censoring point, the earliest of any diabetic complication, death, the end of CPRD data collection, or ten years post-delivery, rather than being censored separately for each complication type.
In this table, the categories are non-mutually exclusive as such the sum of individual complication counts will exceed the count of any diabetic complication.

Table 3.8 summarises the incidence rates of T2DM complications within 10 years of delivery among women with GDM. In the development cohort, a total of 283 women had any T2DM complication during follow-up, corresponding to an incidence rate of 3.8 per 10,000 person-years (95% CI 3.4–4.3). In the validation cohort, 266 women experienced diabetic complications, with a lower incidence rate of 2.3 per 10,000 person-years (95% CI 2.0–2.5), consistent with the lower overall incidence observed across subgroups in this cohort.

Among specific complications, diabetic acidosis was the most frequently observed individual diagnosis in both cohorts. In the development cohort, 69 women had diabetic acidosis, yielding an incidence rate of 0.9 per 10,000 person-years (95% CI 0.7–1.2). A comparable incidence was observed in the validation cohort, where 104 women experienced acidosis-related complication, with an incidence rate of 0.9 per 10,000 person-years (95% CI 0.7–1.1). This represented the only complication type with similar absolute incidence rates across cohorts.

Renal, ophthalmic, neurological, circulatory and coma-related complications were all less frequent in the validation cohort than in the development cohort. The composite category of other diabetic complications accounted for a substantial proportion of events in the development cohort, with 200 events and an incidence rate of 2.7 per 10,000 person-years (95% CI 2.3–3.1). In contrast, in the validation cohort, there were 65 events and an incidence rate of 0.5 per 10,000 person-years (95% CI 0.4–0.7).

Overall, incidence rates for nearly all specific complication types were higher in the development cohort than in the external validation cohort, except for diabetic acidosis, for which rates were similar.

3.5.4. Performance evaluation for type 2 diabetes complications

When the PI was entered as the sole covariate in a Cox PH model, it was significantly associated with the outcome (T2DM complications), with an estimated regression coefficient of 0.28 (95% CI: 0.22–0.33; $p < 0.001$). This corresponds to a hazard ratio of 1.32 per one-unit increase in the PI (95% CI: 1.25–1.39). This finding indicates that higher values of the PI were associated with an increased hazard of the outcome in the validation cohort. The estimated calibration slope was below 1, suggesting that the relative effects implied by the PI were weaker in the validation population than assumed by the original model.

Discrimination of the PI was moderate, with a Harrell's concordance index of 0.72 (95% CI 0.69–0.74), indicating that the PI retained the ability to rank individuals according to their relative risk in the validation cohort.

Re-estimation of the individual predictor effects, including nonlinear and interaction terms, resulted in a statistically significant improvement in model fit compared with the PI–only model (likelihood ratio test, $p < 0.001$). This indicates that allowing predictor effects to differ from those in the original model improved model fit in the validation cohort. Regression coefficients estimated in the validation cohort were compared with those from the development cohort (Table 3.9). In the validation cohort, only a subset of predictors demonstrated statistically significant associations with the outcome.

Maternal age spline terms no longer showed significant association with the outcome in the validation cohort. In contrast, gestational age at delivery remained associated with the outcome,

with both spline terms statistically significant and of greater magnitude than in the development cohort. Socioeconomic deprivation also remained significantly associated with the outcome, although the coefficient was attenuated, while the association with substance use was no longer statistically significant.

For hypertensive disorders of pregnancy, pre-eclampsia/HELLP syndrome was statistically significant in the development cohort and remained associated with the outcome in the validation cohort, with a larger estimated coefficient. Other hypertensive disorder subtypes and SMM exhibited marked across cohorts, with some coefficients becoming extreme in the validation cohort, reflecting sparse data.

Table 3.9. Regression coefficients of the prediction model for T2DM complications in the development and validation cohorts

Predictors	Model coefficients in development cohort (134)	Model coefficients in validation cohort
Maternal age		
Knot 1	Reference	Reference
Knot 2	− 0.0964	− 0.04 (−0.09, 0.02)
Knot 3	0.0805	− 0.003 (−0.08, 0.07)
Socioeconomically deprived		
No	Reference	Reference
Yes	0.7941	0.51 (0.26, 0.75)***
Substance use		
No	Reference	Reference
Yes	0.4916	0.25 (−0.08, 0.58)
Gestational age at delivery		
Knot 1	Reference	Reference
Knot 2	0.0521	0.12 (0.01, 0.23)*
Knot 3	− 0.3401	− 0.46 (−0.59, −0.33)***
SMM		
No	Reference	Reference
Yes	2.7722	− 656 (−1857, 545)
Previous complications		
No, multiparous	Reference	Reference
Yes, multiparous	0.2469	0.36 (0.02, 0.71)*
Primiparous	0.0447	− 0.15 (−0.43, 0.12)
Hypertensive disorders of pregnancy		
No HDP	Reference	Reference
Pre-existing or unspecified hypertension	− 1.610	− 1.76 (−16.0, 12.5)
Gestational hypertension	− 0.010	− 12.8 (−23353, 23328)
Pre-eclampsia/HELLP syndrome	1.690	4.18 (0.61, 7.76)*
Superimposed pre-eclampsia	− 9.7517	− 12.2 (−41454, 41430)
Maternal age & SMM interaction		

Predictors	Model coefficients in development cohort (134)	Model coefficients in validation cohort
Knot 1 SMM (no)	Reference	Reference
Knot 2 SMM (yes)	0.1121	20.6 (−17.1, 58.3)
Knot 3 SMM (yes)	0.1359	− 14.0 (−39.5, 11.6)
Maternal age & hypertensive disorders of pregnancy interaction		
Knot 1 no hypertension	Reference	Reference
Knot 2 pre-existing or unspecified hypertension	0.0820	0.07 (−0.41, 0.56)
Knot 3 pre-existing or unspecified hypertension	− 0.1052	0.02 (−0.42, 0.46)
Knot 2 gestational hypertension	0.0329	0.03 (−831, 831)
Knot 3 gestational hypertension	− 0.0790	0.02 (−970, 970)
Knot 2 pre-eclampsia/HELLP syndrome	− 0.0422	− 0.13 (−0.27, 0.002)
Knot 3 pre-eclampsia/HELLP syndrome	0.0639	0.19 (0.01, 0.37)*
Knot 2 superimposed pre-eclampsia	0.3724	−0.02 (1549, 1549)
Knot 3 superimposed pre-eclampsia	− 0.2730	0.08 (−1812, 1812)

*p < 0.05; **p < 0.01; ***p < 0.001 denote statistical significance in the validation cohort

In exploratory analyses including additional predictors (Table 3.10), the PI remained significantly associated with the outcome (regression coefficient 0.25, 95% CI 0.18–0.33; p < 0.001). Some ethnic groups were significantly associated with the outcome, with women of Asian or Black ethnicity at a significantly higher hazard compared to White women. Treatment method was also significantly associated with T2DM complications. Compared with women managed with lifestyle modifications alone, both metformin and insulin treatment were associated with higher hazards, with the highest hazard observed for insulin treatment. Higher BMI was also significantly associated with increased hazard of T2DM complications.

The extended model demonstrated a Harrell's C-index of 0.77 (95% CI 0.73–0.81) indicating improvement in discrimination relative to the model including the PI alone.

Table 3.10. Regression coefficient estimates from an exploratory Cox proportional hazards model for T2DM complications with additional predictors

Predictors	Regression Coefficient Estimates (95% CI)	p-value
Prognostic Index (PI)		
PI	0.25 (0.18–0.33)	<0.001
Ethnicity		
White	Reference	
Asian	0.53 (0.16–0.89)	0.005
Black	0.52 (0.06–0.99)	0.03
Mixed	0.14 (-1.01–1.29)	0.81
Other	0.30 (-0.47–1.08)	0.44
Treatment method		
Lifestyle modifications	Reference	
Metformin	0.82 (0.41–1.23)	<0.001
Insulin	1.55 (1.19–1.92)	<0.001
BMI value		
BMI	0.06 (0.04–0.08)	<0.001

Baseline-hazard recalibration alone, performed by entering the published PI as an offset term in a Cox model, yielded a cumulative baseline hazard at 10 years of 0.0003, corresponding to a baseline survival of 0.9997. After shrinkage of the PI and re-estimation of the baseline hazard, the cumulative baseline hazard at 10 years was 0.004, corresponding to a baseline survival of 0.996. Risk stratification based on the updated predicted risks is shown in (Table 3.11). In the development cohort, most women were classified into the lowest predicted risk group (<0.006), accounting for 80.9% of the cohort, with an observed event proportion of 0.2%. Higher predicted risk categories contained smaller proportions of women, with observed event proportions increasing across categories to 2.5% in the highest risk group (≥0.03). Likelihood ratios increased across successive risk groups, from 0.70 in the lowest risk group to 8.68 in the highest risk group.

Table 3.11. Distribution of predicted 10-year risk of T2DM complications and observed outcomes in the development cohort and validation cohort after recalibration

Predicted 10-year risk group	Development cohort (134)			Validation cohort		
	Women n (%)	Events n (%)	LR (95% CI)	Women n (%)	Events n (%)	LR (95% CI)
< 0.006	72,918 (80.9)	160 (0.2)	0.70 (0.63–0.77)	166,086 (99.0)	262 (0.2)	0.995 (0.98–1.0)
≥0.006–<0.008	7,595 (8.4)	33 (0.4)	1.82 (1.33–2.48)	1 (0.0)	0 (0.0)	—
≥0.008–<0.03	9,367 (10.4)	83 (0.9)	2.90 (2.42–3.48)	1,479 (0.9)	1 (0.07)	0.43 (0.06–3.0)
≥0.03	263 (0.3)	7 (2.5)	8.68 (4.14–18.23)	232 (0.1)	3 (1.2)	8.25 (2.7–25.7)
Total	**90,143**	**283**	—	**167,798**	**266**	—

Predicted risks were grouped a priori. Likelihood ratios (LRs) compare the probability of observed outcomes within each risk group relative to the lowest risk group (<0.006). Dashes indicate estimates could not be calculated due to zero events.

In the validation cohort, the distribution of predicted risk differed substantially (Table 3.11). Nearly all women (99.0%) were classified into the lowest predicted risk group. Higher predicted risk categories comprised very small proportions of the validation cohort. Baseline-hazard recalibration alone produced a more extreme concentration of predicted risk in the lowest category and no events in the two intermediate categories.

3.5.5. Performance evaluation for type 2 diabetes

When the model was used to predict any T2DM diagnosis within 10-years, the estimated calibration slope was 0.23. Discrimination of the PI was weaker, with a Harrell's C-index of approximately 0.63 (95% CI: 0.63–0.65). The regression coefficients of the prediction model can be found in Appendix 3 (Supplementary Table 10.9, Supplementary Table 10.10).

3.6. Discussion

3.6.1. Summary of findings

In this study, I performed an external validation of a previously published prognostic model developed by Ukah et al. to predict the risk of T2DM complications following GDM (134). External validation is a necessary step in the evaluation of prediction models, as it assesses whether a model developed in one population performs adequately when applied to a

different population, healthcare system, and data environment. The aim of this analysis was to evaluate the transportability of the original model developed in a Canadian cohort to a large UK cohort using linked primary and secondary care data.

In the validation cohort, the PI retained a statistically significant association with the 10-year risk of T2DM complications, but overall model performance was clearly inferior to that reported in the development study. Discrimination was moderate (C-index = 0.72) and similar to the original cohort (C-index = 0.72). However, calibration was poor, with a calibration slope of 0.28 indicating overestimation of predictor effects when the original coefficients were applied directly to the UK population. These results suggest that, although the model can still rank individuals according to relative risk, it does not generate reliable absolute risk estimates without recalibration.

The reduced performance observed in the validation cohort likely reflects important differences in baseline risk, outcome incidence, predictor measurement, and healthcare delivery between the Canadian and UK settings. Several predictors showed marked attenuation or instability, further limiting the direct applicability of the original model. Although refitting the full model in the validation data significantly improved model fit, and exploratory extensions incorporating ethnicity, BMI and treatment method increased discrimination (C-index = 0.77), these analyses highlight the need for model updating rather than confirm the validity of the original PI. Taken together, these findings indicate that the model, in its original form, does not perform sufficiently well to support unmodified clinical use in the UK context for decision-making.

3.6.2. Model performance in development vs validation cohorts

The comparison of regression coefficients between the development and validation cohorts reveals heterogeneity in the individual predictor effects, indicating limited transportability of several covariate–outcome relationships across healthcare settings. Importantly, the incidence of T2DM-related complications was markedly lower in the validation cohort than in the development cohort, both overall and across nearly all demographic subgroups. One possible explanation for the lower incidence of T2DM complications is variation in antenatal GDM ascertainment between the UK and Canadian settings. In England, NICE recommends a risk-factor-based approach to testing for GDM (21), whereas Canadian guidance has generally supported universal screening at 24 to 28 weeks' gestation (210). As a result, some women

with GDM who do not meet NICE risk criteria may not be identified. This interpretation is supported by evidence suggesting that targeted screening under NICE criteria may miss a substantial portion of women with GDM (24).

While some predictors demonstrated broadly consistent relative patterns of risk, others were markedly attenuated or unstable, reflecting a combination of differences in baseline risk, outcome incidence, measurement, and healthcare context between the Canadian and UK populations.

Socioeconomic deprivation demonstrated a consistent positive association with T2DM complications in both the development and validation cohorts. Although the magnitude of the coefficient differed between settings, the direction and statistical significance of the association were preserved, supporting the robustness of deprivation as a predictor across populations. This finding is consistent with previous evidence that the incidence of T2DM following GDM increases with greater socioeconomic deprivation (175). The attenuation in the magnitude may reflect differences in how deprivation is operationalised, its correlation with unmeasured risk factors, and its interaction with healthcare access and utilisation in the two settings. In the development study, socioeconomic deprivation was defined using a composite individual-level index capturing income, education, and employment within Quebec administrative data. In contrast, the validation study used the IMD, an area-level measure incorporating broader domains such as access to services, crime, and living environment. These indices are not directly comparable and may classify different groups of women as "deprived," limiting direct transportability of the deprivation coefficient.

In the English healthcare context, socioeconomic deprivation may also influence the pathway from disease onset to hospitalisation rather than underlying disease risk itself. Women living in more deprived areas may have reduced engagement with routine antenatal and postnatal care, leading to later diagnosis of post-gestational metabolic disease. Evidence from the 2010 National Maternity Survey showed that with each decrease in socioeconomic position women were 25% less likely to receive any antenatal care and 15% less likely to attend a routine postnatal check-up (211). As a result, diabetic complications in socioeconomically deprived women may be more likely to be detected later and outside the follow-up window captured.

Substance use disorder was positively associated with diabetic complications in both cohorts, but the association was weaker and no longer statistically significant in the validation cohort.

This attenuation is likely due to limitations in how substance use is recorded in routine UK healthcare data. Substance use can be under-recorded as it depends on patient disclosure (212,213). Stigma and fear of losing their child prevent women from disclosing substance use to clinicians, which can lead to misclassification. When exposure is misclassified in this way, true associations can be weakened, making effects harder to detect. In addition, substance use may be linked to higher risks of death or loss to follow-up, which could reduce the number of women who are followed up long enough to develop diabetic complications, further weakening the observed association.

Gestational age at delivery demonstrated broadly consistent nonlinear associations across cohorts, with both spline terms remaining statistically significant. This suggests that shorter gestation is associated with subsequent diabetic complications across settings. The preservation of this association indicates that some predictors may retain stable prognostic meaning despite broader model miscalibration.

Multiparous women with previous complications had a higher hazard of future diabetic complications in both the development and validation cohorts. This association is plausible as women with previous pregnancy complications are at increased risk of metabolic or cardiovascular diseases (214). This suggests that adverse obstetric history may add prognostic information for predicting severe diabetic complications once other pregnancy and maternal factors are accounted for.

Hypertensive disorders of pregnancy displayed the greatest heterogeneity across subtypes. Pre-eclampsia and HELLP syndrome remained strongly and positively associated with diabetic complications in the validation cohort, with an even larger coefficient than observed in the development cohort. This finding is biologically plausible as pre-eclampsia is characterised by systemic endothelial dysfunction and maladaptive placental vascular development, which can persist postpartum and contribute to long-term cardiometabolic risk through shared pathophysiological pathways such as chronic endothelial injury and insulin resistance (215). In contrast, other hypertensive subtypes, particularly gestational hypertension and superimposed pre-eclampsia, showed extreme or non-estimable coefficients due to very small numbers of events in the validation cohort. These estimates should be interpreted cautiously, as sparse data can lead to exaggerated coefficients that do not reflect stable underlying associations. Similarly, SMM had imprecise estimates due to the rarity of events.

The interaction terms involving maternal age further illustrate the instability of complex model structures when transported across populations. While most age–predictor interactions were non-significant in the validation cohorts, interactions between maternal age and pre-eclampsia were statistically significant, suggesting that the impact of pre-eclampsia on diabetic complications may differ by age. However, given the overall low event rate and the multiple interaction terms included, these findings may reflect chance variation rather than meaningful effect modification and underscore the risk of overfitting when complex interaction structures are applied to new data.

Overall, the predictor-specific discrepancies observed between the development and validation cohorts indicate that several coefficients are highly context dependent and sensitive to differences in measurement, healthcare delivery, and population demographics. These findings reinforce the necessity of model updating, rather than direct application, when attempting to use prognostic models across settings with differing healthcare systems and data-generating processes. This interpretation is supported by the exploratory secondary analyses, in which baseline-hazard recalibration and uniform shrinkage of the PI was insufficient, further indicating that the original model would require more substantial updating for use in the English setting.

3.6.3. Model performance in T2DM complications vs T2DM

Identifying women at the highest risk of severe diabetic complications is clinically important as these individuals are likely to benefit most from intensive follow-up and specialist care. However, it is also important to identify women at increased risk of developing T2DM, even without complications. T2DM often develops gradually and may remain asymptomatic for long periods (216), during which opportunities for effective prevention and early intervention exist. Focusing only on women who progress to complications risks missing a much larger group who develop T2DM without complications, but who could still benefit from timely lifestyle or pharmacological interventions. For this reason, I also evaluated model performance for incident T2DM, recognising that broader risk identification is essential for informing population-level prevention strategies and reducing long-term disease burden.

When applied to the broader outcome of any T2DM diagnosis within 10 years, the prognostic model demonstrated poorer calibration and discrimination than when predicting T2DM

complications. The calibration slope of 0.23 indicates attenuation of the relative risk gradients, suggesting that the original model markedly overestimates differences in risk when applied to incident T2DM in the validation cohort. The model had a Harrell's C-index of 0.63, indicating that the model retained some ability to rank individuals according to risk.

The weaker performance of the model for incident T2DM may be partly explained by differences between this outcome and the one used in the original model development. The PI was designed to predict diabetic complications, which reflect a later and more severe stage of disease, whereas incident T2DM is a more common outcome that is typically diagnosed and managed in primary care. Differences in outcome definition, incidence, and detection pathways may therefore contribute to the observed reduction in calibration and overall performance. These findings suggest that the model is not suited for predicting incident T2DM.

3.6.4. Comparison with other studies

To our knowledge, there are currently no published external validation studies of prediction models specifically developed to estimate the risk of T2DM or T2DM complications following GDM. As a result, direct comparisons with externally validated models targeting the same outcome are not possible. However, the broader literature on external validation of prediction models for GDM and for incident T2DM in other populations has produced mixed findings.

Some external validation studies of GDM prediction models have reported acceptable performance. For example, an external validation study evaluated several published prognostic models for GDM and found that many demonstrated reasonable discrimination and calibration when applied to a new population of 3723 women recruited from hospitals and midwifery practices in the Netherlands (217). The model developed by Teede et al. (218) was identified as having one of the best overall performance in terms of discrimination, calibration, and clinical usefulness when compared with other GDM prediction models. However, that same model showed poor performance in another external validation study conducted in a different population of 673 women recruited from the University Hospital of Pavia, Italy (219). Another external validation of 12 GDM prediction models found that nearly all models overestimated the risk of GDM when applied to new populations,

indicating poor calibration despite acceptable discrimination in some cases (220). This is consistent with our findings of poor calibration but acceptable discrimination.
Similar findings have been observed in the external validation of T2DM prediction models. An external validation study using data from the Dutch cohort of the European Prospective Investigation into Cancer and Nutrition (EPIC-NL) found that most published T2DM prediction models showed moderate discrimination but poor calibration and overestimated the actual risk of developing diabetes. These findings are consistent with our results, which likewise demonstrated acceptable discrimination but poor calibration. This variability highlights how strongly model performance depends on the characteristics of the population in which it is applied, including baseline risk, case mix, and healthcare context, and underscores the importance of validating prediction models in the specific population where they are intended for use.

In many published validation studies, recalibration through adjustment of the intercept or baseline survival function improved calibration, highlighting that differences in underlying disease incidence between development and validation cohorts are a major source of miscalibration (221–223). Although the incidence of T2DM complications in our validation cohort was lower, assessment of absolute calibration was not performed. This was because the baseline survival function from the original model development study was not reported.

Updating strategies such as re-estimation of coefficients or extension of models with additional predictors have been proposed to improve transportability, although these approaches effectively generate a new model that requires further external validation. Recent work by Cooray et al. involving temporal validation and updating of an early pregnancy GDM prediction model illustrates how model updating can sustain and enhance predictive performance (222). In an Australian cohort defined by universal screening and current diagnostic criteria, the original model demonstrated reasonable discrimination but poor calibration. Updating methods including re-estimation of the intercept and slope, and revision of predictor coefficients with revised ethnicity categories, resulted in an updated model with superior discrimination and better overall performance compared with the original specification (222).

Consistent with this literature, our exploratory analyses showed that updating the model coefficients and extending the original PI by adding ethnicity, BMI and treatment method improved discriminatory performance in the validation cohort, indicating that incorporating

context-specific predictors can enhance risk stratification when models are transported to new settings. This improvement is likely to reflect differences in case mix between the development and validation populations, as well as variation in the prognostic relevance of individual predictors between the Canadian and UK systems. In particular, the distribution and relative importance of several original predictors differed in the validation cohort, potentially due to differences in population demographics, variation in predictor measurement, and changes in clinical practice over time. However, because such extensions effectively constitute a new model specification, any updated model would require external validation in independent populations to assess its generalisability and suitability for clinical use.

3.6.5. Clinical implications

This study highlights important limitations in the current availability of clinically useful prediction models for T2DM and T2DM complications following GDM. Although several prognostic models have been developed for this purpose, our findings, together with evidence from the wider literature, indicate that many existing models do not transport well across healthcare settings. In particular, models developed in one population often demonstrate reduced calibration and altered predictor effects when applied to another population, limiting their applicability in routine clinical practice.

This limitation is clinically relevant because women with a history of GDM represent a well-defined group at increased risk of future T2DM, yet risk stratification remains imprecise. Without reliable and locally validated prediction tools, post-partum care is often delivered uniformly, rather than being tailored to individual risk. This may reduce the efficiency of prevention efforts, as some women who are at particularly high risk may not receive sufficiently intensive follow-up, while others at lower risk may undergo unnecessary monitoring. Given that T2DM typically develops gradually and may be asymptomatic for long periods, improved risk stratification could support earlier intervention during a window when preventive strategies are most effective.

The results of this external validation indicate that the evaluated PI cannot be used without modification to estimate absolute risk of T2DM complications in a UK setting. This finding reinforces existing recommendations that prediction models should undergo external

validation and, where necessary, recalibration before being considered for clinical use in new populations.

3.6.6. Strengths and limitations

A key strength of this study is that it represents the first external validation of a prognostic model for incident T2DM or T2DM complications following GDM using linked UK primary and secondary care data. By using CPRD Aurum linked with HES and ONS records, this study was able to follow women longitudinally after a GDM-affected pregnancy and capture both incident T2DM and T2DM complications across healthcare settings. The large sample size and national coverage enhance the generalisability of the findings to routine clinical practice in England. In addition, by preserving the original model structure and coefficients during validation, this study provides a clear assessment of model transportability rather than model redevelopment, which strengthens the interpretation of the validation results.

However, this study also had several limitations. First, the incidence of T2DM complications in the validation cohort was low, reflecting both the rarity of complications and differences in outcome ascertainment between the development and validation settings. The low number of events limited statistical power for some subgroup analyses and contributed to instability of regression coefficients for less common predictors, particularly certain hypertensive disorder subtypes and SMM.

Second, although extensive efforts were made to harmonise outcome and predictor definitions, some variables have not been measured equivalently across datasets. For example, socioeconomic deprivation, and SMM were defined using different constructs and coding systems compared with the development study, which may have led to misclassification and attenuation of associations. Even where variables were nominally defined in the same way, differences in healthcare systems, clinical coding practices, and data recording processes may have resulted in systematic variation across populations.

Third, missing data were present for several key covariates, including BMI and gestational age. To maintain consistency with the original model development, no imputation was performed and analyses were restricted to complete cases (84.8% of all cases). While comparisons suggested only small differences between included and excluded women, this approach may still have introduced selection bias and reduced precision. I explore the

patterns of missing data in more details in Chapter 5. High levels of missing data for lifestyle and anthropometric variables are a known limitation of routinely collected primary care data and may have limited the ability to fully account for confounding factors.

Fourth, the baseline survival function from the original model development study was not available, which precluded full assessment of absolute calibration. Absolute calibration (calibration-in-the-large) assesses whether predicted risks correspond to observed event rates on an absolute scale (for example, whether a predicted 10% risk translates to a 10% observed incidence in the validation cohort). Without access to the baseline survival function, it was not possible to directly compare predicted absolute risks with observed outcomes in a clinically interpretable manner.

Consequently, evaluation was limited to relative calibration, including assessment of the calibration slope, which reflects whether the model appropriately ranks individuals by risk and whether predicted risks are proportionally scaled across risk groups. While acceptable relative calibration indicates that the model preserves risk ordering, it does not guarantee accurate estimation of absolute risk. This limitation reduces the model's immediate clinical applicability, where decision-making depends on reliable absolute risk estimates, and highlights the importance of complete reporting in model development studies to support future external validation.

3.6.7. Conclusions

Overall, although the published PI retained moderate discrimination in this UK cohort, its limited calibration and poor transportability indicate that it is not suitable for unmodified clinical use. It would require updating and further validation before being used to estimate 10-year risk of T2DM complications after GDM.

CHAPTER 4

Development of a data-driven care pathway to improve referral to the diabetes prevention programme for women with a history of gestational diabetes

4. CHAPTER 4: Development of a data-driven care pathway to improve referral to the diabetes prevention programme for women with a history of gestational diabetes

4.1. Chapter Overview

This chapter describes the development and pilot evaluation of a data-driven care pathway to improve referral to the NHS Diabetes Prevention Programme (DPP) for women with a history of GDM. Specifically, it outlines the design of an automated primary-care-based search strategy to identify eligible women, its integration into routine general practice workflows, and its initial evaluation in a pilot practice.

4.2. Background and Rationale

4.2.1. National guidelines around T2DM prevention after GDM

The need to focus on T2DM prevention after GDM has been voiced by several national bodies. The guidelines developed by NICE in 2015 (21) and the NICE quality standards updated in January 2023 (224) both highlight the need for postnatal follow-up for women with GDM including postnatal screening and referral to the NHS DPP when eligible. The National Institute for Health Research (NIHR) calls for research that encourages the establishment of effective follow-up mechanisms for women post-pregnancy, particularly within primary care settings, to reduce the future risk of T2DM. In 2021, the James Lind Alliance Priority Setting Partnerships published the top 10 priorities for research in diabetes and pregnancy in the UK based on a consultation involving women, their support networks and healthcare professionals (225). Research priority 8 was identifying the best way to reduce the risk or prevent women with GDM developing other types of diabetes any time after pregnancy.

4.2.2. NHS Diabetes Prevention Program (DPP)

The evidence base for diabetes prevention through lifestyle intervention is well established (226–230). The US Diabetes Prevention Program demonstrated a 58% relative risk reduction in progression to T2DM among individuals receiving intensive lifestyle intervention compared with placebo (226). Long-term follow-up data confirmed sustained benefits extending beyond 10 years (231).

These findings informed public health policy and led to the implementation of large-scale, population-based diabetes prevention programmes internationally. The NHS DPP, also known as the Healthier You Programme, was launched by NHS England in 2016 as a national behavioural intervention targeting individuals at high risk of developing T2DM (232). The programme is primarily offered to adults identified with non-diabetic hyperglycaemia (NDH), defined as HbA1c 42–47 mmol/mol (6.0–6.4%) or FPG 5.5–6.9 mmol/L (232).

The NHS DPP delivers sessions over nine months, focusing on weight reduction, dietary modification, and increased physical activity. Since its inception, the programme has evolved to include digital and remote delivery models, improving accessibility and engagement (233,234). Early evaluation of the NHS DPP has demonstrated clinically meaningful outcomes in routine practice, with intention-to-treat analyses showing mean reductions of 2.3 kg in weight and 1.26 mmol/mol in HbA1c, rising to 3.3 kg and 2.04 mmol/mol, respectively, among participants who completed the programme (235). Additionally, 37% of completers achieved at least 5% reduction in body weight and outcomes improved as the number of sessions attended increased (235).

Referral into the programme is typically initiated in primary care following identification of risk through routine blood testing or NHS Health Checks. However, recognising the elevated risk of T2DM among women with previous GDM, NHS England expanded the NHS DPP to include women with a history of GDM, allowing direct access via self-referral pathways (236). Women with a history of GDM can access the programme even without a recent HbA1c result, removing an additional barrier to entry (236). However, despite clear eligibility and elevated risk, referral rates for this population remain suboptimal, indicating a gap between guideline recommendations and clinical practice (192).

4.2.3. Challenges in postnatal follow up for GDM patients

The National GDM Audit 2024–25 reveals notable deficiencies in postnatal follow-up and preventive care for women diagnosed with GDM. Although GDM is the most common medical condition affecting pregnant women in England, only 57.4% of women with GDM received an annual HbA1c measurement, despite NICE recommendations for annual postnatal glycaemic monitoring (192). Similarly, a retrospective CPRD-HES cohort study found that while most women with previous GDM received at least one glucose test within

five years postpartum, fewer than one-quarter received one test per year of follow-up (191). Audit findings also indicate considerable deficits in broader cardiometabolic follow-up: only 52.2% had blood pressure checks, 44.7% had BMI measurements, and only 35.4% received cholesterol tests after pregnancy (192). These care gaps further reduce opportunities for holistic risk assessment and reinforcement of lifestyle advice that could support DPP engagement.

Most strikingly, audit data demonstrate extremely low referral and participation in the NHS DPP among women with a history of GDM. Despite NICE guidance and specific NHS England policy enabling both GP referral and self-referral for this group, only 13.8% of women with a GDM diagnosis had been referred to the DPP and 4.5% had ever participated in the programme (192). This figure highlights a critical implementation gap between guideline recommendations and clinical practice, and suggests that postnatal referral pathways are not successfully translating into patient uptake at scale.

4.2.4. Opportunities using electronic health records

Primary care EHR systems contain structured diagnostic codes, laboratory results, and demographic data that can be leveraged to generate automated searches identifying women with a documented history of GDM.

An illustrative example of this approach is the collaboration between Optum's EMIS Health and the Cheshire and Merseyside Operational Delivery Network (ODN) in efforts to eliminate hepatitis C (237). In the initial pilot phase, a search pathway integrated in primary care systems was deployed across three GP practices to conduct structured searches of coded patient records. The search identified 465 patients who met predefined hepatitis C risk factor criteria, in addition to 47 patients with a confirmed diagnosis of hepatitis C but no recorded treatment in their primary care record (237). This pilot demonstrated that a substantial number of at-risk or untreated individuals could be identified directly from existing primary care data through systematic interrogation of EHRs.

Such population-based case-finding offers a scalable mechanism to improve identification and referral of women with prior GDM to the NHS DPP. Embedding structured searches and automated prompts within primary care records reduces reliance on clinician memory and

opportunistic identification during consultations. In the context of increasing workload and competing priorities in primary care, system-generated patient lists and streamlined referral processes can minimise administrative burden and support more consistent implementation of preventive care.

4.3. Aims of this Research

The aim of this project is to develop and implement a data-driven referral pathway within primary care systems that systematically identifies women with a history of GDM who are eligible for the NHS DPP. By leveraging structured EHR data, this research seeks to reduce reliance on opportunistic clinician identification, streamline referral processes, and improve alignment with national guidelines for T2DM prevention.

4.4. Methods

4.4.1. Eligibility criteria

The eligibility criteria were developed based on the NHS DPP eligibility criteria and in consultation with primary care physicians. Patients are identified based on their NHS numbers and their registration status within the healthcare system. To be included in the eligible cohort, patients must have a recorded GDM diagnosis, as defined by the clinical ref set 999017331000230105, and be within the 18 to 80 years age range. Patients who already have a recorded diagnosis of T1DM or T2DM are excluded. Additionally, patients who have successfully completed the NHS DPP and patients who have been referred to the DPP in the past two years are excluded, ensuring the pathway focuses on newly identified at-risk individuals. A complete list of codes used in the query can be found in Appendix 4 (Appendix 4. Supplementary Material for Chapter 4
Supplementary Table 10.11). The code lists were developed using the NHS digital ref set and confirmed by the clinical informatics team working within the EHR provider, and our GP contact.

4.4.2. Pathway development

Eligible patients are identified using a structured SQL query, retrieving key clinical indicators such as patient ID, GDM diagnosis date, age, HbA1c levels, FPG levels, and BMI. The query

calculates the patient's age based on their date of birth and formats the latest observation dates for HbA1c and FPG results. It also applies logical conditions to flag values exceeding risk thresholds: specifically, HbA1c levels greater than 48 mmol/mol and FPG levels greater than 7.0 mmol/L. The extracted dataset is structured to facilitate systematic analysis and informed decision-making within GP practices.

4.4.3. Pathway evaluation

Pilot practice and pathway refinement

We initially worked with one GP practice in Oxfordshire, Buckinghamshire and Berkshire West to validate the search strategy and refine the pathway within a real-world primary care setting. This pilot phase was used to test the feasibility of identifying eligible women with a history of GDM through the EHR and to gather feedback on features that would support routine clinical use. For example, following discussion with the GP, functionality was added to enable coding back of the referral into the patient record. This iterative process ensured that the pathway was aligned with existing workflows before wider implementation.

In addition to informing pathway refinement, the pilot phase provided an opportunity to describe the characteristics of the women identified through the search strategy. A descriptive analysis was performed to summarise the baseline demographic and clinical characteristics of women identified as eligible for the pathway in the pilot practice. Variables extracted from the EHR included age, ethnicity, year of GDM diagnosis, latest recorded HbA1c category, and latest recorded BMI category, and were summarised using appropriate descriptive statistics.

The pilot search was conducted on April 14th, 2026.

Power calculation

A sample size calculation was performed to estimate the number of participants required to detect a significant increase in invitation to self-refer rates following implementation of the pathway.

Null Hypothesis (H_0): There is no significant change in invitation to self-refer rates.
Alternative Hypothesis (H_1): There is a significant increase in invitation to self-refer rates.

The sample size depends on:

- Baseline referral rate (p_1): The proportion of eligible women invited to self-refer to DPP before intervention (20%)
- Expected referral rate after intervention (p_2): The proportion of women expected to be invited to self-refer after implementation (60%)
- Significance level (α): 0.05
- Power (1-β): 80% to ensure sufficient sensitivity to detect differences

Formula for Sample Size Calculation (Paired Proportions Test)

$$n = \frac{\left(Z_{\alpha/2} \times \sqrt{2p_{\text{avg}}(1-p_{\text{avg}})} + Z_{\beta} \times \sqrt{p_1(1-p_1)+p_2(1-p_2)}\right)^2}{(p_2-p_1)^2}$$

Absolute effect size: $\Delta p = |p_2 - p_1|$

Pooled proportion: $p_{avg} = (p_2 + p_1)/2$

$Z_{\alpha/2}$ = Critical value for the significance level (α=0.05 → $Z_{\alpha/2}$ =1.96)

Z_{β} = Critical value for power (80% power → Z_{β}=0.84)

Based on the paired proportions test, the required sample size to detect an increase from 20% to 60% uptake with 80% power and 5% significance level is 23 patients with GDM.

Wider implementation across GP practices

Following the pilot practice, additional GP practices were recruited to join the pathway evaluation. The validation process will be conducted over a 12-month period, during which 6 GP will be given access to the module. Implementation success will be evaluated by tracking key adoption metrics, ensuring that the module is functioning as expected and reaching the intended patient population.

Performance metrics

The primary and secondary outcomes will focus on changes in patient referral and participation rates following the implementation of the pathway.

Primary Outcome:

- Change in the proportion of women with a history of GDM who are invited to self-refer to DPP before and after pathway implementation

Secondary Outcomes:

- Change in the proportion of women with a history of GDM who decline participation in DPP
- Change in the proportion of women who start the DPP after referral
- Change in the proportion of women who successfully complete the DPP

To evaluate the effectiveness of the referral pathway, we will conduct a pre- and post-implementation analysis over a 12-month period before and after the intervention. During the 12 months prior to implementation, for each included GP practice, we will extract data to establish a baseline for key performance metrics. This includes:

- The total number of women with a documented history of GDM
- The proportion of eligible women who were invited to self-refer to the DPP
- The proportion of women who declined participation after being referred
- The proportion of women who, after self-referral, actively enrolled in the DPP
- The proportion of women who successfully completed the DPP

Additionally, to monitor patient engagement, the following reports will be generated at regular monthly intervals:

- Number of patients who received the text notification regarding the program
- Number of patients who opened the notification link, providing insight into patient engagement levels

Following the introduction of the structured referral pathway, we will analyse the same performance metrics during the year after implementation. This will help assess the intervention's impact on referral and engagement. Additionally, statistical analyses will be conducted where applicable to determine whether observed differences are statistically significant. The findings will help assess whether the intervention effectively improves DPP referral rates and participation, providing insight into potential areas for further optimisation.

4.5. Results

4.5.1. Description of the pathway tool workflow

The pathway provides a structured, system-enabled workflow to identify and invite women with GDM to self-refer to the NHS DPP. The key steps are summarised below.

Step 1: Activating the Pathway and Data Sharing Agreements

A member of staff from the GP practice with appropriate access rights must first activate the relevant data sharing and pathway agreements within the GP facing platform.

Step 2: Reviewing the Patient Cohort

The system generates a dashboard listing eligible patients identified through the predefined coded criteria (Figure 4.1). For each patient, the system displays: age, latest recorded BMI, confirmation of GDM diagnosis, and the date of GDM diagnosis. Glycaemic monitoring data are also visible, including the most recent HbA1c result, HbA1c test date, and an automated flag indicating whether HbA1c exceeds 47 mmol/mol. Similarly, the dashboard shows the latest FPG result, FPG test date, and a binary indicator of whether FPG exceeds 6.9 mmol/L.

Selecting an individual patient allows the clinician to view further details, including a side-panel summary of demographics, medications, and a timeline of pathway-related actions.

During review of the generated patient cohort, clinicians can move individuals to an Excluded tab if they are not appropriate for contact or referral at that time. The excluded list remains accessible and can be reviewed at any point. Patients may be reinstated into the active pathway if eligibility criteria are later met or circumstances change. Conversely, patients selected for contact are moved to the Diabetes Prevention tab.

Figure 4.1. Cohort review dashboard showing eligible patients and latest clinical monitoring data



Type 2 Diabetes Prevention Programme referral after Gestational Diabetes Mellitus 2 > Patients list

Type 2 Diabetes Prevention Programme referral after Gestational Diabetes Mellitus

Patients (4)

Search

Awaiting triage 3 | Excluded | Diabetes prevention 1 | Completed

Include Patients | Exclude Patients

The data used to create the list of potentially eligible patients has a latency with a maximum of 4 days and therefore any changes you make to patient data (eg. contact details) can take up to 4 days to appear within Pathway.

Name	Age	Latest BMI	GDM diagnosis	GDM diagnosis date	Latest HbA1c result	HbA1c date	HbA1c above 47	Latest FPG result	FPG date	FPG above 6.9	SMS Status
NASSER, Imman	47	28	Yes	01/01/2024	46 mmol/mol	01/01/2026	No	124 mg/dL	01/01/2026	No	
LUPTON, Louise Connie (Mrs)	25	28	Yes	01/01/2024	46 mmol/mol	01/01/2026	No	124 mg/dL	01/01/2026	No	
EAVE, Jerem	59	28	Yes	01/01/2024	46 mmol/mol	01/01/2026	No	124 mg/dL	01/01/2026	No	

Step 3: Sending an SMS Invitation

Once patients have been moved to the Diabetes Prevention tab, clinicians can select individual patients or use the "select all" function to proceed with contact. An automated SMS invitation to the NHS DPP is then generated directly from the system interface (Figure 4.2). The standardised message informs patients of their increased risk of T2DM following GDM and invites them to self-refer to the programme via a registration link. The SMS template is provided in Appendix 4 (Supplementary File 10.4).

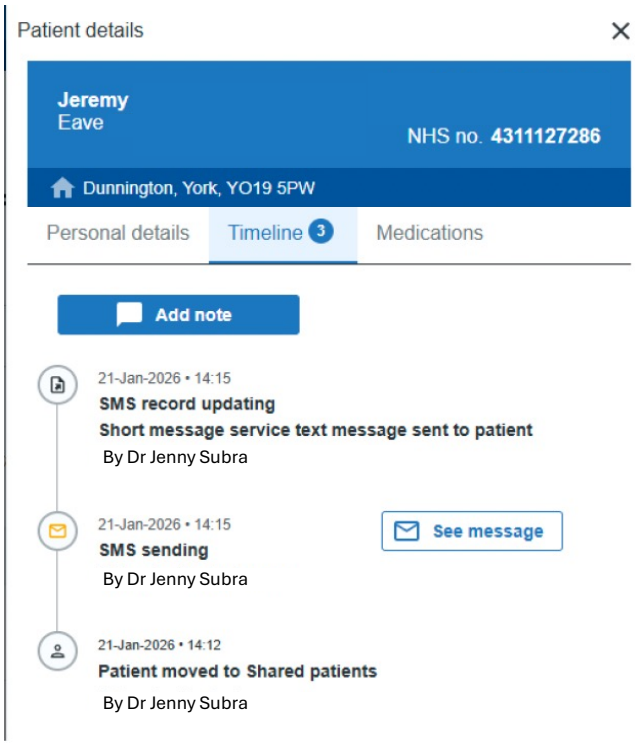
The system automatically verifies whether a mobile number is recorded and whether the patient has opted to receive text communications. Where a mobile number is available but messaging preferences are restricted, clinicians have the option to override communication preferences where appropriate. Following confirmation, the message is sent via the system.

Figure 4.2. SMS invitation interface used to send a standardised self-referral message to eligible patients



The SMS status is recorded in real time within the patient's pathway timeline, with statuses displayed as "SMS sending", "SMS sent", or "SMS failed". If successfully delivered, the SMS is automatically documented as a consultation entry in the patient's EHR (Figure 4.3). The associated record update status is also tracked in the timeline and displayed as "SMS record updating", "SMS record updated", or "SMS record update error". This ensures that patient contact and documentation are fully auditable within the primary care system.

Figure 4.3. Individual patient side-panel displaying demographic details and the timeline of pathway-related actions



Step 4: Recording Referral in the Electronic Health Record

After confirming successful SMS delivery ("SMS Sent" status), clinicians record the SNOMED code "Referral to NHS Diabetes Prevention Programme" in the patient's electronic healthcare record via the Actions menu. The update is stored as a consultation entry and logged within the patient timeline (Figure 4.4).

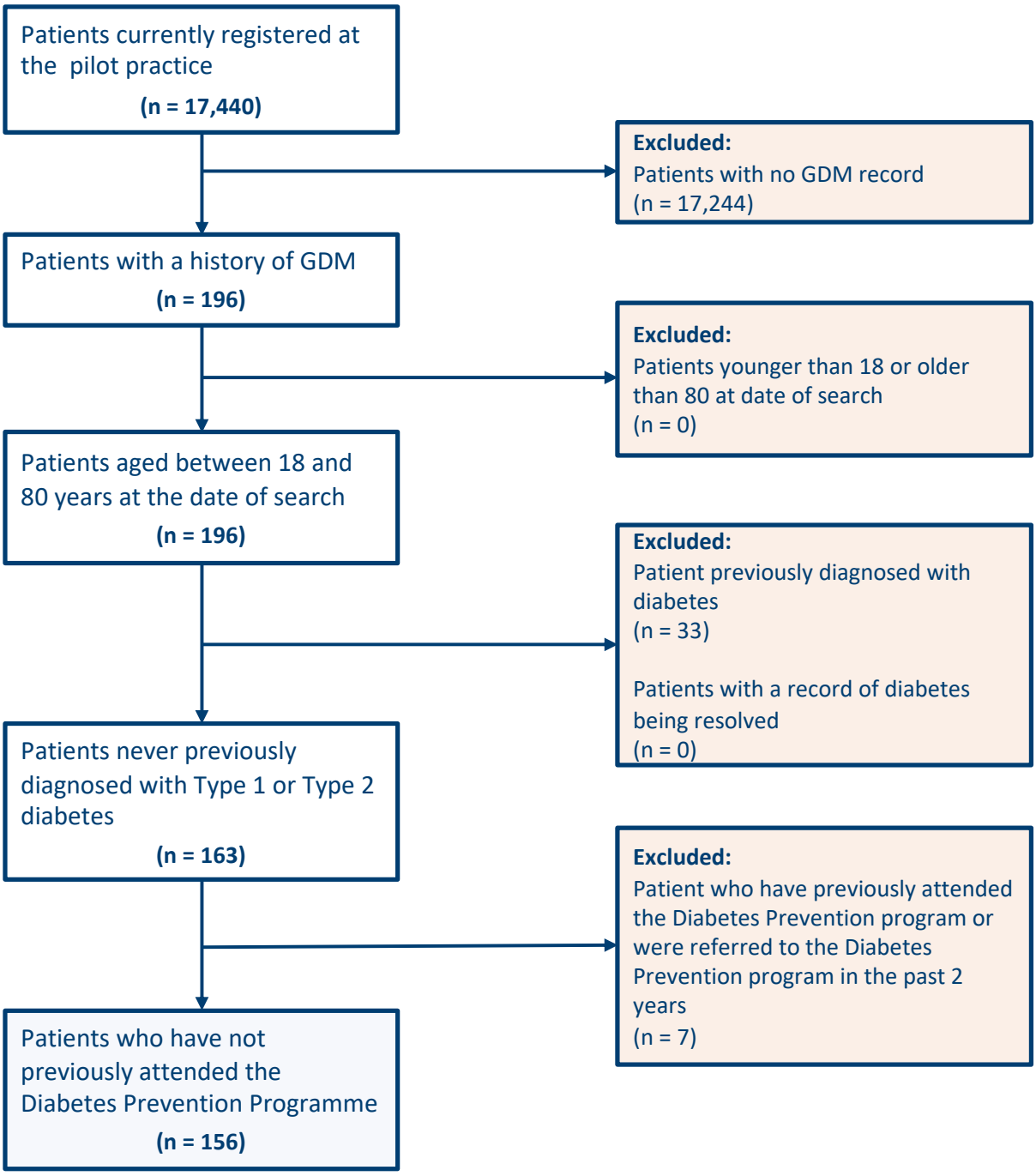
Figure 4.4. Electronic health record update screen used to record referral to the NHS DPP using SNOMED coding



4.5.2. Pilot evaluation

Of 17,440 patients registered at the pilot practice, 196 women had a recorded history of GDM (Figure 4.5). After excluding patients with prior diabetes diagnoses (n = 33) and previous attendance/referral to the NHS DPP (n = 7), 163 patients were eligible for the DPP. Of those, only 7 (4.3%) had previously attended the program. The remaining 156 women met the DPP eligibility criteria but had never been referred before.

Figure 4.5. Consort diagram of the diabetes prevention pathway for one pilot practice



The proportion of women invited to self-refer to the DPP increased from 4.3% (7/163) before pathway implementation to 99% after implementation. This change was statistically significant (chi-squared test, $p < 0.001$). The one exception was a woman whose HbA1c already met the diagnostic threshold for T2DM despite no coded diagnosis.

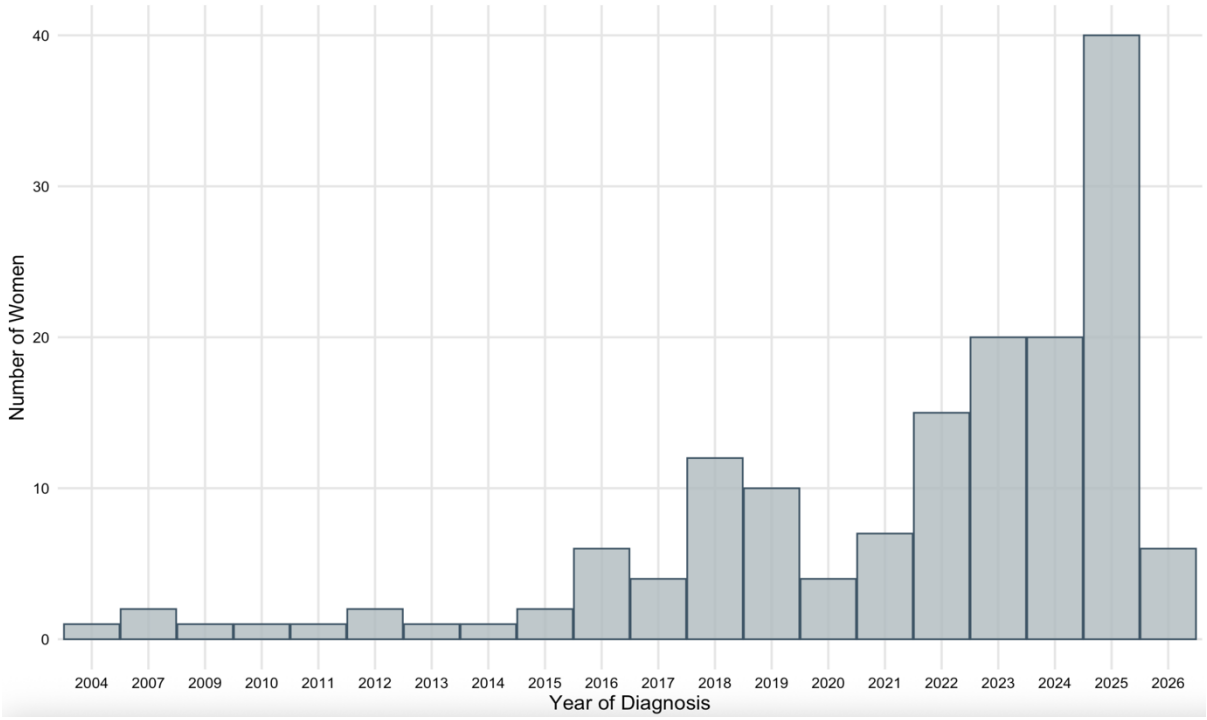
Among these 156 eligible women, the mean age was 37.0 years (SD 6.1), and the mean BMI was 28.4 kg/m² (SD 5.2). The majority (60.3%) were of Asian ethnicity (primarily South Asian), followed by White (13.5%), Black (10.9%), and Mixed (5.8%) ethnic groups (Table 4.1). Two-thirds of the eligible cohort has HbA1c values in the normal range (64.7%), while 17.3% were in the pre-diabetes range and 0.6% in the diabetes range. An additional 17.3% did not have any recorded HbA1c result. BMI measurements indicated that the cohort was largely above the healthy weight range, with 37.8% classified as overweight and 30.1% as obese.

Table 4.1. Characteristics of women identified as eligible for the DPP pathway in the pilot practice

Characteristics	N (%)
Ethnicity	
Asian	94 (60.3)
White	21 (13.5)
Black	17 (10.9)
Mixed	9 (5.8)
Other	11 (7.1)
Missing	4 (2.6)
HbA1c Category	
< 42 mmol/mol	101 (64.7)
42-47 mmol/mol (pre-diabetes)	27 (17.3)
≥48 mmol/mol (diabetes)	1 (0.6)
Missing	27 (17.3)
BMI Category	
Underweight	0 (0)
Normal weight	42 (26.9)
Overweight	59 (37.8)
Obese	47 (30.1)
Missing	8 (5.1)

At the pilot practice, recorded GDM diagnoses ranged from 2004 to 2026, with diagnoses concentrated in more recent years (Figure 4.6).

Figure 4.6. Year of recorded GDM diagnosis among eligible women



4.5.3. Secondary outcomes

Due to challenges in data access and delay in pathway implementation, the secondary outcome analysis will not be shared in this thesis. The results will compare pre- and post-implementation data. The findings will help assess whether the intervention effectively improves DPP referral rates and participation, providing insight into potential areas for further optimisation. This evaluation is currently underway, and the protocol is presented in the Methods section of this chapter.

4.6. Discussion

4.6.1. Summary of findings

This chapter described the development and pilot of a data-driven referral pathway designed to improve the identification and referral of women with a history of GDM to the NHS DPP. By leveraging primary care records, the pathway uses an automated search to identify

patients eligible for DPP referral, removing reliance on opportunistic GP recognition. In the pilot practice, the tool identified 156 eligible women for referral to the DPP. The implementation of the pathway increased the proportion invited to self-refer from 4.3% to 99%. This pilot demonstrates that embedding structure searches, automated invitations and standardised documentation within routine practice workflows can significantly improve alignment with guideline-recommended preventative care.

4.6.2. Clinical and policy implications

In primary care, identification of women with a history of GDM can be missed when preventative care relies on clinician memory, opportunistic consultations or fragmented follow-up between maternity services and GP practices. This pathway helps shift referral activity from an ad hoc process to a systematic search hosted within the electronic health system already used by GPs. As such, this pathway is clinically important because it increases invitations to self-refer to the NHS DPP but also creates a mechanism through which diabetes preventive care can be delivered more consistently. This is especially important given the existing implementation gap in postnatal follow-up: national audit findings show that only 57.4% of women with previous GDM had HbA1c monitoring recorded, 13.8% had ever been offered a DPP course, and only 4.5% had attended. Within the pilot practice, the women identified through the pathway also had a clinical profile consistent with elevated future risk, with most above the healthy weight range and 17.3% already having HbA1c values in the pre-diabetes range. A further 17.3% had no recorded HbA1c result, suggesting that the pathway may also help practices identify women who are overdue for recommended glycaemic follow-up and require clinical review. In addition, one woman had an HbA1c value meeting the diagnostic threshold for T2DM despite no coded diagnosis being present in the record, suggesting that the pathway may also help bring clinical attention to women who require further review or follow-up of potentially unrecognised T2DM.

Additionally, this pathway has direct relevance to national policy, as several national bodies have emphasised the need to focus on T2DM prevention after GDM. This tool helps operationalise these policy expectations by identifying eligible women, supporting outreach and referral at scale and ensuring that referral activity is documented within the EHRs, with little additional burden to clinicians. This is particularly relevant in primary care settings where competing demands make sustained follow up difficult. Automated EHR searches and

notifications may also have wider value beyond clinical service delivery, as similar systems have been used to support identification of eligible patients for clinical studies (50).

4.6.3. Strengths and limitations

A key strength of this work is that the tool was developed within a real-world primary care environment and designed around routine clinical workflows, enabling it to leverage infrastructure already embedded in routine practice. This supports the feasibility of the pathway's implementation and reduces the need for substantial changes to usual care processes. A second strength is that the eligibility criteria were clinically informed and validated in consultation with primary care clinicians and the clinical informatics team. This strengthens confidence that the search is identifying an appropriate population for referral. In addition, the automated and auditable recording of messaging and referral actions increases efficiency and transparency. However, several limitations should be acknowledged.

The pathway was piloted in a single GP practice, so the findings may not be fully generalisable. The demographic and clinical profile of the women identified is likely to reflect the local practice population, and this may differ from other practices or regions in terms of demographic characteristics, cardiometabolic risk, and completeness of coding and follow-up. In addition, local variation in workflows and data quality may affect pathway performance. Additionally, the primary outcome in the pilot was the invitation to self-refer rather than the actual programme uptake, completion, or metabolic improvement. While invitation to refer is a necessary first step, it does not guarantee patient engagement. Women may not open messages, may choose not to register, or may start but not complete the programme. For this reason, the pilot should be interpreted primarily as evidence of improved identification and outreach, rather than evidence of improved uptake or clinical outcomes. The complete evaluation is currently under way but due to data access issues and delay in implementation, the full results are not presented in this thesis.

There are also limitations inherent in using routinely coded primary care data. Women with a history of GDM may be missed if coding is incomplete such as in the case of the diagnosis being recorded in maternity services or hospital records but not transferred to primary care. Exclusions such as prior DPP completion or previous diabetes diagnoses also depend on accurate and up-to-date coding. The reliability of the pathway thus depends on the quality of the underlying recoded data. Studies are needed to evaluate the sensitivity and specificity of

coded searches for previous GDM by comparing primary care records against secondary care data sources.

4.6.4. Recommendations for future research

Increased invitation is not sufficient if it does not translate into greater participation in the NHS DPP and improved clinical outcomes. Future evaluation should examine whether this pathway improves outcomes across the full prevention cascade, such as self-referral, programme uptake, attendance, completion and longer-term clinical markers such as HbA1c, weight change, and incident T2DM.

Future work should also examine whether pathway impact differs across demographic groups, including ethnicity, deprivation, age, and BMI category. Given the national patterning of GDM and the pilot cohort composition, it will be important to determine whether automated searches improve access equitably or whether some groups remain less likely to respond to SMS invitations or proceed to DPP enrolment. This would help distinguish whether the pathway reduces inequalities or simply shifts them to a later stage in the care pathway.

Another important area for future research is the referral model itself. In this pilot, women were invited to self-refer to the NHS DPP following receipt of an SMS message. While this approach is practical and scalable, it places responsibility on the patient to initiate the next step. Future work should explore whether direct referral from primary care to the DPP, with the programme provider contacting the patient directly, leads to higher uptake and improved engagement. This model may reduce patient burden and minimise drop-off between invitation and registration. It may be particularly beneficial for women who face digital barriers that limit their ability to self-refer into the DPP.

4.6.5. Conclusions

Overall, this chapter shows that a data-driven, EHR-enabled referral pathway is a feasible and promising approach to systematically identify women with a history of GDM and improve referral to the NHS DPP, although further evaluation is needed to determine whether this translates into greater uptake, completion, and long-term diabetes prevention.

CHAPTER 5

Comparative analysis of women with and without a primary care GDM record: a retrospective cohort study

5. CHAPTER 5: Comparative analysis of women with and without a primary care GDM record: a retrospective cohort study

5.1. Chapter Overview

This chapter provides a retrospective cohort analysis of women with and without a primary care record of GDM using linked CPRD Aurum and HES data, including deliveries in England from 01/01/2010 and 31/03/2021. Specifically, it examines the extent to which women with GDM may be identifiable in secondary care but not coded in primary care. It also investigates the factors associated with absence of a primary care GDM code and assesses whether a lack of primary care GDM record is associated with subsequent risk of T2DM. In doing so, it evaluates the implications of incomplete primary care ascertainment for post-pregnancy follow-up and diabetes prevention.

5.2. Background and Rationale

The referral pathway in **Chapter 4** was designed to identify women with a history of GDM using primary care records. The goal of the pathway was to address some of the gaps in postnatal follow-up identified by the GDM audit: particularly low rates of annual HbA1c monitoring and very low referral and participation in the NHS DPP among women with previous GDM. However, women may have their GDM diagnosis recorded in secondary care records but not coded in primary care, meaning they may not be captured by a primary-care-based search strategy.

This potential gap in ascertainment is important as reliance on primary care coding alone may underestimate the number of women with prior GDM and bias the population identified for follow-up or intervention. Additionally, women whose GDM is not recorded in primary care may be less likely to be recognised for long-term glycaemic surveillance and diabetes prevention after pregnancy.

Differences in ascertainment between primary and secondary care are also unlikely to occur at random. The completeness of a patient's EHR may plausibly vary according to factors that influence contact with health services, continuity of care, or the intensity of pregnancy management. Maternal age, ethnicity and socioeconomic status can influence how often patients interact with the primary care system. A GP record study looking at the continuity of

care among different ethnic groups found that younger patients, patients from ethnic minorities and from more deprived areas experienced significantly less continuity of care (238). Similarly, BMI may impact the frequency of contact with primary care services. A study looking at 80 general practices found that obese patients had more frequent GP visits than patients with normal BMI (239). Previous complications and parity may also increase clinical surveillance and healthcare contact in subsequent pregnancies. Treatment method is a marker of clinical severity and intensity of management. As such, it can influence the extent of contact across care settings, and consequently, the likelihood that GDM is recorded in primary care. Geographic region and calendar year may also contribute to variation through differences in local practice and changes over time in screening and ascertainment. If women without a primary care GDM code differ systematically from those with one, then a primary-care-based search may preferentially miss subgroups of women.

It is therefore important to quantify how many women are missed by primary care coding and determine whether these women differ from those who are recorded in primary care in terms of demographic and clinical characteristics, as well as in subsequent T2DM risk. To examine this, I used the dataset from Chapter 3 to compare women with a recorded GDM code in primary care with women who had no primary care GDM record but were identified through linked HES data.

5.3. Aims of this research

The aim of this chapter is to evaluate the extent and implications of incomplete primary care recording of GDM. Specifically, it seeks to compare the demographic and clinical characteristics of women with a primary care GDM code with those identified only through linked HES data, to identify factors associated with absence of a primary care GDM code, and to examine whether absence of a primary care GDM code was associated with subsequent risk of T2DM during follow-up.

5.4. Methods

This study is reported in accordance with the RECORD statement for observational studies using routinely collected health data (240). The RECORD checklist is presented in Appendix 5 (Appendix 5. Supplementary Material for Chapter 5

Supplementary Table 10.12). All analyses were performed using R, version 4.5.2 (184). All codes used for the analysis are available at https://github.com/yasminaalghadban/dphil.git.

5.4.1. Study dataset

The linked CPRD dataset including deliveries in England from 01/01/2010 and 31/03/2021 described in Chapter 3 was used for this study. The Chapter 3 cohort was derived to identify women with a first recorded GDM-affected delivery using coded evidence from either primary care or linked HES records. In this chapter, the same cohort was used to examine differences between women whose GDM was coded in primary care and those whose GDM was identifiable only through linked HES data.

5.4.2. Classification of GDM ascertainment source

Women with GDM were classified into two mutually exclusive groups according to the source through which they could have been identified. Women with at least one GDM code recorded in primary care were classified as 'coded in primary care', irrespective of whether a hospital record also occurred, and irrespective of whether that hospital record preceded or followed the primary care code. This group therefore includes women identified through primary care records alone, with no linked HES record, as well as women identified through both primary care and HES. Women were classified as 'not coded in primary care' if they had a qualifying GDM record in linked HES data but no GDM code in primary care at any point; this group is therefore identified through HES alone.

5.4.3. Baseline characteristics by ascertainment source

Demographic and clinical characteristics were compared between the two groups to determine whether women not captured by primary care coding differed from those who were identified in primary care. Variables included maternal age, BMI, previous pregnancy complications stratified by parity, smoking status, alcohol status, ethnicity, GDM treatment method, IMD quintile, region and year of delivery. Continuous variables were described using means and standard deviations, and categorical variables using frequencies and percentages. Given the large cohort size, small differences may become statistically

significant. As such, SMDs were calculated to quantify the magnitude of between-group differences.

5.4.4. Missing data

The extent of missing data in variables considered for analysis is presented in Table 5.1. Missingness was concentrated primarily in BMI and smoking status, while IMD, ethnicity, and region had very low levels of missing data. Alcohol status was excluded from subsequent multivariable analyses because it had 51.6% missing data.

Table 5.1. Missing data

Variable	Missing data, n (%)
BMI value	58,102 (29.3)
IMD	247 (0.1)
Ethnicity	1782 (0.9)
Region	1278 (0.6)
Smoking status	21,611 (10.9)
Alcohol status	102,097 (51.6)

Any variable not included in this table did not have missing data.

To explore the missing data structure, logistic regression models were fitted for indicators of missingness. Separate models were fitted for: (i) any missingness among variables considered for the model, (ii) missing BMI, (iii) missing smoking status. Variable-specific models were restricted to BMI and smoking status because these were the only covariates with large amounts of missing data. Candidate predictors included the ascertainment source, diabetes status 10 years after follow-up, maternal age, ethnicity, deprivation quintile, previous pregnancy complications stratified by parity, treatment method, region, and delivery period. These analyses were used to assess whether missingness was consistent with missing completely at random and to inform the specification of the multiple imputation model.

Multiple imputation by chained equations (MICE) was used to address missing data (241). The imputation model was specified to be broader than the individual analysis models and included both study outcomes, defined covariates as well as auxiliary variables such as hypertensive disorders, gestational age, birthweight, and SMM. This approach was used to

improve prediction of missing values (242). Imputation methods were matched to variable type: predictive mean matching for continuous variables (BMI); polytomous logistic regression for unordered categorical variables (smoking status) and proportional odds regression for ordered categorical variable (IMD quintile).

For continuous variables, convergence of the multiple imputation procedure was assessed visually using trace plots of the mean and standard deviation of imputed values across iterations, together with density plots. Visual inspection of the trace plots suggested stability of the imputation process, with no evidence of drift or separation between chains (Appendix 5, Supplementary Figure 10.1). The density plot showed close agreement across imputed datasets, with near-complete overlap of the density curves, suggesting that the imputation procedure preserved the overall distribution of BMI (Appendix 5, Supplementary Figure 10.2). For categorical variables, the stability of the imputation was assessed by plotting the proportion of observations in each category across imputed datasets. These proportions showed minimal variation across imputations, suggestion stable imputation of smoking status (Appendix 5, Supplementary Figure 10.3).

5.4.5. Multivariable model for ascertainment source

To examine characteristics associated with the absence of a primary care GDM code, multivariable logistic regression was performed with a binary outcome ‘coded in primary care’ or ‘not coded in primary care’. Following multiple imputation, the regression model was fitted separately within each imputed dataset, and the resulting estimates were combined using Rubin’s rules to obtain pooled odds ratios, 95% confidence intervals and p-values.

Included covariates were selected a priori based on clinical relevance, data availability and temporal plausibility. The covariates included maternal age, BMI, smoking status, ethnicity, IMD quintile, previous pregnancy complications stratified by parity, treatment method, region and year of delivery. Year of delivery, grouped into categories, was included in the model to account for potential temporal changes in screening, coding and ascertainment practices. Region was also included to allow for possible geographic variation in GDM identification and recording practices between regions.

Delivery characteristics were not included in the model as they occur after GDM ascertainment and may reflect consequences of disease severity or clinical management, rather than factors associated with whether GDM is recorded in primary care. Data availability was also considered when defining the covariates included in the model; for example, alcohol status was excluded because more than 50% of values were missing.

Covariates are defined as in Chapter 3. All analyses were performed using R, version 4.5.2 (184). All codes used for the analysis are available at https://github.com/yasminaalghadban/dphil.git.

5.4.6. Multivariable model for diabetes status at 10 years

A second multivariable Cox PH regression model was used to examine the association between GDM ascertainment source and incident diabetes during follow-up. The outcome was time to T2DM diagnosis, and the main exposure was whether the woman had been identified through secondary care only rather than primary care coding. Women were followed from the date of delivery of the index GDM-affected pregnancy until the earliest of the following events: (i) the first recorded diagnosis of T2DM, (ii) death, (iii) the end of CPRD data collection, or (iv) ten years after delivery. After multiple imputation, the Cox PH model was fitted separately within each imputed dataset, and the resulting estimates were combined using Rubin's rules to obtain hazard ratios, 95% confidence intervals and p-values.

The model was adjusted for maternal age, BMI, smoking status, ethnicity, IMD quintile, previous pregnancy complications stratified by parity, and treatment method. These covariates were included to account for potential differences in baseline characteristics that may be associated with both ascertainment source and subsequent diabetes risk.

5.4.7. Proportional hazards assumption

The proportional hazards assumption was assessed using scaled Schoenfeld residuals within each imputed dataset, with consistency of findings evaluated across imputations. I found consistent evidence of non-proportionality across imputations, with the global test statistically significant across all 40 imputed datasets. Accordingly, hazard ratios from the Cox PH model were interpreted as average effects over follow-up, and standardised adjusted

survival curves were used to provide complementary time-varying description of diabetes-free survival.

5.4.8. Standardised adjusted survival curves

Standardised adjusted survival curves were estimated using pooled logistic regression in a discrete-time hazards framework to provide an adjusted graphical comparison of diabetes-free survival between women with and without a primary care GDM code (243).

Follow-up time was divided into 1-year intervals up to a maximum of 10 years, and each imputed dataset was expanded into person-period format such that each woman contributed one observation for every interval during which she remained at risk. The interval-specific outcome indicated whether diabetes occurred during that interval, with follow-up censored at diabetes diagnosis, death, end of data collection, or 10 years, whichever occurred first. A pooled logistic model was used because, in discrete-time survival analysis, logistic regression can be used to model the conditional probability of an event within each follow-up interval, and with sufficiently short intervals this approach closely approximates a continuous-time Cox model. Time was modelled flexibly using natural cubic splines, and an interaction between ascertainment group and follow-up time was included to allow the association with T2DM to vary over time (244). The model adjusted for the same covariates as the Cox PH model: maternal age, BMI, smoking status, ethnicity, IMD quintile, previous pregnancy complications stratified by parity and treatment method.

To obtain standardised adjusted survival curves, predicted interval-specific T2DM probabilities were generated for every woman under two counterfactual exposure scenarios: presence and absence of a primary care code. For each scenario, predicted diabetes-free survival was calculated for each woman by multiplying the conditional probabilities of remaining event-free across follow-up intervals. These individual predicted survival curves were then averaged over the full study population to estimate marginal standardised survival curves for each ascertainment group. This standardisation approach was used so that both curves were based on the same overall covariate distribution, rather than the differing distributions observed within each ascertainment group, allowing a fairer comparison of adjusted absolute survival (244). The procedure was repeated across imputed datasets, and

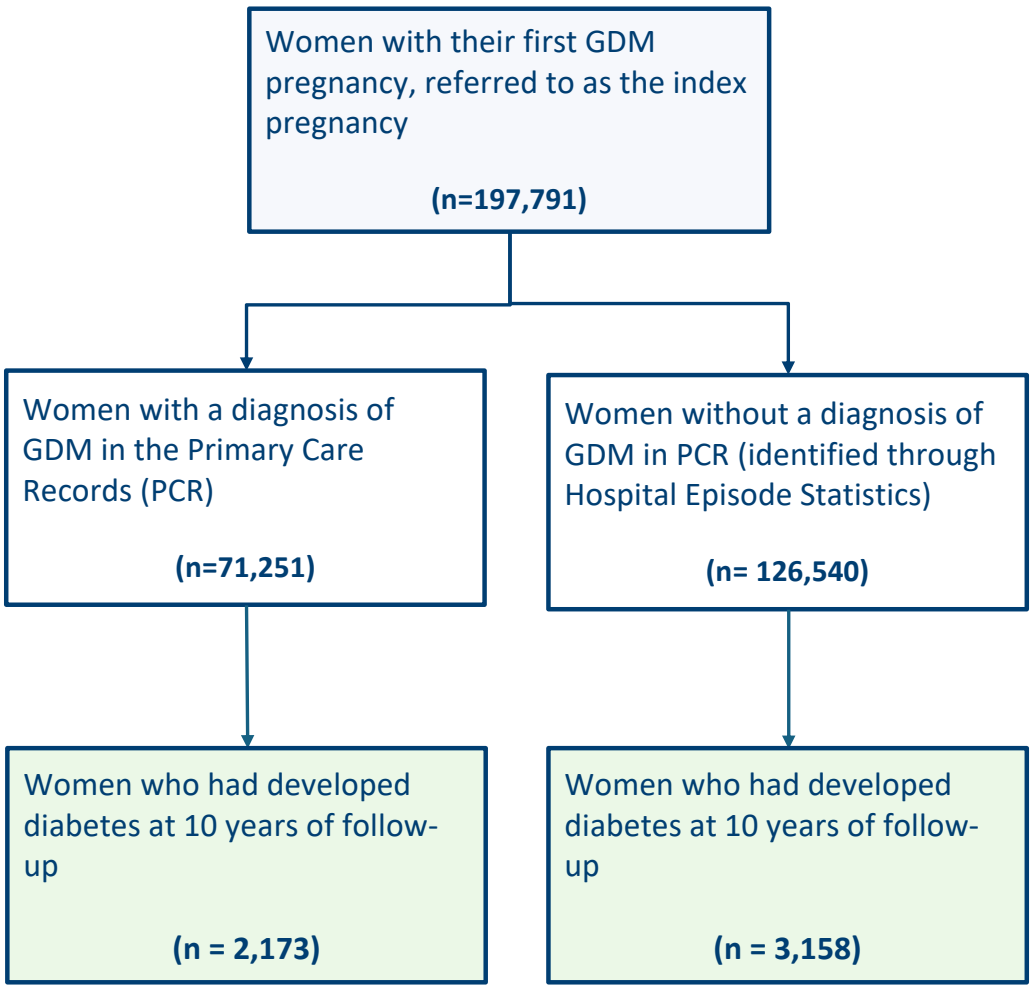
survival probabilities were averaged at each time point to obtain pooled adjusted survival curves.

5.5. Results

5.5.1. Cohort description

A total of 197,791 women with a first recorded GDM delivery were included in the study (Figure 5.1). Of these, 36.0% had GDM coded in primary care records, whereas 64.0% had no GDM code in primary care records and were identified through HES, with a mean follow-up time of 7.1 years (SD 2.4) and 6.7 years (SD 2.5), respectively. By the end of the study period, 2,173 women in the primary care coded group and 3,158 women in the secondary-care-only group developed diabetes.

Figure 5.1. Cohort classification by GDM ascertainment source and subsequent T2DM events



Note. These numbers differ from those presented in Figure 3.1 because this figure is restricted to the final index pregnancy cohort after applying the exclusion criteria and categorizes women by GDM ascertainment source (PCR vs. HES only), whereas Figure 3.1 presents the overall cohort derivation and exclusion process.

5.5.2. Baseline characteristics by ascertainment source

Baseline characteristics differed between women with and without a primary care GDM code (Table 5.2) for treatment method, BMI and smoking status. Women without a primary care code had lower BMI on average (26.3 vs 28.3 kg/m^2, SMD 0.31) and were more likely to be current smokers (26.7% vs 16.2%, SMD 0.29). Additionally, women without a primary care code were more likely to be managed with lifestyle modifications alone, whereas metformin and insulin treatment were more common among women with a primary care code (SMD 0.82). Differences in other baseline characteristics were smaller (SMD < 0.20).

Table 5.2. Baseline characteristics by GDM ascertainment source

Characteristics	Primary care coded (n = 71,602)	Not primary care coded (n = 126,568)	SMD (*p*-value)
Maternal age, years			
Mean (SD)	32.0 (5.4)	32.7 (5.3)	0.14 (<0.001)
BMI, kg/m^2			
Mean (SD)	28.3 (6.7)	26.3 (6.2)	**0.31** (<0.001)
Missing	19,195 (26.8%)	38,432 (30.4%)	
Smoking status, n (%)			
Never	44,580 (68.3%)	70,583 (63.6%)	
Former	10,134 (15.5%)	10,705 (9.7%)	**0.29** (<0.001)
Current	10,548 (16.2%)	29,630 (26.7%)	
Missing	5,989 (8.4%)	15,622 (12.3%)	
Alcohol status, n (%)			
Never	9,604 (24.0%)	12,780 (23.0%)	
Former	449 (1.1%)	392 (0.7%)	0.05 (<0.001)
Current	29,963 (74.9%)	42,506 (76.3%)	
Missing	31,235 (43.8%)	70,862 (56.0%)	
IMD quintile, n (%)			
1 (least deprived)	10,379 (14.6%)	16,394 (13.0%)	
2	11,429 (16.1%)	19,527 (15.5%)	0.06 (<0.001)
3	12,851 (18.1%)	24,117 (19.1%)	

Characteristics	Primary care coded (n = 71,602)	Not primary care coded (n = 126,568)	SMD (*p*-value)
4	17,518 (24.6%)	33,276 (26.3%)	
5 (most deprived)	19,018 (26.7%)	33,035 (26.1%)	
Missing	56 (0.1%)	191 (0.2%)	
Region, n (%)			
London	21,200 (29.9%)	43,127 (34.3%)	
Southeast	13,789 (19.5%)	21,648 (17.2%)	
West Midlands	12,552 (17.7%)	19,085 (15.2%)	
North West	10,014 (14.1%)	16,540 (13.2%)	
South West	6,125 (8.6%)	11,743 (9.3%)	0.14 (<0.001)
East of England	2,313 (3.3%)	3,653 (2.9%)	
Yorkshire and the Humber	1,819 (2.6%)	3,910 (3.1%)	
North East	1,789 (2.5%)	2,783 (2.2%)	
East Midlands	1,227 (1.7%)	3,196 (2.5%)	
Missing	423 (0.6%)	855 (0.7%)	
Year of delivery, n (%)			
2010–2012	13,286 (18.6%)	18,990 (15.0%)	
2013–2015	18,445 (25.9%)	29,710 (23.5%)	0.16 (<0.001)
2016–2018	23,401 (32.8%)	42,153 (33.3%)	
2019–2021	16,119 (22.6%)	35,687 (28.2%)	
Ethnicity, n (%)			
White	40,722 (57.5%)	79,118 (63.2%)	
Asian	18,629 (26.3%)	25,395 (20.3%)	
Black	6,191 (8.7%)	11,794 (9.4%)	0.15 (<0.001)
Mixed	1,503 (2.1%)	2,945 (2.4%)	
Other	3,812 (5.4%)	5,900 (4.7%)	
Missing	394 (0.6%)	1,388 (1.1%)	
Previous pregnancy complications			
Primiparous	34,637 (48.6%)	66,714 (52.7%)	
No, multiparous	30,961 (43.5%)	47,303 (37.4%)	0.13 (<0.001)
Yes, multiparous	5,653 (7.9%)	12,523 (9.9%)	
Treatment method, n (%)			
Lifestyle only	47,504 (66.7%)	121,986 (96.4%)	
Metformin	14,988 (21.0%)	2,949 (2.3%)	**0.83** (<0.001)
Insulin	8,759 (12.3%)	1,605 (1.3%)	

Values are mean (SD) for continuous variables and n (%) for categorical variables. Percentages for category levels are calculated among non-missing observations; missing values are shown separately. SMD = standardised mean difference. SMDs were calculated using observed (non-imputed) data.

5.5.3. Missing data patterns

In the diagnostic model for any missing covariate data, women identified through secondary care had higher odds of incomplete data than women with a primary care code (OR 1.12, 95% CI 1.09–1.15). Women who developed T2DM by 10 years of follow-up also had higher odds of incomplete data (OR 1.19, 95% CI 1.12–1.27). Missing data was also more common in younger women, women from ethnic minority groups, primiparous women, and those managed with lifestyle treatment. The full results are presented in Appendix 5 (Supplementary Table 10.13). Variable-specific models for missing BMI and missing smoking status showed similar patterns. These results make a missing completely at random assumption implausible and support the use of MICE under a missing at random assumption, to reduce the risk of bias associated with complete-case analysis.

5.5.4. Multivariable model for the absence of a primary care GDM code

In the multivariable logistic regression model, several maternal and pregnancy characteristics were independently associated with absence of primary care GDM code (Table 5.3). Older maternal age was associated with a slightly higher likelihood of not being coded in primary care, with each additional year corresponding to 4% higher odds. In contrast, higher BMI was associated with a lower likelihood of not being coded in primary care, with each 1 kg/m^2 increase corresponding to 3% lower odds. Compared with never smokers, current smokers had 72% higher odds of not being coded in primary care, whereas former smokers had 31% lower odds.

Ethnicity was also associated with ascertainment source. Compared with White women, women from Asian and Other ethnic groups had about 30% lower odds of missing a primary care code, while Black and Mixed ethnic groups had 10% lower odds. Increasing deprivation was associated with progressively greater likelihood of not being coded in primary care, ranging from 8% higher odds in IMD quintile 2 to 22% higher odds in the most deprived quintile (quintile 5) compared with the least deprived group (quintile 1).

Compared with primiparous women, multiparous women without pregnancy complications had 21% higher odds of not being coded in primary care, while multiparous women with previous complications had 37% higher odds. Treatment method showed one of the strongest associations with ascertainment source: compared with women treated with lifestyle modification alone, women treated with metformin or insulin had about 92% lower odds of lacking a primary care code.

There were also both temporal and geographical differences. Women delivering in more recent years were increasingly likely to lack a primary code: compared with women who delivered in 2010-2012, the odds were 19% higher in 2013-2015, 27% higher in 2016-2018, and 53% higher in 2019-2021. Compared to women in London, women in other regions had generally lower odds of lacking a primary care record, except women in East Midlands and Yorkshire and the Humber.

Table 5.3. Adjusted odds ratios for characteristics associated with absence of a primary care GDM code

Characteristics	Adjusted OR	95% CI	p-value
Maternal age, years			
Per 1-year increase	1.04	1.04 to 1.04	<0.001
BMI, kg/m²			
Per 1-unit increase	0.97	0.97 to 0.97	<0.001
Ethnicity			
White	Ref	Ref	Ref
Asian	0.70	0.68 to 0.72	<0.001
Black	0.90	0.87 to 0.94	<0.001
Mixed	0.91	0.85 to 0.98	0.01
Other	0.70	0.67 to 0.74	<0.001
IMD quintile			
1 (least deprived)	Ref	Ref	Ref
2	1.08	1.04 to 1.13	<0.001
3	1.20	1.15 to 1.24	<0.001
4	1.23	1.19 to 1.28	<0.001
5 (most deprived)	1.22	1.17 to 1.26	<0.001
Previous pregnancy complications			
Primiparous	Ref	Ref	Ref
No, multiparous	1.21	1.18 to 1.23	<0.001
Yes, multiparous	1.37	1.32 to 1.43	<0.001
Region			
London	Ref	Ref	Ref
East Midlands	1.12	1.04 to 1.20	0.004
East of England	0.77	0.72 to 0.82	<0.001
North East	0.75	0.70 to 0.81	<0.001
North West	0.83	0.80 to 0.86	<0.001
South East	0.74	0.72 to 0.77	<0.001
South West	0.92	0.88 to 0.95	<0.001
West Midlands	0.74	0.71 to 0.76	<0.001
Yorkshire and the Humber	1.09	1.01 to 1.16	<0.001
Smoking status			
Never smoker	Ref	Ref	Ref
Former smoker	0.69	0.67 to 0.72	<0.001
Current smoker	1.72	1.67 to 1.78	<0.001
Treatment method			
Lifestyle modifications	Ref	Ref	Ref
Metformin	0.08	0.078 to 0.085	<0.001
Insulin	0.08	0.074 to 0.083	<0.001
Year of delivery			
2010-2012	Ref	Ref	Ref
2013–2015	1.19	1.15 to 1.23	<0.001
2016–2018	1.27	1.24 to 1.31	<0.001
2019–2021	1.53	1.47 to 1.58	<0.001

OR = odds ratio; CI = confidence interval. Estimates are pooled across multiply imputed datasets using Rubin's rules. Outcome: absence of a primary care GDM code.

5.5.5. Multivariable model for T2DM incidence

In the Cox PH model, absence of a primary care GDM code was associated with a 29% higher hazard of incident T2DM during follow-up after adjustment for baseline covariates (Table 5.4).

Higher maternal age and higher BMI were both associated with increased T2DM risk, although the effect of BMI was much stronger. Each additional year of maternal age was associated with a 1% higher hazard of developing T2DM within 10 years, whereas each 1 kg/m^2 increase in BMI was associated with an 8% higher hazard. Compared with never smokers, current smokers had a 68% higher hazard of developing diabetes, while former smokers did not differ from never smokers after adjustment.

There were also significant ethnic and socioeconomic differences in the hazard of developing T2DM. Compared to white women, Asian and Black women had more than twice the hazard of developing T2DM within 10 years. Additionally, the hazard of developing T2DM increased progressively deprivation, with women in the most deprived quintile having a 58% higher hazard than those in the least deprived quintile.

Previous pregnancy complications and treatment method were also independently associated with incident T2DM. Compared with primiparous women, multiparous women with previous pregnancy complications had a 14% higher hazard of developing T2DM. Compared to lifestyle modification alone, metformin treatment was associated with a 21% higher hazard of diabetes, while insulin treatment was associated with a more than threefold higher hazard.

Table 5.4. Adjusted hazard ratios for the association between GDM ascertainment source and incident diabetes during follow-up

Characteristic	Adjusted HR	95% CI	P-value
Ascertainment source			
Coded in primary care records	Ref	Ref	Ref
Not coded in primary care records	1.29	1.21 to 1.38	<0.001
Maternal age, years			
Per 1-year increase	1.01	1.01 to 1.02	<0.001
BMI, kg/m²			
Per 1-unit increase	1.08	1.07 to 1.08	<0.001
Ethnicity			
White	Ref	Ref	Ref
Asian	2.10	1.95 to 2.26	<0.001
Black	2.04	1.87 to 2.22	<0.001
Mixed	1.32	1.10 to 1.60	0.004
Other	1.37	1.19 to 1.57	<0.001
Previous pregnancy complications			
Primiparous	Ref	Ref	Ref
No, multiparous	0.96	0.90 to 1.02	0.159
Yes, multiparous	1.14	1.04 to 1.25	0.005
IMD quintile			
1 (least deprived)	Ref	Ref	Ref
2 vs 1 (least deprived)	1.16	1.03 to 1.32	0.02
3 vs 1 (least deprived)	1.42	1.26 to 1.59	<0.001
4 vs 1 (least deprived)	1.45	1.30 to 1.62	<0.001
5 (most deprived)	1.58	1.42 to 1.77	<0.001
Smoking status			
Never	Ref	Ref	Ref
Former	1.06	0.96 to 1.18	0.241
Current	1.68	1.59 to 1.84	<0.001
Treatment method			
Lifestyle modifications	Ref	Ref	Ref
Metformin	1.22	1.11 to 1.34	<0.001
Insulin	3.40	3.13 to 3.68	<0.001

HR = hazard ratio; CI = confidence interval. Estimates are pooled across multiply imputed datasets using Rubin's rules. Outcome: T2DM at 10 years of follow up

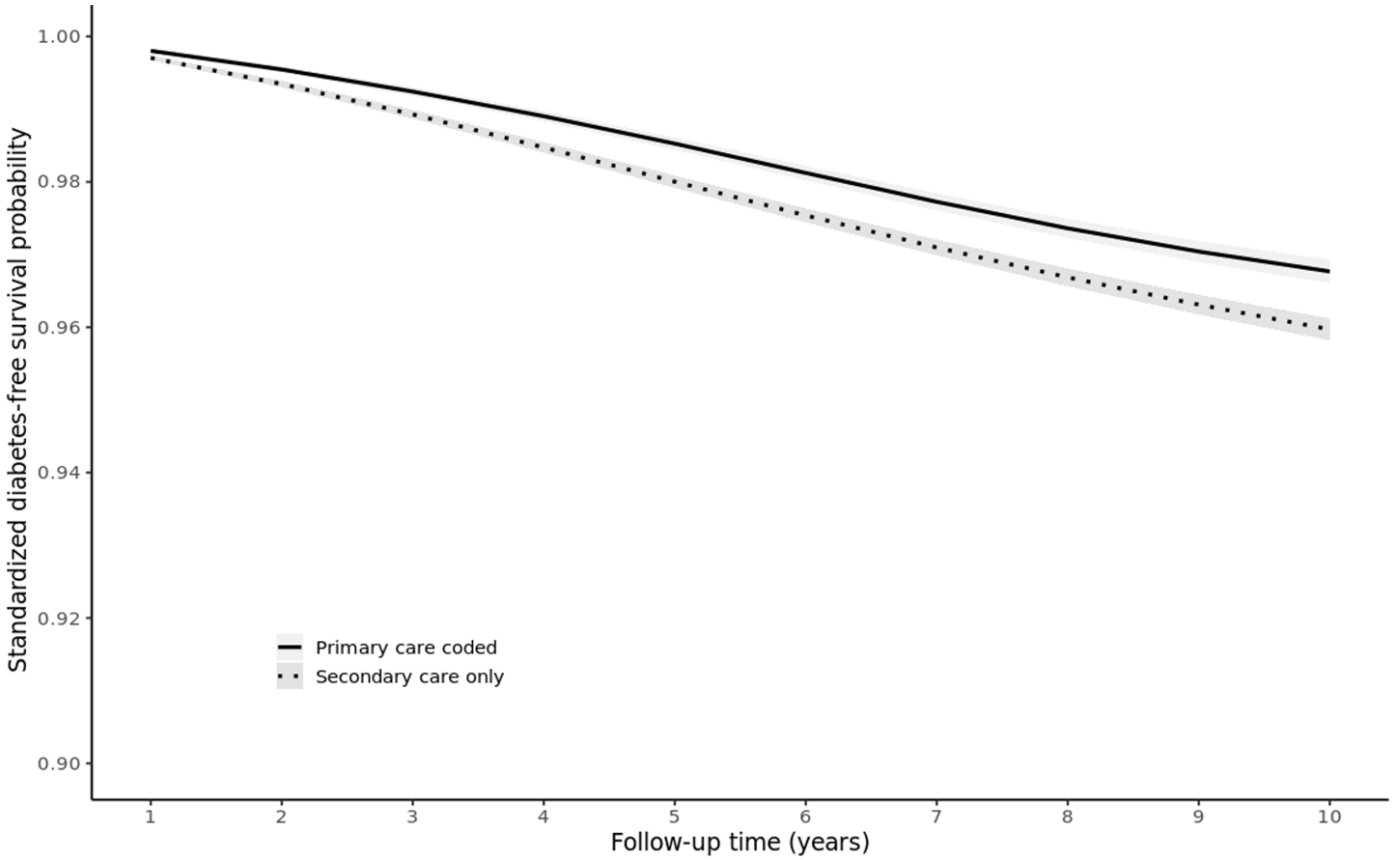
5.5.6. Standardised adjusted survival curves

After standardisation to the covariate distribution of the full study population, diabetes-free survival was consistently lower among women whose GDM was not recorded in primary are records (Figure 5.2). While the absolute difference between curves was small, the curves

separated gradually over follow-up, indicating a higher cumulative probability of developing T2DM in women whose GDM was not recorded in primary care.

At 10 years, the standardised probability of remaining diabetes-free was 97% among women with a primary care GDM code and 96% among women without a primary care GDM code, corresponding to standardised diabetes risk of 3% and 4%, respectively.

Figure 5.2. Standardised adjusted survival curves for incident T2DM by GDM ascertainment source



Note. The y-axis is truncated and starts at 0.90 to allow clearer visualisation of the small differences in standardised diabetes-free survival probability between groups.

5.6. Discussion

5.6.1. Summary of findings

In this cohort, almost two-thirds of women with a first recorded GDM-affected delivery had no GDM code in primary care and were identified only through linked HES data. Women without a primary care code differed significantly from those with a primary care GDM code and these differences persisted after multivariable adjustment in the model with

ascertainment source. Absence of a primary care GDM code was associated with older maternal age, lower BMI, current smoking status, greater deprivation, more recent delivery year, and most strongly lifestyle modifications only treatment rather than metformin or insulin. These findings indicate that incomplete primary care cording may relate to social, clinical and service-related characteristics.

In the second model, absence of a primary care GDM code was associated with a higher hazard of incident T2DM during follow-up after adjustment for baseline covariates. This suggests that women with GDM who are not recorded in primary care may be a clinically important subgroup at elevated future T2DM risk.

5.6.2. Incomplete primary care recording as a barrier to T2DM prevention

Women with GDM are at an increased risk of future T2DM and depend on effective systems for post-pregnancy monitoring and prevention. NICE guidance recommends that women with previous GDM should be offered postnatal FPG testing 6 to 13 weeks after birth, and if this is negative, annual HbA1c testing thereafter (21). While responsibility for the immediate postnatal follow-up may vary locally between maternity and primary care services, long-term follow-up depends on recognition of prior GDM within general practice, where regular appointments, risk counselling and preventive management are most likely to occur. However, the transition from maternity care to general practice is poorly coordinated. In a national survey of GDM follow-up in England, almost three-quarters of consultants reported asking GPs to undertake long-term follow-up and only a minority of GPs and specialists reported having joint follow-up protocols. Importantly, 20% of GPs reported difficulty identifying women whose GDM had been diagnosed in secondary care (245).

As such, primary care coding may function as a gateway to long-term follow-up and T2DM prevention, and women with prior GDM who are not recorded in primary care are less likely to benefit from the prevention strategy recommended by NICE.

5.6.3. Determinants of being missed by primary care coding

Several characteristics were associated with the absence of a primary care GDM code, suggesting that incomplete coding may not be random. The strongest association was seen for

treatment method: women managed with lifestyle modification alone were more likely to lack a primary care code than those treated with metformin or insulin. Women requiring pharmacological treatment are likely to have more intensive management and need for prescriptions, which may increase the number of contacts with healthcare professionals and the likelihood that the diagnosis is recorded in primary care. Previous studies have similarly reported better postpartum follow-up among women treated with pharmacological interventions during pregnancy, supporting the interpretation that greater treatment intensity may increase visibility within healthcare systems (246).

The associations with BMI and smoking status were also broadly consistent with differential healthcare contact. Women with lower BMI and current smokers were less likely to be recorded in primary care. This is plausible as obesity has been associated with more frequent GP contact, while smoking has been linked to poorer GDM follow-up (239,246). By contrast, the association with older maternal age was less straightforward, as older age has been associated with better postpartum follow-up after GDM (246) and greater continuity of care in general practice (238).

Socioeconomic deprivation was also associated with greater odds of lacking a GDM code in primary care. This is consistent with the literature showing that women from more deprived backgrounds have less interaction with the healthcare system (238,246). Coupled with the higher subsequent T2DM hazard observed in more deprived women, this suggests that those at greatest long-term risk may also be less likely to be captured through routine primary-care-based identification.

Compared with White women, minority ethnic groups were less likely to be missing a GDM code in primary care. This was surprising as minority ethnic groups have been associated with lower continuity of care in general practice (238). It is possible that in the context of GDM, clinicians may be more alert to the future risk of T2DM in certain ethnic groups (247) and therefore more likely to ensure follow-up.

Finally, women with previous pregnancy complications were more likely to lack a GDM code in primary care. A possible explanation is that women with more complex obstetric histories may have a greater proportion of their care documented within hospital systems. Additionally women with higher parity were less likely to attend postpartum glucose testing

(246), suggesting that women with GDM in later pregnancies may be less well captured by routine follow-up systems.

5.6.4. Temporal and regional variation in ascertainment

Women delivering in more recent years were increasingly likely to be missing a primary care GDM code. This may reflect the deterioration in continuity and coordination within primary care over time. In England, continuity of care in general practice declined between 2012 and 2017, and this decline was observed across practice types (238). Additionally, the rapid increase in GDM prevalence may have place greater pressure on maternity service and general practices and impacted the coding quality.

Regional variation was also evident, suggesting that recording pathways and follow-up arrangements are not uniform across England. The regional heterogeneity suggests that improving ascertainment is likely to require system-level solutions tailored to local practice rather than a single national intervention.

5.6.5. Clinical and policy implications

While the primary-care identification strategy described in Chapter 4 provides a pragmatic starting point for identifying women with previous GDM, the findings of this chapter show that it is not sufficient on its own. Relying on primary-care coding alone would miss a substantial proportion of women with prior GDM and may therefore exclude them from NICE-recommended postnatal and long-term glycaemic surveillance. As such, improving coding completeness should be treated as part of diabetes prevention after pregnancy, with particular attention to groups most likely to be missed by routine primary-care pathways. In this study, missing primary-care coding was socially and clinically patterned, and regional variation was also evident, suggesting that follow-up pathways should not rely on passive identification alone. Instead, services should consider automated coding and recall systems, and targeted follow up for higher-risk groups, particularly women from more deprived backgrounds. The regional differences observed also support routine local audit of coding and follow-up pathways, so that gaps in ascertainment can be identified and addressed.

5.6.6. Strengths and limitations

Many of the strengths and limitations of the linked CPRD Aurum-HES dataset have already been discussed in Section 3.6.6. and apply equally here. In the context of this chapter, an additional strength is that linkage between primary care and secondary care data made it possible to examine the ascertainment gap in GDM recording, by comparing women with a primary care GDM code against those identified only through HES. This research question could not have been evaluated using a single-source dataset alone.

There are also several limitations specific to this analysis. First, the absence of a GDM code in primary care should not be interpreted as definitive absence of GP awareness, as information may have been communicated in free text, hospital letters or other parts not captured in coded analyses. Additionally, the use of CPRD data may also lead to some misclassification. This includes possible misclassification of GDM as pre-existing diabetes, such as T2DM, T1DM or maturity-onset diabetes of the young (MODY), as well as misclassification of subsequent T2DM outcomes in both primary care and HES records. This may have affected both ascertainment of prior GDM and estimation of later diabetes risk. Finally, this study was designed to examine associations rather than causality. Although absence of a primary care GDM record was associated with a higher subsequent hazard of T2DM, the absolute risk difference was small. Our findings should be interpreted as identifying a subgroup at potentially increased risk and reduced follow-up, rather than demonstrating a large absolute increase in diabetes incidence attributable to missing coding itself.

5.6.7. Conclusions

This study found that primary care coding substantially under-ascertains GDM, with almost two-thirds of women with a first recorded GDM-affected delivery identified only through linked secondary care data. Women without a primary care GDM code differed systematically from those who were coded and had a higher subsequent risk of T2DM, suggesting that incomplete primary care recording may undermine equitable post-pregnancy surveillance and diabetes prevention.

CHAPTER 6

Development and Clinical Validation of SMART*health* GPT: A Chatbot for Women's Health and Community Health Workers in India

6. CHAPTER 6: Development and Clinical Validation of SMART*health* GPT: A Chatbot for Women's Health and Community Health Workers in India

6.1. Chapter Overview

This chapter provides a detailed description of the development and validation process of SMART*health* GPT (SHP GPT), an LLM–based chatbot designed to support maternal healthcare delivery within the SMART*health* Pregnancy (SHP) platform. Specifically, it outlines the conceptual rationale underpinning the integration of LLM technology into the existing SHP intervention, the participatory methods used to define use cases and generate training data, the technical architecture adopted for model development and the clinical validation conducted.

6.2. Background and Rationale

6.2.1. Large language models in healthcare

Recently, the natural language processing (NLP) landscape has seen spectacular advances with the increasing availability of pre-trained LLMs, such as BERT (248), RoBERTa (249), and GPT3 (250), among others. The fast advances in NLP have had applications in several fields and are increasingly being employed in medical education and healthcare (251,252).

Clinically, LLMs are being applied in three broad domains: documentation, patient support and clinical decision (253–255). First, adapted medical LLMs can summarise medical reports, progress notes, patient questions, and doctor–patient dialogues (253–255). In a clinical reader study, physicians rated 45% of LLM summaries as equivalent to expert-written ones and 36% as superior, suggesting real potential to reduce documentation burden and improve information transfer between teams (256). Second, LLMs are also being used for patient-facing communication and have shown promise in making medical knowledge accessible to the public and responding to patient inquiries (253). In telehealth contexts, LLMs functioned as chatbots and clinician-AI assistants, bridging communication challenges related to health literacy and language barriers (257). However, LLMs can produce scientifically plausible but incorrect information, fabricate false references and hallucinate information (253). As such, responses could prove inaccurate or outdated, impacting the accuracy of responses and patient safety. Third, LLMs can be used for clinical decision support such as synthesising guidelines, suggesting differential diagnoses, and

supporting specialty decision-making (253–255). Although LLMs excel at retrieving information, they remain limited in complex clinical reasoning. In tasks requiring specialised expertise and contextual judgment, their performance remains inferior to that of human clinicians. For example, ChatGPT achieved only 60.17% (the mean passing score is 70.42%) on the Membership of the Royal College of General Practitioners Applied Knowledge Test (258). As such, LLMs are not ready for autonomous clinical decision-making and require stringent evaluation and human oversight.

6.2.2. Challenges of AI deployment in maternal health

The enthusiasm around AI can sometimes lead to a technologically deterministic outlook, viewing these technologies as inherent solutions for healthcare challenges (259). This perspective risks oversimplifying the complex socio-cultural, infrastructural, and ethical dynamics of healthcare systems (260). AI systems lacking adequate adaptation to local contexts can inadvertently worsen existing inequalities (261). While they hold potential for various applications, their responsible development and deployment are critical as misinformation can have serious consequences (262).

In response to the increasing interest in AI, a growing body of research emphasises the importance of designing AI systems for healthcare using a human-centric socio-technical approach (261). This means focusing on AI that is sensitive to the specific context it is being used in, considering both the social and technical aspects of healthcare systems. It stresses the importance of working directly with end-users and experts to design solutions, adapting to cultural needs, and ensuring the technology fits the local environment (263). This stands in contrast to "top-down" models of technology development, which often fail to adequately support their users because they don't take their needs and context into account.

6.2.3. Maternal health in India and role of community workers

Maternal health outcomes in India have improved over the past two decades. However, substantial levels of maternal mortality, morbidity, and inequality persist. India continues to account for a significant proportion of global maternal deaths, many of which are preventable and disproportionately concentrated in poorer states and rural regions (264). Inadequate access to essential maternal health services remains a key challenge: data from the 2019–

2021 National Family Health Survey indicate that 41% of women did not receive the recommended number of antenatal care visits, with women in rural areas facing significantly higher odds of inadequate care (265). These gaps reflect broader socioeconomic and demographic inequities that shape access to and continuity of maternal healthcare across the care pathway. For example, geographic analyses of service utilisation have shown that women without formal education and those in the poorest wealth quintile are significantly less likely to fully utilise the continuum of maternal and newborn care (266).

Within this context, community health workers play a critical role in bridging gaps in maternal healthcare delivery in rural and underserved settings. India's network of over one million Accredited Social Health Activists (ASHAs) serves as a trusted first point of contact for pregnant women, providing antenatal counselling, postnatal follow-up, health education, and referral support (267,268). Beyond delivering medical information, ASHAs operate as culturally embedded mediators who negotiate family dynamics, address misconceptions, and adapt health advice to local sociocultural realities (269). Despite their critical role, ASHAs often have limited training and lack access to up to date, comprehensive, evidence-based informational resources (270).

6.2.4. Introduction to the SMART*health* Pregnancy intervention and trial

To address this challenge, the SHP platform was developed. It equips ASHAs with point-of-care devices and an Android-based application offering decision support to identify, refer and follow-up women with high-risk pregnancies in their communities (271). This system has been co-designed with end users in rural India, demonstrated to be feasible and acceptable, and is currently being assessed in a large cluster implementation effectiveness trial across 60 villages in the states of Telangana and Haryana. To date, approximately 144 ASHAs have used the SHP platform for a period of nearly three years.

Whilst the system gives clinical decision support recommendations based on test values entered by the ASHAs, it is not responsive to spontaneous questions the woman or the ASHA have, nor can it provide any explanation about the tests or other pregnancy issues. LLMs could be used to enhance ASHAs' capacities by supporting personalised, health information delivery in real time. Despite this potential, there is limited research on how to safely design an LLM-based tool for maternal health. Deploying such applications requires careful

consideration of the particular sensitivities around maternal health to avoid the assumption of technological determinism (259).

6.3. Aims of this Research

The aim of this study is to co-design and clinically evaluate SHP GPT, an LLM-based chatbot developed as an early-stage prototype integrated within the existing SHP system.

Specifically, this study aims to develop the chatbot through a participatory, human-centred approach involving ASHAs and clinical experts, optimise its technical performance, and assess its clinical validity across domains of accuracy, completeness, appropriateness, and equity within a maternal healthcare context.

6.4. Methods

Reporting of the development and evaluation of SHP GPT was guided by the Chatbot Assessment Reporting Tool (CHART) (272), and the completed checklist is provided in Appendix 6 (Supplementary Table 10.14).

6.4.1. Team structure

The work presented in Chapters 6 & 7 was conducted within a multidisciplinary team between The George Institute for Global Health (TGI), India and the University of Oxford. Model development was led by myself under the supervision of Uday Adavi (TGI), while the clinical validation and field implementation components were led by my colleague Ankita Sharma and the clinical team in India. My contribution focused on the design and development of the SHP GPT system, including model architecture, prompt development, retrieval pipeline design, parameter optimisation, and technical refinement. The clinical team led focus groups, interviews and participant inductions, coordinated and conducted on-the-ground testing with ASHAs, collected feedback and validation data, and provided clinical interpretation of model outputs within the maternal health context in rural India. The project was developed iteratively through close collaboration between the two teams. I would develop and update the model; the clinical team would test it in the field and return the results. After analysing the data, I would incorporate the feedback into the next model iteration and return the updated system for further testing. Accordingly, while all data

presented in these chapters were analysed by myself (unless otherwise specified), they depended fundamentally on the field leadership, clinical expertise and data collection work conducted by Ankita Sharma and the clinical team. Ankita Sharma and I also co-authored the manuscript arising from this work that is currently submitted for publication.

6.4.2. Participatory AI development approach

The SHP GPT chatbot was developed using a participatory, human-centred approach that actively engaged ASHAs and clinical experts throughout the design, development, and validation process. This approach was selected to support responsible LLM development by centering end-user perspectives and ensuring the resulting system was equitable, safe, and context sensitive. ASHAs were involved in defining use cases, generating training data, and evaluating the relevance and appropriateness of model outputs, while clinical experts ensured medical accuracy and alignment with national guidelines.

6.4.3. Study setting and participants

The study was conducted in two states in India, Haryana and Telangana. Study participants were selected from the 60 ASHA workers from the intervention arm of the SHP trial (26) (clinicaltrial.gov NCT05752955). A table detailing the participants throughout the study is provided in Appendix 6 (Supplementary Table 10.15).

The study protocol was approved by the Ethics Committee of TGI, India, and the ethics board of PGIMS, Rohtak, Haryana (for data collection in Haryana). This approval encompassed all data collection tools, including questionnaires, workshop details, and the study protocol.

All methods adhered to the relevant guidelines and regulations of TGI, India. Prior to participation, written informed consent was obtained from all participants in their local language (Hindi or Telugu).

6.4.4. Supporting qualitative research conducted by the clinical team

A range of qualitative methods were employed as part of the broader SHP programme to contextualise ASHAs' training needs and incorporate key stakeholders into the co-development process. This work was conducted by the clinical team, led by Ankita Sharma. I

did not conduct this component of the work, and I am only presenting it here briefly to provide a complete overview of the end-to-end development of SHP GPT.

Data were collected in Telangana and Haryana using focus group discussions with ASHAs, in-depth interviews with key stakeholders (pregnant women, Auxiliary Nurse Midwives, field supervisors, and senior health system stakeholders), participant observation of ASHAs' routine household visits and refresher trainings, and participatory workshops.

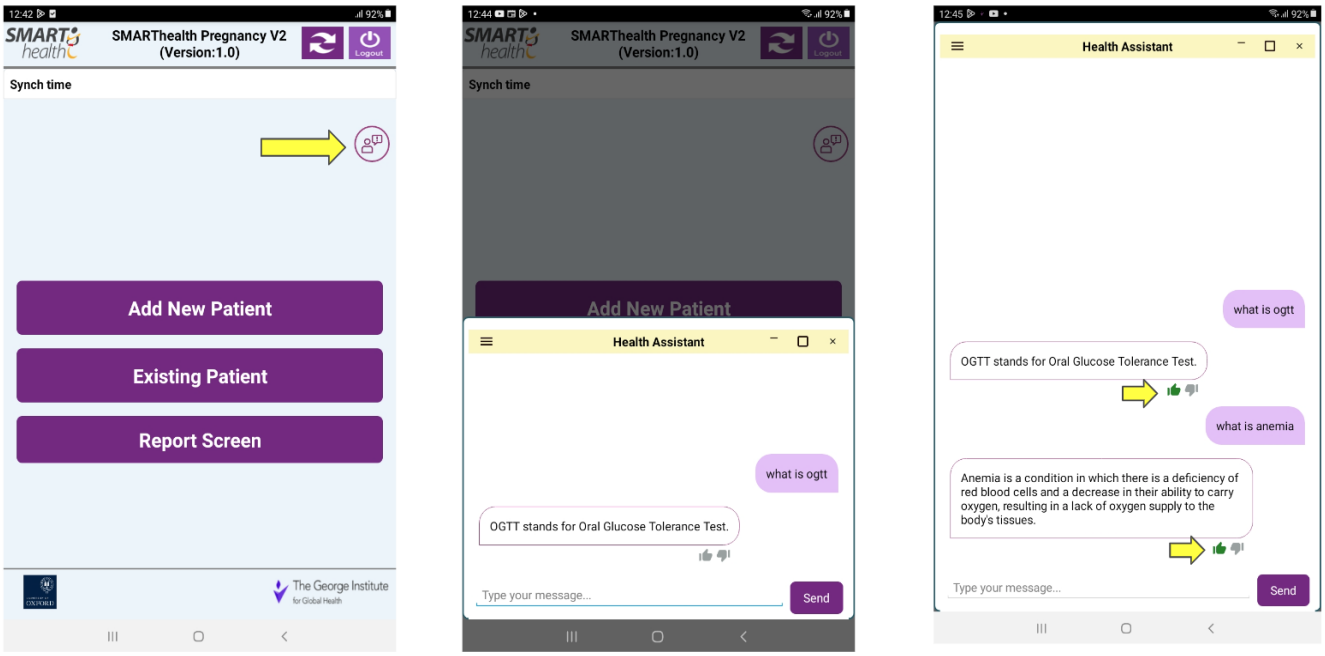
The workshops employed structured, participatory elicitation techniques to capture ASHAs' needs. In a pile sorting exercise, ASHAs collectively reviewed maternal health questions and categorised them as "frequently asked," "sometimes asked," or "never asked," enabling prioritisation based on field relevance. This was followed by a free listing exercise, in which ASHAs independently generated additional frequently asked questions (FAQs) and identified topics they considered sensitive or inappropriate for automated responses. These exercises led to 179 FAQs generated by ASHAs, which were then used for validation.

Additional details on the qualitative research methods are presented in Appendix 6 (Supplementary File 10.6).

6.4.5. Defining model use case

Based on the qualitative findings, to enhance the SHP system, we developed SHP GPT an LLM-based chatbot designed as an early-stage prototype integrated into the existing SHP system (Figure 6.1). To protect patient data, the chatbot sat as a separate app within the SHP Platform, with no access to patient data. All chat communications are stored offline on the ASHA's tablet and on a backend system for monitoring and quality assurance. SHP GPT supports local language communication in Telugu and Hindi, with features like text and voice chat, as well as voice-over reading of answers. ASHAs can provide continuous feedback via like/dislike buttons and free-text comments, enabling ongoing refinement of the tool.

Figure 6.1. SHP GPT System

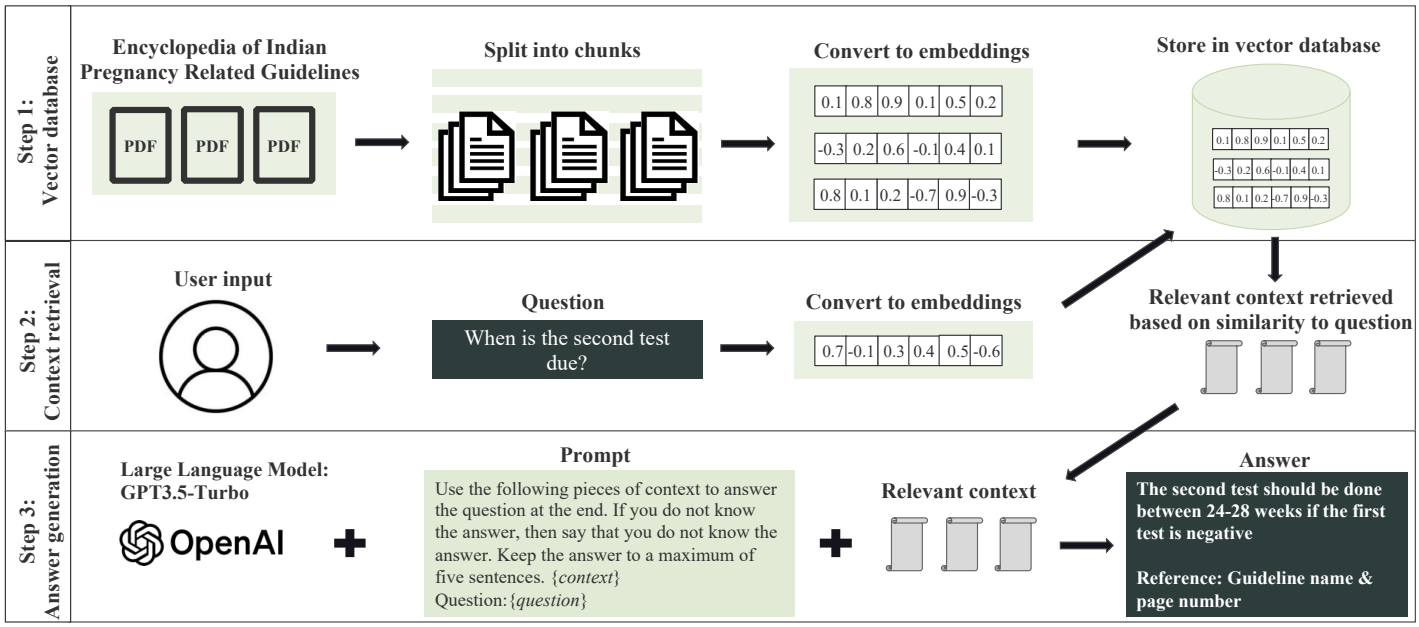


6.4.6. Development of SMART*health* GPT-1

Retrieval-Augmented Generation model design

The SHP GPT model was built using a Retrieval-Augmented Generation (RAG) methodology, which retrieves relevant external information to generate responses. The RAG process is shown in Figure 6.2.

Figure 6.2. Flow diagram of the RAG process in SHP GPT



Formal definition of RAG

RAG enables LLMs to access information from non-parametric storage, making it highly adaptable to new tasks and reducing the need for extensive annotated training data. Within the RAG framework, external information sources are transformed to embeddings and stored in a vector database. This process forms the basis for the subsequent steps. To illustrate the RAG process formally, I express it using conditional probabilities, dividing it into two key components: retrieval and generation.

In the retrieval step, the objective is to select a set of relevant documents, D $\{d_1, \ldots, d_k\}$, from a repository of documents (E) based on a user's question (Q). This can be expressed as P(D | Q), the likelihood of choosing documents D from E, given the question Q. This probability is computed by the retriever.

Once the relevant documents (D) have been retrieved, the answer (A) needs to be generated. This generation step can be expressed as P(A | D, Q), representing the probability distribution of generating the answer A, given the retrieved documents D and the question Q. This probability is computed by a text generator.

The entire RAG process can be expressed as follows:

$$P(A \mid Q) = \sum_{i=1}^{k} P(A \mid D, Q) * P(D \mid Q)$$

Here, P (A | Q) signifies the probability of generating answer A given the question Q.

In summary, RAG selects pertinent documents based on the input context and then generates the output text, conditioned on both the selected documents and the input context. These steps are often implemented using neural network models, which are trained to maximise the likelihood of generating the correct output, aligning with the retrieved documents.

Rationale for the use of RAG

We selected RAG for our use case for several reasons. First, the pedagogical nature of our application necessitates that responses provided by the model are accurate and traceable back to their sources. RAG's ability to trace responses back to their respective sources increases explainability and trustworthiness in the educational content and reduces potential model hallucinations. This also aligns with the needs of our application where ASHAs not only require a response to their question but also a source guideline to refer to. Second, our model needs to be scalable, especially in the context of vast knowledge bases within the healthcare domain. RAG models are highly scalable as they leverage retrieval mechanisms to accommodate large knowledge bases. Third, given the continuous evolvement of clinical guidelines, our model needs to be flexible and swiftly updated to align with the latest recommendations. By using RAG, our model can be easily and quickly updated by incorporating new guidelines or updates into the knowledge base, ensuring the relevance and accuracy of our model.

Model details

The underlying LLMs evaluated in this study were OpenAI's gpt-3.5-turbo and gpt-4, which are proprietary, closed-source models. These models were used as base models within the SHP GPT RAG pipeline. Model identification and technical details were referenced using OpenAI's official model documentation for gpt-3.5-turbo and gpt-4 (273,274).

Model parameter optimisation pipeline

SHP GPT-1 was developed using 20 guidelines from national health websites (275) and 10 real-world questions with answers provided by an obstetrician.

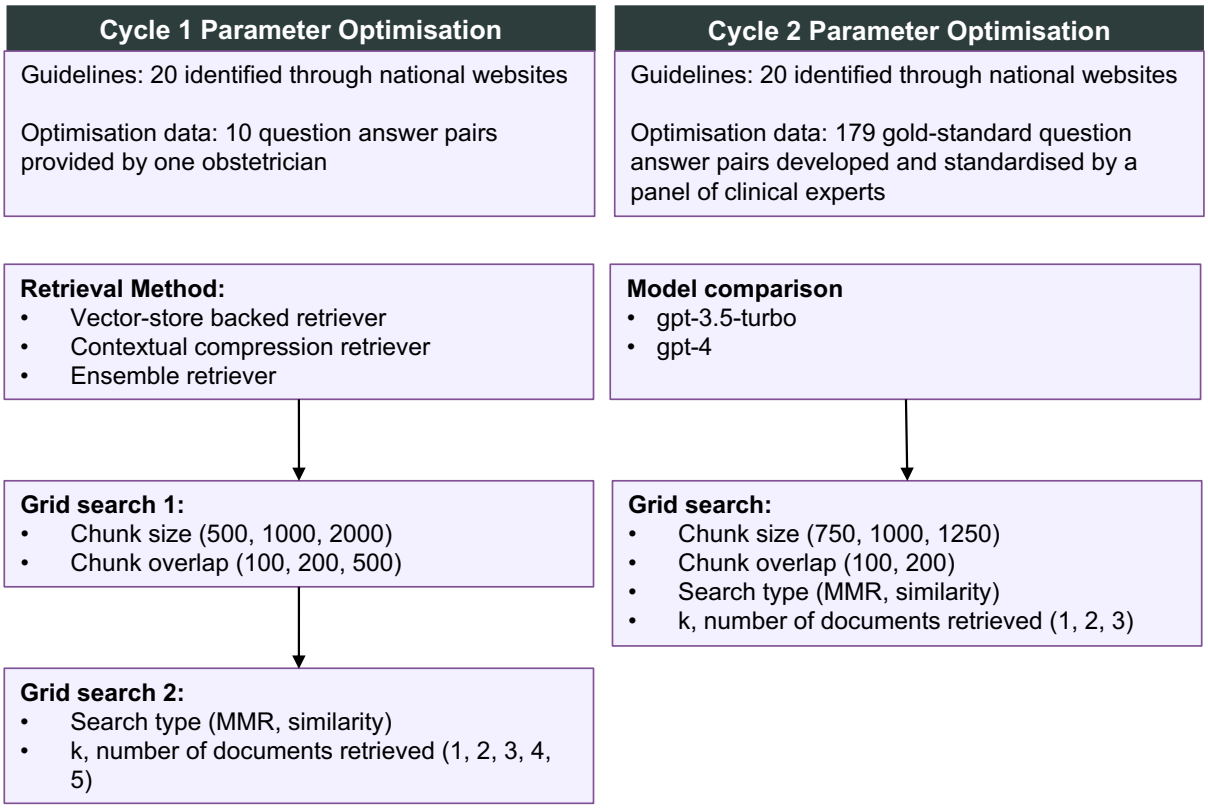
To select initial model parameters, I developed a parameter optimisation pipeline based on processing time and how closely the model's answers matched those provided by an obstetrician. This match is quantified using the ClinicalBERT similarity score (276). The ClinicalBERT similarity score measures how closely the model's generated answers are aligned with expert-provided answers, with a higher score indicating greater similarity (276). I selected three commonly used retrieval methods in RAG: vector-store backed retriever, contextual compression retriever and ensemble retriever and compared their impact on model performance. The vector-store backed retriever is the simplest method, which retrieves documents with the highest similarity to the question.

All retriever methods were compared for both similarity search and Maximal Marginal Relevance (MMR) search. MMR balances between relevance and diversity. It finds documents with embeddings that have the greatest similarity with the inputs and adds them iteratively while penalising them for similarity to already selected documents. Similarity is measured using cosine similarity between vectors:

$$\cos(\theta) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

I then investigated the impact of 4 model parameters (chunk size, chunk overlap, number of documents retrieved (k) and search type) on model performance. For this first cycle of parameter optimisation, I limited our retrieval method to a vector-store backed retrieval but compared similarity search and MMR. Due to the limited number of questions, I carried out two grid search tests on 1) chunk size and chunk overlap, and 2) search type and number of documents retrieved (k) (Figure 6.3). To determine whether there were statistically significant differences in performance across models, I conducted a one-way ANOVA for each evaluation metric. The independent variable was the model, and the dependent variables were the various performance metrics (similarity score and processing time). Following ANOVA, HSD test was used to identify which specific pairs of models differed significantly.

Figure 6.3. Parameter optimisation and evaluation pipeline



The base-model was developed and integrated into the SHP. This model was used for the initial clinical validation and was iteratively updated throughout the co-development process.

Prompt engineering

Three structured prompts were used within the SHP GPT pipeline: (i) a question-rewriting prompt to convert informal or incomplete user inputs into question format, (ii) a categorisation prompt used to identify sensitive or out-of-scope topics and (iii) a main response-generation prompt. The full prompt texts are provided in Appendix 6 (Supplementary File 10.5).

For each user input, the rewriting, categorisation, and response-generation prompts were executed as separate backend processing steps within a single query pipeline. Each user question was handled independently, and outputs from prior questions were not carried forward into subsequent queries.

6.4.7. Clinical validation process

Performance metrics for accuracy, completeness, appropriateness and equity

To ensure the responsible and safe development of SHP GPT, a diverse panel of 14 medical doctors was assembled, consisting of 12 community medicine physicians and two obstetricians from Telangana and Haryana. Selection criteria for the expert panel included recent experience with ASHAs and active involvement in rural Indian maternal health initiatives.

The panel participated in a half-day induction session with the clinical team covering conversational AI technology and common challenges such as hallucinations and biases in AI systems (277). Following this, each clinician received secure access to an online validation platform to evaluate the chatbot's responses. Each clinician rated at least 50 chatbot responses to questions gathered from the co-design workshops using a 3-point Likert scale across four domains: (i) accuracy, (ii) completeness, (iii) appropriateness, and (iv) presence of bias (277).

Clinicians were aware that the responses being evaluated had been generated by SHP GPT. As this study was designed as a formative clinical validation of a single prototype rather than a comparative evaluation of multiple named models, no blinding procedure was implemented.

Gold-standard dataset creation

Each clinical expert independently provided "ideal" responses to at least 50 randomly selected questions from the dataset of questions gathered in the co-design phase, using a secure online portal. Experts were instructed to ensure responses were guideline-based, appropriate for ASHA workers, uncontroversial, and unbiased. To avoid influence, experts worked independently, without access to the AI model's outputs or each other's answers. These responses were then aggregated into a single combined answer.

A subset of these combined responses was reviewed by two internal clinical experts (an obstetrician and a community medicine doctor) and 16 ASHA workers for further feedback. This feedback was presented to a Consensus Development Panel, which included six clinical experts from the initial rating phase, led by two community medicine doctors from each state.

The panel collaborated to finalise the gold standard responses for all 179 FAQs generated by ASHAs.

6.4.8. Model optimisation

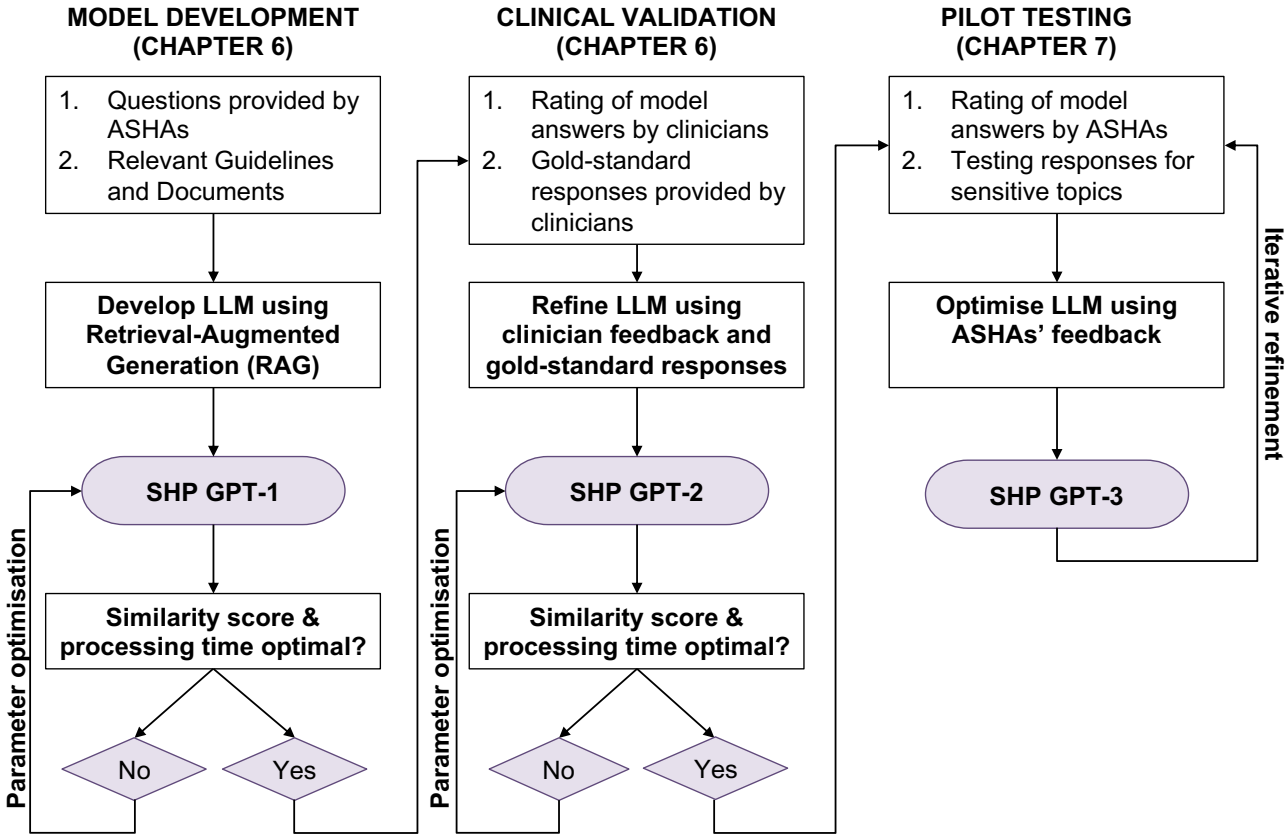
Following clinical validation, a second cycle of parameter optimisation was performed (Figure 6.3). The model performance was first compared for gpt-3.5-turbo and gpt-4 using processing time and ClinicalBERT similarity score. Using the 179-gold standard question answer pairs, a grid search was performed to identify the optimal parameters for chunk size, chunk overlap, search type and number of documents retrieved, k. For each combination of parameters, the model generated an answer to all 179 questions. The performance of the model for each combination of parameters was measured using processing time and ClinicalBERT similarity scores between the model answer and the clinical gold standard. As in the first development stage, ANOVA and HSD test were used to identify which pairs of models differed significantly.

6.5. Results

6.5.1. Development Framework

The development of SHP GPT followed a human-centred design process structured across three stages (Figure 6.4). The iterative development and validation of SHP GPT led to progressive improvements in the chatbot's performance and usability. In the initial development of SHP GPT-1, we successfully identified key use cases by compiling FAQs from ASHAs, built an initial version of the chatbot and clinically validated it. To enhance accuracy, we created a gold standard dataset of expert-generated responses to the FAQs, which informed the development of SHP GPT-2. This iteration refined the chatbot's ability to deliver precise and actionable information. The final stage involved pilot testing with ASHAs whose detailed, context-specific feedback led to further refinements, resulting in SHP GPT-3 (Chapter 7). Throughout the process, collaboration with human stakeholders was integral to refining each version, exemplifying a responsible framework for deploying LLMs in maternal healthcare settings.

Figure 6.4. Framework for the Development and Validation of SMART*health* GPT



6.5.2. Initial prototype

The base model, SHP GPT-1 was built using RAG. This method allows the chatbot to search through trusted healthcare documents to generate responses. We selected 20 Indian clinical guidelines and government training materials for ASHAs as the primary information sources (278).

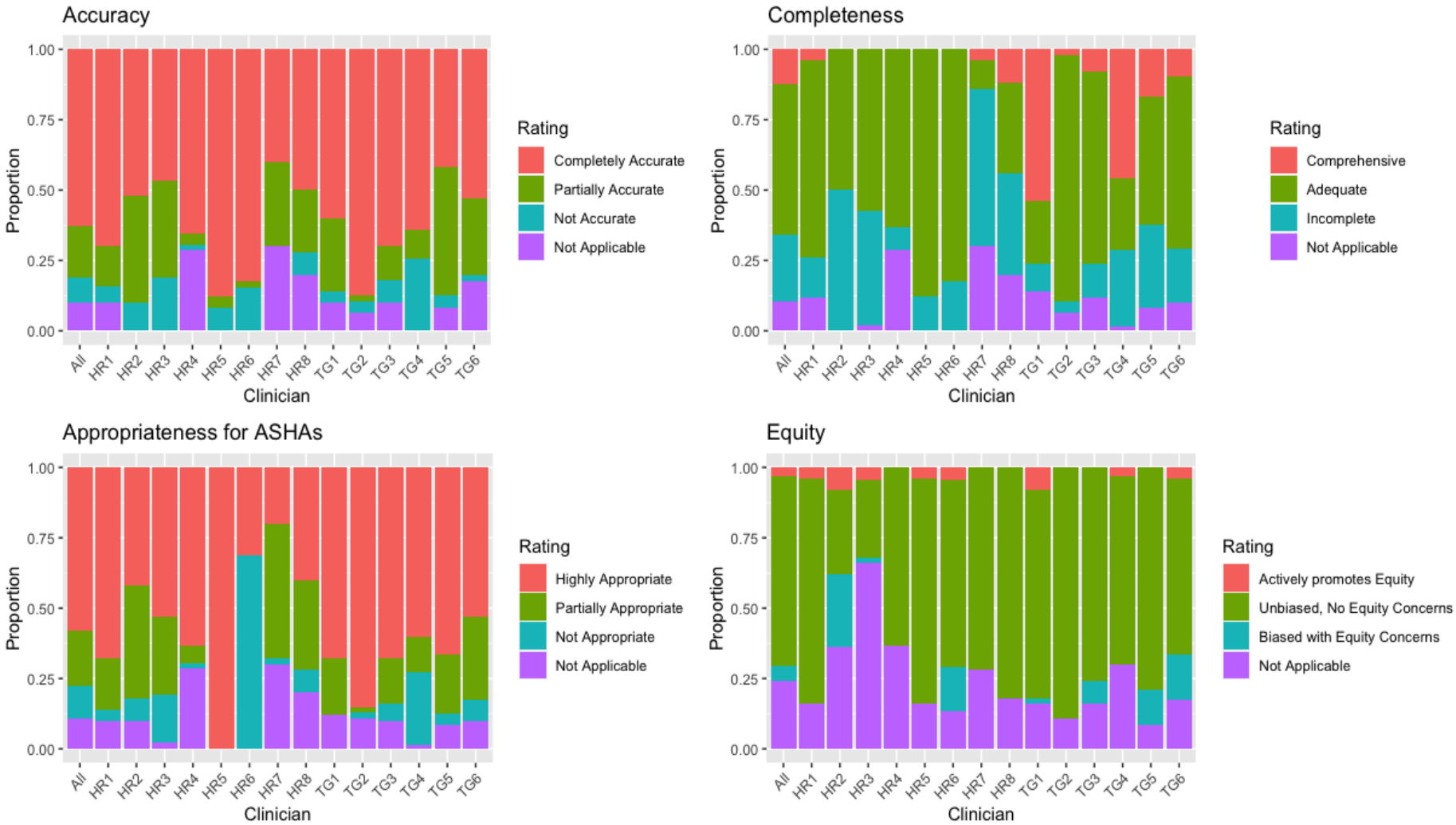
In optimising the model, I compared different methods the chatbot uses to search for information, specifically vector-store, compression, and ensemble retrievers. I found that the choice of retriever did not significantly affect the quality of responses (measured by ClinicalBERT similarity, $p = 0.89$). However, more complex retrievers led to slower response times ($p < 0.001$). Similarly, altering the search type and the number of documents retrieved (k) had no significant impact on model performance but did influence processing time ($p < 0.001$). Adjusting the size of text chunks and how much these chunks overlapped did not significantly impact model performance ($p = 0.53$) or processing time ($p = 0.30$). Therefore, the model parameters for SHP GPT-1 were selected based on technical considerations to

prioritise faster processing times and minimise resource use. The final parameters included a vector-store retriever, chunk size of 1000 characters, chunk overlap of 200 characters, the Maximal Marginal Relevance (MMR) search type, and retrieving 2 chunks.

6.5.3. Clinical validation results

The clinical validation of SHP GPT-1 was conducted with an expert panel of 14 local clinicians. The 14 local clinicians were comprised of six community health doctors from Telangana, six community health doctors from Haryana and two obstetrics and gynaecology doctors from Haryana. Overall, the chatbot was rated by the clinicians as having moderate to high performance in accuracy, appropriateness, and equity across. However, completeness of responses was identified as an area for improvement (Figure 6.5).

Figure 6.5. Clinicians' ratings of model's answers based on accuracy, completeness, appropriateness for ASHAs and equity



6.5.4. Gold standard dataset

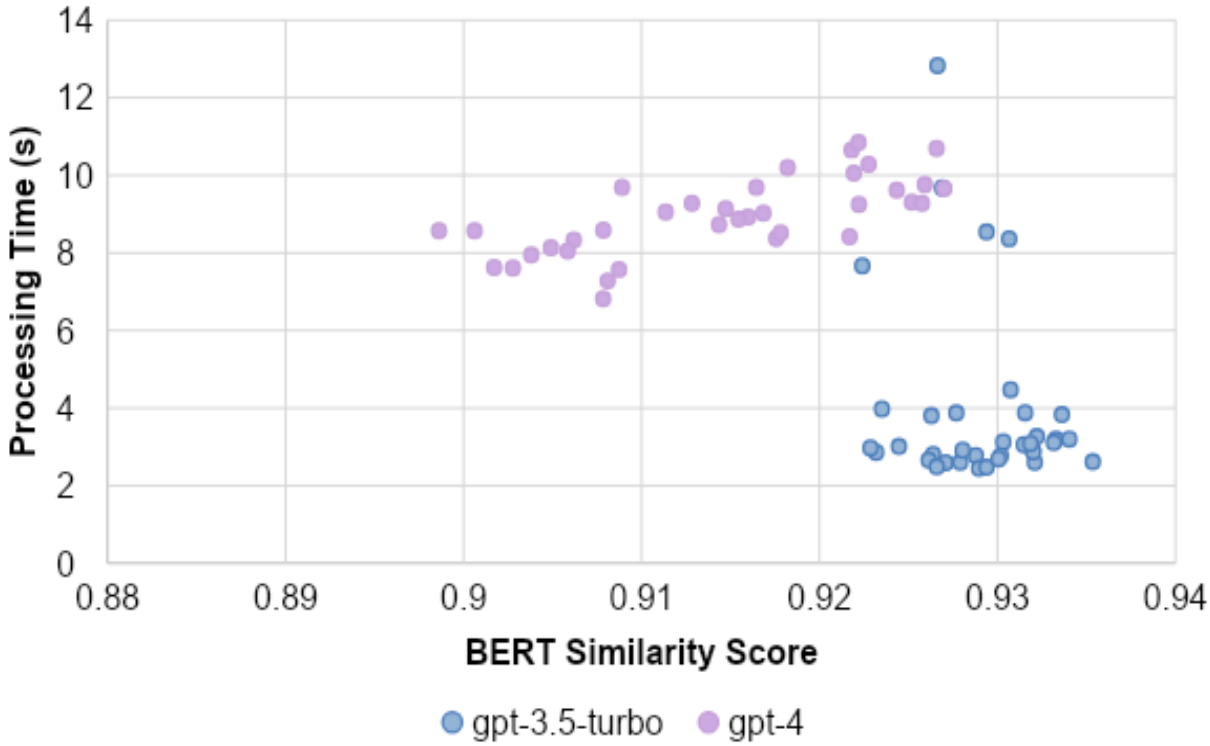
In the co-design workshop, the ASHAs identified 179 unique FAQs. These questions were categorised into four main clusters: educational explanations (42%), clinical risk assessment and referral decisions (31%), practical diet and lifestyle guidance (22%), and social and mental health support (5%). Additionally, the ASHAs identified issues beyond their scope of practice such as infertility, pregnancy termination decisions, family disputes with the potential for violence, religiously sensitive questions, and serious mental health concerns, including self-harm.

Expert clinicians were then asked to give ideal answers to a random selection of the ASHA FAQs. From these combined responses, the clinical team developed 179 gold standard responses for model training and refinement (Appendix 6, Supplementary Table 10.16). Clinician-provided gold-standard responses provided more comprehensive and culturally tailored advice and had a stronger emphasis on the need for professional medical assistance compared to the information offered by the model response. Additionally, clinician-provided responses had a more reassuring and supportive tone, and used simple, accessible language without complex medical terminology. These gold standard responses were used as benchmarks to train the next model iteration.

6.5.5. Model optimisation

For the technical optimisation of SHP GPT-2, we tested performance using different base gpt models. A significant difference was observed between models using gpt-4 and gpt-3.5-turbo (Figure 6.6). The model using gpt-4 had a lower ClinicalBERT similarity score ($p < 0.001$) but required significantly more processing time ($p < 0.001$). Other parameters, such as chunk size, chunk overlap, search type, and the number of documents retrieved, did not significantly affect the ClinicalBERT similarity score ($p=0.91$) but impacted processing time ($p < 0.001$). As a result, SHP GPT-2 was optimised using gpt-3.5-turbo with a chunk size of 1250 characters, chunk overlap of 200, a similarity search type, and retrieving 3 chunks.

Figure 6.6. Comparison of the performance of gpt-3.5-turbo and gpt-4 models



During the co-design workshops with the ASHAs, it was observed that they preferred using voice functionality over typing for entering questions into a prototype chatbot and often posed unstructured questions. A question reframing feature was therefore implemented in SHP GPT-2 to bridge the gap between the ASHAs' natural, unstructured questioning style and the chatbot's need for clear, concise input. This feature rephrases the ASHAs' questions into a clearer question format to improve the model's answer.

6.6. Discussion

6.6.1. Summary of findings

This study presents the stages of development and clinical validation of an LLM-based chatbot, SHP GPT, co-designed with ASHA workers and validated by community medicine experts in rural India. The development process was guided by a sociotechnical humanist perspective, focusing on augmenting ASHA workflows rather than replacing their existing capabilities. This approach aligns with the roadmap for equitable conversational AI development proposed by Nadarzynski et al., which emphasises the importance of designing AI systems in collaboration with the communities they serve (279).

6.6.2. Participatory approach in comparison to other studies

The co-design approach employed in this study aligns with the participatory design principles emphasised by Antoniak et al., underscoring the value of iterative user feedback in developing LLM tools for healthcare (260). By engaging ASHAs during the early stages, we identified four main categories of maternal health questions ASHAs encountered in their fieldwork. These categories closely align with the key question topics identified during the development of an LLM-based WhatsApp based-chatbot, ASHAbot, which include general knowledge, pregnancy-related queries, and societal issues (280). Understanding these question classifications can aid developers in specifying chatbot use case and refining its tone, functionality and type based on previous studies. A systematic review of AI chatbots for healthcare and oncology applications highlights the importance of customising chatbots based on their primary function, whether for providing factual knowledge or offering emotional support (281). This distinction was crucial in defining SHP GPT's tone and scope, setting it apart from systems focusing solely on static, knowledge-based interactions.

There is a lack of established benchmarks for clinically validating LLM tools and no clear regulatory standards. A systematic review of clinical decision support systems found that few receive robust evaluations in healthcare practice (45). One study evaluated the accuracy and completeness of ChatGPT in responding to medical queries using physician-generated questions across specialties (277). Our work employed a similar approach but instead relied on user-derived questions reflective of rural maternal health challenges. This real-world focus aligns with principles of LLM use in maternal healthcare, where discrepancies between user expectations and chatbot outputs necessitated iterative refinement (260).

Clinical validation by domain experts in this study provided critical insights that informed subsequent iterations of the chatbot. It highlighted gaps in response tone and completeness, particularly concerning sensitive topics, dietary guidance, and social support queries. These gaps underscored the limitations of relying solely on generic guidelines to address local nuances, necessitating gold-standard responses that encapsulate cultural and contextual knowledge.

Curating such gold-standard responses is a common practice in chatbot development. For instance, a study developed a Hindi chatbot using 1,365 FAQs vetted by healthcare

professionals, achieving a 70% success rate by matching user queries to pre-annotated responses (282). However, SHP GPT did not use gold-standard responses as training material but instead as benchmarks for validation. The development of the Hindi chatbot faced challenges such as handling diverse query formats written in Devanagari and Hinglish scripts, addressing the polysemous nature of Hindi words, and managing the lack of extensive linguistic resources (282). These limitations highlight the additional complexities involved in expanding chatbot systems to other regional languages.

6.6.3. Safety and bias in AI development

Maternal health is a high-stakes domain in which misinformation can have serious clinical and social consequences. Inaccurate guidance regarding danger signs, medication use, referral timing, or nutrition may delay appropriate care and contribute to preventable maternal and neonatal morbidity. In addition, inappropriate or biased responses risk undermining the credibility of ASHAs within their communities and the broader health system. Recognising these risks, this study incorporated multiple safeguards to mitigate known limitations of LLMs, including hallucinations, opacity in reasoning processes, and embedded biases.

First, the use of a RAG-based architecture constrained the model to retrieve information from specified national guidelines and government training materials. By grounding outputs in curated, context-specific documents, this design reduced reliance on the model's parametric memory and improved traceability of responses. RAG approaches have been shown to reduce hallucinations by anchoring model outputs to external sources, although they do not eliminate the risk entirely (283). Importantly, the ability to link responses back to identifiable guideline documents enhances explainability and accountability, which are particularly critical in community-based healthcare delivery. Being able to reference recognised national guidance strengthens both ASHA's confidence and professional legitimacy. More broadly, concerns about transparency and explainability are pervasive in LLM research, with such systems frequently described as "black boxes" due to limited insight into their training data and internal reasoning processes (253). By explicitly defining and constraining the knowledge base, this study attempted to partially address these transparency concerns within a maternal health application.

Second, clinical validation extended beyond traditional measures of accuracy to include completeness, appropriateness for ASHAs, and equity considerations. This multidimensional evaluation acknowledges that safety in AI systems involves more than factual correctness. Responses that are technically accurate may still be incomplete, overly complex, or misaligned with the scope of practice of community health workers. Assessing appropriateness ensured that recommendations were feasible within ASHAs' training and referral pathways, reducing the risk of overreach. Explicit evaluation of equity is relatively uncommon in LLM validation studies but particularly important in the Indian context, where maternal health disparities are shaped by caste, wealth, geography, and education (265,266). By incorporating equity into clinician assessments, this study foregrounded distributive fairness and social sensitivity as core components of AI safety, aligning with the WHO AI ethics principles (284).

6.6.4. Strengths and limitations

A key strength of this study lies in the integration of technical development within a real-world maternal health implementation platform. SHP GPT was embedded within the ongoing SHP trial, ensuring that model design, optimisation, and validation were conducted under authentic health system constraints rather than in a controlled or simulated setting. This ecological grounding enhanced both feasibility and contextual relevance. The participatory, human-centred approach further strengthened the system's alignment with frontline realities. ASHAs were actively involved in defining use cases, identifying frequently asked and sensitive questions, and shaping iterative refinements. In parallel, a diverse panel of local clinicians contributed to structured validation and the creation of a gold-standard dataset. This multi-stakeholder engagement ensured that the chatbot was technically functional and responsive to sociocultural norms, professional hierarchies, and national clinical guidelines.

Importantly, the evaluation strategy combined automated NLP metrics with clinician-led assessment. This is a methodological strength, given that conventional NLP performance measures, particularly in question-answering tasks, often correlate poorly with clinical relevance, factual correctness, and patient safety (253,285). By incorporating clinician ratings across domains of accuracy, completeness, appropriateness, and equity, the evaluation moved beyond semantic similarity to examine practical safety and contextual suitability within maternal healthcare delivery. This layered approach reflects the recognition that safe AI

deployment in healthcare requires both quantitative benchmarking and expert human judgement. Finally, an additional strength is that the study was reported using the CHART (272), which strengthened the transparency and completeness of reporting across key domains including model identification, prompt engineering, evaluation procedures, and safety considerations.

Despite these strengths, limitations remain. For example, the English gold-standard responses, adapted for translation, failed to capture state-specific nuances such as advice for predominantly vegetarian communities in Haryana versus meat-inclusive diets in Telangana. Validation was also conducted primarily by clinicians rather than ASHAs, who represent the intended end-users of the system. While clinicians are well positioned to assess medical accuracy and guideline fidelity, they may not fully capture usability challenges, linguistic clarity, or contextual feasibility within ASHAs' day-to-day workflows. As the tool is designed to support frontline counselling, structured evaluation by ASHAs is essential to assess comprehension, trust, and integration into community visits.

A further limitation is that this work was conducted during a period of rapid development in generative AI. Because the underlying base models were proprietary and subject to ongoing updates, the findings may reflect the capabilities of the models available at the time of study rather than those of subsequently released versions (272). In addition, the present findings are most directly applicable to a retrieval-augmented chatbot architecture and may not generalise to later AI systems with expanded capabilities for memory, multi-modal tools, and multi-step task execution.

More broadly, the study highlights the need for comprehensive and standardised evaluation frameworks tailored to LLM applications in maternal and community health contexts. Such frameworks should integrate automated metrics, expert clinical review, bias auditing, and real-world implementation outcomes. Longitudinal monitoring will also be critical to assess model drift, ensure alignment with evolving guidelines, and evaluate the system's influence on referral behaviour and maternal health decision-making over time.

CHAPTER 7

User Testing and Iterative Refinement of SMART*health* GPT

7. CHAPTER 7: User Testing and Iterative Refinement of SMART*health* GPT

7.1. Chapter overview

This chapter describes the user testing and iterative refinement of the SHP GPT model developed in the previous chapter. Specifically, it presents two rounds of user testing with ASHAs, the feedback generated during each round and the changes made to improve the model's relevance, clarity, safety and contextual appropriateness.

7.2. Background and Rationale

7.2.1. Need for user testing for AI-based healthcare tools

AI-based healthcare tools, particularly those powered by LLMs, are increasingly being explored to support frontline health workers in low-resource settings. These systems demonstrate strong performance in controlled validation studies but real-world deployment introduces contextual, linguistic, and workflow complexities that are often not captured in technical evaluations.

While expert-driven validation is important, it does not adequately assess usability, comprehension, contextual appropriateness, or acceptability among intended users. In settings where community health workers such as ASHAs act as intermediaries between formal healthcare systems and pregnant women, the effectiveness of AI tools depends heavily on how well these tools integrate into existing workflows and communication styles.

Human-centred and participatory design literature strongly supports involving frontline workers in digital tool development to ensure contextual fit and sustained adoption (260,261,284). User-testing and iterative evaluation can reduce the risk of harm, improve trust, and ensure that AI tools are aligned with frontline realities. Given the absence of standardised regulatory pathways for LLM-based health tools, structured user testing also serves as a critical safeguard for ethical and responsible implementation.

7.2.2. Importance of ASHA feedback for model optimisation

Incorporating ASHA feedback during model development enables optimisation across several critical domains.

First, frontline feedback improves relevance and contextualisation ensuring that chatbot responses align with the real-world, field-level questions ASHAs encounter during household visits. Digital health technologies that fail to align with existing workflows are at high risk of non-adoption or abandonment, as highlighted by the NASSS (Non-adoption, Abandonment, Scale-up, Spread, and Sustainability) framework (286).

Second, structured feedback enhances clarity, language simplicity and tone appropriateness, which is essential for tools intended to be translated into local dialects or communicated verbally to beneficiaries (269). Usability research in clinical informatics consistently demonstrates that end-user testing is necessary to identify comprehension barriers not evident in expert validation (287).

Third, ASHAs can support scope alignment, identifying when chatbot outputs exceed their professional boundaries or require referral to higher-level care, an important safeguard in maternal health settings.

7.3. Aims of this Research

The development of SHP GPT builds upon these lessons by embedding structured user testing, guideline refinement, safety safeguards, and participatory optimisation into the model development process prior to wider deployment. By integrating ASHAs' feedback across iterative testing rounds, this approach evaluates relevance, accuracy, contextual appropriateness, and safety, domains identified in prior literature as critical for sustainable AI integration in maternal health systems.

7.4. Methods

7.4.1. Study setting and participants

Two rounds of user testing were conducted with ASHAs to gather rapid feedback and support iterative model updates. The sample was determined pragmatically to include a small but diverse group of representative ASHAs across the two study sites, while remaining feasible for supervised workshop-based testing and rapid iterative refinement. Eight ASHAs were included, with four recruited from Telangana and four from Haryana. Informed by prior observations in the SHP trial, the testing groups included a mix of ASHAs who often

required assistance with technology and tech-savvy ASHAs to ensure diverse user experiences. The same ASHAs participated in both rounds, using a standardised feedback form.

7.4.2. Data collection

Each round began with a half-day workshop to introduce ASHAs and their field supervisors to AI safety and user testing procedures. To minimise interference with regular fieldwork, testing was conducted outside routine visits. Supervised by their field supervisors, each ASHA was instructed to enter at least 20 real-world questions into SHP GPT and then work with the supervisor to complete a structured online feedback form in the local language. This mobile-accessible form used visual aids to support comprehension. The user testing tool was developed by the clinical team based on theoretical frameworks related to technology assessment such as the Task-Technology Fit Theory (288), the Technology Acceptance Model (TAM) (289) and the WHO AI ethics principles (284).

The feedback form provided data on the proportion of questions (i) answered by the chatbot, (ii) relevant, appropriate, and well-tailored to ASHA needs, (iii) accurate and useful, (iv) clear, and (v) respectful and safe for the ASHA's context. Each response was matched with the chatbot question using a unique ID in the backend portal. Responses with multiple answers were excluded.

7.4.3. Changes implemented between testing rounds

Inclusion of Maternal Health Guidelines

Following the first round of user testing, the team refined the training dataset by expanding the guidelines to better address ASHAs' most FAQs. During clinical validation, clinicians were invited to suggest additional guidelines to improve chatbot responses. After removing duplicates, references were checked for further relevant materials.

Two reviewers (AS & ZS) evaluated each resource for reliability and usability for ASHAs. Reliable resources were defined as those from Indian, South Asian, or global contexts, including peer-reviewed articles or online publications by reputable organisations or research consortiums. Single-author reports and materials intended for non-Indian audiences were

excluded. Appropriateness was determined by whether the information was understandable at a Grade 8 reading level.

The model was trained on different combinations of these guidelines, with each configuration tested on the questions inputted by ASHAs in the first user testing. Model performance was assessed based on the proportion of questions it successfully answered.

Incorporation of Safety Features

The model parameters from SHP GPT-2 were retained. However, additional safety features were introduced to SHP GPT-3 to handle sensitive or out-of-scope topics, such as infertility or pregnancy termination. A complete list of sensitive topics with their respective predefined responses can be found in Appendix 7 (Supplementary Table 10.18).

7.4.4. Pilot Testing (SHP GPT-3)

After updating the model with the expanded guidelines, a second round of pilot was conducted, following the same process as for SHP GPT-2. The same group of ASHAs participated in this round, using the same feedback form. This allowed for direct comparison between the two rounds of testing to assess changes in the model's performance. User testing results were compared between rounds across all metrics using Fisher's Exact tests to identify statistically significant differences in user feedback.

7.5. Results

7.5.1. Participant characteristics

A total of eight participants were included in the study, with four recruited from Telangana and four from Haryana. Participants' ages ranged from 37 to 49 years in Telangana and 31 to 53 years in Haryana. The mean age was 41.5 years (SD 5.3) for participants from Telangana and 42.3 years (SD 10.6) for those from Haryana, indicating a wider age distribution in the Haryana cohort. Based on findings from the qualitative interviews with clinical team members, the two younger ASHAs at each study site were described as more comfortable and proficient with technology.

Educational attainment differed between sites. Participants from Telangana demonstrated heterogeneous educational backgrounds, including completion of Grade 10, vocational training, and high school degrees. In contrast, all participants recruited from Haryana had completed education up to Grade 10.

7.5.2. User testing results (Round 1)

During the first round of testing using SHP GPT-2, 388 questions were entered by the 8 ASHAs, with 57.8% of questions generating model responses. In addition, the ASHAs provided structured feedback to 236 questions. Feedback highlighted issues related to relevance, clarity and appropriateness of response length (

Measure	SHP GPT-2 (n=236)	SHP GPT-3 (n=143)	p-value
Input Method			
Typing	3 (1.3)	2 (1.4)	0.7
Voice	232 (98.3)	141 (98.6)	
Google handwriting	1 (0.4)	0 (0)	
Missing	0 (0)	0 (0)	
Difficulty entering question			
Yes	30 (12.7)	9 (6.3)	0.05
No	205 (86.9)	133 (93.0)	
Missing	1 (0.4)	1 (0.7)	
Supervisor help			
Yes	90 (38.1)	50 (35.0)	0.3
No	144 (61.0)	93 (65.0)	
Missing	2 (0.9)	0 (0)	
Response Relevance			
No	21 (8.9)	1 (0.7)	< 0.001
Partially	32 (13.6)	3 (2.1)	
Yes	176 (74.6)	138 (96.5)	
Missing	7 (3.0)	1 (0.7)	
Response Length			
Good	161 (68.2)	114 (79.7)	0.006
Too long	23 (9.7)	16 (11.2)	
Too short	44 (18.6)	10 (7.0)	
Missing	8 (3.4)	3 (2.1)	
Response Clarity			
Simple	177 (75.0)	114 (79.7)	0.09
Moderate	32 (13.6)	24 (16.8)	
Difficult	16 (6.8)	3 (2.1)	
Missing	11 (4.7)	3 (2.1)	
Response Perceived Accuracy			

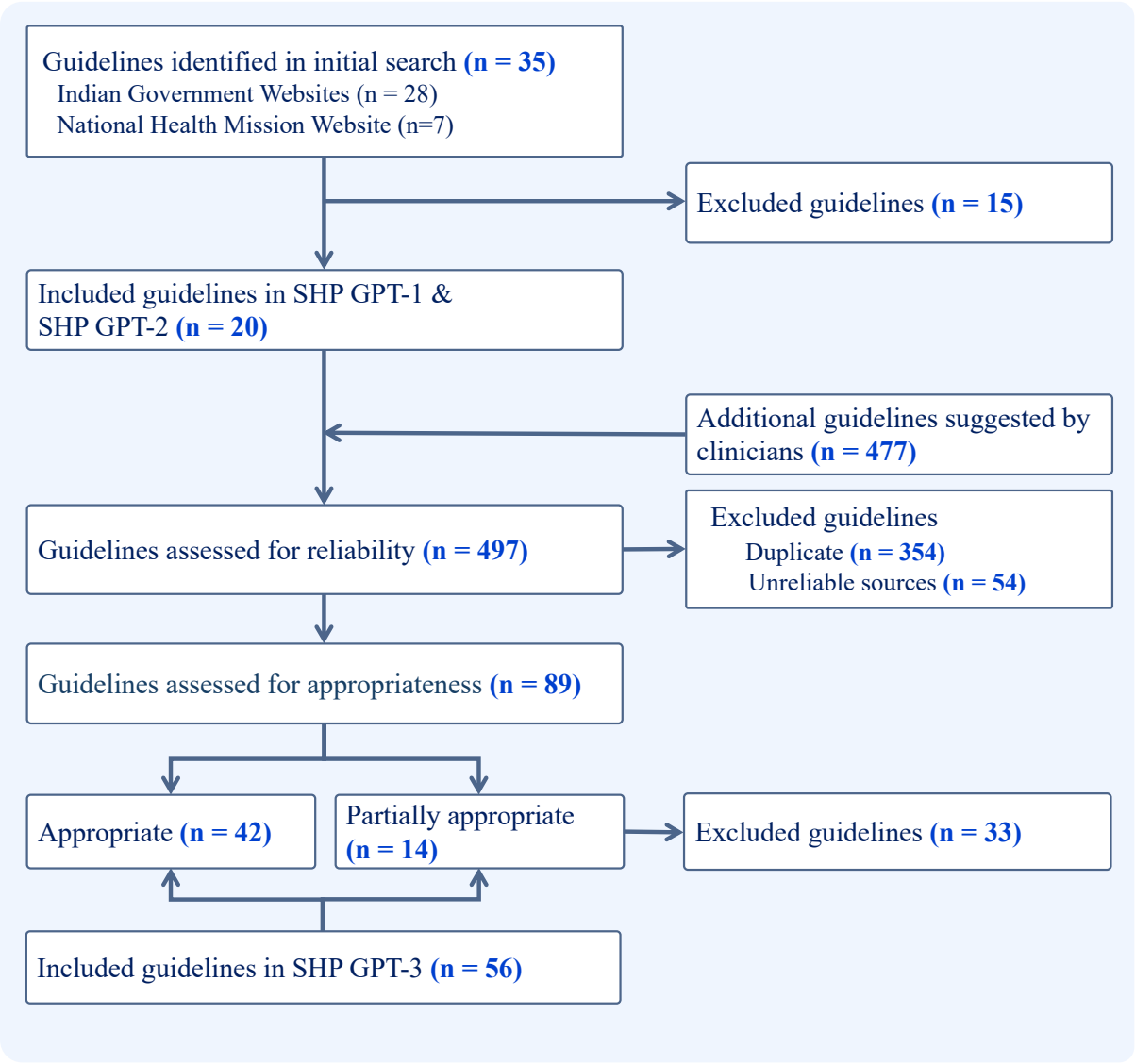
Measure	SHP GPT-2 (n=236)	SHP GPT-3 (n=143)	p-value
0%	20 (8.5)	0 (0)	0.002
50%	40 (16.9)	19 (13.3)	
80%	63 (26.7)	45 (31.5)	
100%	109 (46.2)	78 (54.5)	
Missing	4 (1.7)	1 (0.7)	
Response Perceived Usefulness			
Very useful	120 (50.8)	99 (69.2)	< 0.001
Moderately useful	81 (34.3)	40 (28.0)	
Not useful	28 (11.9)	4 (2.8)	
Missing	7 (3.0)	0 (0)	
Appropriate for Context			
Yes	220 (93.2)	138 (96.5)	0.8
No	8 (3.4)	5 (3.5)	
Missing	8 (3.4)	0 (0)	
Respectful Tone			
Yes	217 (91.9)	141 (98.6)	0.03
No	11 (4.7)	2 (1.4)	
Missing	8 (3.4)	0 (0)	
Lack of Harmful Content			
Yes	230 (97.5)	143 (100)	0.3
No	2 (0.8)	0 (0)	
Missing	4 (1.7)	0 (0)	

). These findings were used to further refine the model.

7.5.3. Refinements following Round 1

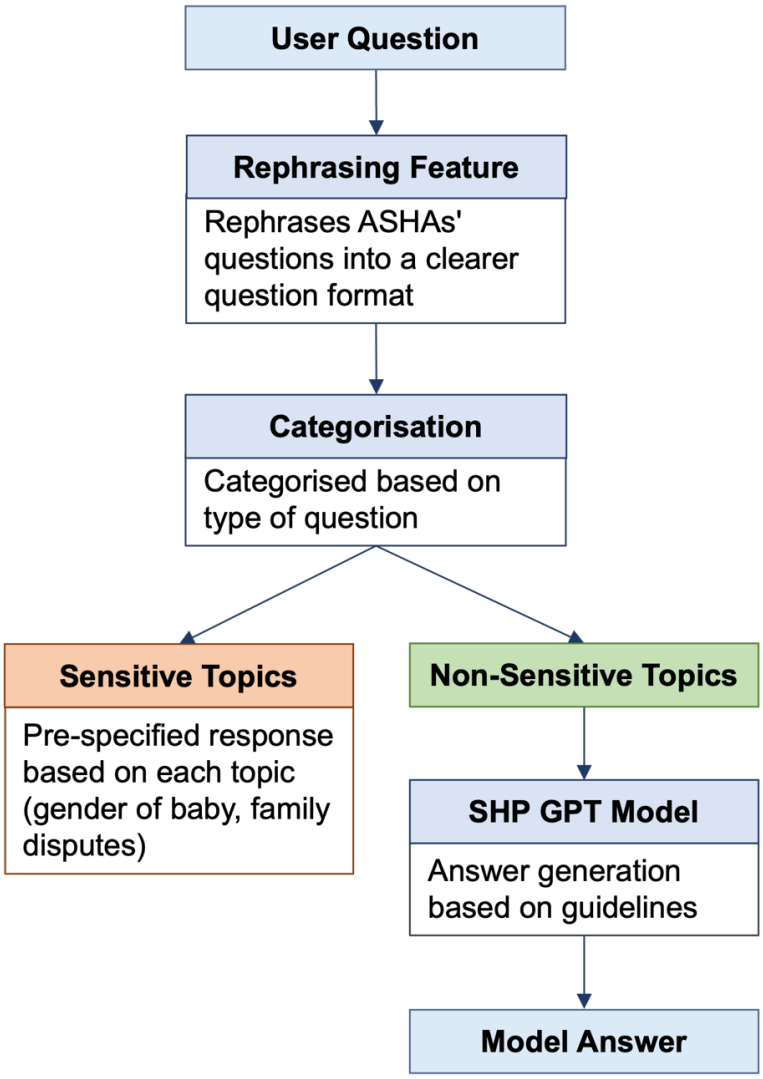
The 14 expert clinicians provided suggestions for a further 477 supporting resources (textbooks, guidelines, web pages, and journal articles) that directly related to the FAQs by ASHAs in addition to the 20 reference documents used for SHP GPT-1. After removing duplicates, these guidelines were screened for reliability and appropriateness. This process resulted in 36 additional appropriate resources in addition to the original 20 guidelines (Figure 7.1). Testing revealed that the model trained on the initial 20 guidelines failed to respond to 41% of ASHAs' questions. With the full 56 guidelines, the model only failed to answer 15% of the questions. Based on these results, the SHP GPT-3 model was trained using the complete set of 56 guidelines for optimal accuracy and response coverage. A complete list of guidelines included can be found in Appendix 7 (Supplementary Table 10.17).

Figure 7.1. Guideline selection process for SHP GPT development



The SHP GPT-3 chatbot was trained to recognize ethically sensitive topics and those out of scope for ASHAs. Responses were pre-programmed to give a limited script written by clinicians, redirecting users to appropriate healthcare professionals when necessary (Figure 7.2). This helped ensure that the chatbot only provided ethically safe advice while remaining within the scope of ASHAs' responsibilities.

Figure 7.2. Model pipeline for sensitive and out of scope topics in SHP GPT-3



7.5.4. User testing results (Round 2)

During the second round of testing using SHP GPT-3, a total of 205 questions were entered by the same 8 ASHAs, who also provided structured feedback for 143 of the responses. Out of these, 176 (85.9%) generated a response, a significant improvement compared to SHP GPT-2 ($p < 0.0001$). The results are provided in

Table 7.1. Pilot User Testing Results for SHP GPT-2 and SHP GPT-3

Measure	SHP GPT-2 (n=236)	SHP GPT-3 (n=143)	p-value
Input Method			
Typing	3 (1.3)	2 (1.4)	0.7
Voice	232 (98.3)	141 (98.6)	
Google handwriting	1 (0.4)	0 (0)	
Missing	0 (0)	0 (0)	
Difficulty entering question			
Yes	30 (12.7)	9 (6.3)	0.05
No	205 (86.9)	133 (93.0)	
Missing	1 (0.4)	1 (0.7)	
Supervisor help			
Yes	90 (38.1)	50 (35.0)	0.3
No	144 (61.0)	93 (65.0)	
Missing	2 (0.9)	0 (0)	
Response Relevance			
No	21 (8.9)	1 (0.7)	< 0.001
Partially	32 (13.6)	3 (2.1)	
Yes	176 (74.6)	138 (96.5)	
Missing	7 (3.0)	1 (0.7)	
Response Length			
Good	161 (68.2)	114 (79.7)	0.006
Too long	23 (9.7)	16 (11.2)	
Too short	44 (18.6)	10 (7.0)	
Missing	8 (3.4)	3 (2.1)	
Response Clarity			
Simple	177 (75.0)	114 (79.7)	0.09
Moderate	32 (13.6)	24 (16.8)	
Difficult	16 (6.8)	3 (2.1)	
Missing	11 (4.7)	3 (2.1)	
Response Perceived Accuracy			
0%	20 (8.5)	0 (0)	0.002
50%	40 (16.9)	19 (13.3)	
80%	63 (26.7)	45 (31.5)	
100%	109 (46.2)	78 (54.5)	
Missing	4 (1.7)	1 (0.7)	
Response Perceived Usefulness			
Very useful	120 (50.8)	99 (69.2)	< 0.001
Moderately useful	81 (34.3)	40 (28.0)	
Not useful	28 (11.9)	4 (2.8)	
Missing	7 (3.0)	0 (0)	
Appropriate for Context			
Yes	220 (93.2)	138 (96.5)	0.8

Measure	SHP GPT-2 (n=236)	SHP GPT-3 (n=143)	p-value
No	8 (3.4)	5 (3.5)	
Missing	8 (3.4)	0 (0)	
Respectful Tone			
Yes	217 (91.9)	141 (98.6)	0.03
No	11 (4.7)	2 (1.4)	
Missing	8 (3.4)	0 (0)	
Lack of Harmful Content			
Yes	230 (97.5)	143 (100)	0.3
No	2 (0.8)	0 (0)	
Missing	4 (1.7)	0 (0)	

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Table 7.1. Pilot User Testing Results for SHP GPT-2 and SHP GPT-3

Measure	SHP GPT-2 (n=236)	SHP GPT-3 (n=143)	p-value
Input Method			
Typing	3 (1.3)	2 (1.4)	0.7
Voice	232 (98.3)	141 (98.6)	
Google handwriting	1 (0.4)	0 (0)	
Missing	0 (0)	0 (0)	
Difficulty entering question			
Yes	30 (12.7)	9 (6.3)	0.05
No	205 (86.9)	133 (93.0)	
Missing	1 (0.4)	1 (0.7)	
Supervisor help			
Yes	90 (38.1)	50 (35.0)	0.3
No	144 (61.0)	93 (65.0)	
Missing	2 (0.9)	0 (0)	
Response Relevance			
No	21 (8.9)	1 (0.7)	< 0.001
Partially	32 (13.6)	3 (2.1)	
Yes	176 (74.6)	138 (96.5)	
Missing	7 (3.0)	1 (0.7)	
Response Length			
Good	161 (68.2)	114 (79.7)	0.006
Too long	23 (9.7)	16 (11.2)	
Too short	44 (18.6)	10 (7.0)	
Missing	8 (3.4)	3 (2.1)	
Response Clarity			
Simple	177 (75.0)	114 (79.7)	0.09
Moderate	32 (13.6)	24 (16.8)	
Difficult	16 (6.8)	3 (2.1)	
Missing	11 (4.7)	3 (2.1)	
Response Perceived Accuracy			
0%	20 (8.5)	0 (0)	0.002
50%	40 (16.9)	19 (13.3)	
80%	63 (26.7)	45 (31.5)	
100%	109 (46.2)	78 (54.5)	
Missing	4 (1.7)	1 (0.7)	
Response Perceived Usefulness			
Very useful	120 (50.8)	99 (69.2)	< 0.001
Moderately useful	81 (34.3)	40 (28.0)	
Not useful	28 (11.9)	4 (2.8)	
Missing	7 (3.0)	0 (0)	
Appropriate for Context			
Yes	220 (93.2)	138 (96.5)	0.8

Measure	SHP GPT-2 (n=236)	SHP GPT-3 (n=143)	p-value
No	8 (3.4)	5 (3.5)	
Missing	8 (3.4)	0 (0)	
Respectful Tone			
Yes	217 (91.9)	141 (98.6)	0.03
No	11 (4.7)	2 (1.4)	
Missing	8 (3.4)	0 (0)	
Lack of Harmful Content			
Yes	230 (97.5)	143 (100)	0.3
No	2 (0.8)	0 (0)	
Missing	4 (1.7)	0 (0)	

The results of user testing for SHP GPT-2 and SHP GPT-3 demonstrate significant improvements in chatbot performance in several measures. The proportion of responses rated as fully relevant increased from 74.6% in SHP GPT-2 to 96.5% in SHP GPT-3 ($p < 0.001$). The percentage of responses perceived as 100% accurate also rose, from 46.2% to 54.5% ($p = 0.002$), while responses rated as 0% accurate dropped to 0% in SHP GPT-3, down from 8.5% in SHP GPT-2. Similarly, the proportion of responses rated as "very useful" rose significantly from 50.8% in SHP GPT-2 to 69.2% in SHP GPT-3 ($p < 0.001$), while responses rated as "not useful" declined from 11.9% to 2.8%. Improvements in length and tone were also significant between the two models. Other measures, such as the difficulty in entering questions, need for supervisor assistance, clarity, and the appropriateness of responses for the context, did not show statistically significant differences between the models. The high use of voice input over typing remained consistent, reflecting the ASHAs' preference for voice input over typing.

7.6. Discussion

7.6.1. Summary of findings

This study evaluated the impact of structured user testing and iterative refinement on the performance and acceptability of SHP GPT, an LLM-based chatbot designed to support ASHAs in maternal healthcare delivery. Across two rounds of testing, significant improvements were observed in response coverage, relevance, perceived accuracy, usefulness, clarity, and tone.

These findings demonstrate that iterative, end-user–informed refinement meaningfully enhances perceived utility and contextual appropriateness. Improvements were achieved

without significant changes in user burden, as measures such as difficulty entering questions and need for supervisor assistance remained stable. Collectively, these results suggest that participatory user testing is a critical bridge between technical validation and real-world readiness.

7.6.2. Iterative refinement process

While clinical validation ensured the accuracy of responses, these assessments were conducted by experts rather than end-users. Pilot testing with ASHAs revealed additional insights into user expectations and perceived relevance. This approach aligns with recommendations in the literature, which emphasise participatory design for NLP tools in maternal healthcare (260). During pilot testing of SHP GPT, ASHA workers perceived only 46.2% of guideline-based responses as fully accurate. These findings highlighted the necessity of iterative refinement informed by end-user feedback, particularly in addressing the sociocultural intricacies of rural maternal healthcare.

This resonates with broader trends observed in systematic reviews of health-related chatbots. A systematic review of chatbots for health behavioural changes noted the need for holistic validation approaches that go beyond metrics assessing the chatbot's responses alone, capturing more nuanced factors such as user trust and the practical impact of responses on behaviour change (267). Similarly, a second systematic review of chatbots for lifestyle modifications highlighted their potential to leverage persuasive and relational capabilities to enhance user engagement (290). However, it noted gaps in understanding their efficacy for specific health outcomes, such as physical activity and dietary changes. This review also emphasised the importance of adopting structured evaluation frameworks for chatbot interventions. Standardised measures of user satisfaction and engagement were identified as essential for enabling meaningful comparisons across studies and fostering improvements in chatbot design and implementation (290).

7.6.3. Strengths and limitations

A major strength of this study lies in its iterative design and the direct comparison between two model versions using the same participant group and a standardised feedback instrument. This design strengthened internal validity by allowing observed improvements to be more

confidently attributed to specific refinements. The structured feedback tool, informed by established technology assessment frameworks, enabled systematic evaluation across multiple domains beyond technical accuracy, including relevance, clarity, usefulness, and contextual appropriateness. Embedding the user testing within the existing SHP platform further enhanced ecological validity, as participants were already familiar with the broader digital environment.

However, this study also has several limitations. The small sample size limits generalisability and restricted our ability to explore heterogeneity in responses across different levels of digital literacy, age, or experience. The potential risks associated with deploying the chatbot meant that we had to evaluate it in controlled environments to account for potential regulatory and ethical constraints. As a result, the study involved a small, supervised sample of ASHAs who tested the chatbot outside of their routine field visits and did not allow for unsupervised use with pregnant and postpartum women. As such, the testing conditions may not fully reflect the time constraints, cognitive load, and environmental pressures encountered during real-world fieldwork. The presence of supervisors during testing may also have introduced social desirability bias in feedback responses.

Additionally, the ASHAs involved in this study operated in regions with relatively stable digital infrastructure and prior exposure to the SHP platform. Their familiarity with tablet-based tools may not reflect conditions in more resource-constrained or digitally underserved districts. As such, the findings may overestimate usability in settings with lower connectivity, lower literacy levels, or limited prior exposure to digital decision-support systems.

Importantly, this study focused on user-perceived performance and did not evaluate downstream clinical or behavioural outcomes. While improvements in perceived usefulness, relevance, and perceived accuracy are encouraging, they do not necessarily translate into improved referral decisions, enhanced counselling quality, behavioural change among pregnant women, or measurable maternal health outcomes. Evidence from the deployment of an LLM-based decision-support tool in two outpatient clinics in Nigeria found that while academic reviewers rated LLM-assisted care plans more favourably, on-site physicians who directly evaluated and treated the same patients observed little to no improvement in diagnostic accuracy or treatment decisions (291). This discrepancy highlights the distinction between perceived usefulness and actual clinical impact in real-world settings.

7.6.4. Challenges and recommendations for future work

The development and user-testing of SHP GPT highlighted challenges in contextualisation, sociocultural integration, and the absence of regulatory frameworks. Identifying suitable guidelines for model training proved difficult as many Indian guidelines are written in regional languages or incorporate visuals unsuitable for LLMs. Engaging local medical experts aided in guideline selection, but future iterations must account for evolving national guidelines and conflicts between national and local recommendations. Responses grounded in formal guidelines often lacked the cultural relatability needed for ASHAs' workflows, necessitating iterative feedback to refine tone and format. Balancing clinical precision with cultural relevance remains an ongoing challenge.

Contextualisation was further complicated by linguistic and cultural diversity. Google-based translations are often misaligned with local dialects. Advanced multilingual LLMs and the creation of user personas tailored to local contexts could address these limitations in future work.

The lack of regulatory, safety, and evaluation guidelines for LLMs posed an additional challenge (292). Ensuring bias mitigation and output safety within the rural Indian context added complexity, as bias is context-dependent and what constitutes bias in one setting may not apply in another. The involvement of human stakeholders in evaluating bias does not eliminate the risk of their own inherent biases (293). Concerns related to data privacy and security also warrant consideration. While this study did not capture or store personal user data, and the chatbot did not explicitly request identifiable information, future real-world deployment would require robust safeguards to protect user-entered data and ensure compliance with evolving digital health governance standards.

Integrating the LLM-based chatbot into local sociocultural contexts and healthcare systems posed additional complexities. Although the ASHAs involved in this study operated in regions with robust digital infrastructure and demonstrated proficient digital literacy, future efforts must ensure the chatbot's inclusivity for ASHAs in areas with limited infrastructure and lower levels of digital literacy. To promote equitable access, LLM chatbots must be designed to accommodate users across diverse literacy levels, ages, and abilities (294). In the

sensitive domain of maternal healthcare, addressing power dynamics is critical. ASHA workers may over-rely on chatbot-generated information, potentially undervaluing their own experiential knowledge, particularly when technology is perceived as inherently authoritative. This raises concerns about how chatbot-generated advice is conveyed to women and whether it translates into meaningful behavioural or health outcomes. Future work should prioritise women, the ultimate beneficiaries of LLM chatbots, by ensuring that these tools directly address their needs, rather than focusing solely on ASHAs (295).

Addressing these challenges requires a deeper understanding of the broader implications of embedding AI tools into healthcare workflows. This includes evaluating how such technologies reshape interactions between healthcare workers and beneficiaries, ensuring they complement existing human-centred care models while avoiding unintended dependencies or gaps in trust and impact.

7.6.5. Conclusions

This study demonstrates how SHP GPT can be developed and refined as a context-sensitive maternal health chatbot through a participatory, human-centred approach involving both clinical experts and ASHAs. Initial clinical validation showed that the model had generally good performance in accuracy, appropriateness, and equity, while also identifying important gaps in completeness and contextual tailoring. Subsequent user testing and iterative refinement improved response coverage, relevance, usefulness, and tone, highlighting the importance of embedding frontline user feedback into AI development. Overall, these findings support the feasibility of developing a safe, locally relevant, and acceptable LLM-based support tool for community maternal healthcare, while underscoring the need for continued evaluation in real-world settings.

CHAPTER 8

Discussion and Conclusions

8. CHAPTER 8: Discussion and Conclusions

8.1. Summary of key findings and learnings

This thesis examined how machine learning and translational approaches can contribute to more personalised care for women with high-risk pregnancies. The systematic review in Chapter 2 showed that most published models were at high risk of bias and had limited evidence of external validation. In the field of risk prediction, model development has often been treated as the end goal, while the harder questions of calibration, validation and clinical usefulness have received less attention. In the context of risk prediction for GDM outcomes, progress will depend less on producing additional models and more on testing whether existing models can perform well in new populations and prove to be clinically useful.

The external validation study in Chapter 3 reinforced this finding. Although the validated model retained moderate discrimination when applied to the UK dataset, it had poor relative calibration. Its applicability was further limited by the lack of reporting of baseline risk, which prevented assessment of absolute calibration.

In relation to postnatal management of women after GDM, Chapter 4 showed that referral to the NHS DPP remains suboptimal, and that automated queries like that developed and tested in this thesis can contribute to improved prevention in line with NICE guidelines. However, the effectiveness of these queries in primary care depends heavily on the quality of routine GDM recording. The analysis of linked HES and primary care data in Chapter 5 showed that nearly two-thirds of women identified with GDM in hospital records did not have a corresponding GDM code in primary care. Women who are not appropriately coded in primary care are less likely to be identified for follow up and may be excluded from recommended preventive pathways, including DPP referral. This is particularly important as the recording gaps were not random but were socially patterned. For example, women from more deprived backgrounds were more likely to be missed within routine coding pathways, despite remaining at increased risk of T2DM.

In Chapters 6 & 7, the development of SHP GPT illustrated how LLM-based tools might be used to support frontline maternal healthcare, if they are grounded in user-led design. This part of the thesis reinforces that the value of digital innovation is directly related to whether it can be translated into tools that are practical, safe and embedded within care pathways.

8.2. Implications for clinical practice

The findings from this thesis have several clinical implications for the care of high-risk pregnancies. Findings from the National GDM audit showed that 10.8% of women identified as having GDM through primary care records had a diagnosis of NDH after GDM diagnosis, and 5.6% had a diagnosis of T2DM after GDM (192). However, despite the well-established association between GDM and later T2DM (29,167), the findings of this thesis show that prediction models for T2DM after GDM are still far from clinical implementation due to biased development methods, poor evaluation and lack of transportability to new settings. By contrast, automated search tools like the one described in Chapter 4 may have more immediate clinical value. In the pilot practice, 163 patients were identified as eligible for referral to the NHS DPP, but only 7 had ever attended or been referred to the programme. The automated search allowed the GP to invite the remaining 158 eligible patients to self-refer, increasing awareness about the DPP without adding burden on GPs. This is important because referral to the DPP remains suboptimal. The National GDM audit that found that, despite NICE guidance, only 13.8% of women with a GDM diagnosis had been offered a DPP referral and only 4.5% had ever participated in the programme. The audit report concluded that action should be taken to proactively support women with a history of GDM to access the DPP (192). These figures are also reflected when looking at glycaemic control: only 54.5% had any recorded glycaemic monitoring, and only 1.3% had a FPG test recorded (192). This is consistent with earlier literature showing low rates of postpartum follow-up (296,297) and poor adherence to recommended glycaemic testing after GDM (191).

Systematic reviews of barriers across the GDM care pathway found that poor postpartum follow-up may arise from poor communication between healthcare providers, lack of clear responsibility for testing, inconsistent use of guidelines, and limited patient understanding of the need for long-term screening (298,299). A UK study of postpartum follow up after GDM in England showed that suboptimal monitoring was linked to ambiguity between primary and secondary care responsibilities and absence of agreed recall processes (245). An additional important barrier that surfaces across studies is the loss of women to follow-up after discharge from maternity services, when responsibility for postpartum care may not be clearly transferred to primary care. In this thesis, a large proportion of the women with hospital-recorded GDM had no corresponding primary-care code. This means that interventions based on primary care records, like the DPP pathway, are likely to miss part of

the at-risk population. Importantly, this missingness was not random with women from more deprived backgrounds being more likely to be missed, despite having higher future risk of T2DM (300). As such, these pathways may reproduce existing inequalities unless services make a specific effort to identify women who are less likely to be captured through automated searches. Targeted interventions are therefore needed alongside universal follow-up and DPP referral. Without this, attempts to improve follow-up and DPP referral may benefit women who are easier for the system to reach, rather than the highest at risk population (300).

These findings support a model of care in which women with prior GDM are actively recalled for postpartum follow-up, preventive intervention, and appropriate referral rather than being discharged to routine care with the assumption that future risk will be picked up opportunistically. A GDM diagnosis should be treated as an opportunity for long term diabetes prevention. Some of the implications are organisational as well as clinical. Better interoperability between records and more consistent coding standards would make it easier to identify women accurately and maintain continuity of care.

The different strands of this thesis suggest that machine learning and translational tools are most useful when they are not developed in silos and instead incorporated as interacting parts of a wider care pathway. The transformative potential of these approaches lies in creating digital systems that improve continuity, reduce missed follow-up and make care easier to deliver within real workflows. This is particularly relevant in the context of current NHS priorities to move from analogue to digital models of care (301). This shift aims to improve patient outcomes and release staff time for direct care. This includes making it easier for patients to communicate with services digitally, improving access to core functions such as records, appointments, messaging and prescriptions, and ensuring that information flows more effectively across services through better connected data, referral and record systems. The broader aim is to create a health system in which digital tools strengthen coordination and efficiency across pathways.

At the same time, these technological opportunities need to be balanced against important limitations in the current evidence and in the safe deployment of digital tools in high-risk pregnancy. Chapters 2 & 3 showed that prediction models for adverse outcomes after GDM are often poorly developed and reported, are rarely externally validated and difficult to

transfer across healthcare settings. Chapters 6 & 7 also raise concerns for LLM-based tools. They may produce answers that appear clear and confident even when they are inaccurate, incomplete or not appropriate to the clinical context. Their internal reasoning is also difficult to inspect, which makes errors and hallucinations harder to detect. In developing SHP GPT, we used RAG to minimise hallucinations and enhance traceability to trusted guidelines, offering an alternative over black box models. The LLM development also highlighted that technical performance can be improved through user-centred design. The value of the system we developed depended on co-design with end-users, alignment with workflow, and presenting information in a way that was understandable and useful in real clinical settings. These findings suggest that digital tools are most likely to add value when they are explainable, grounded in trusted evidence and designed around the needs of the people who will use them.

Throughout the development of SHP GPT, I have witnessed the fast development of LLM tools, with new models with updated capabilities becoming available every day. The technology is advancing faster than the clinical guidance, legal standards and regulatory systems. As a result, there are still important gaps around accountability, privacy, transparency and liability. As such, digital tools in high-risk pregnancy should be implemented cautiously in clearly defined tasks such as improving access to guideline-based information, supporting patient education or helping frontline workers deliver more consistent advice. Their use should remain under human oversight to ensure that outputs are safe, appropriate and interpreted in context. In this way, such tools can support clinical care without replacing clinical judgement or professional responsibility.

8.3. Implications for research

The findings from this thesis have several implications for future research on machine learning and translational tools for high-risk pregnancies. The systematic review in Chapter 2 highlighted that there is an abundance of prediction models. As such instead of developing new models, there is a need to invest in the validation and updating of existing ones. The continuous development of new models wastes resources and data that could be used on validating existing models and testing their clinical usefulness. Chapter 3 showed the importance of external validation as a model may perform adequately in its development setting and still fail to transport well to a different population.

Additionally, one of the clearest lessons from this work was that poor reporting in original studies can limit validation and assessment of clinical usefulness. In Chapter 3, the absence of baseline hazard prevented assessment of absolute calibration, which reduced interpretability and limited how much could be learnt from external validation. As such poor reporting is a barrier to replication, validation, updating and clinical translation. The TRIPOD statement (164) was developed to improve transparency in prediction model studies, and the more recent TRIPOD + AI guidance (302) makes the same point for models developed or evaluated using machine learning methods.

The use of routine health data in Chapters 3 and 5 also showed the value of large observational datasets for studying follow-up after GDM and identifying women at risk of later disease. At the same time, the findings showed coding gaps and significant missing data. These affect case definition, follow-up and estimates of risk (242). Future research should therefore pay greater attention to data quality, linkage quality and the meaning of missingness. This includes more work on case ascertainment, data triangulation across sources, sensitivity analyses for incomplete recording, and methods that examine how missing data may affect both association studies and prediction modelling (303). In this work, missingness was informative because it reflected fragmentation between primary care and secondary care.

A further implication concerns model validation and updating. This applies to both prediction models and LLM-based tools. These models need to be evaluated under real-use conditions using impact studies, rather than relying on technical performance alone (304). Additionally, even when systems perform well in validation, these systems may drift over time and performance may deteriorate as populations, care pathways, outcome incidence, clinical guidelines and recording practices change. In both cases, updating becomes necessary. For the LLM work in Chapters 6 and 7, for example, the RAG database would need to be updated as guidelines change. It is currently unclear who is responsible for updating models, when updating should occur and how revalidation should be carried out. Additionally, the prediction-model literature suggests that models need to be updated as calibration deteriorates over time, rather than on pre-defined schedules. As such, systems that alert users to the presence of calibration drift or deterioration in performance are needed (305). Additionally,

governance structures are required to ensure changes are made appropriately and performance is assessed before reuse.

Additionally, in our study we used expert validation and user-testing in addition to NLP performance measures as NLP performance measures, particularly in question-answering tasks, often correlate poorly with clinical relevance, factual correctness, and patient safety (253,285). As LLM-based interventions become more ubiquitous, there is a need to develop validation frameworks that encourage co-design with users and are able to capture clinical relevance, accuracy and patient safety to complement the current NLP metrics. Additionally, as these interventions become more common, researchers need to adhere to reporting standards to ensure transparency in model development, training and evaluation methods and safeguards used (306). This would help standardise how LLM-based interventions are described and assessed across studies, making it easier to compare findings and determine whether a system is ready for real-world clinical use. Without such frameworks and reporting standards, LLM-based tools risk facing the same fate as many existing prediction models: repeated development without sufficient validation, limited clinical trust, and little meaningful use in practice.

Finally, end-user perspectives need to be incorporated more systematically across the full lifecycle of innovation. Chapters 6 and 7 showed that users revealed problems of relevance, clarity, workflow fit, and usefulness that were not apparent from technical metrics alone. A model, pathway, or digital tool will have limited value if the intended users do not trust it, understand it, or use it in routine care. Future research should be clearer about when users are involved, how their feedback shapes the intervention, and whether co-design results in better usability, stronger adoption, improved workflow fit and ultimately improved behavioural and health outcomes (307).

8.4. Limitations

The work described in this thesis has limitations. The systematic review in Chapter 2 did not include a meta-analysis due to poor reporting and substantial heterogeneity across the included studies. The development and validation studies varied in their predictors, outcomes, modelling methods, and performance measures, with many not reporting their

methods in enough detail to allow direct comparison. As a result, it was not possible to produce pooled estimates of model performance.

The use of CPRD-linked data, in Chapters 3 & 5, made it possible to examine longitudinal trajectories across large numbers of women, link pregnancy-related events to primary care records and examine GDM coding patterns. The use of this dataset was important and cost-effective in evaluating questions about postnatal follow-up and long-term prevention after GDM that are difficult to address using smaller clinical cohorts. However, it has notable limitations. CPRD linked data are routine data collected during real clinical practice, rather than for research purposes. As such, the quality of the data is variable. One issue that directly impacts our studies is that women can only be included when linkage between primary care records and HES data is possible. This means that delivery records that existed only in secondary-care datasets, such as maternity services, without successful linkage back to primary care, would not have been captured in our analysis. Similarly, GDM records in primary care without successful linkage to HES would also be excluded in our analysis. The National GDM Audit illustrates the extent of this limitation. In the audit, 422,135 women were identified with GDM in primary care. Of these 30,980 women (7.3%) did not have any HES delivery episode and would therefore have been excluded in our datasets.

The differences between our cohort and the National GDM Audit also show how strongly findings depend on the datasets used (Table 8.1). In our cohort, only 32.7% of women with a GDM diagnosis recorded in secondary care also appeared in the primary-care cohort, compared with 58.3% in the National GDM Audit. Differences are also reflected in the estimates of later T2DM. The audit identified 5.6% of women as developing T2DM after GDM, compared with 2.7% in our cohort (192). Several factors may explain this difference. First, the National GDM Audit did not exclude patients who could not be linked to a delivery record. Although 7.3% of women with a GDM record had no HES delivery episode, they were still included in the audit cohort. Second, the audit used broader data sources. Primary-care data were extracted through the General Practice Extraction Service, which has wider coverage than CPRD Aurum, while hospital data included not only admitted HES events but also outpatient appointments and accident and emergency attendances. This points to how routine data studies may produce different estimates depending on the datasets used and the assumptions made.

Table 8.1. Comparison of GDM ascertainment in primary and secondary care between the cohort used in this thesis and the cohort used in the National GDM Audit

Description	Women n (%)	
	Cohort used in this thesis	**Cohort used for the GDM Audit (192)**
GDM secondary care cohort: Women with a GDM diagnosis recorded in HES at any time	187,974	586,280
Women in the GDM secondary care cohort that are:		
- In the GDM primary care cohort	61,434 (32.7)	342,050 (58.3)
- Not in the GDM primary care cohort	126,540 (67.3)	244,230 (41.7)
GDM primary care cohort: Women diagnosed with GDM at any time	71,251	422,135
Women in the GDM primary care cohort that are:		
- In the GDM secondary care cohort	61,434 (86.2)	342,050 (81.0)
- Not in the GDM secondary care cohort	9,817 (13.8)	80,085 (19.0)

The LLM work in this thesis has broader limitations related to language, culture and digital access. LLMs are often developed and evaluated in English-dominant and high-resource settings. As such training data may underrepresent the linguistic and cultural context in which maternal health tools are later used, such as in the case of SHP GPT. This limits performance in settings where language, health beliefs or patterns of care differ from those reflected in the underlying model training. Although this was partly addressed through the use of Indian-specific guidelines, RAG, and testing with Indian users and clinicians, it remains a broader limitation in the field that cannot be fully resolved without the development and evaluation of models that are more culturally and linguistically diverse.

The benefits of digital tools are also unlikely to be distributed equally. Access to internet connectivity, devices that can host digital tools, confidence in technology and digital literacy vary across settings (308). As a result, digital interventions such as SHP GPT may be more useful to ASHAs who already have stronger digital access and support, while offering less benefit to those working in more constrained settings or with fewer digital resources. This creates the possibility that digital tools could reproduce existing inequities if they are implemented without attention to access, usability and context.

Finally, a further limitation of my work is that it focuses more on evaluating methodologies and interventions but less on final patient outcomes. Across the thesis, there is evidence on model quality, coding gaps, identification of eligible women, usability of digital tools and acceptability to users. However, the thesis does not show whether improvements in these areas leads to better clinical outcomes, such as improved postpartum follow-up, reduced progression to T2DM, or better maternal or neonatal outcomes. Further work is needed to determine whether the approaches examined in this thesis lead to meaningful outcomes in real-world practice.

8.5. Directions of future work

Future work should build on the findings of this thesis in several areas. First, for prediction models, more work is needed on how to translate prediction into practice. Much of the existing literature has focused on model development, but less attention has been paid to whether these models improve decisions, fit into workflows, or support better care.

Second, further work is needed on the DPP pathway after GDM. As noted in Chapter 4, an evaluation of the pathway is currently underway using a pre-post design across multiple GP practices to investigate its impact on programme uptake, attendance and completion. Due to time constraints, this work could not be presented in this thesis. Beyond this, it will also be important to assess whether the pathway impacts long-term metabolic health. Although there has been some evidence of DPP effectiveness in the general population (235), there remains little evidence focused on women with prior GDM. Women with prior GDM represent a distinct high-risk group and it should not be assumed that evidence from the general population will apply directly to them.

A further priority is better identification of women who are currently missed by routine systems. The findings of this thesis showed that a large proportion of women with GDM are not captured in primary care records. Future work should therefore examine better ways of identifying these missed cases, including more systematic reconciliation between primary and secondary care records, improved linkages and potentially diagnostic models designed to identify likely unrecorded GDM.

Future work should also place greater emphasis on involving women and their families. Patient trust is likely to influence whether prediction models and LLM tools are used, how their outputs are interpreted and whether they are accepted in routine care. Although earlier stages of the LLM work focused on clinicians and ASHAs, more recent work, not presented in this thesis, included testing with women. Eight observational sessions were conducted across Telangana and Haryana, involving AI-assisted counselling with pregnant and postpartum women, clinician observation, and structured interviews after the consultation. The women's feedback was generally positive, but not uniformly so. For example, one response reported that the chatbot-supported information was not easy to understand.

Finally, cost effectiveness is another important area that was not addressed in this thesis. This applies to prediction models, implementation strategies and LLM tools. A tool may appear promising in principle, but its value will depend on whether it produces benefits that justify the resources required for its implementation, maintenance and oversight. As such, future studies should include economic evaluation.

8.6. Conclusions

In conclusion, the research carried out as part of this thesis investigated how machine learning and translational approaches may support personalised care for women with high-risk pregnancies. The different studies addressed different stages in the pathway from evidence synthesis to implementation: understanding the existing evidence for prediction models, testing the performance of an existing model, translating risk identification into actionable referral systems, and exploring how conversational AI tools might extend evidence-based support at the point of care. In doing so, this thesis seeks to bridge the gap between computational innovation and clinically meaningful, patient-centred application in maternal health. The thesis showed important weaknesses in existing models, gaps in follow-up and coding after GDM, and the potential value of LLM-tools to support frontline workers in rural settings. While the studies presented have several strengths, there are also important limitations, related to the datasets used and the early-stage nature of the LLM work. Future studies can build on these findings by addressing these gaps.

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10. Appendices

10.1.1. Appendix 1. List of publications and trainings

Publications

- Identification of women without a primary care GDM record: a retrospective cohort study (In preparation)
- External validation of a model to predict type 2 diabetes and type 2 diabetes complications after gestational diabetes (In preparation)
- Development and Clinical Validation of SMART*health* GPT: An Artificial Intelligence Chatbot for Women's Health and Community Health Workers in India (Submitted to Scientific Reports in February, 2025)
- Developing SMARThealth Pregnancy (SHP) GPT: Addressing Gender Bias in LLM for Community Health Workers in Rural India (2025 Gender and Technology Conference)
- Prediction models for maternal and offspring short- and long-term outcomes following gestational diabetes: systematic review (Published in Obesity Reviews in September, 2025)
- Systematic review protocol published on PROSPERO
- Conference workshop paper accepted at NeurIPS Generative AI for Education workshop in New Orleans, USA (December, 2024)
- Complex Clinical Data and Gestational Diabetes Mellitus published report on NCRM website
- Book chapter on AI in diabetic pregnancy (Hod et al., eds, Textbook of Diabetes and Pregnancy, January, 2025)

Awards

- NCRM impact prize for "Complex clinical data and Gestational Diabetes Mellitus" workshop (2022)
- Medical Sciences Division Teaching Excellence Project Team Award (2025)

Conferences

- GLOW 2024 - Global Women's Research Society AI Workshop: Co-Led a Workshop on how to create an AI Chatbot for Women's Health in LMICs
- Oral abstract on SMART*health* GPT presented at the Global Women's Research Society conference
- Systematic review poster accepted at International Conference of Health and Technology and RCOG World Congress
- SMART*health* GPT poster accepted at the RCOG World Congress

Trainings

Research design and systematic review:

- Systematic review of prognosis studies – Cochrane training course
- Introduction to Systematic Review and Evidence Syntheses – iSkills for Medical Sciences
- Planning, designing and critically appraising clinical research – Equator Network

Prediction models:

- Statistical methods for risk prediction and prognosis models – University of Birmingham
- Creating code lists – CPRD training

Large language models:

- Prompt Engineering for Developers – DeepLearning.AI Course
- Building systems with the ChatGPT API – DeepLearning.AI Course
- LangChain for LLM Application Development – DeepLearning.AI Course
- LangChain: Chat with Your Data – DeepLearning.AI Course
- Finetuning Large Language Models – DeepLearning.AI Course
- Building and Evaluating Advanced RAG Applications – DeepLearning.AI Course
- Towards a gender-transformative approach in generative AI practice – BMGF Workshop

Writing:

- Preparation for thesis submission and a successful final viva – Medical Sciences Division
- Confirmation of status – Medical Sciences Division
- Completing my viva – Conted Grad Education
- Working with your supervisor – Conted Grad Education

10.1.2. Appendix 2. Supplementary Material for Chapter 2

Supplementary Table 10.1. PRISMA checklist for the systematic review

Section and Topic	Item #	Checklist item	Section
TITLE			
Title	1	Identify the report as a systematic review.	2
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	2.1
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	2.2
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	2.3
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	2.4.2, 2.4.3, 2.4.4
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	2.4.2, Appendix 2
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Appendix 2
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	2.4.4
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	2.4.4
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	2.4.5 + CHARMS table
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	2.4.5, 2.4.6
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	2.4.5 + PROBAST table
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	2.4.6
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	NA
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	2.4.6, 2.5.2
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	2.4.6
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s),	2.4.6

Section and Topic	Item #	Checklist item	Section
		method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	NA
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	NA
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	2.5.11, 2.6.4
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	NA
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	2.5.1
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	2.4.3
Study characteristics	17	Cite each included study and present its characteristics.	2.5.2
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	2.5.10
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Appendix 2
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	2.5.10
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	NA
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	2.5.2
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	NA
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	2.5.4
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	NA
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	2.6.1, 2.6.2
	23b	Discuss any limitations of the evidence included in the review.	2.6.4
	23c	Discuss any limitations of the review processes used.	2.6.4
	23d	Discuss implications of the results for practice, policy, and future research.	2.6.3
OTHER INFORMATION			

Section and Topic	Item #	Checklist item	Section
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	2.4
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	2.4
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	2.4
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Acknowledgements
Competing interests	26	Declare any competing interests of review authors.	Acknowledgements
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	2.4.5, Appendix 2

Supplementary File 10.1. Search strategies for the databases used for the systematic review

The databases used were EMBASE, MEDLINE, Scopus, Web of Science, and the Cochrane Central Register of Controlled Trials (CENTRAL). The search used in all databases can be found below.

Embase and Medline (Ovid):

1. ((adverse OR undesirable OR harm* OR toxic OR injurious OR serious OR fatal OR unsafe OR negative) ADJ3 (effect* OR reaction* OR event* OR outcome* OR incident* OR consequence* OR complication*)).mp.
2. (((((((C-section OR "C section" OR cesarean OR caesarean OR cesarian OR caesarian OR cesarien OR caesarien OR (Instrumental ADJ2 delivery) OR (Instrumental ADJ2 birth) OR "Assisted birth" OR "Assisted delivery" OR (Forcep* ADJ2 birth) OR (Forcep* ADJ2 delivery) OR (Vacuum ADJ2 delivery) OR (Vacuum ADJ2 birth) OR (Ventouse ADJ2 delivery) OR (Ventouse ADJ2 birth) OR "Operative vaginal delivery" OR "Operative vaginal birth" OR (Induc* ADJ2 labor) OR (Induc* ADJ2 labour) OR "Preterm delivery" OR "Preterm labor" OR "Preterm labour" OR "Preterm birth" OR "Premature delivery" OR "Premature labor" OR "Premature labour" OR "Premature birth" OR Prematurity OR "Preterm premature rupture of the membranes" OR PPROM OR "Perineal trauma" OR "Perineal tear*" OR "Vaginal tear*" OR "Perineal laceration*" OR "Postpartum hemorrhage" OR "Postpartum haemorrhage" OR PPH OR "Excessive bleeding" OR Macrosomia OR "Large for gestational age" OR LGA OR "Large for age" OR "Large for date" OR Adiposity OR "Low birth weight" OR "Small for gestational age" OR SGA OR "Small for age" OR "Small for date" OR Low) ADJ2 Apgar) OR Mortality OR Death OR "Still birth" OR Morbidity OR "Bone* injur*" OR "Bone* fractur*" OR Clavicle) ADJ2 Fracture*) OR Collarbone) ADJ2 Fracture*) OR "Birth* injur*" OR "Birth* fracture*" OR "Birth trauma" OR "Infant fracture*" OR "Infant injur*" OR "Shoulder dystocia" OR "Brachial plexus injur*" OR "Erb* palsy" OR BPI OR "Nerve palsy" OR "Respiratory distress syndrome" OR RDS OR Hypoglyc* OR "Low blood sugar" OR Jaundice OR Hyperbilirubinemia OR "Excess bilirubin" OR "Neonatal intensive care unit" OR NICU OR "Intensive care nursery" OR ICN OR "Special care baby unit" OR SCBU OR (Length ADJ3 stay)).mp.
3. (pregnan* OR gestation* OR gravid* OR multigravid* OR parous OR multiparous OR nulliparous OR primagravid* OR prenatal OR perinatal OR matern* OR obstetric* OR labor OR labour OR parturition OR "ante natal" OR antenatal* OR pre-natal* OR prenatal* OR puerper* OR "child birth" OR childbirth OR postnatal* OR postpartum OR post-partum OR post-natal* OR peripartum OR peri-partum OR prepregnancy OR pre-pregnancy OR preconception* OR pre-conception* OR periconception* OR peri-conception* OR C-section OR "C section" OR cesarean OR caesarean OR cesarian OR caesarian OR cesarien OR caesarien OR newborn* OR "new born*" OR tocoly* OR fetal OR foetal OR fetus OR foetus OR miscarriage*).mp.
4. (diabet* OR GDM OR hyperglyc* OR "glucose intolerance" OR "impaired glucose regulation" OR IGR OR "impaired fasting glucose" OR IFG OR "impaired glucose tolerance" OR IGT OR "insulin resistance").mp.
5. (predict* OR "predictive value of tests" OR scor* OR observ OR "observer variation" OR (stratification OR "ROC Curve" OR discrimination OR discriminate OR c-statistic OR "c statistic" OR "area under the curve" OR AUC OR calibration OR indices OR algorithm OR multivariable OR "machine learning" OR ML OR "artificial intelligence" OR AI)).mp.

6. (1 OR 2) AND 3 AND 4 AND 5
7. limit 6 to (human AND (french OR arabic OR english OR spanish) AND "yr="2000 - Current""

Scopus:

1. ((adverse OR undesirable OR harm* OR toxic OR injurious OR serious OR fatal OR unsafe OR negative) W/3 (effect* OR reaction* OR event* OR outcome* OR incident* OR consequence* OR complication*))
2. (((((((C-section OR "C section" OR cesarean OR caesarean OR cesarian OR caesarian OR cesarien OR caesarien OR (Instrumental W/2 delivery) OR (Instrumental W/2 birth) OR "Assisted birth" OR "Assisted delivery" OR (Forcep* W/2 birth) OR (Forcep* W/2 delivery) OR (Vacuum W/2 delivery) OR (Vacuum W/2 birth) OR (Ventouse W/2 delivery) OR (Ventouse W/2 birth) OR "Operative vaginal delivery" OR "Operative vaginal birth" OR (Induc* W/2 labor) OR (Induc* W/2 labour) OR "Preterm delivery" OR "Preterm labor" OR "Preterm labour" OR "Preterm birth" OR "Premature delivery" OR "Premature labor" OR "Premature labour" OR "Premature birth" OR Prematurity OR "Preterm premature rupture of the membranes" OR PPROM OR "Perineal trauma" OR "Perineal tear*" OR "Vaginal tear*" OR "Perineal laceration*" OR "Postpartum hemorrhage" OR "Postpartum haemorrhage" OR PPH OR "Excessive bleeding" OR Macrosomia OR "Large for gestational age" OR LGA OR "Large for age" OR "Large for date" OR Adiposity OR "Low birth weight" OR "Small for gestational age" OR SGA OR "Small for age" OR "Small for date" OR Low) W/2 Apgar) OR Mortality OR Death OR "Still birth" OR Morbidity OR "Bone* injur*" OR "Bone* fractur*" OR Clavicle) W/2 Fracture*) OR Collarbone) W/2 Fracture*) OR "Birth* injur*" OR "Birth* fracture*" OR "Birth trauma" OR "Infant fracture*" OR "Infant injur*" OR "Shoulder dystocia" OR "Brachial plexus injur*" OR "Erb* palsy" OR BPI OR "Nerve palsy" OR "Respiratory distress syndrome" OR RDS OR Hypoglyc* OR "Low blood sugar" OR Jaundice OR Hyperbilirubinemia OR "Excess bilirubin" OR "Neonatal intensive care unit" OR NICU OR "Intensive care nursery" OR ICN OR "Special care baby unit" OR SCBU OR (Length W/3 stay))
3. (pregnan* OR gestation* OR gravid* OR multigravid* OR parous OR multiparous OR nulliparous OR primagravid* OR prenatal OR perinatal OR matern* OR obstetric* OR labor OR labour OR parturition OR "ante natal" OR antenatal* OR pre-natal* OR prenatal* OR puerper* OR "child birth" OR childbirth OR postnatal* OR postpartum OR post-partum OR post-natal* OR peripartum OR peri-partum OR prepregnancy OR pre-pregnancy OR preconception* OR pre-conception* OR periconception* OR peri-conception* OR C-section OR "C section" OR cesarean OR caesarean OR cesarian OR caesarian OR cesarien OR caesarien OR newborn* OR "new born*" OR tocoly* OR fetal OR foetal OR fetus OR foetus OR miscarriage*)
4. (diabet* OR GDM OR hyperglyc* OR "glucose intolerance" OR "impaired glucose regulation" OR IGR OR "impaired fasting glucose" OR IFG OR "impaired glucose tolerance" OR IGT OR "insulin resistance")
5. (predict* OR "predictive value of tests" OR scor* OR observ OR "observer variation" OR (stratification OR "ROC Curve" OR discrimination OR discriminate OR c-statistic OR "c statistic" OR "area under the curve" OR AUC OR calibration OR indices OR algorithm OR multivariable OR "machine learning" OR ML OR "artificial intelligence" OR AI))
6. (1 OR 2) AND 3 AND 4 AND 5
7. limit 6 to (human AND (french OR arabic OR english OR spanish) AND "yr="2000 - Current"")

Web of Science:

1. ((adverse OR undesirable OR harm* OR toxic OR injurious OR serious OR fatal OR unsafe OR negative) NEAR/3 (effect* OR reaction* OR event* OR outcome* OR incident* OR consequence* OR complication*))
2. (((((((C-section OR "C section" OR cesarean OR caesarean OR cesarian OR caesarian OR cesarien OR caesarien OR (Instrumental NEAR/2 delivery) OR (Instrumental NEAR/2 birth) OR "Assisted birth" OR "Assisted delivery" OR (Forcep* NEAR/2 birth) OR (Forcep* NEAR/2 delivery) OR (Vacuum NEAR/2 delivery) OR (Vacuum NEAR/2 birth) OR (Ventouse NEAR/2 delivery) OR (Ventouse NEAR/2 birth) OR "Operative vaginal delivery" OR "Operative vaginal birth" OR (Induc* NEAR/2 labor) OR (Induc* NEAR/2 labour) OR "Preterm delivery" OR "Preterm labor" OR "Preterm labour" OR "Preterm birth" OR "Premature delivery" OR "Premature labor" OR "Premature labour" OR "Premature birth" OR Prematurity OR "Preterm premature rupture of the membranes" OR PPROM OR "Perineal trauma" OR "Perineal tear*" OR "Vaginal tear*" OR "Perineal laceration*" OR "Postpartum hemorrhage" OR "Postpartum haemorrhage" OR PPH OR "Excessive bleeding" OR Macrosomia OR "Large for gestational age" OR LGA OR "Large for age" OR "Large for date" OR Adiposity OR "Low birth weight" OR "Small for gestational age" OR SGA OR "Small for age" OR "Small for date" OR Low) NEAR/2 Apgar) OR Mortality OR Death OR "Still birth" OR Morbidity OR "Bone* injur*" OR "Bone* fractur*" OR Clavicle) NEAR/2 Fracture*) OR Collarbone) NEAR/2 Fracture*) OR "Birth* injur*" OR "Birth* fracture*" OR "Birth trauma" OR "Infant fracture*" OR "Infant injur*" OR "Shoulder dystocia" OR "Brachial plexus injur*" OR "Erb* palsy" OR BPI OR "Nerve palsy" OR "Respiratory distress syndrome" OR RDS OR Hypoglyc* OR "Low blood sugar" OR Jaundice OR Hyperbilirubinemia OR "Excess bilirubin" OR "Neonatal intensive care unit" OR NICU OR "Intensive care nursery" OR ICN OR "Special care baby unit" OR SCBU OR (Length NEAR/3 stay))
3. (pregnan* OR gestation* OR gravid* OR multigravid* OR parous OR multiparous OR nulliparous OR primagravid* OR prenatal OR perinatal OR matern* OR obstetric* OR labor OR labour OR parturition OR "ante natal" OR antenatal* OR pre-natal* OR prenatal* OR puerper* OR "child birth" OR childbirth OR postnatal* OR postpartum OR post-partum OR post-natal* OR peripartum OR peri-partum OR prepregnancy OR pre-pregnancy OR preconception* OR pre-conception* OR periconception* OR peri-conception* OR C-section OR "C section" OR cesarean OR caesarean OR cesarian OR caesarian OR cesarien OR caesarien OR newborn* OR "new born*" OR tocoly* OR fetal OR foetal OR fetus OR foetus OR miscarriage*)
4. (diabet* OR GDM OR hyperglyc* OR "glucose intolerance" OR "impaired glucose regulation" OR IGR OR "impaired fasting glucose" OR IFG OR "impaired glucose tolerance" OR IGT OR "insulin resistance")
5. (predict* OR "predictive value of tests" OR scor* OR observ OR "observer variation" OR (stratification OR "ROC Curve" OR discrimination OR discriminate OR c-statistic OR "c statistic" OR "area under the curve" OR AUC OR calibration OR indices OR algorithm OR multivariable OR "machine learning" OR ML OR "artificial intelligence" OR AI))
6. (1 OR 2) AND 3 AND 4 AND 5
7. limit 6 to (human AND (french OR arabic OR english OR spanish) AND "yr="2000 - Current"")

Cochrane Library:

1. ((adverse:ti,ab,kw OR undesirable:ti,ab,kw OR harm*:ti,ab,kw OR toxic:ti,ab,kw OR injurious:ti,ab,kw OR serious:ti,ab,kw OR fatal:ti,ab,kw OR unsafe:ti,ab,kw OR

negative:ti,ab,kw) NEAR/3 (effect*:ti,ab,kw OR reaction*:ti,ab,kw OR event*:ti,ab,kw OR outcome*:ti,ab,kw OR incident*:ti,ab,kw OR consequence*:ti,ab,kw OR complication*:ti,ab,kw))

2. (((((((C-section:ti,ab,kw OR "C section":ti,ab,kw OR cesarean:ti,ab,kw OR caesarean:ti,ab,kw OR cesarian:ti,ab,kw OR caesarian:ti,ab,kw OR cesarien:ti,ab,kw OR caesarien:ti,ab,kw OR (Instrumental:ti,ab,kw NEAR/2 delivery:ti,ab,kw) OR (Instrumental:ti,ab,kw NEAR/2 birth:ti,ab,kw) OR "Assisted birth":ti,ab,kw OR "Assisted delivery":ti,ab,kw OR (Forcep*:ti,ab,kw NEAR/2 birth:ti,ab,kw) OR (Forcep*:ti,ab,kw NEAR/2 delivery:ti,ab,kw) OR (Vacuum:ti,ab,kw NEAR/2 delivery:ti,ab,kw) OR (Vacuum:ti,ab,kw NEAR/2 birth:ti,ab,kw) OR (Ventouse:ti,ab,kw NEAR/2 delivery:ti,ab,kw) OR (Ventouse:ti,ab,kw NEAR/2 birth:ti,ab,kw) OR "Operative vaginal delivery":ti,ab,kw OR "Operative vaginal birth":ti,ab,kw OR (Induc*:ti,ab,kw NEAR/2 labor:ti,ab,kw) OR (Induc*:ti,ab,kw NEAR/2 labour:ti,ab,kw) OR "Preterm delivery":ti,ab,kw OR "Preterm labor":ti,ab,kw OR "Preterm labour":ti,ab,kw OR "Preterm birth":ti,ab,kw OR "Premature delivery":ti,ab,kw OR "Premature labor":ti,ab,kw OR "Premature labour":ti,ab,kw OR "Premature birth":ti,ab,kw OR Prematurity:ti,ab,kw OR "Preterm premature rupture of the membranes":ti,ab,kw OR PPROM:ti,ab,kw OR "Perineal trauma":ti,ab,kw OR ("Perineal" NEXT tear*):ti,ab,kw OR ("Vaginal" NEXT tear*):ti,ab,kw OR ("Perineal" NEXT laceration*):ti,ab,kw OR "Postpartum hemorrhage":ti,ab,kw OR "Postpartum haemorrhage":ti,ab,kw OR PPH:ti,ab,kw OR "Excessive bleeding":ti,ab,kw OR Macrosomia:ti,ab,kw OR "Large for gestational age":ti,ab,kw OR LGA:ti,ab,kw OR "Large for age":ti,ab,kw OR "Large for date":ti,ab,kw OR Adiposity:ti,ab,kw OR "Low birth weight":ti,ab,kw OR "Small for gestational age":ti,ab,kw OR SGA:ti,ab,kw OR "Small for age":ti,ab,kw OR "Small for date":ti,ab,kw OR Low:ti,ab,kw) NEAR/2 Apgar:ti,ab,kw) OR Mortality:ti,ab,kw OR Death:ti,ab,kw OR "Still birth":ti,ab,kw OR Morbidity:ti,ab,kw OR (Bone* NEXT injur*):ti,ab,kw OR (Bone* NEXT fractur*):ti,ab,kw OR Clavicle:ti,ab,kw) NEAR/2 Fracture*:ti,ab,kw) OR Collarbone:ti,ab,kw) NEAR/2 Fracture*:ti,ab,kw) OR (Birth* NEXT injur*):ti,ab,kw OR (Birth* NEXT fracture*):ti,ab,kw OR "Birth trauma":ti,ab,kw OR ("Infant" NEXT fracture*):ti,ab,kw OR ("Infant" NEXT injur*):ti,ab,kw OR "Shoulder dystocia":ti,ab,kw OR ("Brachial plexus" NEXT injur*):ti,ab,kw OR (Erb* NEXT "palsy"):ti,ab,kw OR BPI:ti,ab,kw OR "Nerve palsy":ti,ab,kw OR "Respiratory distress syndrome":ti,ab,kw OR RDS:ti,ab,kw OR Hypoglyc*:ti,ab,kw OR "Low blood sugar":ti,ab,kw OR Jaundice:ti,ab,kw OR Hyperbilirubinemia:ti,ab,kw OR "Excess bilirubin":ti,ab,kw OR "Neonatal intensive care unit":ti,ab,kw OR NICU:ti,ab,kw OR "Intensive care nursery":ti,ab,kw OR ICN:ti,ab,kw OR "Special care baby unit":ti,ab,kw OR SCBU:ti,ab,kw OR (Length:ti,ab,kw NEAR/3 stay:ti,ab,kw))
3. (pregnan*:ti,ab,kw OR gestation*:ti,ab,kw OR gravid*:ti,ab,kw OR multigravid*:ti,ab,kw OR parous:ti,ab,kw OR multiparous:ti,ab,kw OR nulliparous:ti,ab,kw OR primagravid*:ti,ab,kw OR prenatal:ti,ab,kw OR perinatal:ti,ab,kw OR matern*:ti,ab,kw OR obstetric*:ti,ab,kw OR labor:ti,ab,kw OR labour:ti,ab,kw OR parturition:ti,ab,kw OR "ante natal":ti,ab,kw OR antenatal*:ti,ab,kw OR pre-natal*:ti,ab,kw OR prenatal*:ti,ab,kw OR puerper*:ti,ab,kw OR "child birth":ti,ab,kw OR childbirth:ti,ab,kw OR postnatal*:ti,ab,kw OR postpartum:ti,ab,kw OR post-partum:ti,ab,kw OR post-natal*:ti,ab,kw OR peripartum:ti,ab,kw OR peri-partum:ti,ab,kw OR prepregnancy:ti,ab,kw OR pre-pregnancy:ti,ab,kw OR preconception*:ti,ab,kw OR pre-conception*:ti,ab,kw OR periconception*:ti,ab,kw OR peri-conception*:ti,ab,kw OR C-section:ti,ab,kw OR "C section":ti,ab,kw OR cesarean:ti,ab,kw OR

caesarean:ti,ab,kw OR cesarian:ti,ab,kw OR caesarian:ti,ab,kw OR cesarien:ti,ab,kw OR caesarien:ti,ab,kw OR newborn*:ti,ab,kw OR ("new" NEXT born*):ti,ab,kw OR tocoly*:ti,ab,kw OR fetal:ti,ab,kw OR foetal:ti,ab,kw OR fetus:ti,ab,kw OR foetus:ti,ab,kw OR miscarriage*:ti,ab,kw)

4. (diabet*:ti,ab,kw OR GDM:ti,ab,kw OR hyperglyc*:ti,ab,kw OR "glucose intolerance":ti,ab,kw OR "impaired glucose regulation":ti,ab,kw OR IGR:ti,ab,kw OR "impaired fasting glucose":ti,ab,kw OR IFG:ti,ab,kw OR "impaired glucose tolerance":ti,ab,kw OR IGT:ti,ab,kw OR "insulin resistance":ti,ab,kw)
5. (predict*:ti,ab,kw OR "predictive value of tests":ti,ab,kw OR scor*:ti,ab,kw OR observ:ti,ab,kw OR "observer variation":ti,ab,kw OR (stratification:ti,ab,kw OR "ROC Curve":ti,ab,kw OR discrimination:ti,ab,kw OR discriminate:ti,ab,kw OR c-statistic:ti,ab,kw OR "c statistic":ti,ab,kw OR "area under the curve":ti,ab,kw OR AUC:ti,ab,kw OR calibration:ti,ab,kw OR indices:ti,ab,kw OR algorithm:ti,ab,kw OR multivariable:ti,ab,kw OR "machine learning":ti,ab,kw OR ML:ti,ab,kw OR "artificial intelligence":ti,ab,kw OR AI:ti,ab,kw))
6. limit 6 to (human AND (french OR arabic OR english OR spanish) AND "yr="2000 - Current"")

Supplementary Table 10.2. Characteristics of the models included in the systematic review

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EP V	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Allalou (a), 2016	Type 2 Diabetes diagnosed based on American Diabetes Association criteria	Machine learning techniques (Decision Tree)	244 (122)	22	4	5.5	Based on univariable associations	Decision Trees	Metabolites [PCaeC40:5, BCAA, hexose, SM (OH) C14:1]	n (%): Unkown Method: Complete-case analysis	Int: Random split data Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Allalou (b), 2016	Type 2 Diabetes diagnosed based on American Diabetes Association criteria	Machine learning techniques (Decision Tree)	244 (122)	2	2	61.0	Based on univariable associations	NI	2hPG, FPG	n (%): Unkown Method: Complete-case analysis	Int: Random split data Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Allalou (c), 2016	Type 2 Diabetes diagnosed based on American Diabetes Association criteria	Machine learning techniques (Naïve Bayes Classifier)	244 (122)	6	6	20.3	Based on prior knowledge	Decision Trees	2hPG, FPG + Metabolites [PCaeC40:5, BCAA, hexose, SM (OH) C14:1]	n (%): Unkown Method: Complete-case analysis	Int: Random split data Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Badr (a), 2022	Need for pharmacological treatment according to institutional protocol	Other	399 (77)	31	12	2.5	Based on univariable associations	Pre-specified model (not selection)	Pre-gestational weight; BMI; Multiparity; History of GDM; History of insulin therapy; Family history of DM; First-degree family history of DM; FPG; 1-h OGTT; 2-h OGTT; 2 or 3 abnormal OGTT values; HbA1c	n (%): 0 (0.0) Method: Complete-case analysis	Int: None (Apparent performance) Ext : Temporal	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
		Other		26	6	2.9						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Badr (b), 2022	Need for pharmacological treatment according to institutional protocol		186 (76)				Based on univariable associations	Pre-specified model (not selection)	Pre-gestational weight; Pre-gestational BMI; Personal history of GDM; Personal history of insulin therapy; FPG; HbA1c	n (%): 0 (0.0) Method: Complete-case analysis	Int: None (Apparent performance) Ext : Temporal	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Badr (c), 2022	Need for pharmacological treatment according to institutional protocol	Other	375	NI	12	NI	NA	NA	Pre-gestational weight; Pre-gestational BMI; Multiparity; Personal history of GDM; Personal history of insulin therapy; Family history of DM; First-degree family history of DM; FPG; 1-h OGTT; 2-h OGTT; 2 or 3 abnormal OGTT values; HbA1c	n (%): 84 (22.4) Method: No information	Int: NA Ext : NA	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Badr (d), 2022	Need for pharmacological treatment according to institutional protocol	Other	186	NI	6	NI	NA	NA	Pre-gestational weight; Pre-gestational BMI; Personal history of GDM; Personal history of insulin therapy; FPG; HbA1c	n (%): 84 (45.2) Method: No information	Int: NA Ext : NA	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Barden, 2013	Type 2 diabetes ascertained from medical records and measurement of fasting glucose (>= 7 mmol/l)	Machine learning techniques (Cluster Analysis)	150 (20)	6	6	3.3	Based on prior knowledge	Decision Trees	BMI; Fasting Glucose; Fasting Insulin; Fasting Triglycerides; HDL cholesterol; Systolic blood pressure	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : Not evaluated Ov : Not evaluated Util: Not evaluated
				14	7	93.0						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Barnes (a), 2016	Need for pharmacological treatment according to institutional protocol	Logistic regression	4,015 (1302)				Based on univariable associations	Backward elimination	Maternal age; family history of diabetes; pre-pregnancy obesity; prior GDM; early diagnosis of GDM; fasting venous blood glucose level; HbA1c at GDM diagnosis	n (%): 698 (17.4) Method: No information	Int: None (Apparent performance) Ext : Different setting	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Barnes (b), 2016	NI	Logistic regression	1,040 (491)	NI	7	NI	NA	NA	Maternal age; Family history of diabetes; pre-pregnancy obesity; Prior GDM; Early diagnosis of GDM; Fasting venous blood glucose level; HbA1c at GDM diagnosis	n (%): Unkown Method: No information	Int: NA Ext : NA	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Bartakova, 2021	Persistent postpartum glucose intolerance based on the WHO criteria for non-pregnant subjects	Logistic regression	244 (22)	28	5	0.8	Based on univariable associations	Backward elimination	FPG in mid-trimester OGTT; obesity; family history of diabetes; instrumental delivery; personal history of hypothyroidism	n (%): 57 (23.4) Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Bengtson, 2022	Impaired glucose tolerance diagnosed with HbA1c >= 5.7% at 1-year postpartum	Logistic regression	203 (71)	31	8	2.3	Based on univariable associations	LASSO selection	Prepregnancy weight; BMI prepregnancy; BMI prepregnancy; previous GDM gravidity; family history of diabetes; GDM diagnosis <24wkGA; FPG 2 days postpartum; 2h plasma glucose 2 days postpartum	n (%): Unkown Method: Multiple imputation	Int: Cross-validation Ext : None	Cal: Calibration plot Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
				18	12	26.4						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Cooray (a), 2022	Maternal and perinatal complications (Hypertensive disorders of pregnancy, large-for-gestational age neonate, neonatal hypoglycaemia requiring intravenous therapy, shoulder dystocia, perinatal death, neonatal bone fracture and nerve palsy)	Logistic regression	1,747 (476)				Based on prior knowledge	LASSO selection	Maternal age; Pre-pregnancy BMI; Fasting glucose OGTT; 1-hour glucose OGTT; Gestation at GDM diagnosis; Southern and Central Asian; East Asian; Nulliparity; Previous pre-eclampsia; Gestational weight gain to GDM diagnosis per week; Family history of diabetes; Previous LGA baby	n (%): Unkown Method: Multiple imputation	Int: Bootstrap Ext : Temporal	Cal: Calibration plot / Slope / CITL / E:O ratio Disc : C-Statistic Ov : Not evaluated Util: DCA
Cooray (b), 2022	As above	Logistic regression	955 (244)	NI	12	NI	NA	NA	As above	n (%): Unkown Method: Multiple imputation	Int: NA Ext : NA	Cal: Calibration plot / Slope / CITL / E:O ratio Disc : C-Statistic / AUC graph Ov : Not evaluated Util: DCA
Cormier (a), 2014	Pre-diabetes diagnosed based on the 2013 Canadian Diabetes Association guidelines	Logistic Regression	214 (135)	NI	NI	NI	NI	NI	NI	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
				NI	NI	NI	NI	NI	Unclear			

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Cormier (b), 2014	Type 2 Diabetes defined as fasting plasma glucose ≥7.0 mmol/l, and/or 2-hour plasma glucose post-OGTT ≥ 11.1 mmol/l, and/or A1C ≥ 6.5%.	Logistic Regression	214 (40)							n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Du, 2021	Need for insulin according to institutional protocol	Cox regression	626 (188)	19	7	9.9	Based on prior knowledge	LASSO selection	Age; gestational age at GDM diagnosis; BMI at GDM diagnosis; first degree family history of T2DM; GDM history; FPG; HbA1c	n (%): 220 (35.1) Method: Complete-case analysis	Int: Bootstrap Ext : None	Cal: Calibration plot Disc : C-Statistic Ov : Not evaluated Util: DCA
Eleftheriades (a), 2021	Need for insulin according to institutional protocol	Machine learning techniques (CART)	775 (130)	8	8	16.3	Based on prior knowledge	Backward elimination	Maternal age; smoking; method of conception; maternal BMI before conception; blood glucose levels at baseline; blood glucose levels at 1 h; blood glucose levels at 2 h during the OGTT; and z scores for the fetal abdominal circumference in the second trimester	n (%): Unkown Method: No information	Int: Cross-validation Ext : Different setting	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Eleftheriades (b), 2021	Need for insulin according to institutional protocol	Machine learning techniques (CART)	168 (28)	NI	8	NI	NA	NA	As above	n (%): Unkown Method: No information	Int: NA Ext : NA	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Elnour, 2006				18	4	1.9						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
	Postpartum diabetes diagnosed based on the Expert Committee on the Diagnosis and Classification of Diabetes Mellitus criteria	Logistic regression	165 (34)				Based on univariable associations	Backward elimination	Severe hyperglycaemia; Family history of diabetes mellitus; Gravidity; Gestational age at diagnosis	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Calibration plot / HL test Disc : C-Statistic / AUC graph Util: Not evaluated
Ford, 2022	Need for insulin according to institutional protocol	Logistic regression	2,048 (647)	11	12	58.8	Based on prior knowledge	Backward elimination	Age; BMI; ethnicity previous GDM; previous birthweight > 90%; gestational age at OGTT; OGTT fasting result; OGTT 1hr result; OGTT 2hr result	n (%): 62 (3.0) Method: Multiple imputation	Int: Cross-validation Ext : None	Cal: Calibration plot / Slope / CITL / E:O ratio Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Hahn, 2023	Recurrent GDM (GDM in the pregnancy following the index pregnancy with GDM)	Logistic Regression	159 (115)	8	3	5.5	Based on univariable associations	Other	Family history; overweight (in subsequent pregnancy); caesarean section (in index pregnancy)	n (%): Unkown Method: No Information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Harper, 2016	Glyburide failure was defined as reaching glyburide 20 mg/day and receiving insulin. Glyburide success was defined as any glyburide dose without insulin and > 70% of visits with glycemic control.	Logistic regression	220 (67)	23	6	2.9	Based on univariable associations	Backward elimination	GDM in prior pregnancy; Gestational age at diagnosis; 1h glucose challenge test; Blood sugar measurements	n (%): Unkown Method: No information	Int: Bootstrap Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Huang (a), 2023	Preterm delivery <37 weeks' gestation	Logistic Regression	564 (71)	13	4	5.5	Based on univariable associations	Pre-specified model (not selection)	Maternal age; Insulin use; neutrophil-lymphocyte ratio; monocyte count	n (%): Unkown Method: No Information	Int: Bootstrap Ext : Temporal	Cal: Calibration plot / HL test Disc : C-Statistic / AUC graph Util: DCA
Huang (b), 2023	Preterm delivery <37 weeks' gestation	Logistic Regression	242 (32)	NI	4	NI	NA	NA	As above	n (%): Unkown Method: No Information	Int: NA Ext : NA	Cal: Calibration plot / HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: DCA
Ignell (a), 2016	Postpartum diabetes diagnosed based on WHO 1999 criteria	Logistic regression	200 (67)	16	3	4.2	Based on univariable associations	Backward elimination	European ethnicity; 2hr glucose concentration during pregnancy; BMI from the 1- to 2-year follow-up	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Ignell (b), 2016	Postpartum diabetes diagnosed based on WHO 1999 criteria	Logistic regression	64 (28)	16	3	1.8	Based on univariable associations	Forward selection	Age at delivery; 2hr glucose concentration during pregnancy; BMI from the 1- to 2-year follow-up	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Ingram (a), 2017	Return for OGTT at 6-12 weeks postpartum	Other	165 (48)	16	4	3.0	Based on prior knowledge	Backward elimination	Parity; Smoker during pregnancy; BMI; pregnancy OGTT results	n (%): 16 (9.7) Method: Single imputation	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
		Other		16	4	1.4						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Ingram (b), 2017	Abnormal result on postpartum OGTT consisting of impaired fasting glucose, impaired glucose tolerance and diabetes at 6-12 weeks postpartum. Impaired fasting glucose, IGT and diabetes were combined to create a composite variable coded as abnormal for the primary outcome measure.		117 (23)				Based on prior knowledge	Backward elimination	High risk ethnicity; induction of labour; past history of GDM; pregnancy OGTT results	n (%): 16 (13.7) Method: Single imputation	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Ingram (c), 2017	As above	Other	148 (37)	16	4	2.3	Based on prior knowledge	Backward elimination	High risk ethnicity; induction of labour; past history of GDM; pregnancy OGTT results	n (%): 16 (10.8) Method: Single imputation	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Joglekar (a), 2021	Type 2 Diabetes diagnosed based on American Diabetes Association criteria	NI	82 (11)	10	6	1.1	Based on univariable associations	Pre-specified model (not selection)	Age; BMI; Pregnancy fasting glucose; Postnatal fasting glucose; Cholesterol; Triacylglycerol;	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
		NI	82 (11)	10	7	1.1	As above					

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Joglekar (b), 2021	Type 2 Diabetes diagnosed based on American Diabetes Association criteria						Based on univariable associations	Pre-specified model (not selection)		n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Jotic, 2023	Postpartum dyslipidemia diagnosed according according to the Third Report of the National Cholesterol Education Program (NCEP) Expert Panel on Detection, Evaluation, and Treatment of High Blood Cholesterol in Adults (Adult Treatment Panel III)	Logistic Regression	147 (63)	11	6	5.7	Based on univariable associations	Pre-specified model (not selection)	Age; preconception BMI; HbA1c; FPG; LDL; triglycerides	n (%): Unkown Method: No Information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Kang (a), 2019	Macrosomia defined as a birth weight $\geq$ 4000g	Machine learning techniques (Neural network)	1,891 (268)	NI	10	NI	Based on univariable associations	Pre-specified model (not selection)	Antenatal uterine height; prenatal BMI; abdominal girth; HbA1c; HDL-c; gestational weeks; TG; ketone body; family history of diabetes; times of antenatal examination	n (%): Unkown Method: Complete-case analysis	Int: Random split data Ext : None	Cal: Not evaluated Disc : AUC graph Ov : Not evaluated Util: Not evaluated
				NI	7	NI						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Kang (b), 2019	Macrosomia defined as a birth weight ≥4000g	Machine learning techniques (Neural network)	1,891 (268)				Based on univariable associations	Stepwise selection	Antenatal uterine height; abdominal girth; HDL-c; gestational weeks; family history of diabetes; times of antenatal examination; prenatal BMI	n (%): Unkown Method: Complete-case analysis	Int: Random split data Ext : None	Cal: Not evaluated Disc : AUC graph Ov : Not evaluated Util: Not evaluated
Khan, 2019	Type 2 Diabetes diagnosed based on American Diabetes Association criteria	Machine learning techniques (Filtered Classifier Algorithm)	140 (55)	75	7	0.7	Based on univariable associations	No NI	CE(16:0); NEFA(22:4); TAG 48:2 FA 16:1; CE(20:4); PE(P-18:0/18:1); TAG 54:0 FA 16:0; TAG 50:1 FA 16:0	n (%): Unkown Method: Complete-case analysis	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Kim, 2022	Large for Gestational Age defined as having a birth weight of ≥90%.	Logistic regression	660 (77)	18	3	4.3	Based on prior knowledge	Backward elimination	Head circumference measured at GDM screening Z-score; Abdominal circumference within 2 weeks before delivery Z-score; Pre-pregnancy BMI	n (%): Unkown Method: No information	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Koefoed, 2023	Pharmacological treatment according to Danish Guidelines	Logistic Regression	1,104 (282)	12	7	23.5	Based on univariable associations	Pre-specified model (not selection)	Family history of diabetes; Current smoker; Parity; Prepregnancy BMI; gestational age at OGTT; 2-h OGTT result; HbA1c at diagnosis	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Kohler, 2016	Postpartum diabetes diagnosed based on American Diabetes Association criteria	Cox regression	304 (147)	6	4	24.5	Based on prior knowledge	LASSO selection	BMI in early pregnancy; Insulin treatment; Family history of diabetes; Lactation	n (%): 47 (15.5) Method: Complete-case analysis	Int: Random split data Ext : None	Cal: Slope Disc : C-Statistic / Risk group curves Ov : R-squared Util: Not evaluated
				18	4	2.5						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Kondo (a), 2018	Postpartum diabetes diagnosed based on WHO 1999 criteria	Logistic regression	123 (45)				Based on univariable associations	Pre-specified model (not selection)	Age; family history of diabetes; BMI; use of insulin during pregnancy	n (%): Unkown Method: No information	Int: Bootstrap Ext : None	Cal: HL test Disc : C-Statistic Ov : Not evaluated Util: DCA
Kondo (b), 2018	Postpartum diabetes diagnosed based on WHO 1999 criteria	Logistic regression	123 (45)	18	5	2.5	Based on univariable associations	Pre-specified model (not selection)	Age; family history of diabetes; BMI; use of insulin during pregnancy; insulinogenic index/fasting immunoreactive insulin	n (%): Unkown Method: No information	Int: Bootstrap Ext : None	Cal: Calibration plot / HL test Disc : C-Statistic Ov : Not evaluated Util: DCA
Kondo (c), 2018	Postpartum diabetes diagnosed based on WHO 1999 criteria	Logistic regression	123 (45)	18	5	2.5	Based on univariable associations	Pre-specified model (not selection)	Age; family history of diabetes; BMI; use of insulin during pregnancy; total glucose	n (%): Unkown Method: No information	Int: Bootstrap Ext : None	Cal: Calibration plot / HL test Disc : C-Statistic Ov : Not evaluated Util: DCA
Kwak (a), 2013	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	395 (116)	NI	3	NI	NI	NI	Age; family history of diabetes; prepregnancy BMI	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Kwak (b), 2013	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	395 (116)	NI	4	NI	NI	NI	Age; family history of diabetes; prepregnancy BMI; wGRS	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Kwak (c), 2013	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	395 (116)	NI	6	NI	NI	NI	Age; family history of diabetes; prepregnancy BMI; mean arterial pressure; fasting glucose; fasting insulin concentrations	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
				NI	7	NI	NI	NI				

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Kwak (d), 2013	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	395 (116)						Age, family history of diabetes; prepregnancy BMI; mean arterial pressure; fasting glucose; fasting insulin concentrations; wGRS	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Lai, 2020	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Machine learning techniques (Random Forest)	337 (98)	30	20	3.3	Based on univariable associations	Bootstrap selection	Metabolic signature (hexose; his; spermidine; AC10; kynurenine; lysoPC a C26:0; total DMA; PC ae C40:4; Ser; Glu; PC aa C30:0; Ile; AC3; lyso PC a C26:1; SM (OH) C22:2; Gln; PC aa C32:1; SM C20:2)	n (%): Unkown Method: No information	Int: Random split data Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Lappas (a), 2015	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	104 (21)	6	6	3.5	Based on prior knowledge	Pre-specified model (not selection)	Age; BMI; pregnancy fasting glucose; postnatal fasting glucose; triacylglycerol and total cholesterol	n (%): Unkown Method: Complete-case analysis	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Lappas (b), 2015	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	104 (21)	11	3	1.9	Based on univariable associations	Stepwise selection	CE 20:4; PE(P-36:2) and PS 38:4	n (%): Unkown Method: Complete-case analysis	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Lappas (c), 2015	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	104 (21)	19	9	1.1	Based on univariable associations	Stepwise selection	Age; BMI; pregnancy fasting glucose; postnatal fasting glucose; triacylglycerol; total cholesterol; CE 20:4; PE(P-36:2) and PS 38:4	n (%): Unkown Method: Complete-case analysis	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
			95 (21)	4	4	5.3						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Lappas (a), 2016	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression					Based on prior knowledge	Pre-specified model (not selection)	Age; BMI; pregnancy fasting glucose; postnatal fasting glucose	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Lappas (b), 2016	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	95 (21)	4	2	5.3	Based on univariable associations	Pre-specified model (not selection)	IGF-I; IGFBP-2	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Lappas (c), 2016	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	95 (21)	8	6	2.6	Based on univariable associations	Pre-specified model (not selection)	Age; BMI; pregnancy fasting glucose; postnatal fasting glucose; IGF-I; IGFBP-2	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Lappas (a), 2018	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	98 (20)	4	4	5.0	Based on prior knowledge	Pre-specified model (not selection)	Age; BMI; pregnancy fasting glucose; postnatal fasting glucose	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Lappas (b), 2018	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression	98 (20)	11	5	1.8	Based on univariable associations	Pre-specified model (not selection)	Apo CIII; Apo CIII/Apo AI; Apo CIII/Apo AII; Apo CIII/Apo CII; Apo CIII/Apo E	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
			98 (20)	15	9	1.3						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Lappas (c), 2018	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Logistic regression					Based on univariable associations	Pre-specified model (not selection)	Age; BMI; pregnancy fasting glucose; postnatal fasting glucose; Apo CIII; Apo CIII/Apo AI; Apo CIII/Apo AII; Apo CIII/Apo CII; Apo CIII/Apo E	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Liao (a), 2022	Treatment modality (MNT or pharmacological treatment) according to institutional protocol	Logistic regression	27,240 (10289)	68	3	151.3	Based on prior knowledge	Other	History of GDM, pre-pregnancy obesity, and prediabetes before pregnancy	n (%): Unkown Method: Multiple imputation	Int: Cross-validation Ext : Temporal	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Liao (b), 2022	As above	Logistic regression	27,240 (10289)	94	4	109.5	Based on prior knowledge	Other	History of GDM; pre-pregnancy obesity; glucose levels at 50-g, 1-h glucose challenge test for GDM screening; prediabetes before pregnancy	n (%): Unkown Method: Multiple imputation	Int: Cross-validation Ext : Temporal	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Liao (c), 2022	As above	Logistic regression	27,240 (10289)	106	3	97.1	Based on prior knowledge	Other	Fasting glucose value at 100g, 3h oral glucose tolerance test; gestational week at GDM diagnosis; GDM diagnosis by Carpenter-Coustan criteria (versus by fasting hyperglycemia)	n (%): Unkown Method: Multiple imputation	Int: Cross-validation Ext : Temporal	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
	As above			176	4	58.5		Other				

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Liao (d), 2022		Logistic regression	27,240 (10289)				Based on prior knowledge		Gestational week at GDM diagnosis; fasting glucose value at 100-g, 3-h oral glucose tolerance test; self-monitored glycemic control status at fasting; number of fasting self-monitored blood glucose measurements	n (%): Unkown Method: Multiple imputation	Int: Cross-validation Ext : Temporal	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Liao (e), 2022	As above	Logistic regression	3,234 (1528)	NA	3	NA	NA	NA	History of GDM; pre-pregnancy obesity; prediabetes before pregnancy	n (%): Unkown Method: Multiple imputation	Int: NA Ext : NA	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Liao (f), 2022	As above	Logistic regression	3,234 (1528)	NA	4	NA	NA	NA	History of GDM; pre-pregnancy obesity; glucose levels at 50-g, 1-h glucose challenge test for GDM screening; prediabetes before pregnancy	n (%): Unkown Method: Multiple imputation	Int: NA Ext : NA	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Liao (g), 2022	As above	Logistic regression	3,234 (1528)	NA	3	NA	NA	NA	Fasting glucose value at 100-g, 3-h oral glucose tolerance test; gestational week at GDM diagnosis; GDM diagnosis by Carpenter-Coustan criteria (versus by fasting hyperglycemia)	n (%): Unkown Method: Multiple imputation	Int: NA Ext : NA	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
	As above			NA	4	NA	NA	NA				

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Liao (h), 2022		Logistic regression	3,234 (1528)						Gestational week at GDM diagnosis; fasting glucose value at 100-g, 3-h oral glucose tolerance test; self-monitored glycemic control status at fasting; number of fasting self-monitored blood glucose measurements	n (%): Unkown Method: Multiple imputation	Int: NA Ext : NA	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Lin, 2011	Diabetes mellitus (diagmosed with a fasting value ≥126 mg/dl or 2-h 75-g OGTT value ≥200 mg/dl); and pre-diabetes mellitus (diagnosed with a 110 mg/dl ≤ fasting value <126 mg/dl or 140 mg/dl ≤2-h 75-g OGTT value <200 mg/ dl)	Machine learning techniques (AIRS)	152 (42)	12	NI	3.5	All available predictors	Other	Unclear	n (%): Unkown Method: No Information	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : Not evaluated Ov : Not evaluated Util: Not evaluated
Li (a), 2018	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Cox regression	1,263 (83)	5	4	16.6	Based on prior knowledge	Backward elimination	Family history of diabetes; BMI category before pregnancy; pregnancy-induced hypertension; 2h 75g glucose category at 26-30 gestational weeks	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Calibration plot Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Li (b), 2018				5	4	16.6			As above			

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Cox regression	1,263 (83)				Based on prior knowledge	Backward elimination		n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Calibration plot Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Lu (a), 2022	Mode of delivery (spontaneous vaginal delivery or assisted delivery vs planned or emergency caesarean)	Logistic regression	155 (35)	12	5	2.9	Based on univariable associations	Backward elimination	Maternal weight gain category; maternal height category; HbA1C category; parity category, and OGGT fasting category	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Lu (b), 2022	Mode of delivery (spontaneous vaginal delivery or assisted delivery vs planned or emergency caesarean)	Logistic regression	97 (26)	26	5	1.0	All available predictors	LASSO selection	Previous caesarean sectionl OGGT2hour; HbA1c; Fasting BG Mean3336 (mean blood glucose of all six-tag readings at or before 32 weeks of pregnancy and between 33 and 36 weeks of pregnancy); Fasting BG BBWeek1 (first week average fasting blood glucose values before the last blood glucose measurements)	n (%): Unkown Method: Multiple imputation	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Man, 2021	Type 2 diabetes diagnosed based on American Diabetes Association criteria	Cox regression	317 (82)	11	5	7.5	Based on univariable associations	Pre-specified model (not selection)	GDM treatment method; BMI; fasting glucose; Hb1Ac; interaction between treatment and BMI	n (%): Unkown Method: No information	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph / Risk group curves Ov : R-squared Util: Not evaluated

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Marozas (a), 2018	No informaton	Machine learning techniques (Ensemble model)	151 (85)	44	12	1.5	Based on prior knowledge	Other	Income level; sugar consumption; rs7903146_CC; rs12255372_GG; desserts; year of first given birth; weight before pregnancy with GDM; weight of first born child; physical activity; number of given births; residence; time needed to get to work	n (%): Unkown Method: Other	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Marozas (b), 2018	No informaton	Machine learning techniques (Ensemble model)	151 (85)	44	9	1.5	Based on prior knowledge	Other	Sugar consumption; income level; number of given births; education; weight of first born child; year of first given birth; weight before pregnancy with GDM; rs12255372_GT; desserts	n (%): Unkown Method: Other	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
McIntyre (a), 2018	Primary caesarean delivery	Logistic regression	1,248 (241)	7	7	34.4	All available predictors	Pre-specified model (not selection)	Fasting, one hour and two hour OGTT results; age; height; BMI; parity	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
McIntyre (b), 2018	Birth injury including shoulder dystocia	Logistic regression	1,248 (29)	7	7	4.1	All available predictors	Pre-specified model (not selection)	Fasting, one hour and two hour OGTT results; age; height; BMI; parity	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
				7	7	25.0						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
McIntyre (c), 2018	Birth > 90th centile in comparison to the Australian national standard values published by Roberts and Lancaster	Logistic regression	1,248 (175)				All available predictors	Pre-specified model (not selection)	Fasting, one hour and two hour OGTT results; age; height; BMI; parity	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
McIntyre (d), 2018	Neonatal adiposity defined as % body fat > 90th centile derived from within the Mater HAPO dataset	Logistic regression	1,000 (100)	7	7	14.3	All available predictors	Pre-specified model (not selection)	Fasting, one hour and two hour OGTT results; age; height; BMI; parity	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
McIntyre (e), 2018	Hyperinsulinaemia defined as an elevated cord c-peptide (>1.7 µg/L, 90th centile in the HAPO dataset)	Logistic regression	992 (76)	7	7	10.9	All available predictors	Pre-specified model (not selection)	Fasting, one hour and two hour OGTT results; age; height; BMI; parity	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
McIntyre (f), 2018	Hypoglycaemia defined as blood glucose level of <2.2 mmol/L (10th centile in the HAPO dataset)	Logistic regression	695 (73)	7	7	10.4	All available predictors	Pre-specified model (not selection)	Fasting, one hour and two hour OGTT results; age; height; BMI; parity	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Mendez-Figueroa, 2014	Treatment modality according to institutional protocol	Logistic regression	367 (143)	8	3	17.9	Based on univariable associations	Pre-specified model (not selection)	BMI at 26–30 weeks; GA at OGTT; fasting blood glucose at OGTT	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Much, 2015					3	NI	NI	NI				

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
	Treatment modality according to institutional protocol	Logistic Regression	856 (183)	Unkown					Fasting glucose; BMI at OGTT; 1-h glucose	n (%): Unkown Method: No Information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : Not evaluated Ov : Not evaluated Util: Not evaluated
Muche, 2020	Impaired fasting glucose defined as FPG 100–125mg/dL; impaired glucose tolerance defined as 2-hour plasma glucose in 75g OGTT 140–199mg/ dL) or diabetes (FPG ≥126mg/dL, or 2-hour plasma glucose ≥200 mg/dL in OGTT or random plasma glucose ≥200mg/dL	Logistic regression	112 (24)	15	4	1.6	Based on univariable associations	Backward elimination	Maternal age; mid-upper arm circumference; FPG at GDM diagnosis; Antenatal depression	n (%): Unkown Method: No information	Int: Bootstrap Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Mukherjee (a), 2023	Neonatal hypoglycemia (<2.6 mmol/L or 46.8 mg/dL in symptomatic and preterm babies; <2.0 mmol/L or 36 mg/dL in asymptomatic term babies)	Logistic Regression	627 (160)	3	3	53.3	All available predictors	Pre-specified model (not selection)	Age; BMI at first antenatal presentation; DRIPP score	n (%): 23 (3.7) Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
				3	3	17.3						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Mukherjee (b), 2023	Preterm delivery < 37 weeks	Logistic Regression	627 (52)				All available predictors	Pre-specified model (not selection)	Age; BMI at first antenatal presentation; DRIPP score	n (%): 23 (3.7) Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Mukherjee (c), 2023	Hyperbilirubinemia based on variable diagnostic thresholds according to gestational and postnatal age	Logistic Regression	627 (26)	3	3	8.7	All available predictors	Pre-specified model (not selection)	Age; BMI at first antenatal presentation; DRIPP score	n (%): 23 (3.7) Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Mukherjee (d), 2023	NICU admission	Logistic Regression	627 (71)	3	3	23.7	All available predictors	Pre-specified model (not selection)	Age; BMI at first antenatal presentation; DRIPP score	n (%): 23 (3.7) Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Mukherjee (e), 2023	Macrosomia defined as a birth weight $\geq$ 4000g	Logistic Regression	627 (30)	3	3	10.0	All available predictors	Pre-specified model (not selection)	Age; BMI at first antenatal presentation; DRIPP score	n (%): 23 (3.7) Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Mukherjee (f), 2023	Shoulder dystocia or birth injury	Logistic Regression	627 (4)	3	3	1.3	All available predictors	Pre-specified model (not selection)	Age; BMI at first antenatal presentation; DRIPP score	n (%): 23 (3.7) Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
				3	3	94.7						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Mukherjee (g), 2023	Neonatal complication composite (composite of any of the six morbidity-related outcomes, within 30 days of birth)	Logistic Regression	627 (343)				All available predictors	Pre-specified model (not selection)	Age; BMI at first antenatal presentation; DRIPP score	n (%): 23 (3.7) Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Odinokova, 2019	Macrosomia defined as a birth weight ≥ 4000g	Machine learning techniques (OPLS-DA)	120 (40)	NI	13	NI	All available predictors	Other	Unclear but lipids	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Park, 2015	Adverse outcomes(neonatal hypoglycemia, hyperbilirubinemia, and hyperinsulinemia; admission to the neonatal intensive care unit; large for gestational age; gestational insulin therapy; and gestational hypertension)	Logistic regression	802 (458)	9	2	38.2	Based on univariable associations	Pre-specified model (not selection)	BMI at entry and FBG	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Pei, 2023	Remission of impaired glucose toelrance defined as 3.9 mmol/L ≤ FPG < 6.1 mmol/L and 2 h PG < 7.8 mmol/L.	Logistic Regression	113 (55)	8	8	6.9	Unclear	Unclear	Age; income; education; GDM history; family diabetes history; pre-BMI; waist at recruitment, PANDER level	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
				27	16	7.9						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Periyathambi, 2022	Non-attendance at postpartum glucose test (OGTT 6-12 weeks post delivery, HbA1C 3 months post delivery)	Logistic regression	607 (213)				All available predictors	LASSO selection	Maternal age; antenatal FPG, 2hrs, Hb1Ac; gestational age at diagnosis; BMI; smoker; unmarried; diastolic BP; Ethnicity; Gestational age at birth, Instrument assisted delivery, SGA infants, male babies, Breastfeeding before discharge, Parity	n (%): 133 (21.9) Method: Multiple imputation	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: DCA
Phaloprakarn, 2009	Preeclampsia diagnosed using the criteria of the International Society for the Study of Hypertension in Pregnancy	Logistic regression	813 (78)	11	3	7.1	Based on univariable associations	Pre-specified model (not selection)	First-trimester BMI; GA at GDM diagnosis; Poor glycemic control	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Phaloprakarn (a), 2020	Primary caesarean delivery	Logistic regression	385 (130)	5	3	26.0	Based on univariable associations	Pre-specified model (not selection)	Parity; Gestational weight gain; Insulin Use	n (%): 3 (0.8) Method: Multiple imputation	Int: None (Apparent performance) Ext : Temporal	Cal: Calibration plot / HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Phaloprakarn (b), 2020	Primary caesarean delivery	Logistic Regression	448 (178)	NA	3	NA	NA	NA	Parity; Gestational weight gain; Insulin Use	n (%): Unkown Method: No information	Int: NA Ext : NA	Cal: Calibration plot / HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
				7	3			Other				

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Pintaudi, 2018	Neonatal adverse outcome (fetal growth, LGA, SGA mortality, malformations, shoulder distocia, neonatal intensive care need, hypoglycaemia, hypocalcemia, hyperbilirubinemia, and respiratory distress	Machine learning techniques (RECPAM)	2,736 (815)			116.4	Based on prior knowledge		Pre-pregnancy BMI; Pre-pregnancy BMI; family history of diabetes	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : Not evaluated Ov : Not evaluated Util: Not evaluated
Ramos, 2023	Primary caesarean delivery	Logistic Regression	3,570 (987)	24	8	41.1	Based on prior knowledge	Stepwise backward elimination	Insulin required in pregnancy; Nulliparous; Preeclampsia; Polyhydramnios; Large for gestational age; Age at delivery; Early pregnancy BMI; HbA1C	n (%): Unkown Method: Complete-case analysis	Int: Bootstrap Ext : None	Cal: Calibration plot / Slope / CITL / HL test Disc : C-Statistic / AUC graph Ov : R-squared Util: Not evaluated
Schwartz, 2016	GDM recurrence (GDM in a pregnancy following the index pregnancy complicated by GDM)	Logistic regression	788 (432)	25	9	14.2	Based on univariable associations	Pre-specified model (not selection)	Maternal age; multiparity; GDM diagnosis week; fasting OGTT; OGTT after 1 h; OGTT after 2 hrs; insulin use; inter-pregnancy interval; BMI gain	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: HL test Disc : Not evaluated Ov : Not evaluated Util: Not evaluated
Souza, 2018				13	5	10.4						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
	When glycemic targets were not achieved with diet and exercise (fasting >95mg/dL and 1 h post-prandial >140 mg/dL), insulin therapy was initiated along with continuing the dietary treatment.	Logistic regression	408 (135)				Based on prior knowledge	Stepwise selection	Previous GDM; family history of DM; BMI; age; FBG	n (%): Unkown Method: No information	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
Sun, 2020	Macrosomia defined as a birth weight ≥ 4000g	Logistic Regression	64 (12)	8	5	1.5	Based on univariable associations	Other	Prepregnancy BMI; Weight gain; C0; C16; C3 (cartinine metabolites)	n (%): Unkown Method: No Information	Int: No Informatio n Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Sun, 2023	Macrosomia defined as a birth weight ≥ 4000g	Logistic Regression	991 (73)	20	5	3.7	Based on univariable associations	Stepwise selection	Gravidity; pre-pregnancy BMI; family history of hypertension; abdominal circumference; and biparietal diameter	n (%): Unkown Method: No information	Int: Random split data Ext : None	Cal: Calibration plot / Slope / CITL / HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: DCA
Tomlinson, 2018	Fetal overgrowth defined as a birthweight that is ≥ 90th gestation-related optimal weight (GROW) centile	Logistic regression	275 (51)	24	5	2.1	Based on univariable associations	Forward selection	Age; history of macrosomia; excessive gestational weight gain; enlarged fetal abdominal circumference; and high fasting glucose	n (%): Unkown Method: No information	Int: Bootstrap Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Tomlinson, 2021	As above	Logistic regression	477 (100)	NA	5	NA	NA	NA	As above	n (%): Unkown Method: Other	Int: NA Ext : NA	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Ukah (a), 2022	Hospitalization for type 2 diabetic complications within 10 years after delivery of the first pregnancy affected by GDM. Type 2 diabetic complications was defined as a diagnosis of type 2 diabetes with the development of one or more of the following complications: diabetic coma, acidosis, kidney, ophthalmic, neurological, circulatory, or other complications resulting from diabetes.	Cox regression	90,143 (283)	13	7	21.8	Based on prior knowledge	LASSO selection	Maternal age; Socioeconomically deprived; Substance use; Gestational age at delivery; SMM; Previous complications; Hypertensive disorders of pregnancy	n (%): Unkown Method: No information	Int: Bootstrap Ext : None	Cal: Calibration plot / Slope / CITL Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Ukah (b), 2022	Hospitalization for type 2 diabetic complications within 29 years after delivery of the first pregnancy affected by GDM.	Cox regression	90,143 (1025)	13	7	78.8	Based on prior knowledge	LASSO selection	Maternal age; Socioeconomically deprived; Substance use; Gestational age at delivery; SMM; Previous complications; Hypertensive disorders of pregnancy	n (%): Unkown Method: No information	Int: Bootstrap Ext : None	Cal: Not evaluated Disc : C-Statistic Ov : Not evaluated Util: Not evaluated
				28	NI	16.2			NI			

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
Velardo, 2021	Need for pharmacological treatment (metformin and/or insulin) according to institutional protocol	Logistic regression	1,543 (454)				Based on prior knowledge	LASSO selection		n (%): Unkown Method: Single imputation	Int: Random split data Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Yerlikaya (a), 2018	Need for pharmacological treatment according to institutional protocol	Logistic regression	203 (95)	3	3	31.7	All available predictors	Pre-specified model (not selection)	OGTT glucose measurements at fasting; 60min; and 120min	n (%): Unkown Method: Multiple imputation	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Yerlikaya (b), 2018	Need for pharmacological treatment according to institutional protocol	Logistic regression	203 (95)	6	6	15.8	All available predictors	Pre-specified model (not selection)	Age; pregestational BMI; parity; history of GDM; family history with type 2 diabetes; and time of diagnosis	n (%): Unkown Method: Multiple imputation	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Yerlikaya (c), 2018	Need for pharmacological treatment according to institutional protocol	Logistic regression	203 (95)	9	9	10.6	All available predictors	Pre-specified model (not selection)	OGTT glucose measurements at fasting; 60min; and 120min; age; pregestational BMI; parity; history of GDM; family history of diabetes; and time of diagnosis	n (%): Unkown Method: Multiple imputation	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Yuan, 2022	Macrosomia defined as a birth weight ≥ 4000g	Logistic regression	40 (20)	NI	5	NI	Based on univariable associations	Pre-specified model (not selection)	Maternal age; fasting plasma glucose; 2-h plasma glucose; GDF3 expression; AC006064.4 expression in peripheral blood exosomes	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Yuan, 2023			88 (44)	12	9	3.7						

Author, Year	Outcome	Modelling method	Sample size (event)	No predictors		EPV	Selection of candidate predictors	Selection of final predictors	Predictors	Number (%) and handling of missing data	Type of validation	Performance measures
				Cand	Final							
	Macrosomia defined as a birth weight ≥ 4000g	Logistic Regression					Based on univariable associations	LASSO selection	Pre-pregnancy BMI; weight gain; OGTT 2h glucose; parity; HDL; LDL; plasma CLUL1 expression; plasma VCAN expression; plasma RNASE3 expression	n (%): Unkown Method: Other	Int: Cross-validation Ext : None	Cal: Calibration plot / HL test Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Clinical impact curve
Zaccara, 2023	Treatment modality according to institutional protocol	Logistic Regression	869 (145)	6	6	24.2	Based on univariable associations	Other	Previous GDM; BMI; age; FPG OGTT; 1hPG; 2hPG	n (%): Unkown Method: No information	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Zhang, 2021	Type 2 Diabetes diagnosed based on American Diabetes Association criteria	Machine learning techniques (Random Forest)	216 (98)	69	10	1.4	Based on univariable associations	Decision Trees	AC16; Orn; PC aa C30:0; Putrescine; Val; PC ae C32:2; SM (OH) C22:2; Spermidine; Phe; lyso PC a C28:0	n (%): Unkown Method: Single imputation	Int: Cross-validation Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Zhang, 2023	Macrosomia defined as a birth weight ≥ 4000g	Logistic Regression	322 (21)	11	4	1.9	Based on univariable associations	Other	Pregnancy gain weight; Amniotic fluid index; OGTT Fasting glucose; Fetal weight estimated by ultrasound	n (%): Unkown Method: Complete-case analysis	Int: None (Apparent performance) Ext : None	Cal: Not evaluated Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated
Zou, 2021	Macrosomia defined as a birth weight ≥ 4000g	Logistic Regression	783 (83)	21	6	4.0	Based on univariable associations	Forward selection	BMI; weight gain during pregnancy; fasting plasma glucose; triglycerides; biparietal diameter; amniotic fluid index	n (%): Unkown Method: No information	Int: Bootstrap Ext : None	Cal: Calibration plot Disc : C-Statistic / AUC graph Ov : Not evaluated Util: Not evaluated

Abbreviations: No information (NI); Area under the curve (AUC); Calibration in the large (CITL); Hosmer-Lemeshow (HL); Classification and Regression Trees (CART); Artificial Immune Recognition System (AIRS); Orthogonal Partial Least Squares Discriminant Analysis (OPLS-DA); REcursive Partition and Amalgamation (RECPAM)
Completed information on data extraction using CHARMS and critical appraisal PROBAST for each study is available upon request

Supplementary Table 10.3. Critical appraisal and applicability assessment of included models

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
Allalou (a), 2016	RoB	-	+	+	-	-
	App	-	-	+		-
Allalou (b), 2016	RoB	-	+	+	-	-
	App	-	+	+		-
Allalou (c), 2016	RoB	-	+	+	-	-
	App	-	-	+		-
Badr (a), 2022	RoB	-	+	+	-	-
	App	-	+	+		-
Badr (b), 2022	RoB	-	+	+	-	-
	App	-	+	+		-
Badr (c), 2022	RoB	-	+	+	-	-
	App	-	+	+		-
Badr (d), 2022	RoB	-	+	+	-	-
	App	-	+	+		-
Barden, 2013	RoB	+	+	-	-	-
	App	+	+	+		+
Barnes (a), 2016	RoB	-	+	-	-	-
	App	+	+	+		+
Barnes (b), 2016	RoB	?	+	-	-	-

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	?	+	+		?
Bartakova, 2021	RoB	+	+	+	-	-
	App	-	+	+		-
Bengtson, 2022	RoB	+	+	+	-	-
	App	+	+	+		+
Cooray (a), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Cooray (b), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Cormier (a), 2014	RoB	-	-	+	-	-
	App	-	-	+		-
Cormier (b), 2014	RoB	-	-	+	-	-
	App	-	-	+		-
Du, 2021	RoB	-	+	-	-	-
	App	-	+	+		-
Eleftheriades (a), 2021	RoB	+	+	-	-	-
	App	+	+	+		+
Eleftheriades (b), 2021	RoB	?	?	-	-	-
	App	?	?	?		?
Elnour, 2006	RoB	?	-	?	-	-

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	?	-	?		-
Ford, 2022	RoB	+	+	-	+	-
	App	+	+	-		-
Hahn, 2023	RoB	+	-	+	-	-
	App	+	+	+		+
Harper, 2016	RoB	-	+	+	-	-
	App	-	+	+		-
Huang (a), 2023	RoB	+	+	+	-	-
	App	+	+	+		+
Huang (b), 2023	RoB	+	+	+	-	-
	App	+	+	+		+
Ignell (a), 2016	RoB	+	-	-	-	-
	App	+	-	-		-
Ignell (b), 2016	RoB	+	-	-	-	-
	App	+	-	-		-
Ingram (a), 2017	RoB	+	-	+	-	-
	App	+	+	+		+
Ingram (b), 2017	RoB	+	-	?	-	-
	App	+	+	?		?
Ingram (c), 2017	RoB	+	-	?	-	-

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	+	+	?		?
Joglekar (a), 2021	RoB	+	-	+	-	-
	App	+	+	+		+
Joglekar (b), 2021	RoB	+	-	+	-	-
	App	+	-	+		-
Jotic, 2023	RoB	-	-	+	-	-
	App	-	+	+		-
Kang (a), 2019	RoB	-	-	+	-	-
	App	+	+	+		+
Kang (b), 2019	RoB	-	-	+	-	-
	App	+	+	+		+
Khan, 2019	RoB	-	+	+	-	-
	App	-	-	+		-
Kim, 2022	RoB	+	-	+	-	-
	App	+	+	+		+
Koefoed, 2023	RoB	+	+	+	-	-
	App	+	+	+		+
Kohler, 2016	RoB	+	+	-	-	-
	App	+	+	+		+
Kondo (a), 2018	RoB	+	-	+	-	-

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	+	+	+		+
Kondo (b), 2018	RoB	+	-	+	-	-
	App	+	+	+		+
Kondo (c), 2018	RoB	+	-	+	-	-
	App	+	+	+		+
Kwak (a), 2013	RoB	+	+	+	-	-
	App	-	+	+		-
Kwak (b), 2013	RoB	+	+	+	-	-
	App	-	-	+		-
Kwak (c), 2013	RoB	+	+	+	-	-
	App	-	+	+		-
Kwak (d), 2013	RoB	+	+	+	-	-
	App	-	-	+		-
Lai, 2020	RoB	-	+	+	-	-
	App	-	-	+		-
Lappas (a), 2015	RoB	+	+	+	-	-
	App	+	+	+		+
Lappas (b), 2015	RoB	+	+	+	-	-
	App	+	-	+		-
Lappas (c), 2015	RoB	+	+	+	-	-

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	+	-	+		-
Lappas (a), 2016	RoB	+	+	+	-	-
	App	+	+	+		+
Lappas (b), 2016	RoB	+	+	+	-	-
	App	+	-	+		-
Lappas (c), 2016	RoB	+	+	+	-	-
	App	+	-	+		-
Lappas (a), 2018	RoB	+	+	+	-	-
	App	+	+	+		+
Lappas (b), 2018	RoB	+	+	+	-	-
	App	+	-	+		-
Lappas (c), 2018	RoB	+	+	+	-	-
	App	+	-	+		-
Liao (a), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Liao (b), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Liao (c), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Liao (d), 2022	RoB	+	+	+	+	+

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	+	+	+		+
Liao (e), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Liao (f), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Liao (g), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Liao (h), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Lin, 2011	RoB	?	?	+	-	-
	App	?	?	+		?
Li (a), 2018	RoB	-	-	+	-	-
	App	+	+	+		+
Li (b), 2018	RoB	-	-	+	-	-
	App	+	+	+		+
Lu (a), 2022	RoB	+	+	+	-	-
	App	+	+	+		+
Lu (b), 2022	RoB	+	+	+	-	-
	App	+	-	+		-
Man, 2021	RoB	+	+	+	-	-

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	-	+	+		-
Marozas (a), 2018	RoB	?	?	?	-	-
	App	?	-	?		-
Marozas (b), 2018	RoB	?	?	?	-	-
	App	?	-	?		-
McIntyre (a), 2018	RoB	+	+	+	-	-
	App	-	+	+		-
McIntyre (b), 2018	RoB	+	+	+	-	-
	App	-	+	+		-
McIntyre (c), 2018	RoB	+	+	+	-	-
	App	-	+	+		-
McIntyre (d), 2018	RoB	+	+	+	-	-
	App	-	+	+		-
McIntyre (e), 2018	RoB	+	+	+	-	-
	App	-	+	+		-
McIntyre (f), 2018	RoB	+	+	+	-	-
	App	-	+	+		-
Mendez-Figueroa, 2014	RoB	+	+	+	-	-
	App	-	+	+		-
Much, 2015	RoB	?	+	+	-	-

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	?	+	+		?
Muche, 2020	RoB	+	+	+	-	-
	App	-	+	+		-
Mukherjee (a), 2023	RoB	?	-	+	-	-
	App	?	+	+		?
Mukherjee (b), 2023	RoB	?	-	+	-	-
	App	?	+	+		?
Mukherjee (c), 2023	RoB	?	-	+	-	-
	App	?	+	+		?
Mukherjee (d), 2023	RoB	?	-	+	-	-
	App	?	+	+		?
Mukherjee (e), 2023	RoB	?	-	+	-	-
	App	?	+	+		?
Mukherjee (f), 2023	RoB	?	-	+	-	-
	App	?	+	+		?
Mukherjee (g), 2023	RoB	?	-	+	-	-
	App	?	+	+		?
Odinokova, 2019	RoB	+	+	+	-	-
	App	-	-	+		-
Park, 2015	RoB	+	-	+	-	-

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	-	+	+		-
Pei, 2023	RoB	-	+	+	-	-
	App	?	+	+		?
Periyathambi, 2022	RoB	+	+	+	-	-
	App	+	+	+		+
Phaloprakarn, 2009	RoB	+	+	+	-	-
	App	+	+	+		+
Phaloprakarn (a), 2020	RoB	+	+	+	+	+
	App	+	+	+		+
Phaloprakarn (b), 2020	RoB	+	+	+	+	+
	App	+	+	+		+
Pintaudi, 2018	RoB	+	+	+	-	-
	App	+	+	+		+
Ramos, 2023	RoB	+	+	+	+	+
	App	+	+	+		+
Schwartz, 2016	RoB	+	-	+	-	-
	App	+	+	+		+
Souza, 2018	RoB	+	+	-	-	-
	App	+	+	+		+
Sun, 2020	RoB	?	+	+	-	-

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	?	-	+		-
Sun, 2023	RoB	+	+	+	-	-
	App	+	+	+		+
Tomlinson, 2018	RoB	+	+	+	-	-
	App	+	+	+		+
Tomlinson, 2021	RoB	+	+	+	-	-
	App	+	+	+		+
Ukah (a), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Ukah (b), 2022	RoB	+	+	+	+	+
	App	+	+	+		+
Velardo, 2021	RoB	+	+	-	-	-
	App	+	+	+		+
Yerlikaya (a), 2018	RoB	+	+	-	-	-
	App	+	+	+		+
Yerlikaya (b), 2018	RoB	+	+	-	-	-
	App	+	+	+		+
Yerlikaya (c), 2018	RoB	+	+	-	-	-
	App	+	+	+		+
Yuan, 2022	RoB	?	-	+	-	-

Author, Year		Critical appraisal (PROBAST)				
		P	Pr	O	A	Overall
	App	+	-	+		-
Yuan, 2023	RoB	-	+	+	-	-
	App	-	-	+		-
Zaccara, 2023	RoB	+	+	-	-	-
	App	+	+	+		+
Zhang, 2021	RoB	+	+	+	-	-
	App	-	-	+		-
Zhang, 2023	RoB	-	+	+	-	-
	App	-	+	+		-
Zou, 2021	RoB	+	+	+	-	-
	App	+	+	+		+

Abbreviations: Prediction model Risk Of Bias ASsessment Tool (PROBAST); Population (P); Predictors (Pr); Outcome (O); Analysis (A); Risk of Bias (RoB); Applicability (App)

Completed information on data extraction using CHARMS and critical appraisal PROBAST for each study is available upon request

10.1.3. Appendix 3. Supplementary Material for Chapter 3

Supplementary Table 10.4. TRIPOD Checklist: Prediction Model Validation

Section/Topic	Item	Checklist Item	Section
Title and abstract			
Title	1	Identify the study as developing and/or validating a multivariable prediction model, the target population, and the outcome to be predicted.	3
Abstract	2	Provide a summary of objectives, study design, setting, participants, sample size, predictors, outcome, statistical analysis, results, and conclusions.	3.1
Introduction			
Background and objectives	3a	Explain the medical context (including whether diagnostic or prognostic) and rationale for developing or validating the multivariable prediction model, including references to existing models.	3.2
	3b	Specify the objectives, including whether the study describes the development or validation of the model or both.	3.3
Methods			
Source of data	4a	Describe the study design or source of data (e.g., randomized trial, cohort, or registry data), separately for the development and validation data sets, if applicable.	3.4.1, 3.4.2, 3.4.3
	4b	Specify the key study dates, including start of accrual; end of accrual; and, if applicable, end of follow-up.	3.4.1
Participants	5a	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including number and location of centres.	3.4.1
	5b	Describe eligibility criteria for participants.	3.4.2, 3.4.3
	5c	Give details of treatments received, if relevant.	NA
Outcome	6a	Clearly define the outcome that is predicted by the prediction model, including how and when assessed.	3.4.4
	6b	Report any actions to blind assessment of the outcome to be predicted.	NA
Predictors	7a	Clearly define all predictors used in developing or validating the multivariable prediction model, including how and when they were measured.	3.4.5
	7b	Report any actions to blind assessment of predictors for the outcome and other predictors.	NA
Sample size	8	Explain how the study size was arrived at.	3.4.6, 3.5.1
Missing data	9	Describe how missing data were handled (e.g., complete-case analysis, single imputation, multiple imputation) with details of any imputation method.	3.4.7
Statistical analysis methods	10c	For validation, describe how the predictions were calculated.	3.4.9
	10d	Specify all measures used to assess model performance and, if relevant, to compare multiple models.	3.4.10
	10e	Describe any model updating (e.g., recalibration) arising from the validation, if done.	3.4.10
Risk groups	11	Provide details on how risk groups were created, if done.	3.4.11
Development vs. validation	12	For validation, identify any differences from the development data in setting, eligibility criteria, outcome, and predictors.	3.5.3
Results			
Participants	13a	Describe the flow of participants through the study, including the number of participants with and without the outcome and, if applicable, a summary of the follow-up time. A diagram may be helpful.	3.5.1
	13b	Describe the characteristics of the participants (basic demographics, clinical features, available predictors), including the number of participants with missing data for predictors and outcome.	3.5.2
	13c	For validation, show a comparison with the development data of the distribution of important variables (demographics, predictors and outcome).	Not possible (not reported in dev cohort)

Model performance	16	Report performance measures (with CIs) for the prediction model.	3.5.4, 3.5.5
Model-updating	17	If done, report the results from any model updating (i.e., model specification, model performance).	3.5.4
Discussion			
Limitations	18	Discuss any limitations of the study (such as nonrepresentative sample, few events per predictor, missing data).	3.6.6
Interpretation	19a	For validation, discuss the results with reference to performance in the development data, and any other validation data.	3.6.2
	19b	Give an overall interpretation of the results, considering objectives, limitations, results from similar studies, and other relevant evidence.	3.6.1 & 3.6.4
Implications	20	Discuss the potential clinical use of the model and implications for future research.	3.6.5
Other information			
Supplementary information	21	Provide information about the availability of supplementary resources, such as study protocol, Web calculator, and data sets.	Appendix 3
Funding	22	Give the source of funding and the role of the funders for the present study.	Acknowled gements

Supplementary File 10.2. Protocol and Linkage Requests

Medicines & Healthcare products Regulatory Agency

CPRD

1 General information

Protocol reference Id
22_002383

Study title
Risk prediction modelling for gestational diabetes

Research Area

Disease Epidemiology

Does this protocol describe an observational study using purely CPRD data?
Yes

Does this protocol involve requesting any additional information from GPs, or contact with patients?
No

2 Research team

Role	Chief Investigator
Title	Senior Researcher
Full name	Nerys Astbury
Affiliation/organisation	University of Oxford
Email	nerys.astbury@phc.ox.ac.uk
Will this person be analysing the data?	Yes
Status	Confirmed

Role	Corresponding Applicant
Title	Senior Researcher
Full name	Nerys Astbury
Affiliation/organisation	University of Oxford
Email	nerys.astbury@phc.ox.ac.uk
Will this person be analysing the data?	Yes
Status	Confirmed

Role	Collaborator
Title	Phil Student
Full name	Yasmina Al Ghadban
Affiliation/organisation	University of Oxford
Email	yasmina.alghadban@wrh.ox.ac.uk
Will this person be analysing the data?	Yes
Status	Confirmed

Role	Collaborator
Title	Research fellow
Full name	Huiqi Yvonne Lu
Affiliation/organisation	University of Oxford
Email	yvonne.lu@eng.ox.ac.uk
Will this person be analysing the data?	Yes
Status	Confirmed

3

Access to data

Sponsor

University of Oxford

Funding source for the study

Is the funding source for the study the same as Chief Investigator's affiliation?
Yes
Funding source for the study
University of Oxford

Institution conducting the research

Is the institution conducting the research the same as Chief Investigator's affiliation?
Yes
Institution conducting the research
University of Oxford

Method to access the data

Indicate the method that will be used to access the data
Institutional multi-study licence
Is the institution the same as Chief Investigator's affiliation?
Yes
Institution name
University of Oxford

Extraction by CPRD

Will the dataset be extracted by CPRD
No

Multiple data delivery

This study requires multiple data extractions over its lifespan
No

Data processors

Data processor is	Same as the chief investigator's affiliation
Processing	Yes
Accessing	Yes
Storing	Yes
Processing area	UK

Data processor is	Same as the chief investigator's affiliation
Processing	Yes
Accessing	Yes
Storing	Yes
Processing area	UK

4

Information on data

Primary care data

CPRD Aurum

Do you require data linkages

Yes

Patient level data

HES Admitted Patient Care

ONS Death Registration Data

NCRAS data

Covid 19 linkages

Area level data

Do you require area level data?

Yes

Practice level (UK)

Patient level (England only)

Patient Level Index of Multiple Deprivation

Withheld concepts

Are withheld concepts required?
No

Linkage to a dataset not listed

Are you requesting a linkage to a dataset not listed?
No

Patient data privacy

Does any person named in this application already have access to any of these data in a patient identifiable form, or associated with an identifiable patient index?
No

5

Protocol information

Lay Summary

Gestational diabetes mellitus (GDM) is glucose intolerance first recognized during pregnancy. Around 1 in 7 pregnancies will be affected by GDM, making it the most common pregnancy complication. GDM can have short-term and long-term adverse outcomes for both the mother and her baby, including need for medication, preterm delivery, caesarean section well as longer term health risk risks including itype 2 diabetes and obesity. While appropriate detection, treatment and follow-up can help reduce the complications associated with GDM, they also place a significant burden on overwhelmed health systems as it is unclear which women are at risk. The ability to predict which women are most likely to develop GDM and develop adverse outcomes associated with GDM would allow resources to be directed at these groups who are most at risk.
In this project we will explore ways to help determine the women who will develop GDM and those who are more likely to develop adverse outcomes associated with GDM. We will use traditional statistical approaches including regression and time to event risk prediction models as well as data-driven machine learning techniques. We will compare the performance of the methods in detecting the people at highest risk of GDM or an adverse outcome associated with GDM.
The abaility to accurately detect which people are at highest risk will alow the healthcare professionals responsible for their care to monitor them more closely, and allow implementation of prevention stratergies in the highest risk groups who are likely to benefit the most.

Technical Summary

Gestational diabetes mellitus (GDM), glucose intolerance with first onset or recognition during pregnancy, has a global prevalence of 14.0%, making it one of the most common disorders of pregnancy. With increasing obesity and maternal age worldwide, the incidence of GDM is likely to increase, causing a strain on health systems. Although women who are diagnosed with GDM return to normoglycemia after birth, GDM may lead to short and long-term consequences for both the mother and the child.
Guidelines highlight the need for increased antenatal surveillance for women with GDM and long-term follow up (history and physical examination, blood pressure measurements and screening for diabetes) for all women with GDM starting 6–12 weeks after birth, and periodically thereafter (1). While appropriate detection, treatment and follow-up reduce the complications associated with GDM (2–4), they also place a significant burden on overwhelmed health systems as it is unclear which women are at risk.
Risk stratification is important to effectively allocate resources and direct secondary prevention towards at risk populations, especially with the increasing prevalence of GDM.
Traditional risk prediction models have been used to quantify the risk to women of getting GDM. However a recent systematic review of these models identified that many were of low quality and the vast majority never get used clinically (5).
More recently machine learning approaches, which use data-driven approaches to help predict risk have been used, there is still some sceptisicm with regard to whether they perform better than traditional approaches.
In this project we will develop and validate risk prediction models for GDM and adverse outcomes associated with GDM using two different approaches.
Using this two-step approach allows us to compare the accuracy of the two different methods of deriving prediction models for GDM and adverse outcomes associated with GDM.

Outcomes to be measured

The primary outcome is a diagnosis of GDM recorded either in the primary care record or in the HES APC data assocated with the delivery.
Secondary outcomes include maternal and neonatal adverse outcomes associated with GDM including:
Outcomes that happen during pregnancy and/or delivery:
GDM Treatment method (including lilfestyle, metformin and insulin)
Gestational weight gain
Hypertensive disorders of pregnancy
Number of antenatal visits/admissions
Still birth

Delivery related outcomes:
Mode of delivery (emergency C-section, elective C-section, instrumental delivery)
Perineal trauma/tearing
Induction of labour
Preterm delivery
Length of postnatal stay
Longer-term outcomes:
Development of type 2 diabetes
Return to prepregnancy weight
Postnatal depression.
Cardiovascular morbidity
Obesity
Recurrent GDM

Objectives, specific aims & rationale

The primary outcome is a diagnosis of GDM recorded either in the primary care record or in the HES APC data assocated with the delivery.
Secondary outcomes include maternal and neonatal adverse outcomes associated with GDM including:
Outcomes that happen during pregnancy and/or delivery:
GDM Treatment method (including lilfestyle, metformin and insulin)
Gestational weight gain
Hypertensive disorders of pregnancy
Number of antenatal visits/admissions
Still birth

Delivery related outcomes:
Mode of delivery (emergency C-section, elective C-section, instrumental delivery)
Perineal trauma/tearing
Induction of labour
Preterm delivery
Length of postnatal stay
Longer-term outcomes:
Development of type 2 diabetes
Return to prepregnancy weight
Postnatal depression.
Cardiovascular morbidity
Obesity
Recurrent GDM
Objectives, specific aims and rationale 60000 character(s) remaining
The primary aim of this project is to develop and internally validate a risk prediction model for GDM using data collected during routine clinical care and held in primary healthcare records and linked HES data.
The secondary outcomes are to derive and internally validate models to predict adverse outcomes associated with GDM in the women who get GDM using data collected during routine clinical care and heald in the electronic primary healthcare records and linked HES data.
We will achieve our aims through the following objectives:
1. Develop and validate a prognosis model for GDM using CPRD Aurum and linked NHS Digital (HES) data:
a. Identify predictors for inclusion in the model based on feature selection methods.
b. Internal validation of the model developed, using bootstrapping.
2. Develop a prognosis model for GDM outcomes using CPRD Aurum data and linked NHS Digital (HES).
a. Identify predictors for inclusion in the model based on feature selection methods.
b. Internal validation of the model developed using bootstrapping techniques.
Risk stratification is important to effectively allocate resources and direct prevention towards at risk populations, especially with the increasing prevalence of GDM. Data-driven models have the potential to personalise GDM detection, management, and treatment, allowing clinicians to move away from a one-size-fits-all approach.

Study background

Gestational diabetes mellitus (GDM), glucose intolerance with first onset or recognition during pregnancy, has a global prevalence of 14.0%, making it one of the most common disorders of pregnancy. However, prevalence differs significantly between regions ranging from 7.1% in North America and Caribbean to 27.6% in the Middle East and North Africa (6). With increasing obesity and maternal age worldwide, the incidence of GDM is likely to increase, causing a strain on health systems.

Gestational diabetes can have adverse short-term consequences on both the mother and the fetus. A meta-analysis of 156 studies with 7,506,061 pregnancies found that women with GDM were at a higher risk of experiencing pregnancy complications and adverse neonatal outcomes (7). In particular, the odds of having a caesarian section (C-section), preterm delivery, macrosomia, large for gestational age babies, neonatal respiratory distress syndrome, neonatal jaundice and admission to a neonatal ICU were higher in women with GDM than in women with normoglycemic pregnancies.

Although women who are diagnosed with GDM return to normoglycemia after birth, GDM may lead to long-term consequences for both the mother and the child. The odds of developing type 2 diabetes (T2DM) are substantially higher for women with GDM than without (8–10). A meta-analysis of 20 studies found that women with GDM were 7.4 times as likely to develop T2DM than women with normoglycemic pregnancies (9). Additionally, women with GDM are at a significantly higher risk of hypertension, obesity, and cardiovascular morbidity (10–12). Children exposed to GDM also have a higher risk of obesity, cardiovascular morbidity and glucose intolerance compared to unexposed children (13–17).

The guidelines developed by the National Institute for Health and Care Excellence (NICE) in the UK highlights the need for increased surveillance for women with GDM and recommends a clinical review at least every two weeks (18). Additionally, the International Federation of Gynecology and Obstetrics (FIGO) recommends long-term follow up (history and physical examination, blood pressure measurements and screening for diabetes) with all women with GDM starting 6–12 weeks after birth, and periodically thereafter (1). While appropriate detection, treatment and follow-up reduce the complications associated with GDM (2–4), they also place a significant burden on overwhelmed health systems as it is unclear which women are at risk. Data-driven machine learning models have the potential to personalise GDM management and treatment, allowing clinicians to move away from a one-size-fits-all approach. For example, Yang et al. developed and validated a stratication model which identifies women at risk of hyperglycemia based on their daily glucose measurements and electronic health records (EHR) (19). This data was also used to develop a caesarean prediction score for mothers with GDM (20). Appropriate identification of and follow up with women at high risk of developing adverse GDM outcomes can have significant benefits for patients as well as an efficient allocation of resources.

Our goal is to explore risk of future disease in mothers diagnosed with GDM and investigate if more accurate prediction models for GDM can be developed from the healthcare record data alone.

Study type

This project is a prognosis model development and validation study.

Study design

For the primary prognosis model determining risk of GDM, GDM will be treated as the outcome. As such, all pregnancies will be included- and we will use prediction variables including maternal age, ethnicity, SES (IMD score) as well as other clinical indicators to help predict risk of GDM.

For the prognosis model of GDM outcomes, the adverse outcome will be treated as the outcomes of interest. We will use data on pregnancies that developed a GDM diagnosis, and include candidate prediction variables including maternal age, ethnicity, SES (IMD score) as well as other clinical indicators to help predict risk of developing one of the outcomes of interest in this population.

Feasibility counts

From a previous application with similar inclusion and exclusion criterion, we were able to identify over 55,000 deliveries to unique mothers associated with a diagnosiss of GDM. We believe that this will be sufficient number to enable us to achieve our aims using the proposed methods.

Sample size considerations

To ensure our models are stable and to avoid overfitting, we will ensure a high number of events per variable (EPV). While there is no consensus on the minimum EPV, a general rule of thumb is that we need an EPV of at least 10 to avoid bias. With 50,000 GDM pregnancies in CPRD dataset, we are unlikely to face any issues with small sample size as we are expecting less than 100 predictor variables to be included in the model (EPV of 500).

Planned use of linked data and benefit to patients in England and Wales

We plan to use data linked to NHS Digital HES (APC) data which contain events related to all deliveries over 28 weeks geststaion. This includes misscariges and stillbirths.
We will submit a Type 1 linked data request, as the study population is defined by the presence of one or more of these delivery events within the study time frame in the linked data (HES APC records). We will also request data held in the linked HES (APC) from the eligible population to detmermine whether a primary (GDM diagnosis) or secondary outcome (adverse outcome assication with GDM) has occurred using ICD-10 codes.

The ability to determine the people at highest risk of health outcomes will allow the people at highest risk to me more closely monitored, and preventative stratergies to be implemented in the group of people to mitigate risk, the possible benefits are likely to be greater, as they have more to gain. This would benefit patients in England and Wales, allowing stratified medicine approaches to prevention and treatment.

Definition of the study population

The eligible population will be defined by linked data (HES APC). Women any age who have at least one singleton delivery recorded in the HES APC from 2010- present.

For the secondary outcomes the population will be limited to the records of women with at least one delivery record in the HES APC data between 2010 and present and who have a diagnosis of GDM replated to one or more of those pregnancies. The GDM diagnossi will be determined using ICD-10codes related to the delivery and reacodes in the primary care record.

Selection of comparison groups/controls

The nature of the study mean there are no comparison groups.
For the primary outcome we will determine the records where a diagnosis of GDM has been made by either the presecnce of ICD-10 codes for GDM associated with the delivery event, or the presence of one or more readcodes for GDM in the primary care record.

For secondary outcomes we will determine if the outcome of interest is present by the presence of either ICD-10 codes associated with said outcome, or the presence of readcodes for the outcome of interest in the primary care record.

Exposures, outcomes and covariates

For the primary outcome the exposure, will be a delivery (pregnancy) and we will determine a prediction model for determining risk of having a diagnosis of GDM based on predictor variables including age, ethnicity, socioeconomic status, previous pregnancies, pre-pregnancy BMI and other clinical variables including HbA1c, total cholesterol etc.
For the secondary outcomes, the exposure is a diagnosis of GDM, for which we will develop a prediction model to determine the risk of getting one of the pre-specified secondary outcomes, which are all adverse outcomes that have been established to be linked with GDM.

Data/statistical analysis

Model Development
Models will be trained using all available data.
Binary outcomes:
Following the extraction and selection of features and outcomes, we will explore different models ranging from classical statistical models to more elaborate machine learning methods.
Specifically, we will look at GDM or GDM outcomes as binary outcomes in 6 models: generalised boosted model (GBM), linear discriminant analysis (LDA), penalized logistic regression (LOG), random forest (RF), recursive partitioning and regression analysis (RPART), and support vector machine (SVM). Based on the performance of these models, we may also consider using ensemble methods.
Time-to-event outcomes:
Additionally, for some outcomes, we are interested in when a patient may develop the conditions (time-to-event outcome). For these outcomes, we will compare the penalised Cox Regression, Cox model with gradient boosting (GLMBoost) and random survival forest.
Feature Selection
Feature selection optimises our model in several ways such as improving accuracy, reducing training time, and avoiding overfitting. In addition to selecting potential predictors from the literature, we will attempt to use different statistical methods to extract important features. Specifically, we will use LASSO regularisation, filter methods (variable importance) and wrapper methods (sequential forward selection, recursive feature elimination).
Model selection
When selecting the model, it is important to consider its predictive accuracy, its interpretability and whether it reflects the clinical decision-making process. The ideal model needs to strike a balance between interpretability and predictive power. The model will be internally validated using bootstrapping methods to generate pseudo random datasets based on the original data.
Performance Evaluation and Validation
The performance of the six machine learning algorithms (Rpart, GBM, LOG, RF, SVM, and LDA) will be compared on the basis of discrimination and calibration. For each model, we will report area under the ROC curve (AUROC), sensitivity, specificity, positive likelihood ratio and negative likelihood ratio. The discrimination of the model will be assessed using the AUROC and visualized using the ROC curve. The calibration of the model will be assessed using the calibration slope.

Plan for addressing confounding

There are no confounders as such in this study design. There will be predictor variables which take into account how variables that could vary between individuals affect overall risk.
We will develop a list of possible prediction variables based on a review of the literature as well as clinical insight then use variable selection procedure to determine which variables should be included in the models.

Plans for addressing missing data

Given that our data sources are clinical data that were not designed with research in mind, we can expect a significant amount of missing data. To address missing data, we will implement multiple imputation methods and present sensitivity analyses with different methods of handling missing data (i.e., complete analysis vs. multiple imputation).

Patient or user group involvement

Mrs Amy Wire is the PPI co-applicant on this project. Amy was diagnosed with gestational diabetes in her first pregnancy has first-hand lived experience of the condition. She was surprised by the amount of added stress the condition placed on her, and on her partner (who also did carb counting), and in light of her experience vowed that after her pregnancy she would help other women to prevent and better manage gestational diabetes. Amy volunteers as a patient champion for the NIHR Biomedical Research Centre Oxford Obesity theme, where she values learning about the planned and ongoing research studies relating to obesity and weight management, in particular where they relate to pregnancy and gestational diabetes.
Amy is not a researcher, but hopes that by providing her views based on her own experience she will help researchers and clinicians gain a deeper understanding of the aspects of research that matter most to people who have lived with gestational diabetes. She hopes that in the future more effective GDM prediction models will be available and effective prevention strategies can be offered to women at highest risk.
Amy helped to write the Plan English Summary. She will become a member of the Project Management Group, with monthly meetings planned to review the project's progress and to discuss ideas for dissemination, and also future projects.

Plans for disseminating & communicating

We will develop a formal dissemination strategy which will incorporate plans to systematically communicate the findings to all relevant stakeholders. The results of this project will be incorporated into a broader programme dissemination strategy which includes adjunct studies to explore the longer term health risks associated with GDM.
In parallel, we plan for presentations of the results for public policy-making and patient benefit, such as to the All Parliamentary Group on Diabetes, which will capture key policymakers.
The preliminary dissemination plan also includes submissions to peer-reviewed journals and presentations at international academic research conferences such as European Association for the Study of Diabetes.
Finally, articles or blog posts will be scripted for members of the public on platforms such as The Conversation, Gestational Diabetes UK (GDM support charity) and Mother & Baby Online magazine.

Conflict of interest statement

No conflicts declared

Limitations of study design

In the UK only women who are judged to be "at risk" of developing GDM will be offered a test to diagnose the condition (unless otherwise clinically indicated). Therefore, the exact number of women who have GDM is unclear as there will be an undefined number of untested women who have the condition but do not receive a diagnosis.
Some variables will likely be poorly recorded or missing in primary care records.
The project is biased by including only pregnancies resulting in a delivery recorded in HES. Whilst this will capture all registrable birth past 24 weeks gestation (including stillbirth and planned terminations) it will exclude any pregnancies that do result in miscarriage or planned termination before 24 weeks.
GDM screening, testing and diagnostic thresholds have changed. The most notable change happened in 2010- hence why we have limited our data to deliveries that happened after the implementation of clinical guideleines which changed the way GDM was screened and diagnosed in the UK.

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Appendices

Grant ID

(https://www.gov.uk/government/organisations/medicines-and-healthcare-products-regulatory-agency) Medicines & Healthcare products Regulatory Agency

(https://cprd.com/home)

UK data driving real-world evidence

eRAP Your dashboard Log out

Linkage request (Type 1) 3185 for #22_002383

Linked data will be supplied within 10 working days of receipt of a fully completed request form and valid code list(s), provided any necessary sub-licence agreements are fully executed.

Note that licensing fees may apply to access the requested linked data (please check the licence agreement for your organisation). Where affiliates or collaborators are requesting linked data on behalf of licence holding organisations, an executed CPRD-issued "Affiliate" or "Collaborator" sub-licence must exist between the licence holding organisation and each affiliate/third- party collaborator before requests for linked data are submitted to the CPRD. Please contact enquiries@cprd.com for further information on sub-licence agreements

This form should be completed if you require linked data to finalise the study population for an approved application before submitting a type 2 request. Further information regarding submitting linked data requests can be found on our website (https://cprd.com/guidance-requesting-linked-data-cprd (https://cprd.com/guidance-requesting-linked-data-cprd)).

Basic information

Study title

Risk prediction modelling for gestational diabetes

Application No.

#22_002383

Date of application approval

07/07/2023

Chief investigator

Dr Nerys Astbury

Corresponding applicant

Dr Nerys Astbury

Requestor name

Dr Nerys Astbury

Requestor email address

nerys.astbury@phc.ox.ac.uk

Organisation name

University of Oxford

Date of request

26/07/2023

Who should the data be delivered to

- ○ Dr Nerys Astbury
- ○ Ms Yasmina Al Ghadban
- ○ Dr Huiqi Yvonne Lu
- ◉ Dr Margaret Smith
- ○ Dr Cynthia Wright Drakesmith
- ○ Dr Subhashisa Swain
- ○ Ms Céline Aldenhoven
- ○ Ms Ruya Abdulsalam

Reason for request

We require linked HES data to define the study population - which is based on women who have a delivery record in the HES

976 word(s) remaining

Status: **Delivered**

Data sources requested

HES Admitted Patient Care

Is this data required to finalise the study population?

◉ Yes ○ No

Definition: Code lists

I requre the following variables:
patid
sex
epitype
admidate

957 word(s) remaining

Is a code list available for upload?

○ Yes ◉ No

Reason why there is no upload available

The eligible population are not based on a code list- they are based on event which will be determined using the above variables.

977 word(s) remaining

ONS Death Registration Data

Is this data required to finalise the study population?

○ Yes ◉ No

Patient Level (England only)

Patient Level Index of Multiple Deprivation

Is this data required to finalise the study population?

○ Yes ◉ No

Please enter any further information that is relevant to your linkage request *(optional)*

I will identify the eligible population based on a singleton delivery event in HES and not on a diagnosis- hance there is no code list.
This request is similar to a previous study which had similar population and Type 1 request #22_001731 (linkage request 2691)

955 word(s) remaining

☐ I confirm that I have checked with the Chief Investigator and relevant legal/contracts team that any/all relevant sub-licences are in place for all collaborators who will be accessing requested data prior to sharing

CPRD reserves the right to audit this declaration and request copies of any/all sublicences at any time.

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NIHR | National Institute for Health and Care Research
(https://www.nihr.ac.uk/)

Related resources

Download Application Form in Word Format (https://www.cprd.com/sites/default/files/2024-10/Template%20-%20CPRD%20RDG%20Protocol%20Application%20Form_v1.2.docx)

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Guidance on requesting Linked Data (https://cprd.com/guidance-requesting-linked-data-cprd)

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UK data driving real-world evidence

eRAP **Your dashboard** **Log out**

Linkage request (Type 2) 3587 for #22_002383

Linked data will be supplied within 10 working days of receipt of a fully completed request form and valid list of patient pseudonyms (i.e. patids) with the relevant linkage flags for the study population (e.g. patid, hes_apc_e, ons_death_e, etc) **or** code lists, provided any necessary sub-licence agreements are fully executed.

Note that licensing fees may apply to access the requested linked data (please check the licence agreement for your organisation). Where affiliates or collaborators are requesting linked data on behalf of licence holding organisations, an executed CPRD-issued “Affiliate” or “Collaborator” sub-licence must exist between the licence holding organisation and each affiliate/third- party collaborator before requests for linked data are submitted to the CPRD. Please contact enquiries@cprd.com for further information on sub-licence agreements

The latest available version of linked data will be supplied. Please contact us separately to request an alternative version. Further information regarding submitting linked data requests can be found on our website (https://cprd.com/guidance-requesting-linked-data-cprd (https://cprd.com/guidance-requesting-linked-data-cprd)).

Basic information

Study title

Risk prediction modelling for gestational diabetes

Application No.

#22_002383

Date of application approval

07/07/2023

Chief investigator

Dr Nerys Astbury

Corresponding applicant

Dr Nerys Astbury

Requestor name

Dr Nerys Astbury

Requestor email address

nerys.astbury@phc.ox.ac.uk

Organisation name

University of Oxford

Date of request

23/11/2023

Who should the data be delivered to

- ( ) Dr Nerys Astbury
- ( ) Ms Yasmina Al Ghadban
- ( ) Dr Huiqi Yvonne Lu
- (•) Dr Margaret Smith
- ( ) Dr Cynthia Wright Drakesmith
- ( ) Dr Subhashisa Swain
- ( ) Ms Céline Aldenhoven
- ( ) Ms Ruya Abdulsalam

Status: **Delivered**

CPRD Aurum

State the build of CPRD Aurum that has been used to define the study population

- ( ) Nov 2023
- ( ) Oct 2023
- ( ) Sep 2023
- ( ) Aug 2023
- ( ) Jul 2023
- ( ) Jun 2023
- ( ) May 2023
- ( ) Apr 2023
- ( ) Mar 2023
- ( ) Feb 2023
- ( ) Jan 2023
- ( ) Dec 2022
- (•) Other Build

Feb 2022

Enter the number of patients in list(s)

2902285

Do you require the CPRD Migrator file to allow you to remove duplicate patients from the database of your choice?

( ) Yes ( ) No

Is a data minimisation workbook required?

(•) Yes ( ) No

Please upload the data minimisation workbook

Data_Minimisation_Variable_Restriction_CPRDReview.xlsx
(/system/files/webform/linkage_request_type_2/3587/Data_Minimisation_Variable_Restriction_CPRDReview.xlsx)

Remove

One file only.
30 MB limit.
Allowed types: xls, xlsx, zip.

Linked data required

- [ ] CPRD GOLD Mother-Baby Link
- [ ] CPRD Aurum Mother-Baby Link
- [ ] HES Accident and Emergency
- [x] HES Admitted Patient Care
- [ ] HES Diagnostic Imaging Dataset
- [ ] HES Outpatient
- [ ] Mental Health Services Data Set (MHSDS)
- [x] ONS Death Registration Data
- [ ] CPRD GOLD Pregnancy Register
- [ ] CPRD Aurum Pregnancy Register
- [ ] SGSS (Second Generation Surveillance System)
- [ ] CHESS (Hospitalisation in England Surveillance System)
- [ ] ICNARC (COVID-19 Intensive Care National Audit and Research Centre)
- [ ] Practice Level Rural-Urban Classification
- [ ] Patient Level Rural-Urban Classification
- [ ] CPRD GOLD Ethnicity Record
- [ ] CPRD Aurum Ethnicity Record
- [ ] NCRAS Tumour / Treatment data
- [ ] Maternity Services Data

☐ BSA Dispensing Data

Patient Level (England only)

Patient Level Index of Multiple Deprivation

Stratification level

- ○ Quintiles
- ◉ Deciles
- ○ Twentiles

Please enter any further information that is relevant to your linkage request *(optional)*

1000 word(s) remaining

Patient list

Choose Files no files selected

☐ erap_22_002383_population_patids.txt.zip (/system/files/webform/linkage_request_type_2/3587/erap_22_002383_population_patids.txt.zip)

Remove selected

Unlimited number of files can be uploaded to this field.
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☑ I confirm that I have checked with the Chief Investigator and relevant legal/contracts team that any/all relevant sub-licences are in place for all collaborators who will be accessing requested data prior to sharing

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Supplementary File 10.3. Description of CPRD Aurum, HES APC, ONS and IMD data structure

Description of CPRD Aurum data structure
CPRD Aurum is comprised of multiple interlinked tables, each of which captures different aspects of patient care. The dataset is anonymised, with all identifiers encrypted, but linkage across tables is possible through common keys such as the patient identifier (*patid*) and practice identifier (*pracid*). The tables used in this research are presented below.

- **Patient table** which contains demographic and registration details for each individual. Key variables include the encrypted patient identifier (*patid*), practice identifier (*pracid*), sex, year and month of birth, registration start and end dates, and death date (where available).
- **Practice table** which contains information about the GP practices contributing data, including an encrypted practice identifier (*pracid*) and the geographical region in which the practice is located.
- **Observation table** which contains clinical information entered during consultations, such as symptoms, diagnoses, test results, and lifestyle factors. Each observation is recorded as a MedCodeID, which corresponds to a specific clinical term in the CPRD medical dictionary. This dictionary includes all medical history observations recorded in EMIS Web®. The observation table is used to identify and extract relevant clinical events. This table includes data recorded between 01/01/1995 and 20/12/2023.
- **Drug Issue table** contains prescribing information, including the drug, prescribed dose, quantity, and duration. Each prodcodeid can be mapped to a clinical term using the CPRD **Product Dictionary**, which holds information on all drug and appliance prescriptions recorded in EMIS Web®. This prescribing information is coded according to the Dictionary of Medicines and Devices (DM+D). This table includes data recorded between 01/01/1995 and 09/01/2022.

Description of HES APC
The HES APC dataset is also comprised of multiple interlinked tables that can be linked with the patient identifier (*patid*). The tables used in this research are presented below.

- Patient table which contains information on patients with linked HES records. Key variables include the patient identifier (*patid*), practice identifier (*pracid*), and patient ethnicity derived across all HES sources (admitted patient care, outpatient, and A&E).
- Diagnoses table which contains diagnostic information for each hospital episode, coded using the International Classification of Diseases, Tenth Revision (ICD-10). This table includes data recorded between 01/04/1989 and 31/03/2021.
- Procedures table contains details of operations and clinical interventions undertaken during hospital episodes. Each procedure is coded using the OPCS-4 classification system, which provides standardised codes for surgical and non-surgical interventions recorded in NHS hospitals. This table includes data recorded between 01/04/1989 and 31/03/2021.
- Maternity table provides detailed information on deliveries, such as maternal age at delivery, mode of delivery, gestational age, antenatal and postnatal length of stay, and neonatal outcomes such as sex, birthweight, resuscitation method, and level of neonatal care. This table includes data recorded between 01/04/1989 and 31/03/2021.

Description of ONS Death Registration structure

The ONS Death Registration table provides information on patient mortality, including the date of death, the date of registration, and up to 15 recorded causes of death, coded using ICD-10 codes. This table includes data recorded between 26/02/2000 and 26/03/2021.

Description of Index of Multiple Deprivation (IMD) structure
The IMD table provides socioeconomic status information through the 2019 IMD code (*e2019_imd_10*), which assigns each patient's postcode to a deprivation quintile ranging from 1 (least deprived) to 5 (most deprived). The IMD 2019 is a relative, area-level measure of multiple deprivation across England, calculated for small geographical areas. It is built on the premise that deprivation is multidimensional and arises from deficiencies in several domains of material and social disadvantage. In 2019, seven core domains are used: income deprivation**;** employment deprivation**; e**ducation, skills and training deprivation**;** health deprivation and disability; crime; barriers to housing and services; and living environment deprivation (309).

Supplementary Table 10.5. Summary of CPRD Aurum and Linked Data Tables and Variables

Variable	Description
CPRD Aurum Primary Care Data	
CPRD Aurum Patient Table (Patient)	
patid	Encrypted patient ID in CPRD Aurum
pracid	Encrypted practice ID in CPRD Aurum
gender	Patient's gender
yob	Patient's year of birth
regenddate	End of registration date at the practice
Practice Table (Practice)	
pracid	Encrypted practice ID in CPRD Aurum
region	Region defined by the Strategic Health Authority for English practices
Observation Table (Observation)	
patid	Encrypted patient ID in CPRD Aurum
obsdate	Event date
medcodeid	CPRD unique code for the medical term selected by the GP (MedCodeID)
value	Measurement or test value
numunitid	Unit of measurement
Hospital Episode Statistics - Admitted Patient Care	
HES Patient Table (hes_patient_DM)	
patid	Encrypted patient ID in CPRD Aurum
gen_ethnicity	Patient's ethnicity derived from all HES data (including HES outpatient, HES admitted patient care and HES A&E)
Drug Table (Drug_Issue)	
patid	Encrypted patient ID in CPRD Aurum
issuedate	Event date

prodcodeid	Unique CPRD code for the treatment selected by the GP
issuedate	Date associated with the event
Diagnoses by Episode Table (hes_diagnosis_epi_DM)	
patid	Encrypted patient ID in CPRD Aurum
epistart	Episode start date
ICD	ICD10 diagnosis code
Procedures by Episode Table (hes_procedures_epi_DM)	
patid	Encrypted patient ID in CPRD Aurum
epikey	Episode key uniquely identifying an episode of care
OPCS	OPCS-4 procedure code
evdate	Date of procedure
Maternity (hes_maternity_DM)	
patid	Encrypted patient ID in CPRD Aurum
epistart	Date of start of episode
numbaby	Number of babies (both live and stillborn) delivered
neocare	Neonatal level of care
birstat	Still birth
biresus	Resuscitation method used
birweit	Weight of the baby in grams immediately after birth
delmeth	Delivery method
gestat	Length of gestation
numpreg	Number of previous pregnancies (both live and stillborn)
matage	Mother's age at delivery
antedur	Antenatal days of stay
postdur	Postnatal days of stay
Office for National Statistics (ONS) Death Registration Data	
Patient ONS Table (Death_Patient_DM)	
patid	Encrypted patient ID in CPRD Aurum
dod	Date of death
cause	Underlying cause of death (ICD10 diagnosis code)
cause1	Recorded cause of death (ICD10 diagnosis code)
cause2	Recorded cause of death (ICD10 diagnosis code)
cause3	Recorded cause of death (ICD10 diagnosis code)
cause4	Recorded cause of death (ICD10 diagnosis code)
cause5	Recorded cause of death (ICD10 diagnosis code)
cause6	Recorded cause of death (ICD10 diagnosis code)
cause7	Recorded cause of death (ICD10 diagnosis code)
cause8	Recorded cause of death (ICD10 diagnosis code)
cause9	Recorded cause of death (ICD10 diagnosis code)
cause10	Recorded cause of death (ICD10 diagnosis code)
cause11	Recorded cause of death (ICD10 diagnosis code)

cause12	Recorded cause of death (ICD10 diagnosis code)
cause13	Recorded cause of death (ICD10 diagnosis code)
cause14	Recorded cause of death (ICD10 diagnosis code)
cause15	Recorded cause of death (ICD10 diagnosis code)
Index of Multiple Deprivation	
IMD Table (patient_2019_imd)	
patid	Encrypted patient ID in CPRD Aurum
e2019_imd_10	IMD code

Supplementary Table 10.6. Code List for GDM

Code	Term	Code Type
O24.4	Gestational diabetes mellitus	ICD10
20191016	Gestational diabetes mellitus	MedCodeId
801901000006119	Gestational diabetes mellitus	MedCodeId
1703761000000110	Gestational diabetes information leaflet given	MedCodeId
2128081000000110	Gestational diabetes mellitus annual review	MedCodeId
2686061000006110	GDM	MedCodeId
2686071000006110	Gestational diabetes	MedCodeId
2686101000006110	GDM - Gestational diabetes mellitus	MedCodeId
3258001000006110	Gestational diabetes mellitus, class A>2<	MedCodeId
3719631000006110	Gestational diabetes mellitus, class A>1<	MedCodeId
3719641000006110	GDM, class A>1<	MedCodeId
7217901000006110	Dietary education for gestational diabetes	MedCodeId
8016611000006110	Gestational diabetes, delivered	MedCodeId
8016621000006110	Gestational diabetes mellitus complicating pregnancy	MedCodeId
8264221000006110	Management of gestational diabetes mellitus	MedCodeId
15071651000006100	Gestational diabetes mellitus class A2	MedCodeId
15072391000006100	Gestational diabetes mellitus class A1	MedCodeId

Supplementary Table 10.7. Code List for T2DM and T2DM Complications

Code	Term	Code Type
T2DM without complications		
E11.9	Without complications	ICD10
306113018	Pre-existing diabetes mellitus, non-insulin-dependent	MedCodeId
479571000000110	Diabetes type 2 review	MedCodeId
840971000006112	Diabetes mellitus autosomal dominant type II	MedCodeId
3209431000006110	Diabetes mellitus type II	MedCodeId
3209441000006110	Diabetes mellitus type 2	MedCodeId
5109461000006110	Diabetes type 2 on insulin	MedCodeId
7968751000006110	Diabetes mellitus type 2 without retinopathy	MedCodeId
8084961000006110	Diabetes type II review	MedCodeId
T2DM with coma		

E11.0	Type 2 diabetes With coma	ICD10
459167016	Type 2 diabetes mellitus with hypoglycaemic coma	MedCodeId
84521000006116	Type 2 diabetes mellitus with hypoglycaemic coma	MedCodeId
84891000006116	Type II diabetes mellitus with hypoglycaemic coma	MedCodeId
280511000006113	Non-insulin dependent diabetes mellitus with hypoglyca coma	MedCodeId
928601000006118	Ketoacidotic coma in type 2 diabetes mellitus	MedCodeId
459169018	Hypoglycaemic coma co-occurrent and due to diabetes mellitus type II	MedCodeId
T2DM with acidosis		
E11.1	Type 2 diabetes With acidosis:	ICD10
E11.10	ketoacidosis	ICD10
E11.11	lactic acidosis	ICD10
E11.12	ketoacidosis with lactic acidosis	ICD10
928591000006114	Type II diabetes mellitus with ketoacidosis	MedCodeId
6977431000006110	Diabetes type 2 with ketoacidosis	MedCodeId
928581000006111	Ketoacidosis in type 2 diabetes mellitus	MedCodeId
T2DM with renal complications		
E11.2	Type 2 diabetes with kidney complications:	ICD10
E11.20	incipient diabetic nephropathy	ICD10
E11.23	established or advanced kidney disease	ICD10
E11.28	other specified kidney complication not elsewhere classified	ICD10
84611000006113	Type 2 diabetes mellitus with renal complications	MedCodeId
84981000006114	Type II diabetes mellitus with renal complications	MedCodeId
914041000006111	Type II diabetes mellitus with renal complications	MedCodeId
587521000006111	Non-insulin-dependent diabetes mellitus with renal comps	MedCodeId
84551000006113	Type 2 diabetes mellitus with nephropathy	MedCodeId
280531000006119	Non-insulin dependent diabetes mellitus with nephropathy	MedCodeId
914261000006119	Diabetes type 2 with nephropathy	MedCodeId
914271000006114	Type II diabetes mellitus with nephropathy	MedCodeId
928551000006115	Type II diabetes mellitus with persistent proteinuria	MedCodeId
928571000006113	Type II diabetes mellitus with persistent microalbuminuria	MedCodeId
928541000006117	Persistent proteinuria associated with type 2 diabetes mellitus	MedCodeId
928561000006118	Persistent microalbuminuria associated with type 2 diabetes mellitus	MedCodeId
T2DM with ophthalmic complications		
E11.3	Type 2 diabetes with ophthalmic complications:	ICD10
E11.30	background retinopathy	ICD10
E11.31	preproliferative retinopathy	ICD10

E11.32	proliferative retinopathy	ICD10
E11.33	other retinopathy	ICD10
E11.36	advanced ophthalmic disease	ICD10
E11.38	other specified ophthalmic complication not elsewhere classified	ICD10
84581000006117	Type 2 diabetes mellitus with ophthalmic complications	MedCodeId
9140610000006110	Type II diabetes mellitus with ophthalmic complications	MedCodeId
5871110000006111	Non-insulin-dependent diabetes mellitus with ophthalm comps	MedCodeId
84621000006117	Type 2 diabetes mellitus with retinopathy	MedCodeId
84991000006112	Type II diabetes mellitus with retinopathy	MedCodeId
9141610000006114	Type II diabetes mellitus with retinopathy	MedCodeId
6982521000006110	Diabetes type 2 with retinopathy	MedCodeId
7968881000006110	Proliferative diabetic retinopathy due to type 2 diabetes mellitus	MedCodeId
7968891000006110	Proliferative diabetic retinopathy due to type II diabetes mellitus	MedCodeId
7969151000006110	Nonproliferative diabetic retinopathy due to type 2 diabetes mellitus	MedCodeId
84501000006114	Type 2 diabetes mellitus with diabetic cataract	MedCodeId
281161000006114	Non-insulin dependent diabetes mellitus with diabetic cataract	MedCodeId
9143010000006111	Type 2 diabetes mellitus with diabetic cataract	MedCodeId
9143110000006114	Type II diabetes mellitus with diabetic cataract	MedCodeId
6959811000006110	Diabetes type 2 with cataract	MedCodeId
938321000006116	Exudative maculopathy associated with type 2 diabetes	MedCodeId
84871000006117	Cataract due to diabetes mellitus type 2	MedCodeId
7968821000006110	Diabetic vitreous haemorrhage associated with type II diabetes mellitus	MedCodeId
7968831000006110	Diabetic vitreous hemorrhage associated with type II diabetes mellitus	MedCodeId
14181641000006100	Mild nonproliferative retinopathy of left eye due to diabetes mellitus type 2	MedCodeId
14181661000006100	Mild nonproliferative retinopathy of right eye due to diabetes mellitus type 2	MedCodeId
14181691000006100	Mild nonproliferative retinopathy of both eyes due to diabetes mellitus type 2	MedCodeId
14181911000006100	Bilateral nonproliferative retinopathy due to diabetes mellitus type 2	MedCodeId
14181951000006100	Proliferative retinopathy of left eye due to diabetes mellitus type 2	MedCodeId
14181961000006100	Bilateral proliferative retinopathy due to diabetes mellitus type 2	MedCodeId
14182001000006100	Proliferative retinopathy of right eye due to diabetes mellitus type 2	MedCodeId

14728721000006100	Neovascular glaucoma due to diabetes mellitus type 2	MedCodeId
T2DM with neurological complications		
E11.4	Type 2 diabetes with neurological complications:	ICD10
E11.40	mononeuropathy	ICD10
E11.41	polyneuropathy	ICD10
E11.42	autonomic neuropathy	ICD10
84561000006110	Type 2 diabetes mellitus with neurological complications	MedCodeId
914081000006117	Type II diabetes mellitus with neurological complications	MedCodeId
280591000006115	Non-insulin-dependent diabetes mellitus with neuro comps	MedCodeId
84531000006118	Type 2 diabetes mellitus with mononeuropathy	MedCodeId
84601000006110	Type 2 diabetes mellitus with polyneuropathy	MedCodeId
84971000006111	Type II diabetes mellitus with polyneuropathy	MedCodeId
280521000006117	Non-insulin dependent diabetes mellitus with mononeuropathy	MedCodeId
280541000006112	Non-insulin dependent diabetes mellitus with polyneuropathy	MedCodeId
914221000006113	Type 2 diabetes mellitus with mononeuropathy	MedCodeId
914231000006111	Type II diabetes mellitus with mononeuropathy	MedCodeId
914251000006116	Type II diabetes mellitus with polyneuropathy	MedCodeId
84931000006113	Neurological disorder with diabetes type 2	MedCodeId
6969931000006110	Diabetes type 2 with neurological disorder	MedCodeId
7968951000006110	Diabetic peripheral neuropathy associated with type II diabetes mellitus	MedCodeId
T2DM with circulatory complications		
E11.5	Type 2 diabetes with circulatory complications:	ICD10
E11.50	peripheral angiopathy	ICD10
E11.51	peripheral angiopathy with gangrene	ICD10
E11.52	certain circulatory complications	ICD10
459306016	Type II diabetes mellitus with peripheral angiopathy	MedCodeId
459308015	Type 2 diabetes mellitus with peripheral angiopathy	MedCodeId
84591000006119	Type 2 diabetes mellitus with peripheral angiopathy	MedCodeId
84961000006116	Type II diabetes mellitus with peripheral angiopathy	MedCodeId
280561000006111	Non-insulin-dependent diabetes mellitus with peripheral angiopathy	MedCodeId
T2DM with other complications		
E11.6	With other specified complications:	ICD10
E11.60	musculoskeletal and connective tissue complication	ICD10
E11.61	skin and subcutaneous tissue complication	ICD10
E11.62	periodontal complication	ICD10
E11.63	hypoglycaemia	ICD10
E11.64	poor control	ICD10

E11.68	other specified complication, not elsewhere classified	ICD10
459310018	Type 2 diabetes mellitus with arthropathy	MedCodeId
459311019	Type II diabetes mellitus with arthropathy	MedCodeId
459312014	Type II diabetes mellitus with neuropathic arthropathy	MedCodeId
459313016	Type 2 diabetes mellitus with neuropathic arthropathy	MedCodeId
84491000006118	Type 2 diabetes mellitus with arthropathy	MedCodeId
84571000006115	Type 2 diabetes mellitus with neuropathic arthropathy	MedCodeId
84861000006112	Type II diabetes mellitus with arthropathy	MedCodeId
84941000006115	Type II diabetes mellitus with neuropathic arthropathy	MedCodeId
281181000006116	Non-insulin dependent diabetes mellitus with neuropathic arthropathy	MedCodeId
299621000000117	Gastroparesis with type 2 diabetes mellitus	MedCodeId
292589019	Type II diabetes mellitus - poor control	MedCodeId
292590011	Type II diabetes mellitus poorly controlled	MedCodeId
84481000006116	Type 2 diabetes mellitus - poor control	MedCodeId
84851000006110	Type II diabetes mellitus - poor control	MedCodeId
281171000006119	Type II diabetes mellitus uncontrolled	MedCodeId
T2DM with multiple complications		
E11.7	With multiple complications:	ICD10
E11.70	foot ulcer (angiopathic)(neuropathic)	ICD10
E11.71	foot ulcer (angiopathic) (neuropathic) with gangrene	ICD10
E11.78	multiple other complications	ICD10
E11.8	With unspecified complications	ICD10
292576013	Type II diabetes mellitus with multiple complications	MedCodeId
292577016	Type 2 diabetes mellitus with multiple complications	MedCodeId
84541000006111	Type 2 diabetes mellitus with multiple complications	MedCodeId
84911000006119	Type II diabetes mellitus with multiple complications	MedCodeId
280581000006118	Non-insulin-dependent diabetes mellitus with multiple complications	MedCodeId
292579018	Type 2 diabetes mellitus with ulcer	MedCodeId
292581016	Type II diabetes mellitus with ulcer	MedCodeId
84631000006119	Type 2 diabetes mellitus with ulcer	MedCodeId
85001000006117	Type II diabetes mellitus with ulcer	MedCodeId
280551000006114	Non-insulin-dependent diabetes mellitus with ulcer	MedCodeId
9313441000006110	Diabetes type 2 with diabetic ulcer of left foot	MedCodeId
292582011	Type II diabetes mellitus with gangrene	MedCodeId
292583018	Type 2 diabetes mellitus with gangrene	MedCodeId
84511000006112	Type 2 diabetes mellitus with gangrene	MedCodeId
84881000006119	Type II diabetes mellitus with gangrene	MedCodeId
9313421000006110	Diabetic ulcer of left foot due to diabetes mellitus type 2	MedCodeId

Supplementary Table 10.8. Comparison of baseline characteristics between included and excluded participants

Characteristic	Excluded (missing data) (n = 29,993)	Included (complete-case) (n = 167,798)	p-value	SMD
Follow-up time, years (mean ± SD)	6.89 (2.49)	7.01 (2.43)	<0.001	0.05
Maternal age, years (mean ± SD)	32.60 (5.31)	32.47 (5.36)	<0.001	0.03
BMI, kg/m² (mean ± SD)	26.80 (6.41)	27.09 (6.49)	<0.001	0.04
Gestational age, weeks (mean ± SD)	38.15 (1.82)	38.18 (1.81)	0.83	0.01
Birth weight, g (mean ± SD)	3,335 (554)	3,300 (542)	<0.001	0.06
Number of previous pregnancies (mean ± SD)	1.32 (1.62)	1.40 (1.62)	<0.001	0.05
Diabetic complications within 10 years, n(%)	47 (0.2%)	266 (0.2%)	1.0	0.00

Supplementary Table 10.9. Regression coefficients of the prediction model for T2DM in the validation cohort

Predictors	Model coefficients in validation cohort
Maternal age	
Knot 1	Reference
Knot 2	-0.01*
Knot 3	0.03***
Socioeconomically deprived	
No	Reference
Yes	0.36***
Substance use	
No	Reference
Yes	0.17***
Gestational age at delivery	
Knot 1	Reference
Knot 2	0.04**
Knot 3	-0.26***
SMM	
No	Reference
Yes	-1.0
Previous complications	
No, multiparous	Reference

Predictors	Model coefficients in validation cohort
Yes, multiparous	0.07
Primiparous	-0.07*
Hypertensive disorders of pregnancy	
No HDP	Reference
Pre-existing or unspecified hypertension	2.4
Gestational hypertension	-4.7
Pre-eclampsia/HELLP syndrome	0.64
Superimposed pre-eclampsia	NA[a]
Maternal age & SMM interaction	
Knot 1 SMM (no)	Reference
Knot 2 SMM (yes)	0.06
Knot 3 SMM (yes)	-0.06
Maternal age & hypertensive disorders of pregnancy interaction	
Knot 1 no hypertension	Reference
Knot 2 pre-existing or unspecified hypertension	-0.05
Knot 3 pre-existing or unspecified hypertension	0.04
Knot 2 gestational hypertension	0.13
Knot 3 gestational hypertension	0.03
Knot 2 pre-eclampsia/HELLP syndrome	-0.01
Knot 3 pre-eclampsia/HELLP syndrome	-0.01
Knot 2 superimposed pre-eclampsia	-0.01
Knot 3 superimposed pre-eclampsia	0.01

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ denote statistical significance in the validation cohort
[a]NA denotes coefficients that were non-estimable due to small sample size in the validation cohort

Supplementary Table 10.10. Regression coefficient estimates from an exploratory Cox proportional hazards model for T2DM with additional predictors

Predictors	Regression Coefficient Estimates (95% CI)	p-value
Prognostic Index (PI)		
PI	0.18 (0.16–0.20)	<0.001
Ethnicity		
White	Reference	
Asian	0.61 (0.53–0.70)	<0.001
Black	0.63 (0.53–0.74)	<0.001
Mixed	0.23 (-0.03–0.49)	0.08
Other	0.22 (0.03–0.41)	0.02
Treatment method		
Lifestyle modifications	Reference	
Metformin	0.17 (0.06–0.29)	0.002
Insulin	1.18 (1.09–1.27)	<0.001
BMI		
BMI	0.07 (0.07–0.08)	<0.001

10.1.4. Appendix 4. Supplementary Material for Chapter 4

Supplementary Table 10.11. Code Lists Used to Develop the DPP Pathway Query

Concept & Refset ID	Cluster ID	Cluster description	SNOMED code	SNOMED code description	Inclusion/ Exclusion
Gestational Diabetes (PCD Refset ID: 999017331000230105)	GESTDIAB_COD	Gestational Diabetes Codes	10753491000119101	Gestational diabetes mellitus in childbirth (disorder)	Inclusion
	GESTDIAB_COD	Gestational Diabetes Codes	11687002	Gestational diabetes mellitus (disorder)	Inclusion
	GESTDIAB_COD	Gestational Diabetes Codes	40791000119105	Postpartum gestational diabetes mellitus (disorder)	Inclusion
	GESTDIAB_COD	Gestational Diabetes Codes	40791000119106	Gestational diabetes mellitus complicating pregnancy (disorder)	Inclusion
	GESTDIAB_COD	Gestational Diabetes Codes	46894009	Gestational diabetes mellitus class A2 (disorder)	Inclusion
	GESTDIAB_COD	Gestational Diabetes Codes	472699005	Uncontrolled gestational diabetes mellitus (disorder)	Inclusion
	GESTDIAB_COD	Gestational Diabetes Codes	472971004	Past pregnancy history of gestational diabetes mellitus (situation)	Inclusion
	GESTDIAB_COD	Gestational Diabetes Codes	75022004	Gestational diabetes mellitus class A1 (disorder)	Inclusion
HbA1c (PCD Refset ID: 999003251000230103)	IFCCHBAM_COD	IFCC HbA1c monitoring range codes	1049301000000100	Haemoglobin A1c level (diagnostic reference range) - International Federation of Clinical Chemistry and Laboratory Medicine standardised (observable entity)	To show in column
	IFCCHBAM_COD	IFCC HbA1c monitoring range codes	1049321000000109	Haemoglobin A1c level (monitoring ranges) - International Federation of Clinical Chemistry and Laboratory Medicine standardised (observable entity)	To show in column
	IFCCHBAM_COD	IFCC HbA1c monitoring range codes	1107481000000106	Substance concentration of haemoglobin A1c in blood (observable entity)	To show in column

	IFCCHBAM_COD	IFCC HbA1c monitoring range codes	1971000237103	Substance concentration of haemoglobin A1c diagnostic reference range in blood (observable entity)	To show in column
	IFCCHBAM_COD	IFCC HbA1c monitoring range codes	6181000237109	Substance concentration of haemoglobin A1c monitoring range in blood (observable entity)	To show in column
	IFCCHBAM_COD	IFCC HbA1c monitoring range codes	999791000000106	Haemoglobin A1c level - International Federation of Clinical Chemistry and Laboratory Medicine standardised (observable entity)	To show in column
Fasting Plasma Glucose (PCD Refset ID: 999000971000230105)	FASPLASGLUC_COD	Fasting plasma glucose codes	1003141000000105	Plasma fasting glucose level (observable entity)	To show in column
	FASPLASGLUC_COD	Fasting plasma glucose codes	58111000237107	Fasting substance concentration of glucose in plasma (observable entity)	To show in column
Previous Diabetes (PCD Refset ID: 999004691000230108)	DM_COD	Diabetes mellitus codes	111552007	Diabetes mellitus without complication (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	112991000000101	Lipoatrophic diabetes mellitus without complication (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	1142044000	Pre-existing malnutrition-related diabetes mellitus in pregnancy (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	11530004	Brittle diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	1196922005	Neovascular glaucoma due to diabetes mellitus type 2 (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	1196923000	Neovascular glaucoma due to diabetes mellitus type 1 (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	1217044000	Ketosis-resistant diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	1217068008	Fulminant type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	1217674007	Neurotrophic keratitis due to diabetes mellitus (disorder)	Exclusion

	DM_COD	Diabetes mellitus codes	1255271005	Juvenile-onset diabetes mellitus, central and peripheral neurodegeneration syndrome (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	1222660008	Pancreatic agenesis, holoprosencephaly syndrome (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	127012008	Lipoatrophic diabetes (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	127013003	Disorder of kidney due to diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	127014009	Peripheral angiopathy due to diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	1481000119100	Diabetes mellitus type 2 without retinopathy (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	190368000	Type I diabetes mellitus with ulcer (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	190369008	Type I diabetes mellitus with gangrene (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	190372001	Type I diabetes mellitus maturity onset (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	190388001	Multiple complications due to type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	190389009	Type II diabetes mellitus with ulcer (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	190390000	Type II diabetes mellitus with gangrene (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	201724008	Neuropathic arthropathy due to diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	230577008	Mononeuropathy due to diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	237599002	Insulin treated type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	237604008	Maturity onset diabetes of the young, type 2 (disorder)	Exclusion

	DM_COD	Diabetes mellitus codes	237601000	Secondary endocrine diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	237612000	Photomyoclonus, diabetes mellitus, deafness, nephropathy and cerebral dysfunction (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	237618001	Insulin-dependent diabetes mellitus secretory diarrhea syndrome (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	237619009	Maternally inherited diabetes and deafness (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	268519009	Diabetic - poor control (finding)	Exclusion
	DM_COD	Diabetes mellitus codes	290002008	Brittle type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	313436004	Type II diabetes mellitus without complication (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	313435000	Type I diabetes mellitus without complication (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	314771006	Type I diabetes mellitus with hypoglycemic coma (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	314893005	Arthropathy due to type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	314903002	Arthropathy due to type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	314902007	Peripheral angiopathy due to type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	314904008	Type II diabetes mellitus with neuropathic arthropathy (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	335621000000101	Maternally inherited diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	368711000119106	Mild nonproliferative retinopathy due to secondary diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	385041000000108	Diabetes mellitus with multiple complications (disorder)	Exclusion

	DM_COD	Diabetes mellitus codes	408540003	Diabetes mellitus caused by non-steroid drugs (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	395204000	Hyperosmolar non-ketotic state due to type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	401110002	Type 1 diabetes mellitus with persistent microalbuminuria (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	413183008	Diabetes mellitus caused by non-steroid drugs without complication (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	420270002	Ketoacidosis due to type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	420825003	Gangrene due to type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	420868002	Disorder due to type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	421437000	Hypoglycemic coma due to type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	421305000	Persistent microalbuminuria due to type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	421075007	Ketoacidotic coma due to type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	421750000	Ketoacidosis due to type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	421631007	Gangrene due to type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	421847006	Ketoacidotic coma due to type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	422014003	Disorder due to type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	422228004	Multiple complications due to type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	426705001	Diabetes mellitus co-occurrent and due to cystic fibrosis (disorder)	Exclusion

	DM_COD	Diabetes mellitus codes	426875007	Latent autoimmune diabetes mellitus in adult (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	427089005	Diabetes mellitus due to cystic fibrosis (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	44054006	Diabetes mellitus type 2 (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	443694000	Uncontrolled type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	444073006	Uncontrolled type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	445353002	Brittle type 2 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	4855003	Retinopathy due to diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	46635009	Diabetes mellitus type 1 (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	49455004	Polyneuropathy due to diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	5368009	Drug-induced diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	51002006	Diabetes mellitus associated with pancreatic disease (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	5969009	Diabetes mellitus associated with genetic syndrome (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	609572000	Maturity-onset diabetes of the young, type 5 (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	703138006	Type II diabetes mellitus in remission (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	739681000	Disorder of eye due to type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	8801005	Secondary diabetes mellitus (disorder)	Exclusion

	DM_COD	Diabetes mellitus codes	82581000119105	Rubeosis iridis due to type 1 diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	816067005	Diabetes, hypogonadism, deafness, intellectual disability syndrome (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	768794008	Cataract of bilateral eyes due to diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	768793002	Cataract of left eye due to diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	768792007	Cataract of right eye due to diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	75682002	Diabetes mellitus caused by insulin receptor antibodies (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	70694009	Wolfram syndrome (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	73211009	Diabetes mellitus (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	737212004	Diabetes mellitus caused by chemical (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	703136005	Diabetes mellitus in remission (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	703137001	Type I diabetes mellitus in remission (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	609562003	Maturity onset diabetes of the young, type 1 (disorder)	Exclusion
	DM_COD	Diabetes mellitus codes	609561005	Maturity-onset diabetes of the young (disorder)	Exclusion
Diabetes Resolved (PCD Refset ID: 999003371000230102)	DMRES_COD	Diabetes resolved codes	315051004	Diabetes resolved (finding)	Exclusion
Previous DPP Referral (PCD RefsetID: 999000931000230108)	DPPOFF_COD	Referral to NHS diabetes prevention	1090701000000104	National Health Service Diabetes Prevention Programme invitation (procedure)	Exclusion if within 2 years & no

		programme offered or declined			subsequent completed / started code
	DPPOFF_COD	Referral to NHS diabetes prevention programme offered or declined	1025321000000109	Referral to National Health Service Diabetes Prevention Programme (procedure)	Exclusion if within 2 years & no subsequent completed / started code
	DPPOFF_COD	Referral to NHS diabetes prevention programme offered or declined	1025301000000100	Referral to National Health Service Diabetes Prevention Programme declined (situation)	Exclusion if within 2 years
	DPPCOMP_COD	Referral to NHS diabetes prevention programme completed	1025251000000107	National Health Service Diabetes Prevention Programme completed (situation)	Exclusion
	DPPATT_COD	Referral to NHS diabetes prevention programme attended	1025211000000108	National Health Service Diabetes Prevention Programme not completed (situation)	Exclusion if within 2 years & no subsequent completed / started code
	DPPATT_COD	Referral to NHS diabetes prevention programme attended	1025271000000103	National Health Service Diabetes Prevention Programme started (situation)	Exclusion

Supplementary File 10.4. Text message template for the DPP pathway

- Dear **[Patient-FirstName],**

Your GP has identified that you have a history of gestational diabetes and are eligible for the FREE NHS Diabetes Prevention Programme. To register, visit https://lwtcsupport.co.uk/gestational-diabetes-referral-form/

10.1.5. Appendix 5. Supplementary Material for Chapter 5

Supplementary Table 10.12. RECORD Checklist for observational studies using routinely collected health data

	Item No.	STROBE items	Location in manuscript where items are reported	RECORD items	Location in manuscript where items are reported
Title and abstract					
	1	(a) Indicate the study's design with a commonly used term in the title or the abstract (b) Provide in the abstract an informative and balanced summary of what was done and what was found	5.1	RECORD 1.1: The type of data used should be specified in the title or abstract. When possible, the name of the databases used should be included. RECORD 1.2: If applicable, the geographic region and timeframe within which the study took place should be reported in the title or abstract. RECORD 1.3: If linkage between databases was conducted for the study, this should be clearly stated in the title or abstract.	5.1
Introduction					
Background rationale	2	Explain the scientific background and rationale for the investigation being reported	5.2		

Objectives	3	State specific objectives, including any prespecified hypotheses	5.3		
Methods					
Study Design	4	Present key elements of study design early in the paper	5.4		
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	3.4.1 3.4.2 3.4.3 3.4.4 5.4.1		
Participants	6	*(a) Cohort study* - Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up *Case-control study* - Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls *Cross-sectional study* - Give the eligibility criteria, and the	3.4.4 3.4.5 5.4.1	RECORD 6.1: The methods of study population selection (such as codes or algorithms used to identify subjects) should be listed in detail. If this is not possible, an explanation should be provided. RECORD 6.2: Any validation studies of the codes or algorithms used to select the population should be referenced. If validation was conducted for this study and not published elsewhere, detailed	3.4.5 5.4.1 Appendix 3 3.5.1 Figure 3.1 5.5.1 Figure 5.1

		sources and methods of selection of participants *(b) Cohort study* - For matched studies, give matching criteria and number of exposed and unexposed *Case-control study* - For matched studies, give matching criteria and the number of controls per case		methods and results should be provided. RECORD 6.3: If the study involved linkage of databases, consider use of a flow diagram or other graphical display to demonstrate the data linkage process, including the number of individuals with linked data at each stage.	
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable.	3.4.5 5.4.1 5.4.3 5.4.4	RECORD 7.1: A complete list of codes and algorithms used to classify exposures, outcomes, confounders, and effect modifiers should be provided. If these cannot be reported, an explanation should be provided.	Appendix 3 Github
Data sources/ measurement	8	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	3.4.1 3.4.2		

Bias	9	Describe any efforts to address potential sources of bias	5.4.3 5.4.4 5.4.5 5.6.6		
Study size	10	Explain how the study size was arrived at	3.4.3 3.4.4 3.5.1 5.5.1		
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen, and why	5.4.2 5.4.3 5.4.4 5.4.5		
Statistical methods	12	(a) Describe all statistical methods, including those used to control for confounding (b) Describe any methods used to examine subgroups and interactions (c) Explain how missing data were addressed	5.4.3 5.4.4 5.4.5 5.4.6		

		(d) *Cohort study* - If applicable, explain how loss to follow-up was addressed *Case-control study* - If applicable, explain how matching of cases and controls was addressed *Cross-sectional study* - If applicable, describe analytical methods taking account of sampling strategy (e) Describe any sensitivity analyses	5.4.6 5.4.5 5.4.4		
Data access and cleaning methods				RECORD 12.1: Authors should describe the extent to which the investigators had access to the database population used to create the study population. RECORD 12.2: Authors should provide information on the data cleaning methods used in the study.	3.4.3 3.4.5 5.4.5
Linkage				RECORD 12.3: State whether the study included person-level, institutional-level, or other data linkage across two or more databases. The methods of linkage and methods of linkage quality evaluation should be provided.	3.4.2 3.4.3 5.4.2

Results					
Participants	13	(a) Report the numbers of individuals at each stage of the study (*e.g.*, numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed) (b) Give reasons for non-participation at each stage. (c) Consider use of a flow diagram	3.5.1 Figure 3.1 5.5.1 Figure 5.1	RECORD 13.1: Describe in detail the selection of the persons included in the study (*i.e.,* study population selection) including filtering based on data quality, data availability and linkage. The selection of included persons can be described in the text and/or by means of the study flow diagram.	3.5.1 Figure 3.1 5.5.1 Figure 5.1
Descriptive data	14	(a) Give characteristics of study participants (*e.g.*, demographic, clinical, social) and information on exposures and potential confounders (b) Indicate the number of participants with missing data for each variable of interest (c) *Cohort study* - summarise follow-up time (*e.g.*, average and total amount)	5.5.1 5.5.2 Table 5.2 5.4.5 Table 5.1 5.5.3		

			5.5.1 5.4.4		
Outcome data	15	*Cohort study* - Report numbers of outcome events or summary measures over time *Case-control study* - Report numbers in each exposure category, or summary measures of exposure *Cross-sectional study* - Report numbers of outcome events or summary measures	5.5.1 5.5.5 5.5.6		
Main results	16	(a) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (e.g., 95% confidence interval). Make clear which confounders were adjusted for and why they were included (b) Report category boundaries when continuous variables were categorized (c) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	5.5.4 Table 5.3 5.5.5 Table 5.4 5.4.2 Table 5.2		

			5.5.6 Figure 5.6		
Other analyses	17	Report other analyses done—e.g., analyses of subgroups and interactions, and sensitivity analyses	5.4.6 Appendix 5		
Discussion					
Key results	18	Summarise key results with reference to study objectives	5.6.1		
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	5.6.6	RECORD 19.1: Discuss the implications of using data that were not created or collected to answer the specific research question(s). Include discussion of misclassification bias, unmeasured confounding, missing data, and changing eligibility over time, as they pertain to the study being reported.	5.6.6 5.5.3
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	5.6.1 5.6.2 5.6.3 5.6.4 5.6.5		
Generalisability	21	Discuss the generalisability (external validity) of the study results	5.6.4 5.6.5		

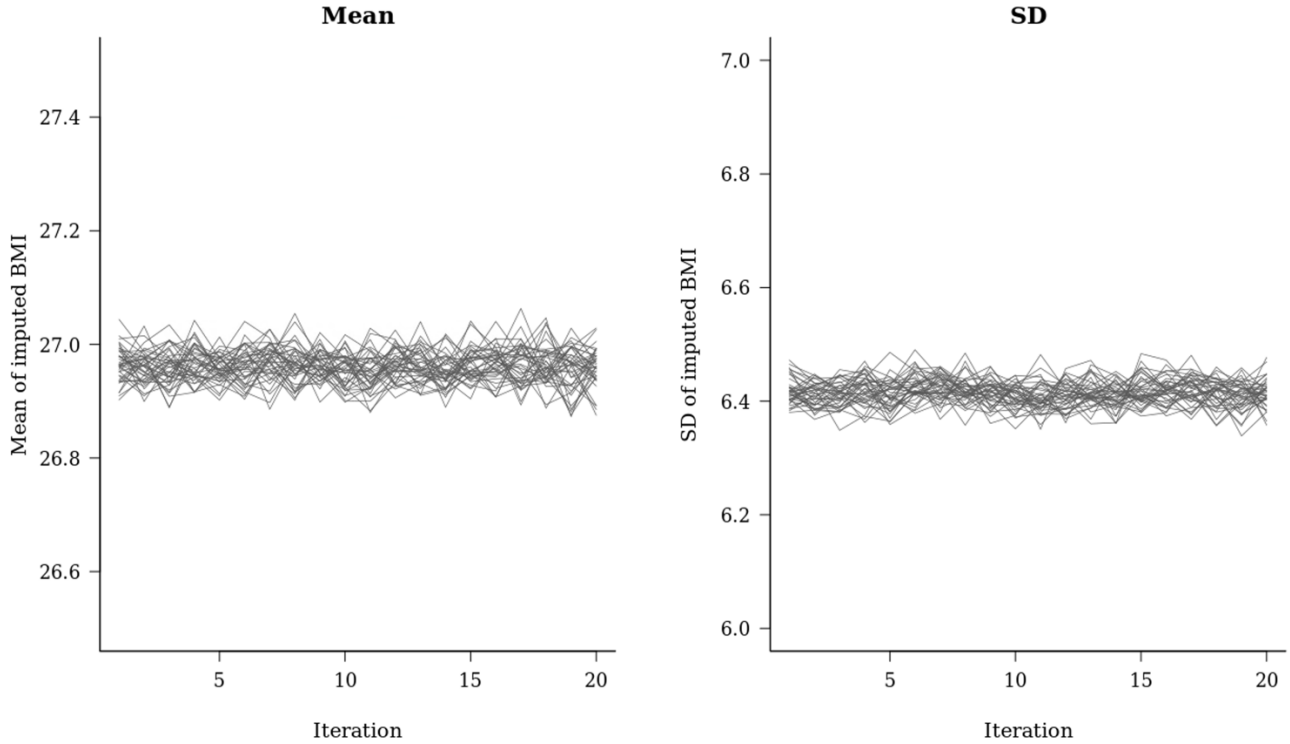
			5.6.6		
Other Information					
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	Acknowledgements		
Accessibility of protocol, raw data, and programming code		..		RECORD 22.1: Authors should provide information on how to access any supplemental information such as the study protocol, raw data, or programming code.	3.4.3 Github Appendix 3

Supplementary Table 10.13. Diagnostic logistic regression model for any missing covariate data

Variable	Adjusted OR	95% CI	p-value
Missed (GDM record in secondary care)	1.12	1.09 to 1.15	<0.001
Diabetes status at 10 years: Yes	1.19	1.12 to 1.27	<0.001
Maternal age (per year)	0.95	0.94 to 0.95	<0.001
Ethnicity: Asian	1.16	1.13 to 1.20	<0.001
Ethnicity: Black	1.34	1.29 to 1.40	<0.001
Ethnicity: Mixed	1.32	1.23 to 1.42	<0.001
Ethnicity: Other	1.44	1.37 to 1.51	<0.001
IMD quintile.2	1.04	1.01 to 1.07	0.01
IMD quintile.3	1.04	1.01 to 1.06	0.007
IMD quintile.4	1.02	0.99 to 1.04	0.226
IMD quintile.5	1.01	0.99 to 1.04	0.302
Previous complications: Primiparous	1.13	1.10 to 1.15	<0.001
Previous complications: Yes, multiparous	0.97	0.94 to 1.01	0.203
Treatment: Lifestyle	2.05	1.93 to 2.17	<0.001
Treatment: Metformin	1.07	1.00 to 1.14	0.064
Region: East of England	1.41	1.28 to 1.55	<0.001
Region: London	1.199	1.11 to 1.30	<0.001
Region: North East	1.13	1.02 to 1.25	0.021
Region: North West	1.61	1.49 to 1.74	<0.001
Region: South East	1.47	1.36 to 1.59	<0.001
Region: South West	1.98	1.83 to 2.15	<0.001
Region: West Midlands	1.32	1.22 to 1.43	<0.001
Region: Yorkshire and the Humber	1.26	1.14 to 1.39	<0.001

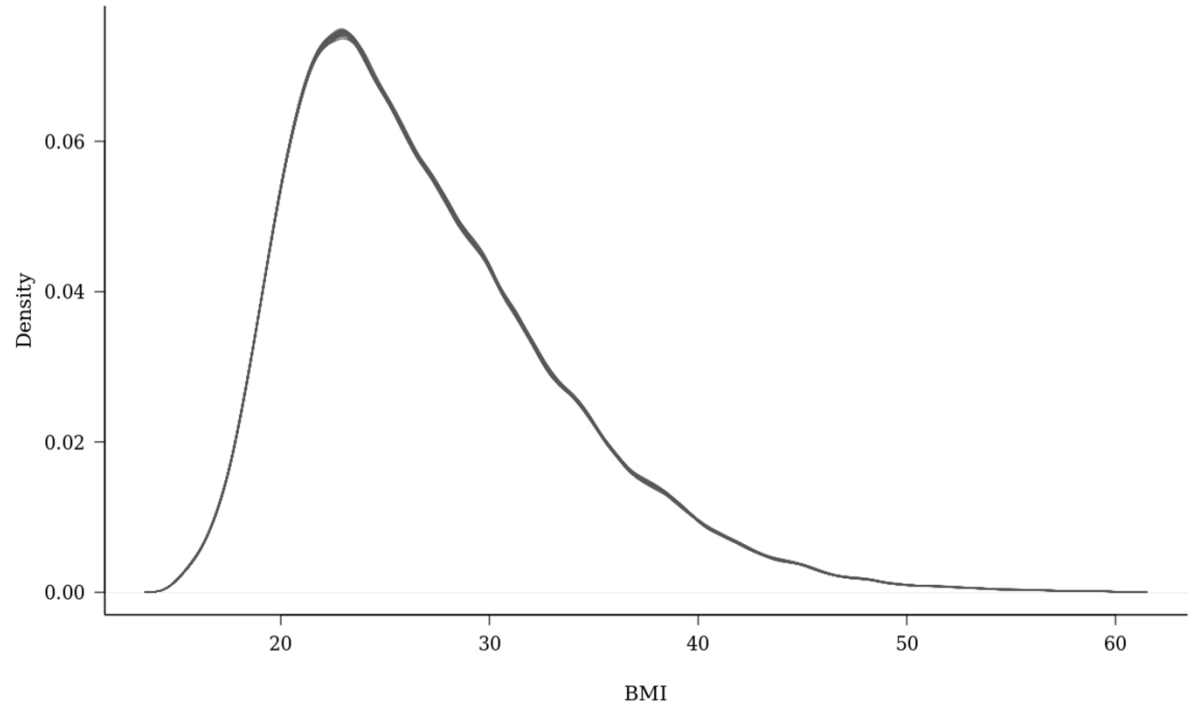
Variable	Adjusted OR	95% CI	p-value
Delivery period 2013-2015	0.60	0.58 to 0.61	<0.001
Delivery period 2016-2018	1.10	1.08 to 1.13	<0.001
Delivery period 2019-2021	1.05	1.03 to 1.08	<0.001
Hypertensive disorders: No	0.97	0.59 to 1.67	0.916
Hypertensive disorders: Preeclampsia/HELLP/eclampsia	0.96	0.58 to 1.65	0.873
Hypertensive disorders: Pre-existing/unspecified	0.89	0.53 to 1.55	0.677
Hypertensive disorders: Superimposed preeclampsia	0.70	0.18 to 2.32	0.58
SMM: Yes	1.02	0.91 to 1.14	0.74
Gestational age	1.00	0.99 to 1.00	0.591
Birthweight	1.00	1.00 to 1.00	0.449

Supplementary Figure 10.1. Convergence plot for imputed BMI values



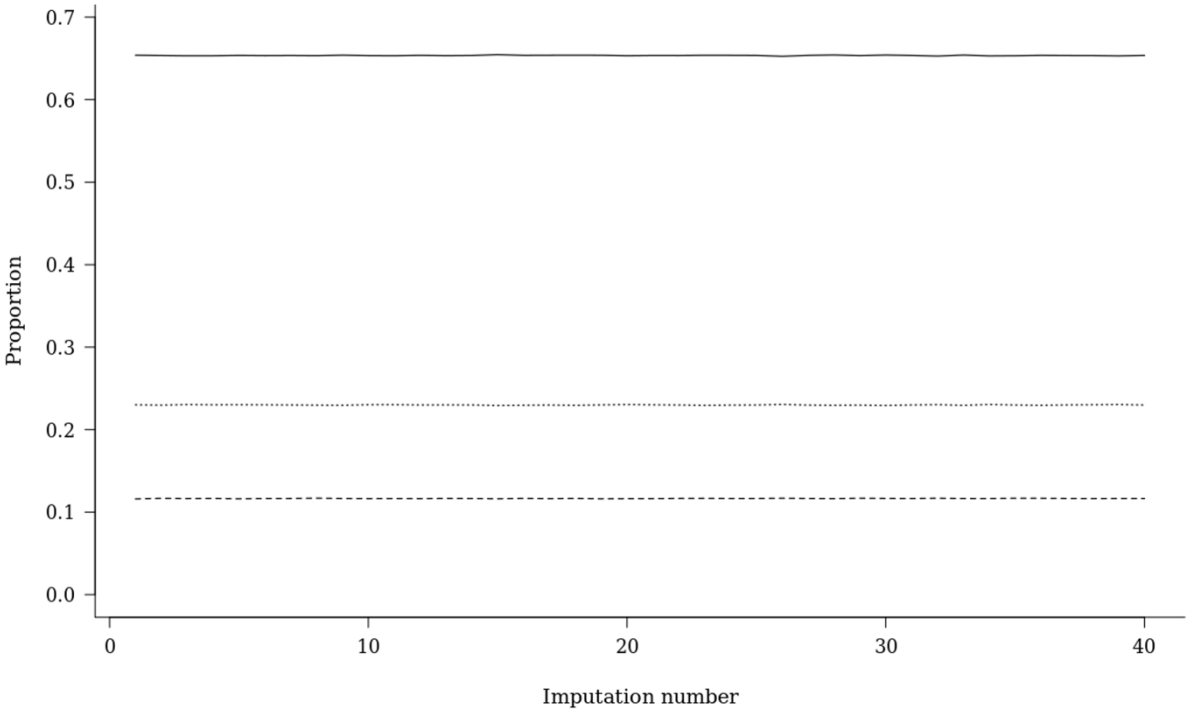
Trace plots show the mean and standard deviation of imputed BMI values across 20 iterations of the multiple imputation procedure. The close overlap of chains and absence of marked trends suggest adequate convergence.

Supplementary Figure 10.2. Density plot of BMI across imputed datasets.



The density curves overlap, indicating that the distribution of imputed BMI values was consistent across datasets**.**

Supplementary Figure 10.3. Proportions of smoking status categories across imputed datasets



The category proportions remain almost constant across the 40 imputations, indicating stable imputation of smoking status.

10.1.6. Appendix 6. Supplementary Material for Chapter 6

Supplementary Table 10.14. CHART checklist mapped to numbered sections of Chapters 6 and 7 (272)

CHART item	Checklist requirement	Numbered section in thesis
1a	State that the study assesses a generative AI-driven chatbot for health advice	Chapter 6, 7 titles
1b	Structured abstract/summary	6.1; 7.1
2a	Scientific background, rationale, healthcare context	6.2; 6.2.1; 6.2.2; 6.2.3; 6.2.4; 7.2.1; 7.2.2
2b	Aims/research questions including audience, intervention, outcomes	6.3; 7.3
3a	Name/version of model(s) and chatbot(s), release/update date	6.5; 6.6.3; 7.4.3.3
3b	Open-source or closed-source/proprietary	6.5.4
4a	State whether model is base, novel base, tuned, or fine-tuned	6.5.1; 6.5.4; 6.6.3
4b	If base model used, cite development details	6.5.4
4c	Describe deployment data and parameters	6.5.4; 6.5.5; 6.6.3; 7.4.3.1; 7.4.3.2
5a	Describe evolution of prompt development	6.4.3; 6.4.4; 6.5.6; 6.7.5; 7.4.3
5ai	Sources of prompts	6.4.3; 6.6.2; 7.5.2
5aii	Number/characteristics of people involved in prompt engineering	6.4.1; 6.4.2; 6.4.3; 6.6.2
5aiii	Patient/public involvement in prompt engineering	6.4.3; 6.4.4
5b	Provide study prompts	6.5.6
6a	Route of access to the model	6.4.4; 6.5.4
6b	Dates and locations of queries	6.4.2; 7.4.2; 7.4.3.3

CHART item	Checklist requirement	Numbered section in thesis
6c	Whether prompts were entered in separate chat sessions	6.5.6
6d	Provide chatbot outputs/responses	6.7.3; 7.5.2; 7.5.4; Table 7.1
7a	Define ground truth/reference standard	6.6.2
7b	Describe performance evaluation process	6.6; 6.6.1; 6.6.2; 7.4.3.3
7bi	Number/characteristics of evaluators	6.6.1; 6.4.2; 7.5.1
7bii	Patient/public involvement in evaluation	6.6.2; 7.5.2; 7.5.4
7biii	Whether evaluators were masked to chatbot identity	6.6.1
8	How sample size was determined	6.4.2; 7.4.1
9a	Statistical analysis methods, including reproducibility	6.5.5; 6.6.3; 7.4.3.3
9ai	Measures used for performance evaluation	6.6.1; 6.5.5; 7.4.2; Table 7.1
10a	Report alignment between chatbot output and reference standard	6.7.3; 6.6.3; 7.5.4; Table 7.1
10b	Report nature of deviations from ground truth	6.7.3; 6.7.4; 6.8.2; 7.5.3
10c	Report harmful, biased, or misleading responses	6.6.1; 6.8.3; 7.4.3.2; Table 7.1
11a	Interpret findings in context of evidence	6.8.1; 6.8.2; 7.6.1; 7.6.2
11b	Strengths and limitations	6.8.4; 7.6.3
11c	Implications for practice, education, policy, regulation, research	6.8.3; 7.6.4; 6.8.4
12a	Conflicts of interest	Funding
12b	Funding and funder role	Funding
12c	Ethical approval process	6.4.2

CHART item	Checklist requirement	Numbered section in thesis
12ci	Safeguards for data privacy	6.4.4; 7.6.4
12cii	Permission/licensing for copyrighted data	NA
12d	Study protocol	6.4.2
12e	Data/code/model parameter access	No public access

Supplementary File 10.5. Prompts used in SHP GPT

Main response-generation prompt:
You are an informational health bot that retrieves information from documents. Indian community health workers will provide you with questions related to health topics. Use the following pieces of context to answer the question. Provide the answer in the English language. Use simple language that is easy to understand for readers educated up to Grade 10. Make sure to use empathetic language in your answer. If you do not know the answer, say that you do not know the answer.

Context:
{context}

Question:
{question}

Question rewriting prompt:
You will be provided with an input related to a health topic. The input will be delimited by four hashtags (####). If the input is not in question format, rewrite it in question format. The new question should be the rewritten question. If the input is already in question format, do not change it. The new question should be the same as the input.

Categorisation prompt:
You will be provided with questions related to a health topic. The question will be delimited by four hashtags (####). Classify each question into one category.

Categories:
- Desire to Have a Male Child
- Reasons for Infertility
- Family Disputes
- Desire to Not Follow National Guidelines
- Decisions about Pregnancy Termination
- Mental Health Issues (Depression, Anxiety, Suicide)
- Clinical Questions
- Skin Complexion

Provide your output in JSON format with the key: "category"

Supplementary Table 10.15. A summary of participants during different phases of development

Stage of Development	State	Participants
Co-Design Workshops	Telangana	16 ASHAs
	Haryana	8 ASHAs
	Haryana	8 ASHAs
Clinical Validation with Experts	Telangana	6 community health doctors
	Haryana	6 community health doctors and 2 obstetrics and gynaecology doctors
Pilot User Testing 1	Telangana	4 ASHAs
	Haryana	4 ASHAs
Pilot User Testing 2	Telangana	4 ASHAs
	Haryana	4 ASHAs

Supplementary File 10.6. Qualitative data collection methods conducted by Ankita Sharma

This work was conducted by the clinical team, led by Ankita Sharma. I did not conduct this component of the work, and I am only presenting it here briefly to provide a complete overview of the end-to-end development of SHP GPT.

Focus Group Discussions (FGDs)

Six FGDs were conducted with ASHAs, with 6–8 participants per group. FGDs were selected based on insights from initial participant observation, which indicated that ASHAs were more comfortable engaging in collective discussions, reflecting the collectivist social context of their work environment. FGDs also enabled the development of group-level consensus and were well suited to exploring shared challenges, training needs, and commonly encountered maternal health questions. The number of FGDs was determined by data saturation.

In Telangana, FGDs were co-facilitated by the primary researcher and a second qualitative researcher involved in the broader process evaluation, with support from a local translator fluent in Telugu and English. The translator provided real-time translation to enable organic discussion. One researcher led the discussion, while the other supported moderation, probing,

and note-taking. In Haryana, FGDs were conducted by the primary researcher in Hindi without a translator. Audio recordings were reviewed after each session, and detailed ethnographic field notes were compiled following each FGD.

In-depth Interviews (IDIs)

IDIs were conducted to support triangulation across data sources and enhance the credibility of findings. Questions related to ASHA training and capacity building were embedded within the broader SHP process evaluation interviews. IDIs were conducted with four stakeholder groups: pregnant women, Auxiliary Nurse Midwives (ANMs), intervention-group field supervisors, and senior health system stakeholders. Two interviews were conducted with participants from each group. The number of IDIs was determined by data saturation and the degree of concordance across data sources.

Participant observation

In addition to FGDs and IDIs, three participant observations were conducted of ASHAs during routine household visits across both states. With participant consent, photographs were taken and detailed ethnographic field notes were recorded. In several instances, ASHAs provided guided tours of villages and local health facilities; in others, customary welcome practices such as dance performances or shared meals were observed. The researcher also conducted observations of two SHP refresher training sessions, one in Telangana and one in Haryana.

Participatory workshops

While FGDs and IDIs addressed research questions i–iii, participatory workshops were designed to address research question iv. This methodological shift was informed by feedback from ASHAs, who reported difficulty understanding the concept of generating frequently asked questions (FAQs) during group discussions, often perceiving the activity as a form of testing.

Two participatory workshops were therefore conducted, one in each state, with 16 ASHAs per workshop. The sample size enabled division into equal sub-groups of four participants, with ASHAs from different primary health centres (PHCs) mixed within each group. To introduce the purpose and structure of the workshop, a one-minute explanatory video was developed and shown at the start of each session.

The workshops consisted of two structured exercises:

Pile sorting exercise: Based on a line-by-line content analysis of transcripts from the FGDs, 120 maternal health questions were generated. These questions were distributed across workshop groups, with each group reviewing 40 questions. ASHAs collectively discussed the relevance of each question and sorted them into three categories: “Frequently asked,” “Sometimes asked,” and “Never asked.” This exercise enabled prioritisation of training needs and informed the selection of questions for chatbot development.

Free listing exercise: To capture additional questions not identified during FGDs, a free listing exercise was conducted. ASHAs were asked to list questions they frequently received from women in the community, followed by a separate prompt to identify questions they considered sensitive.

Supplementary Table 10.16. 179 Questions and Gold Standard Responses

Question			Gold Standard Response
1	We tell women that their baby is fully done forming at 3 months but the ultrasound at 3 months was normal and the ultrasound at 5 months showed that the baby did not have a kidney, another baby did not have a cranium. Why did the ultrasound not show this at 3 months when the baby should be done fully forming by then?	While it's true that major organs and structures have formed by the end of the first trimester (3 months), they continue to develop and mature throughout the pregnancy. The resolution of ultrasound imaging also improves as the pregnancy progresses, making it easier to detect abnormalities. Therefore, some conditions may not be visible or detectable until later in pregnancy.	Ultrasound is a useful tool to screen for fetal anomalies, but it is not 100% accurate or reliable. There are several possible reasons why the ultrasound at 3 months did not detect these defects, such as: 1. Some fetal anomalies may not be visible or fully developed in the first trimester, when the baby is still very small and the organs are not fully formed. For example, the kidneys start to develop around 10 weeks of gestation, but they may not be clearly seen on ultrasound until 18 to 20 weeks. Similarly, the cranium and brain structures may not be well visualized until later in the second trimester. 2. The position and movement of the baby in womb can also influence how well the ultrasound can show their anatomy. Some positions may make it easier or harder to see certain organs or parts of the body. For example, if the baby is lying on their back, their spine may obscure their kidneys or brain. If the baby is moving a lot, it may be difficult to get a clear and stable image. However, even with a normal ultrasound at 3 months, it is still recommended to have another ultrasound at 18 to 20 weeks to confirm the fetal anatomy and screen for any problems that may have been missed or developed later. If woman has still any concerns or questions about ultrasound results, she should talk to medical officer who can explain them and offer her further testing or counseling if needed.
2	Can a woman lift heavy weight after a C-section?	The document does not provide specific information on whether a woman can lift heavy weight after a C-section.	It depends on how recently she had her C-section and the amount of weight. For the first 3 months after c- section a woman should not get involved in any strenuous activity which can put undue pressure on her abdomen due to the risk of reopeningof stictches resulting in rupture of uterus. She can lift weight equal to her baby's weight only. So, woman cannot lift heavy weights more than 10 kg within 3 months of a C-section, after 3 months she can increase lifting 2-4 kg more every month as needed. If she experiences abdominal pain, bleeding or incontinence due to carrying weight, she should stop and avoid that activity.
3	A woman is having leg pain during the third trimester of	The document does not provide information on whether leg pain during the third trimester of pregnancy is normal.	Leg pain during the third trimester of pregnancy can be normal, but caution should be exercised as it could be a sign of venous congestion. This condition occurs in pregnancy and can lead to a more serious condition called DVT (Deep Vein Thrombosis), which can

	pregnancy. Is this normal?		further develop into pulmonary embolism. Therefore, it is not considered normal and immediate referral of the pregnant woman to the Medical Officer of her area is required.
4	Why do I experience shortness of breath when walking?	The shortness of breath when walking could be due to a number of health conditions. It could be a sign of heart conditions such as irregular heartbeats or palpitations, or lung conditions. It could also be a symptom of anemia, which is indicated by paleness of skin, pale conjunctivae, pale tongue, and changes to nails. It's important to consult with a healthcare professional for an accurate diagnosis.	Shortness of breath when walking can be due to several reasons. If you are in late pregnancy, it is quite normal to experience breathlessness due to the increase in size of the uterus (womb) which pushes the diaphragm and lungs upwards, leading to breathlessness. However, breathlessness in early pregnancy or at rest is not normal and you should consult a medical officer. Another possible cause could be anemia, which can also lead to shortness of breath. This will resolve when the anemia is corrected.
5	We get many types of tests from you but why don't you tell gender of baby in womb.	The gender of the baby in the womb is not disclosed due to the Pre-Conception, Prenatal Diagnostic Techniques Act. This law prohibits sex selection, before or after conception. It is an offence to try to find out whether the baby is a boy or a girl using techniques such as ultrasound and amniocentesis. Any laboratory, centre, or clinic conducting any test to see if the baby is a boy or a girl, or anyone letting the pregnant woman or her relatives know the baby's gender in any way, is in violation of this law.	The gender of a baby in the womb is not disclosed due to legal restrictions in India. This law is in place to prevent the abnormal sex ratio caused by the selective abortion of female fetuses. As per the PCPNDT act, it is illegal to reveal the gender of the growing fetus in the womb. This is done to maintain the balance of the male and female sex ratio in the country. why do you want to know the gender of the baby whether its a boy or girl he/she should be treated, loved and respected equally.

6	Why do so many women have blood pressure problems during pregnancy?	I'm sorry, but the provided context does not contain information on why so many women have blood pressure problems during pregnancy.	Women are more likely to experience high blood pressure problems during pregnancy due to several factors. These include a previous history of high blood pressure in a prior pregnancy, being of an older age (over 35 years), obesity, diabetes, hypertension, renal disease, and defective placental implantation. The prevalence of these conditions, such as obesity and diabetes, has been increasing in recent years, contributing to the rise in blood pressure problems during pregnancy. Therefore, it is crucial for blood pressure to be checked at each prenatal visit.
7	A woman has leukorrhea during pregnancy. This is not getting better after taking medication. What should she do?	I'm sorry, but the provided documents do not contain specific information on what a woman should do if she has leukorrhea during pregnancy that is not getting better after taking medication.	Leukorrhea, or vaginal discharge, is a common occurrence during pregnancy due to hormonal changes. This discharge is typically clear, milky white, and has a mild or no smell. If there is no itching, burning, or pain in the vagina or vulva, then it is normal and does not require any treatment. The woman should be counseled in detail about the nature of the discharge and reassured that she does not need any treatment. However, if the discharge becomes very sticky, thick, white, lumpy like curd, foul-smelling, or is associated with itching, burning, or pain in the vagina or vulva, then she should be referred to a medical officer.
8	How many times should a woman change her pad after delivery?	The sanitary pads must be changed every 4-6 hours or more frequently if there is heavy lochia. This is essential to ensure that the woman does not contract any infection.	The frequency of changing a pad after delivery depends on the amount of bleeding a woman is experiencing. In the first few days when bleeding is typically heavier, she should aim to change her pad every 4-6 hours, or before it becomes fully soaked. As the bleeding lessens, she should still change her pad at least 2-3 times a day to avoid any infections and maintain hygiene. Overall, it is normal to change a pad 3-5 times a day after delivery.
9	How do I know if a woman's blood sugar is normal based on the results I get?	The normal reference values for blood sugar are as follows: Random Blood Sugar (RBS) should be between 70-110 mg/dl, Fasting Blood Sugar (FBS) should be between 70-99mg/dl, and Postprandial Blood Sugar (PPBS) should be less than 140mg/dl. If a woman's blood sugar levels fall within these ranges, then her blood sugar is considered normal.	To determine if a woman's blood sugar is normal based on the results, an oral glucose tolerance test is performed. This involves giving the woman 75g of glucose, dissolved in approximately 300ml of water. Her blood sugar is then measured 2 hours later. If the value is less than 140mg/dl, it indicates that her blood sugar is normal. However, if the plasma glucose level is more than or equal to 140 mg/dl, it means she may have gestational diabetes mellitus (GDM) and should consult a medical officer for lifestyle advice and medication as needed.

10	How should we advice women who have breastfeeding problems?	Women experiencing breastfeeding problems should be advised on the correct position to ensure good attachment of the baby. If the nipples are cracked or sore, they should apply hind breast milk, which has a soothing effect, and ensure correct positioning and attachment of the baby. If discomfort continues, they should feed expressed breast milk with a clean spoon from a clean bowl. If the breasts are engorged, they should let the baby continue to suck without causing too much discomfort and a warm compress on the breast may help to relieve breast engorgement.	To advise women who have breastfeeding problems, it is important to observe the breastfeeding process, including the positioning of the mother and baby. If the baby has a tongue tie, it should be addressed. The mother should be encouraged to breastfeed on demand and if there is not enough milk, the baby should feed more often. The father and family members should be advised on how to burp the baby and ensure the mother is properly nourished and hydrated. Common breastfeeding problems include sore nipples, inverted nipples, and not producing enough milk. Sore nipples can be caused by poor latch-on or positioning at the breast. To manage this, improve attachment and/or position, continue breastfeeding, build the mother's confidence, and advise her to wash her breast once a day without soap. After feeding, she can put a little breast milk on her nipples to lubricate them and allow them to air-dry. If the nipples are very red, shiny, flaky, itchy, and their condition does not improve, it may be a fungus infection and she should be referred to a doctor. Inverted nipples can be checked even during pregnancy. The mother should be encouraged to gently pull out the nipple and roll it several times a day. If the mother is not producing enough milk, it could be due to delayed initiation of breastfeeding, infrequent feeding, giving fluids other than breast milk, the mother's anxiety, exhaustion, insecurity, or inadequate family support. To manage this, decide whether there is enough milk or not by checking if the baby passes urine six times or more each day, if the baby has gained sufficient weight, and if the baby is satisfied after feeds. Encourage the mother to rest, drink, and eat more. Praise her and schedule a follow-up. In all cases, reassure the mother and refer her to a higher centre for any further issues.

11	A woman's Hb is 11 - 12 grams. Why is her leg swelling not going down even though her Hb is normalised?	The document does not provide information on why a woman's leg swelling is not going down even though her Hb is normalised.	A woman's Hb level of 11 - 12 grams is within the normal range for adult females. Leg swelling can also be due to other causes, which are not related to the hemoglobin (Hb) level. Additionally, swelling of legs is normal during pregnancy after prolonged standing or in the evenings. If the swelling persists even in the morning after a full night's rest or if there is swelling of the face or hands, she should be referred to a medical professional. Leg swelling can be due to fluid retention, inflammation, infection, injury, blood clots, or problems with the heart, kidneys, or liver. The woman should consult her doctor to find out the exact cause of her leg swelling and get the appropriate treatment.
12	I just did the OGTT test and it is 160, what should I advise next?	The document does not provide specific signs that a pregnant woman with gestational diabetes should watch for or when she should contact the doctor right away.	The OGTT test result of 160 indicates an abnormal reading, suggesting gestational diabetes. The next step should be a referral to the medical officer for initiation of treatment and lifestyle advice related to physical activity, balanced diet and regular periodic check ups. Lifestyle changes such as a healthy and balanced diet and regular mild exercise like walking are often recommended. The woman can also be encouraged to include fenugreek, green vegetables like bitter gourd (Karela), lettuce leaves, lady finger (bhindi), carrot, soya beans, drumstick, and jamun in her diet. During pregnancy one can opt for whole foods that naturally contain less fat such as fruits, vegetables, and grains. Reducing the amount of oil used during cooking . High-fat foods such as nuts, high-fat milk, and ghee should be consumed in moderation. Using low-fat dairy products in place of whole milk or full cream products, choosing low fat snacks like fresh fruit instead of high-fat snacks such as cakes, biscuits, chocolates, and pastries, and using lean meat in place of red meat can also help in reducing fat intake.
13	Is there a risk if a woman has too many pregnancies?	Yes, there is a risk if a woman has too many pregnancies. Women who have had four or more pregnancies, also known as grand multiparas, are at a higher risk of developing complications during pregnancy and labour. Additionally, an interval of less than two years from the previous pregnancy or less than three months from the previous abortion increases	Yes, there is a risk if a woman has too many pregnancies. As the number of pregnancies increases, the risk for both the mother and the baby also increases. The mother is more prone to anemia, which can lead to recurrent infections. There are also increased chances of uterus rupture, pre-term birth, Intra-uterine Growth Retardation (IUGR), and stillbirth. Additionally, the risk of cervical cancer increases with the number of pregnancies. Other risks include multiple births and birth defects, also known as congenital abnormalities, as well as increased chances of abortions.

		the chances of the mother developing anaemia.	
14	A woman has too many headaches during her pregnancy. Is this normal?	Headaches can occur during pregnancy, but if they are frequent or severe, it could indicate a more serious problem such as high blood pressure. It is recommended that a pregnant woman experiencing frequent headaches consult a doctor.	No, having too many headaches during pregnancy is not normal. It could potentially be due to increased blood pressure or pregnancy-induced hypertension. It is recommended to get a health checkup done to ensure the woman's wellbeing.
15	A woman has the urge to pee very often after delivery. Is this normal?	Increased frequency of urination can be a physiological response due to the pressure of the gravid uterus on the urinary bladder. However, if this persists after 12 weeks, or there are other symptoms like burning on urination, tenderness at the sides of the abdomen and back, or raised body temperature, it could indicate a urinary tract infection (UTI). In such cases, the woman should be referred to a medical officer at the primary health care center.	Yes, it is normal for a woman to have the urge to pee very often after delivery. This is often due to stress incontinence that most women experience post-delivery. The woman can be taught simple Kegel exercises to strengthen her pelvic muscles which will resolve this condition in time. However, if urgency or incontinence persists for a longer duration, it should be addressed urgently as frequent urination can also be a sign of a urinary tract infection. A complete urinary examination should be done to confirm the presence of any infection.
16	What is GDM ? Women often ask why and how GDM develops ?	Gestational Diabetes Mellitus (GDM) is a condition where high blood glucose levels occur among women during pregnancy. It usually disappears after the birth of the baby. GDM develops when the mother's	GDM, or Gestational Diabetes Mellitus, is a condition characterized by increased sugar levels in the blood that is first recognized or develops during pregnancy, typically around the 20th week. This happens because during pregnancy, hormone levels change and the body sometimes finds it difficult to process the blood sugar levels efficiently, resulting in high levels of sugar in the blood. The chances of developing GDM are higher in pregnant mothers who are obese, physically inactive, pre-diabetic, have a family history of

		body is not able to make and use all the insulin it needs for pregnancy. As a result, glucose cannot leave the blood and be changed to energy. Glucose builds up in the blood to high levels, a condition called hyperglycemia. This can lead to the baby receiving more glucose than it needs, causing the baby to put on extra weight.	diabetes, have been diagnosed with Polycystic Ovarian Disease, or have previously delivered a baby weighing more than 3kgs. Thyroid disorder is also linked to GDM. GDM carries a high risk of developing diabetes in the mother or child in later stages of life and can have dangerous consequences such as abortion, intra-uterine death, birth defects, respiratory problems, and others in the child.
17	Why is vomiting occurring during pregnancy	Vomiting during pregnancy, especially in the first trimester, may be physiological and is often referred to as morning sickness. This is a common symptom of pregnancy due to hormonal changes in the body. However, if vomiting is excessive, especially after the first trimester, it could be a sign of a more serious condition called hyperemesis gravidarum, which may lead to dehydration and requires medical attention.	Vomiting during pregnancy occurs primarily due to hormonal changes, specifically the increase of the hormone called human Chorionic Gonadotropin. This hormone is responsible for causing morning sickness, which includes vomiting. The intensity of vomiting can vary depending on the number of fetuses, as in twin pregnancies, where there is more vomiting due to increased hormone production. Similarly, in molar pregnancies, there is also more vomiting due to increased hormone production.

18	What type of food should pregnant/ postpartum woman eat?	A pregnant or postpartum woman should eat a nutritious diet rich in iron, calcium, and protein. This includes green, leafy vegetables like palak and sarson, dals, milk, jaggery, eggs, fish, and meat. It's important to avoid taboos and restrictions on certain vegetables, fruits, milk, and ghee as these might harm her and the baby. Pregnant women should not fast as it deprives her and the growing baby of essential food.	Pregnant and postpartum women should eat food rich in protein, calories, minerals, and vitamins. This includes lentils, paneer, and vegetables, as well as foods rich in calcium such as fruits like chikoo and sitaphal. They should also consume protective foods such as eggs if they can. It's recommended to take small and frequent meals, about 4-6 times a day. Vitamin C rich fruits like amla, guava, and orange, green leafy vegetables, legumes, nuts, and other fruits and vegetables should be included in the diet. Cereals can be replaced twice or thrice with millets. It's also beneficial to consume at least half a litre of milk or lassi daily, one big bowl of dal once daily, and to add green leafy vegetables, salads (such as cucumber, cabbage, carrot, radish), fruit, lemon, and jaggery to the diet at least 2-3 times a week. After delivery, it's important to consume a lot of liquids (water, milk) and roughage (green leafy vegetables, cucumber, raw vegetables) to avoid constipation. The amount of salt should be restricted and double fortified salt should be used. Refined wheat flour and highly polished rice should be avoided. There is no prohibition of any food item and family members should also be informed about the woman's diet.
19	Why does bleeding occur during pregnancy?	Bleeding during pregnancy can occur due to several reasons. Before 20 weeks of pregnancy, the probable causes could be a threatened or spontaneous abortion, an ectopic pregnancy, or a hydatidiform mole. In some cases, it may be a very early pregnancy, and the woman might not even be aware that she is pregnant. Alternatively, the woman might not be pregnant, and the vaginal bleeding might instead be menorrhagia (excessive bleeding during periods).	Bleeding during pregnancy is usually considered abnormal, warranting immediate medical attention. It can be a sign of early pregnancy loss, ectopic pregnancy, low lying placenta, placental separation, or an abnormal pregnancy. In the early stages of pregnancy, light bleeding or spotting can occur, which is usually harmless. This bleeding can sometimes occur after intercourse or due to infections. In third trimester of pregnancy, bleeding can occur in the early stages of delivery. If there is fresh blood, one has to be vigilant. Additionally, bleeding can occur if there is a threatened abortion, the presence of the placenta near the opening of the uterus, or any other cause where there is a tendency for bleeding.

20	Why does blood(haemoglobin) decrease during pregnancy?	The document does not provide specific information on why haemoglobin levels decrease during pregnancy.	The decrease in hemoglobin, or anemia, during pregnancy can be attributed to several factors. One common reason is that the woman may already be anemic before becoming pregnant. Other reasons include poor nutrition, worm infestation, and malaria. Hormonal changes during pregnancy also contribute to this decrease, as the blood plasma or fluid in the blood increases. This physiological change is normal and facilitates the flow of blood to the placenta and the developing fetus, catering to its nutrition. Additionally, the body's demand for iron increases during pregnancy, which cannot be met by diet alone and often requires extra iron intake in the form of iron folic acid tablets. Decreased hemoglobin can also be due to nutritional deficiencies, infections, or blood-related disorders. Therefore, monitoring hemoglobin levels during pregnancy is crucial and any significant decrease needs to be treated on a priority basis.
21	Why do thyroid problems come in pregnancy?	Thyroid problems can occur in pregnancy due to hormonal changes and the immune system's response. Pregnancy causes a surge in hormones that can cause the thyroid gland to enlarge and produce more thyroid hormones. Additionally, the immune system can sometimes mistakenly attack the thyroid gland, leading to conditions like hypothyroidism. Uncontrolled hypothyroidism during pregnancy can lead to various complications like preeclampsia, anaemia, miscarriage, low birth weight baby, stillbirth, and rarely congestive heart failure.	Thyroid problems during pregnancy are often due to pre-existing conditions that are diagnosed when a thyroid test is done during pregnancy. However, the hormonal changes that occur during pregnancy can alter the functioning of many glands, including the thyroid. Additionally, the increased demand for iodine during pregnancy can lead to thyroid issues if the mother is iodine deficient, as iodine is needed for normal thyroid function. The developing fetus also requires more iodine, which can exacerbate the mother's iodine deficiency and lead to hypothyroidism. Regular checks and a diet rich in iodine, such as iodised salt, can help manage these issues.

22	Why does blood pressure increase in pregnancy?	The exact cause of blood pressure increase in pregnancy, specifically in conditions like preeclampsia, is still unknown. However, it is thought to be related to problems with the woman's blood vessels and the placenta, which connects the mother and baby, allowing blood to flow between them.	Blood pressure can increase during pregnancy due to a variety of factors. One reason is that the body needs to increase blood pressure to supply the placenta, which is essential for delivering oxygen to the fetus. Other factors that can contribute to increased blood pressure during pregnancy include genetics, family history, advanced maternal age (over 35 years), obesity, multiple pregnancies, pre-existing medical conditions such as diabetes or renal disease, stress, and a history of high blood pressure or pregnancy-induced hypertension in previous pregnancies. It's important to note that high blood pressure during pregnancy can put both the mother and baby at risk for complications during and after delivery. Therefore, regular blood pressure checks are crucial during prenatal visits.
23	Why do abortions (miscarriages) happen?	I'm sorry, but the provided documents do not contain specific information on why abortions or miscarriages happen.	Abortions, or miscarriages, can occur due to a variety of reasons. These can include chromosomal anomalies, hormonal imbalances, coagulation disorders, and uterine abnormalities such as an incompetent cervix, which might open early in pregnancy. Other factors can be related to the age of the mother, with very young or older ages posing a higher risk. Lifestyle factors such as stress, smoking, excessive alcohol consumption, and trauma to the mother during pregnancy can also contribute. Health conditions like diabetes, heart diseases, thyroid problems, and malnutrition can also lead to miscarriages. Infections and certain medications can also be a cause. Sometimes, the cause may not be identified. Additionally, a miscarriage can occur due to defective development of the fetus. For more detailed information, it is recommended to consult a medical officer.
24	What type of food should be taken when blood(haemoglobin) decrease during pregnancy.	Pregnant women with decreased haemoglobin levels should increase their intake of iron-rich foods. This can include foods like red meat, poultry, seafood, leafy green vegetables, and iron-fortified cereals. Additionally, they are advised to have 400 mcg of Folic Acid tablets daily. However, large amounts of carbohydrate foods eaten at one time can lead to high blood glucose levels and should be avoided.	When experiencing a decrease in haemoglobin during pregnancy, it is recommended to consume foods rich in protein, iron, and vitamin C. This includes at least one big katori of whole dal daily, green leafy vegetables, jaggery, whole grains and pulses, nuts and oilseeds. If the family consumes non-vegetarian food, meat, eggs, liver, and fish are also beneficial. Foods such as yogurt and mushrooms, which are rich in B12, can also be consumed. However, for B12, one needs to take animal foods which are rich in it. Vitamin C-rich foods such as lemons, tomatoes, guavas, oranges, amlas, and sprouts are important as they help in the absorption of iron in the body, which is crucial for the health of the mother and the baby. It is also advised to take one lemon with meals and jaggery after meals. Along with these dietary changes, it is recommended to take iron and folic acid tablets as advised by health staff. Regular checks of haemoglobin levels are also

			important, and if the level is less than 7, a referral to a community health worker is advised.
25	Why am I feeling like Heart palpitations and fatigue in early pregnancy?	These symptoms could be due to changes in your body during early pregnancy, such as increased blood volume and hormonal changes. However, they could also be signs of anemia or high blood pressure, which are common in pregnancy. It's important to consult with a healthcare provider to determine the exact cause and appropriate treatment.	Feeling palpitations and fatigue in early pregnancy is quite common and can be due to a variety of factors. These symptoms are often due to hormonal changes that occur during pregnancy. Other potential causes include low blood or haemoglobin levels, which can lead to anemia, anxiety, depression, dehydration or electrolyte imbalance, excessive weight, obesity, low blood pressure, and low blood glucose. If these palpitations are associated with excessive pallor, swelling, breathlessness at rest or during sleep, it is considered abnormal and the woman should consult a medical officer. Sometimes, these symptoms can also be due to heart-related conditions, which can be dangerous to the life of the mother and/or baby. Additionally, these symptoms could be due to a thyroid disorder, such as hyperthyroidism. It's important for the woman to be seen by a doctor for further examination of the case.
26	What can happen if a woman has postpartum Anaemia?	If a woman has postpartum anaemia, she may feel tired, experience shortness of breath, and feel weak. This can affect her ability to care for her baby and to breastfeed. It can also increase her risk of infections. Treating anaemia can help the woman feel more energetic and better able to look after her baby after birth.	If a woman has postpartum anaemia, which can occur if she was anaemic during her pregnancy and was not treated properly, or if there was excessive blood loss during or after delivery, she may experience a range of symptoms and complications. These can include weakness, lethargy, breathlessness, palpitations, and bleeding problems. Mental health issues such as confusion, depression, and anxiety may also develop. Additionally, postpartum anaemia can lead to failed or decreased lactation, potentially due to the mental anxiety or depression associated with the condition. To manage this condition, it is recommended that the woman modify her diet to include foods rich in protein, iron, and vitamin C, such as whole dal, green leafy vegetables, lemon, and jaggery. She should also take iron and folic acid (IFA) tablets. It is important that family members are also

			informed about these dietary changes. Furthermore, the woman should be referred to a primary care doctor for further care and support.
27	This lady had a C-section one week ago and there is some fluid around the scar. What advice can I give her?	You should advise her to seek immediate medical attention as the fluid around the scar could be a sign of a surgical site infection. Symptoms of a surgical site infection include fever, pus discharge from the wound, reopening of the surgical wound, or painful, spreading redness surrounding the surgical site. It's important that she gets this checked out by a medical professional as soon as possible.	Fluid around a C-section scar can be due to poor healing or infection. If there are no other symptoms such as fever, pain, redness, or pus discharge, she can wait for 2-3 days to see if there is any improvement. If not, she should be referred to a medical officer who may need to dress the wound. It's normal to have some redness along the incision line and a small amount of fluid around the scar if the edges are neat and close together. She should wash her hands with warm water and soap before touching the scar, and avoid lifting anything heavy that could put pressure on the stitches. The incision should be cleaned with mild soap and warm water, and patted dry with a clean towel. She should not share her towel or soap, and should avoid applying lotions, powders, or oils unless recommended by a healthcare professional. She should keep an eye on the scar for signs of infection, which may include the area feeling firm and hot, looking red and swollen, and discharging bloody, greenish or yellowish pus with a bad odor. Fever may also develop if the scar is infected. She should show the scar to a medical officer. If the scar is infected, she may need to dress the wound with antiseptics and cotton gauze to soak up the fluid, and she may be prescribed antibiotics to control the fluid.

28	What advice should I give a woman with high blood pressure?	The woman with high blood pressure should be advised to take medications prescribed by her doctor as directed. She should have her blood pressure checked at least every year following her pregnancy. Lifestyle counselling should be provided, advising her to reduce her salt intake, engage in regular exercise, and maintain a healthy weight. She should also be encouraged to engage with the NCD programme at the PHC after her pregnancy.	A woman with high blood pressure should take extra rest and continue with all her medications as advised by her healthcare provider. She should regularly monitor her blood pressure and consult a medical officer urgently if high blood pressure is detected for the first time. Lifestyle modifications are also crucial, such as decreasing salt intake to less than 1 tsp per day, consuming 5-6 servings of fresh fruits and vegetables, and exercising in the form of walking for at least 30 minutes per day for at least 5 days a week. It's important to maintain a calm and stress-free environment, and family can help create such an environment to make her feel safe and loved. She should also be alert about serious symptoms such as severe headaches, visual problems, severe heartburn, pain in the upper abdomen, excessive nausea, vomiting, swelling of the face or hands, and shortness of breath. If any of these symptoms are present, she should be referred to a specialist immediately.
29	If a woman has both thalassemia and severe anaemia, how should she be reffered?	The woman should be referred to a hospital for immediate medical attention. Both thalassemia and severe anaemia are serious conditions that require professional medical treatment. It is important that she is accompanied to the hospital for her safety.	A woman with both thalassemia and severe anemia is considered a high-risk pregnancy and should be referred to a tertiary care center. refer to the health center having specialists such as hematologists, who are doctors specializing in blood disorders, and gynecologists. These specialists can perform various tests including blood tests and genetic tests, and prescribe the appropriate treatment and medication for her condition. This may include regular blood transfusions, which are clinically decided based on the woman's symptoms and fetal growth. If there is worsening maternal anemia or evidence of Fetal Growth Retardation, the woman's hemoglobin should be monitored after 2 to 3 weeks. In addition to this, the woman should undergo a specialist cardiac assessment at 28 weeks of gestation and thereafter as appropriate to determine cardiac function. She should also have an early USG scan at 6-7 weeks of gestation, a routine first trimester scan, a detailed anomaly scan, and serial fetal biometry scans every 4 weeks from 24 weeks of gestation. Furthermore, the woman should be counseled about her disease and the chances of her child inheriting the disease in the future. Thalassemia is a genetic disorder that results in the production of abnormal hemoglobin.

30	A lady has gained 15 kg during the first 24 weeks of pregnancy. Are there any exercises she should be doing?	The document does not provide information on specific exercises a pregnant woman who has gained 15 kg during the first 24 weeks of pregnancy should be doing.	Weight gain during pregnancy is normal, with the average recommended weight gain for a pregnant woman being about 9-11 kg throughout the entire pregnancy. However, if a woman is overweight, she should aim to gain less weight, about 7 to 9 kg. If a woman has gained 15 kg during the first 24 weeks of pregnancy, it is considered high and could be due to complications such as high blood pressure, diabetes, or a twin pregnancy. Excessive weight gain in pregnancy is associated with having a large baby, which can lead to delivery complications like cesarean delivery, and obesity during childhood. Therefore, it is important to keep track of calorie intake, eat a balanced diet including fruits, vegetables, low-fat dairy products, high protein foods, and limit sugars and fats. Recommended exercises include brisk walking for at least 30 minutes a day for 5 days a week or yoga asanas specifically designed for pregnant women, after consulting with a healthcare provider. However, due to the excessive weight gain, it is crucial that the woman is evaluated by a medical officer or gynecologist for further advice and to rule out any other causes for the weight gain.
31	This pregnant lady has mouth ulcers. She wants a home remedy and some diet advice. What can I tell her?	I'm sorry, but the provided documents do not contain information on home remedies or diet advice for mouth ulcers in pregnant women.	Mouth ulcers are painful sores that can occur inside the mouth, on the tongue, or on the gums. They can be caused by various factors, such as stress, hormonal changes, vitamin deficiencies, food allergies, dental problems or infections. While they usually heal by themselves, there are several home remedies that can help alleviate the discomfort. Applying honey, coconut oil, clove oil, turmeric, ghee, or tulsi leaves on the ulcers may help due to their antiseptic and analgesic effects. Rinsing the mouth with warm saline water or salt water 3-4 times a day can also be beneficial. In terms of diet, she should eat foods that are soft, bland, and non-acidic to avoid irritating her mouth ulcers. Foods rich in vitamin B complex such as green leafy vegetables, spinach, and amaranth are recommended. She should avoid spicy foods and maintain good oral hygiene. If the ulcers persist, she should be referred to a medical officer for proper treatment.
32	This woman is 20 weeks pregnant and has very sticky white discharge, is it normal?	Yes, it is normal to have a small amount of sticky white discharge during pregnancy. However, if there is a change in the amount, color, or smell of the discharge, it may indicate an infection. It's important to maintain	It is normal for a woman to experience increase in vaginal discharge during pregnancy, particularly in the second trimester. This discharge, known as leukorrhea, is typically thin, clear, or milky white, and may have a mild smell or no smell at all. The increase in discharge is due to more blood supply to the uterus and vagina during pregnancy and increased levels of certain hormones. However, if the discharge becomes very sticky, thick, any colors other than white, lumpy like curd, has a foul smell, or is associated with

		genital hygiene to prevent infections. If the discharge becomes foul smelling or changes to a bloody-yellow, greenish, or curdy color, it could be a sign of a reproductive tract infection.	itching, burning, or pain in the vagina or vulva or abdomen , it may indicate an infection. In such cases, the woman should be referred to a medical officer for examination and appropriate medication.
33	This lady's ultrasound report says that the baby has a hole in the heart. What does this mean and how can I support her?	A hole in the heart in an ultrasound report indicates a congenital heart defect, where there's an opening in the wall separating the heart's chambers. This can affect the normal flow of blood through the heart. To support her, you can provide her with as much information as possible about the condition, its implications, and potential treatments. Show empathy and understanding, as this can be a stressful time for her. Encourage her to consult with a medical officer for further advice and treatment options.	There are normally several openings in the heart of baby as it develops. These usually close during pregnancy or shortly after birth. But if opening does not close and a hole is left then it might be a cause of concern. Then refer the patient for cardiac consultation. A hole in the heart can affect blood flow through the heart and lungs, potentially causing problems such as low oxygen levels or heart failure in the baby. This condition occurs when the normal openings in the baby's heart, which are present as it develops, do not close during pregnancy or shortly after birth. If an ultrasound report indicates a hole in the heart, the woman should be referred to a tertiary care center with a heart specialist. The specialist can determine the necessary interventions and decide the course of the pregnancy. If the hole is detected early and is due to an infection such as rubella, there may be an option to terminate the pregnancy. However, if the hole is very small, it may be normal and could heal on its own after delivery. Throughout this process, as mother will naturally be under stress due to the situation; it's important to provide the woman with full psychological support and reassurance along with explanation of furthur options about the pregnancy as advised by doctor.
34	How soon after a delivery can a woman have sexual intercourse?	A woman can become pregnant as early as six weeks after delivery if she is not exclusively breastfeeding and has unprotected sex. Therefore, it is important to start thinking in advance about which family planning method to use.	A woman can resume sexual intercourse four to six weeks after delivery, as this is the minimum time required for the body to heal and recover back to a non-pregnant state. This period also allows for the healing of any stitches and prevent risk of infections and bleeding. However, it's important to note that both physical and mental readiness are crucial. If a woman is not emotionally ready, sexual intercourse should be avoided until she feels comfortable. The woman's decision should be respected by her partner. Additionally, it's important to remember that a woman can become pregnant again even before her first menstrual period post-delivery. Therefore, contraception should be used to avoid pregnancy, and a healthcare provider can advise on the best contraceptive method.

35	Are there any exercises a woman can do in her third trimester?	The document does not provide information on specific exercises a pregnant woman who has gained 15 kg during the first 24 weeks of pregnancy should be doing.	Yes, there are several exercises a woman can perform in her third trimester of pregnancy, provided there are no complications and she has consulted with a medical officer. These exercises can improve blood circulation, decrease stress, and strengthen muscle tone. Walking for 30-40 minutes a day, five days a week is usually recommended. Yoga, as recommended by health staff, can also be beneficial. Additionally, squeezing exercises and stretching exercises for the muscles and ligaments surrounding the perineum can be done to facilitate a normal vaginal delivery. However, it's important to avoid running fast, avoid lifting any heavy weights, stop if any pain or discomfort is felt, and to drink plenty of water and wear comfortable clothes and shoes during exercise. Women should stay physically active during her pregnancy until and unless bed rest is recommended by her doctor in some of the medical conditions. It's also crucial to note that there are some contraindications to exercise in certain conditions, such as high blood pressure, placenta problems, and preterm delivery. In such conditions, medical officers advise is needed.
36	Is it safe to have sexual intercourse during pregnancy?	Yes, it is safe to have sexual intercourse throughout pregnancy, as long as the pregnancy is uncomplicated. However, some women may experience a decreased desire for sex during pregnancy, which is normal. The woman's consent should always be sought before engaging in sex. Some couples may find sex uncomfortable during pregnancy, so the comfort of the woman should be prioritized. Safe sex practices, such as using condoms, should be followed, especially if the woman has vaginal discharge or itching, or if the man has urethral discharge or experiences burning while urinating.	Yes, it is generally safe to have sexual intercourse during pregnancy provided it is a normal pregnancy with no complications. However, the sexual activity should not be too vigorous and care should be taken with posture. It is advised to be cautious during the initial and final stages of pregnancy as it may adversely affect the pregnancy outcomes. If there are complications such as bleeding during pregnancy, preterm labor pains, urinary tract or vaginal infections, multiple pregnancies like twins, or cervical incompetency, sexual intercourse should be avoided. During early pregnancy, some women may feel too nauseated or tired to engage in sexual activity, and in the later stages, the size of the belly may make intercourse less enjoyable. It's important to communicate with your partner about your feelings and comfort level. As the female body undergoes many physical and emotional changes during pregnancy, the decision of the woman should be considered and respected.

37	Can a woman conceive if she recently delivered?	Yes, a woman can conceive as early as six weeks after delivery if she is not exclusively breastfeeding and has unprotected sex. Therefore, it is important to consider family planning methods in advance.	Yes, a woman can conceive even if she has recently delivered. This can occur as early as 3 weeks after delivery if the woman's ovary starts releasing mature eggs, due to the return of menstrual cycles early, failure of natural contraception like lactational amenorrhea, or non-feeding of the baby with breast milk. However, it is ideally recommended that there should be at least a three-year gap between two children. This allows for proper healing of the body, especially if the previous delivery was by cesarean section, as the healing of the cesarean wound and scar takes at least one year. It also ensures that the woman's nutrition levels return to normal and that the small baby is well taken care of. If a woman conceives very early, there are chances that she will be undernourished and the young child may not be taken care of in a proper manner.
38	A woman feels like vomitting after taking iron tablets. Why does this happen?	The feeling of nausea or vomiting after taking iron tablets can be a side effect of the medication. It can be reduced by taking the tablet after meals.	A woman may experience feelings of nausea or vomiting after taking iron tablets due to the fact that iron can be a stomach irritant. This is not abnormal and usually resolves after a few days. The discomfort is often caused by incomplete absorption of the iron. To mitigate this, she can try taking the tablets after meals or at night, as food can enhance the absorption of iron. Drinking lemon water with the tablets can also enhance absorption, while avoiding taking them with tea, which can reduce absorption. If the feeling of nausea persists, she may need to consult a medical officer for a possible change in the tablet formulation. Other side effects of iron tablets can include constipation, black stools, or mild diarrhea, which can be managed by drinking more water and eating fruits. Despite these discomforts, the benefits of taking Iron Folic Acid (IFA) tablets are far greater and should be explained to the woman.
39	A woman has taken Iron tablets, and she has also recieved iron sucrose injections, but her Hb is not rising above 7gms. What is the reason for this?	The feeling of nausea or vomiting after taking iron tablets can be a side effect of the medication. It can be reduced by taking the tablet after meals.	The woman's Hb not rising above 7gms despite taking iron tablets and receiving iron sucrose injections could be due to several reasons. She may not be suffering from iron deficiency anemia, but rather other deficiencies such as folic acid, vitamin B12, vitamin C, or protein. Additionally, she may have blood disorders like thalassemia or sickle cell disease, which are characterized by abnormal hemoglobin. Another possibility is that her body isn't absorbing iron properly which may occur in deficiency of Vitamin C also. She may also be experiencing continuous or intermittent bleeding, such as from hemorrhoids, mouth bleeding, or worm infestation. Hypothyroidism could also be a contributing factor to her anemia not improving with treatment. It is recommended that she be referred to a tertiary care center where various tests can be conducted to diagnose the reason and

			provide appropriate treatment. During the course of her treatment, she might require a blood transfusion, and her family should be prepared to donate blood if necessary.
40	A woman feels like vomitting after taking iron tablets. What can she eat so that she does not experience vomiting?	The feeling of nausea or vomiting after taking iron tablets can be a side effect of the medication. It can be reduced by taking the tablet after meals.	The woman may experience feelings of vomiting after taking iron tablets due to the irritant property of the iron. This is not abnormal and usually resolves after a few days. If the feeling persists, she can mitigate this by taking the tablets with or after meals instead of on an empty stomach. She should also consider incorporating a diet rich in iron and Vitamin C, such as green leafy vegetables, whole pulses, meat, lemon, guava, and oranges. Taking the iron tablets with lemon water or a vitamin C chewable tablet can enhance iron absorption and reduce the vomiting sensation. However, she should avoid taking the iron tablets with tea as it reduces absorption. If the feeling of vomiting continues, she should consult a medical officer.
41	A woman is taking calcium tablets regularly, but she is eating properly. But when she gets her calcium checked her blood tests show that she is deficient in calcium. What could be the reason for this?	The woman might be taking her calcium tablets along with iron supplements, which can interfere with the absorption of calcium. Additionally, taking calcium tablets on an empty stomach can cause gastritis, which might affect the absorption of calcium. It's also possible that her diet, despite being proper, might not include enough calcium-rich foods. It's recommended to include milk and milk-rich foods, fox tail millet (ragi), til, etc. in the diet.	The woman's calcium deficiency could be due to several reasons. She may have been severely deficient in calcium prior to pregnancy, or she may be deficient in Vitamin D, which aids in the absorption of calcium from food and supplements. Additionally, during pregnancy, body requires an extra amount of calcium. The woman may also have a kidney or parathyroid gland disorder, or a predisposition to preeclampsia. Furthermore, the need to breastfeed post-pregnancy also necessitates proper calcium management. To address these issues, she should be referred to a healthcare center or a primary healthcare doctor for a proper diagnosis and treatment plan. This could include dietary modifications and calcium-rich supplements like yogurt and milk, as well as adequate exposure to sunlight for Vitamin D, which may improve her calcium levels.

42	Some women get increased fluid after pregnancy and even after medication the fluid does not go down. What is the reason?	The document does not provide information on why some women experience increased fluid retention after pregnancy that does not reduce even after medication.	Increased fluid in the abdomen after pregnancy can be due to various reasons such as diabetes in the mother or abnormalities in the fetus or sometimes there is no cause. There is no definite treatment to decrease the amniotic fluid, but if the cause is known, treatment may be started for that. Additionally, women may experience swelling in the feet, ankles, legs, hands, and arms after delivery for almost a week as the body continues to get rid of excess fluid that accumulated during pregnancy. This occurs due to hormonal changes in the female body. An increase of fluid after medication may indicate some tear or retention of the conception products, or it may arise from an infection that is not properly treated by medication. In such situations, the woman should consult a medical officer so that the cause can be found and treated.
43	A woman gets diarrhea after taking iron tablets. So, then how should the woman consume those iron tablets?	The woman should consume the iron tablets after meals to prevent nausea or occasional vomiting. If she experiences constipation, she should drink more water and eat fruits. However, she should not take the iron tablets along with tea as it reduces its absorption. If the diarrhea persists, she should consult a healthcare professional.	The woman should be aware that diarrhea or constipation can be side effects of taking iron tablets, as iron can irritate the digestive tract. To minimize these side effects, particularly diarrhea, she should consume the iron tablets with or after meals along with lemon water. This can help to reduce stomach discomfort. It is also advised to take the tablets after dinner just before sleeping. However, she should avoid taking the medication with tea, coffee, or milk. If these measures do not provide relief, she should consult a medical officer.
44	There are many women in my area going for an ultrasound and they found no fetal heartbeat or growth at the end of the first trimester. They were even taking folic acid. What could be the reason for this?	There could be several reasons for not detecting a fetal heartbeat or growth at the end of the first trimester, even if the woman is taking folic acid. It could be due to a miscarriage, an ectopic pregnancy, or a molar pregnancy. It could also be due to issues with the ultrasound equipment or operator error. It's also possible that the pregnancy is not as far along as thought, and it's too early to detect a	There are several reasons why no fetal heartbeat or growth might be detected at the end of the first trimester, even if the woman has been taking folic acid. One common reason could be that the woman is not sure of her dates, meaning it may be very early in the pregnancy when the fetal heart has not yet appeared on the ultrasound. Another reason could be that there has been a fetal loss or miscarriage. Early pregnancy loss is common, occurring in about 10% of all known pregnancies, and is usually due to genetic issues in the early development of the baby. It's important to understand that in most cases, miscarriage is not the woman's fault and is usually a random event. It is not caused by working, exercising, stress, arguments, having sex, or having used birth control pills before getting pregnant. Some women may believe that a recent fall, blow, fright, or stress caused the miscarriage, but in most cases, this is not true. If no visible heartbeat is

		heartbeat. It's important for these women to consult with a healthcare provider for further evaluation.	detected during an ultrasound, the doctor will record the size of the fetus and perform a second scan a minimum of 14 days after the first before confirming a miscarriage. It's also important not to use gestational age from the last menstrual period alone to determine whether a fetal heartbeat should be visible. Lastly, there could be an issue with the ultrasound machine itself, in which case the woman should be referred to a higher center where better facilities are available.
45	Sometimes after the 4th month of pregnancy, a woman starts getting allergies that result in itching. What could be the reason for this?	The document does not provide information on why a woman might start getting allergies that result in itching after the 4th month of pregnancy.	There are several reasons why a woman might start experiencing allergies and itching after the 4th month of pregnancy. One common cause is the development of stretch marks on the abdomen, which can cause itching. This is normal and usually requires no specific treatment, but the woman can be counseled about it and may find relief by applying coconut oil to the abdomen. Other less common causes include skin infections like scabies, skin allergic conditions, and jaundice in pregnancy. It's also possible that the woman could be having an allergic reaction to iron tablets. Another cause could be Pruritus, a condition characterized by whole body itching, which is a common in pregnancy. Hormonal and genetic factors are believed to play a significant role in its occurrence. This condition often begins in the third trimester, at the time of peak hormonal concentration, and usually resolves after delivery. However, it can reappear in subsequent pregnancies. The goal of treatment for pruritus should be focused on alleviating symptoms and preventing adverse outcomes in the fetus. Mild cases may be treated with reassurance, antipruritic preparations like calamine lotion, and soothing baths. Patients should be advised to avoid anxiety and irritating clothing, and to follow a diet with low-fat content. Rest should also be encouraged. Patients should be counseled about the temporary nature of the disease and the likelihood of their symptoms resolving after delivery. Regardless of the cause, it's important for the woman to consult a medical officer for further advice.

46	Why do congenital malformations show in the 5th or 6th months of ultrasound and not in the 3rd?	I'm sorry, but the documents provided do not contain information on why congenital malformations show in the 5th or 6th months of ultrasound and not in the 3rd.	Congenital malformations may not be visible in the 3rd month of ultrasound due to their small size or fetal position, making them difficult to detect with the ultrasound resolution. Additionally, some malformations, such as cardiac defects, skeletal dysplasias, or neural tube defects, may develop or progress later in pregnancy. The anomaly scan, which is performed between 20-24 weeks of gestation, is designed to thoroughly assess the pregnancy and determine the presence of any rare conditions, including those of the brain, spine, and heart. Before this period, all parts of the baby cannot be seen in detail, and therefore anomalies or problems cannot be confirmed. While organ development in the baby occurs in the first trimester, proper visualization of congenital malformations is typically possible in the 5th or 6th month. Therefore, a second trimester ultrasound around the 5th or 6th month is recommended to examine the fetal anatomy in more detail and identify any anomalies that may have been missed or developed since the first trimester.
47	Why does a woman get high blood sugar during prengancy, when she did not have high blood sugar before pregnancy or after pregnancy? Why does this only happen after pregnancy?	The document does not provide information on why a woman gets high blood sugar during pregnancy when she did not have high blood sugar before pregnancy or after pregnancy.	During pregnancy, there is an increase in various hormones, which affect glucose metabolism and favor insulin resistance. This can lead to a diabetic state during pregnancy, even in women who did not have high blood sugar before pregnancy. This is because women need more insulin than usual during pregnancy. While most women are able to produce more insulin to meet this demand, some are not able to produce enough, leading to high blood sugar levels. Factors such as obesity, a family history of diabetes, and older age can increase a woman's risk of developing high blood sugar during pregnancy. Therefore, it is crucial for women, especially those with a family history of diabetes, to get their blood sugar tested during pregnancy.
48	Why does a woman get thyroid problems during prengancy and how come this gets better after the baby is born? Why does this happen after pregnancy?	The document does not provide information on why a woman gets thyroid problems during pregnancy and how it gets better after the baby is born, or why this happens after pregnancy.	During pregnancy, there are changes in hormones and an increase in plasma volume in the body that affect the function of the thyroid gland. These changes can lead to thyroid problems, such as subclinical hypothyroidism, even in women who did not have thyroid issues before pregnancy. This is because Thyroid hormone requirements are higher during pregnancy. Thyroid hormones are crucial for the normal development of the baby's brain and nervous system. During the first trimester, the baby depends on the mother's supply of thyroid hormone, which comes through the placenta. If a woman is already taking thyroid medication, the dose often needs to be adjusted early in the first trimester. Additionally, the thyroid uses iodine to make thyroid hormone, making iodine an important mineral during pregnancy. The baby gets iodine from the mother's diet, with good sources being

			dairy foods, seafood, eggs, meat, poultry, and iodized salt. After delivery, as pregnancy hormones change, thyroid problems often subside.
49	Some women don't gain weight during pregnancy even if she is eating well. What is the reason for this?	The document does not provide a specific reason for why some women might not gain weight during pregnancy even if they are eating well.	During a normal pregnancy, a woman typically gains an average of 9-11 kg. However, if a woman is not gaining weight despite eating well, she may be experiencing issues such as worm infestation, thyroid disorder, or chronic diseases. Hyperthyroidism, in particular, can be a reason for this. These conditions can lead to complications during pregnancy, such as low birth weight or premature delivery. Babies born to underweight mothers are at a higher risk for health problems, including premature birth and low birth weight. Additionally, a woman's appetite can fluctuate during pregnancy due to numerous changes in her body. If she loses her appetite, she may experience a general disinterest in all foods or a lack of desire to eat. This can be due to nausea and vomiting, mental health conditions like anxiety and depression, or side effects from certain medications. she should be given small and frequent meals and not heavy meals at one time. To ensure adequate nutrient intake for both the mother and the baby, it's recommended to prioritize certain foods even if the mother feels she can't eat whole meals. These include protein-rich, fiber-packed veggies, grains/starches, soups, and liquids. Iron-rich foods and foods rich in vitamin C should also be introduced. If a woman is not gaining weight during pregnancy despite eating well, it's important for her to consult a medical officer for further treatment.
50	Why does the baby's weight increase not as much in the first 15 days and increase only after 15 days?	The baby's weight does not increase as much in the first 15 days because it is a normal process for newborns to lose some of their birth weight in the first few days after birth. This is often due to the loss of excess fluid. After the initial weight loss, the baby starts gaining weight and typically regains its birth weight by the end of the first	Newborn babies typically lose some weight in the first 10 to 15 days of life due to the loss of extra fluid they are born with. This is a normal part of a newborn's adaptation to life outside the mother's womb, which requires the maintenance of their own temperature, fluid balance, and breathing, leading to high energy requirements. It is common for babies to lose about 7-10% of their body weight after birth, but they should regain this by 2 weeks of age. After this initial period of weight loss, newborns are expected to gain 15 g per day. Generally, infants will double their birth weight by age 6 months and triple it by 1 year. It is also important to note that breastfed babies may lose more weight than formula-fed infants in the first days of life. If a baby loses more than 7-10% of their birth

		week. The weight gain becomes more noticeable after the first 15 days.	weight, it indicates the need for breastfeeding evaluation and support. If the baby is not taking proper feeds, shows signs of lethargy, is not crying, or has fever, it might indicate an infection and a medical officer should be consulted.
51	Why does a woman experience pain in her stomach after delivery?	A woman may experience severe abdominal pain after delivery due to several reasons. One of the reasons could be due to the uterus contracting back to its normal size, a process known as involution. Another reason could be complications such as infection or excessive bleeding. If the uterus remains soft and flabby after delivery, the woman may be suffering from Atonic Postpartum Hemorrhage (PPH). It's important to seek medical attention if severe abdominal pain persists after delivery.	Women commonly experience pain in the lower abdomen after delivery due to a variety of causes. The most common cause is due to contraction of the uterus as it tries to shrink back to its normal size. They are more common during breastfeeding and in women who have already had children. Other common postpartum symptoms include vaginal bleeding, back, neck, or joint pain, pain in the perineum, pain around the incision if a cesarean birth was performed, swollen breasts, bladder problems, bowel problems, and hemorrhoids. The type, intensity, and duration of these symptoms can vary from woman to woman, with some lasting a few days and others several weeks. Applying a heating pad to the abdomen can help relieve discomfort, and pain relief medicines like paracetamol or ibuprofen can be taken. If the pain is severe, persistent, in the upper abdomen, or associated with other symptoms like fever or foul-smelling discharge, it is recommended to consult a medical officer as there may be other serious problem.
52	Why do babies throw up again and again?	I'm sorry, but the provided documents do not contain information on why babies might throw up repeatedly.	Babies often throw up repeatedly due to a variety of factors. In the initial months, their stomach is not accustomed to digesting milk, and they are still learning how not to overfeed or gulp milk too quickly. Additionally, the oesophageal sphincter in babies is not fully developed, which can contribute to this issue. Overfeeding may also play a role in causing babies to throw up. In fact, most of the infants have daily episodes of spitting up due to stomach immaturity. This usually results in small amounts of breast milk or formula coming from the mouth, typically shortly after feeding, and may be more forceful

			with burping. After every feed, the baby should be given gentle pats/caressing on the back for around 15 minutes or till baby burps, before putting the baby back to a lying down position after feeding.
53	Why do babies do potty again and again? Sometimes they do not do potty for 3-4 days.	Babies' bowel movements can vary greatly. Some babies may pass stool after every feeding, while others may go days without a bowel movement. This can be due to differences in metabolism, diet (breastfed babies may have more frequent bowel movements), and individual variation. However, frequent bowel movements can also be a sign of conditions like diarrhea. If a baby is passing watery stools more than three times a day, it could be a sign of diarrhea. If a baby doesn't pass stool for several days but is otherwise healthy and feeding well, it's usually not a cause for concern. However, if there are other symptoms like refusal to feed, fever, or the baby is lethargic, it's important to seek medical advice.	Babies have different patterns of passing stools depending on whether they are breastfed or top-fed. Some babies may pass stools after every meal, while others may go up to a week without doing so. This is usually normal and not a cause for concern. However, it is important to ensure that the baby is gaining proper weight and that the stools are not very watery or very hard. If any of these conditions are present, it is advisable to consult a doctor. This pattern of bowel movement is due to gastric reflux which gets stimulated when baby's stomach fills up with milk. This can cause the baby to pass stools frequently. Additionally, breast milk contains natural laxatives, which can also stimulate bowel movements. In the first week of life, infants often pass stools after each feeding. Over the course of the first several weeks, the frequency of stools may decrease and they may take on a firmer consistency. Most infants will pass stools daily, but it can be normal for them to do so every 2 to 3 days, especially when transitioning from breastfeeding to solid foods. It's also worth noting that grunting, drawing up the legs, and straining are normal behaviors for infants while they are passing stools, as it can be challenging to do so while lying flat on their back. Parents should be reassured about this normal stooling behavior. However, for infants who have always had infrequent stools or who had delayed passage of meconium, an evaluation for Hirschsprung disease may be considered.Babies have different patterns of passing stools depending on whether they are breastfed or formula-fed. Some babies may pass stools after every meal, while others may go up to 7 days

			without doing so. This is usually normal and not a cause for concern. However, it is important to ensure that the baby is gaining proper weight and that the stools are not very watery or very hard. If any of these conditions are present, it is advisable to consult a medical officer. This pattern of bowel movement is due to gastro-colic reflux, where the baby's bowel movement gets stimulated when their stomach fills up with milk. This can cause the baby to pass stools frequently. Additionally, breast milk contains natural laxatives, which can also stimulate bowel movements. In the first week of life, infants often pass stools after each feeding. Over the course of the first several weeks, the frequency of stools may decrease and they may take on a firmer consistency. Most infants will pass stools daily, but it can be normal for them to do so every 2 to 3 days, especially when transitioning from breastfeeding to solid foods. It's also worth noting that grunting, drawing up the legs, and straining are normal behaviors for infants while they are passing stools, as it can be challenging to do so while lying flat on their back. Parents should be reassured about this normal stooling behavior. However, for infants who have always had infrequent stools or who had delayed passage of meconium, an evaluation for Hirschsprung disease may be considered.
54	How do I convert a baby's height from cms to feet?	To convert a baby's height from centimeters to feet, you can use the conversion factor of 0.0328084. This means that each centimeter is equal to 0.0328084 feet. So, if you want to convert a baby's height from centimeters to feet, you would multiply the number of centimeters by 0.0328084.	To convert a baby's height from centimeters to feet, you can use a simple mathematical formula. One foot is equivalent to 30.48 cm. Therefore, you can divide the height in centimeters by 30.48 to get the height in feet. Alternatively, you can multiply the height in centimeters by 0.0328 to achieve the same result. For example, if the baby's height is 10 cm, you can either divide 10 by 30.48 or multiply 10 by 0.0328 to get the height in feet, which is approximately 0.328 feet. Alternatively 1 inch = 2.5 cm and 1 foot =12 inches. This measurement will help you in converting feet into cms.

55	Why do women throw up during pregnancy, specially during the first three months?	Vomiting during the first trimester of pregnancy, often referred to as morning sickness, may be physiological. The exact cause is not known, but it is believed to be related to the hormonal changes that occur during pregnancy. It's important to note that the severity and frequency of morning sickness can vary from woman to woman.	During the first three months of pregnancy, women often experience vomiting due to a variety of factors. One of the main causes is the rise in hormones, which can lead to nausea and vomiting. Additionally, physiological changes that occur during pregnancy can also contribute to this symptom. However, if vomiting leads to dehydration, medical attention is required. Frequent and small meals are recommended. Other potential causes can include chromosomal abnormalities in the baby, hormonal problems in the mother like thyroid disorders, diabetes, polycystic ovary syndrome, or defects in the uterus like fibroids or polyps. In many cases, the exact cause of vomiting during early pregnancy is not known. It's important to provide psychological support and counsel the woman that having these symptoms does not mean she cannot have a normal pregnancy in the future.
56	Why do some women not stop throwing up till 9 months during their pregnancy?	The condition where a pregnant woman experiences excessive vomiting, often beyond the first trimester, is known as Hyperemesis Gravidarum. This condition may lead to dehydration and weight loss. The exact cause of Hyperemesis Gravidarum is not known, but it is believed to be related to the increase in hormones during pregnancy. It's important for women experiencing this to seek medical attention, as they may require intravenous fluids and other treatments.	Some women may experience continuous vomiting throughout their pregnancy due to a variety of reasons. One of these reasons could be the added pressure of the growing baby on internal organs, particularly the stomach and diaphragm. Anxiety or stress related to impending labor and delivery may also cause some women to vomit. Other causes include hormonal changes, gastroenteritis, acid reflux, and constipation. In more severe cases, women may suffer from hyperemesis gravidarum, which is the most severe form of nausea and vomiting during pregnancy. This condition can lead to dehydration. Symptoms of dehydration include a small amount of urine that is dark in color, inability to urinate, inability to keep down liquids, dizziness or fainting when standing up, and increased heartbeat. If nausea and vomiting become so severe that a woman cannot keep down food or fluids and begins to lose weight, it can potentially affect the fetus's growth. In such cases, medical treatment, sometimes in hospital, is necessary to stop the vomiting and restore body fluids.
57	A woman's hb is low. What advice should I give her?	If a woman's haemoglobin level is low, indicating anaemia, she should be started on a therapeutic dose of Iron and Folic Acid (IFA). Her haemoglobin level should be estimated	If a woman's hemoglobin is low, she should first have her Hb correctly measured to classify the severity of her anemia. Based on this, a treatment plan should be made. She should take two tablets of Iron and Folic Acid (100 mg elemental Iron and 500 mcg Folic Acid) daily, orally for mild and moderate anemia. These tablets, also known as IFA tablets, should be taken before meals or on an empty stomach to increase their efficacy. If

		again after one month. If it has not increased, she should be referred to a higher facility with good laboratory infrastructure and trained personnel so that the cause of the anaemia can be determined and the appropriate treatment can be started.	she is pregnant, she should continue taking these tablets even after delivery to maintain her iron stores till 6 months after delivery . If her hemoglobin is less than 7, she should be referred to medical officer as she may need injections and transfusions. After one month, her hemoglobin should be checked again. If there is no increase, she should be referred to a higher center. If there is an increase, she should continue with the IFA tablets. If she has severe anemia, she should be referred to a First Referral Unit (FRU). Alongside this, she should modify her diet to include iron-rich foods. She should eat food rich in protein, iron, and vitamin C, including at least one big bowl of whole dal daily, green leafy vegetables, one lemon, and jaggery. This dietary advice should also be shared with her family members.
58	A woman is not able to breastfeed and she have inverted nipples. Why do a woman's nipple get inverted after delivery?	The document does not provide information on why a woman's nipples get inverted after delivery.	Inverted nipples can occur for a variety of reasons, like aging, breastfeeding, breast surgery, injury, being born with inverted nipples, other medical conditions or infections involving inflmation or abscess or breast cancer. In some cases, the nipple will retract into the breast, which can be identified even before delivery. This condition can create problems with breastfeeding, but there are ways to manage it. The best treatment is to encourage the mother to gently pull out the nipple and roll it several times a day. A 10 cc or 20 cc disposable plastic syringe can also be used for correcting inverted nipples. If there are signs of crusting and soreness of the nipples, the woman must be advised on breast hygiene and the use of emollients such as milk cream. If there are lumps or tenderness, the woman should be referred to a doctor. It's important to identify inverted nipples before delivery so that treatment can be started.
59	Women tell us that the facilities in government hospitals are not very good. What should I tell them?	You can tell them that while they may have concerns about the facilities, government hospitals are equipped with the necessary staff, equipment, supplies, and drugs to provide the best care during delivery. These hospitals are prepared to handle any complications that may arise during pregnancy, delivery, or the postnatal period. If complications occur and are	You should inform them that government hospitals have seen significant improvements recently. The increase in health staff and advancements in healthcare facilities have led to better patient care. It's important for patients to communicate their issues clearly to the doctors for effective treatment. The government is committed to enhance the quality and accessibility of public healthcare, and many initiatives have been taken to improve hospital facilities. These hospitals are now cleaner and better equipped than before. Additionally, the government has launched several schemes for the welfare of pregnant women and newborn children. These include the Janani Suraksha Yojana (JSY), Janani Shishu Suraksha Karyakram (JSSK), Pradhan Mantri Matritva Vandana Yojana

		not handled by professionals, it can be life-threatening for both the mother and the baby. Furthermore, these hospitals have a referral system in place if there is a need for specialized care. If the primary health center is too far and the local health and wellness center is equipped for delivery, they can also choose to deliver there.	(PMMVY), and Pradhan Mantri Surakshit Matritva Abhiyan (PMSMA). These schemes aim to promote institutional delivery and improve maternal health outcomes.
60	Some women have dizziness and vomiting after taking iron medications. What should we advice? I just told her to take the medicine with lemon water.	You should advise her to take the iron tablet after meals to reduce nausea and vomiting. Also, she should not take the iron tablet with tea, coffee, milk, or a calcium tablet. Drinking more water and eating fruits can also help. If she continues to feel unwell, she should seek further medical advice.	Dizziness and vomiting are common side effects of iron medications, but they are usually mild and temporary. To prevent or treat these side effects, the woman should take the iron medication with food or after a meal, which can help reduce the irritation to the stomach and intestines that may cause nausea and vomiting. However, she should avoid taking iron with items such as coffee, tea, dairy products, or wait at least two hours before or after taking iron, as these can interfere with the absorption of iron. Drinking plenty of water or other fluids can help her stay hydrated and prevent dehydration from vomiting. She could also try taking a lower dose of iron or splitting the dose into smaller amounts throughout the day to help her body adjust to the medication and reduce the side effects. It's also suggested that she could take the iron tablets after dinner and just before going to sleep. Despite these side effects, it's essential that she continues to take the medication. However, if these side effects are severe or persistent, she should stop taking the medication and contact her doctor immediately.
61	How come a woman's iron went down from 7gms to 5gms after taking iron sucrose injections?	I'm sorry, but the documents provided do not contain information on why a woman's iron levels would decrease after taking iron sucrose injections.	The decrease in a woman's iron levels from 7gms to 5gms after taking iron sucrose injections could be due to several reasons. She may have a condition causing chronic inflammation, infection, or an autoimmune disease, which can suppress the body's response to iron therapy. Additionally, she may have a genetic disorder that affects the structure or function of her red blood cells, such as thalassemia. A deficiency of other nutrients needed for red blood cell production, such as vitamin B12, folate, or copper, could also be a factor. Furthermore, she may be suffering from an allergic reaction or bleeding disorders in addition to anemia. It is recommended that she be referred to a

			tertiary care center or a specialist for further investigation to determine the cause of her decreased Hb.
62	A lady's husband does not talk to her wife properly because she has had 3 daughters. He is blaming her for not having a son. What can I do to counsel them?	You can counsel them by explaining that the sex of a baby is determined by the chromosomes contributed by both parents, not just the mother. It is the sperm from the father that determines the sex of the baby. Educate them about this biological fact to dispel any misconceptions. Show empathy and understanding towards the woman's situation. Encourage them to communicate and support each other.	To counsel this couple, it is important to first educate the husband that it is the father's sperm that determines the gender of a child, not the mother. Therefore, it is not the wife's fault that they have not had a son. This misconception needs to be corrected to alleviate any blame or guilt the wife may be feeling. Both the husband and wife should be counseled that in today's society, there is no difference between a boy and a girl. If a girl is given equal education and opportunity as a boy, she can become an asset to the family and not a burden. Explain that having a son or a daughter is a matter of chance, not choice, and there is no scientific evidence that any method or intervention can guarantee the sex of a baby. Ask them how they feel about their daughters, and what they can do to nurture and appreciate them more. Assist them in finding positive coping strategies and support systems to deal with any stress or stigma they may face from their family or community. If there are any signs of physical violence, it is crucial to ensure the safety of the wife by shifting her to a safe place and providing her with medical services and emotional support. Inform her about the legal avenues available to her. At the community level, create awareness regarding the issue and build partnerships with local organizations like the gram panchayat, self-help groups, and VHSNC. Tailor your approach according to the couple's situation and goals. Lastly, they should be advised regarding vasectomy as their family is complete even without a son.

63	Some women do not want to get their baby vaccinated because the baby cries a lot. What can I do?	You can counsel the mothers that minor ailments and side effects such as mild fever, mild rash, and pain at the injection site are common after immunization. These can be managed by giving 1/4th tablet of Paracetamol. However, if the baby is crying for more than three hours, has a high-grade fever, or is drowsy, convulsing, or unconscious, they should be referred to a healthcare center. It's important to ensure all babies are immunized, and you can help track those who might miss their immunizations, like orphans and children of migrants.	It's important to advise both parents about the significance of vaccination in protecting their child against diseases. The distress of a child crying can be mitigated by the father either taking the child for vaccination or accompanying the mother and child during the process. It's crucial to communicate that vaccination is vital for the baby's health and well-being, as it can protect them from potentially life-threatening diseases, such as measles, polio, whooping cough, and severe form of TB. The pain from the injection is usually mild and temporary, and it does not indicate that the vaccine is harming the baby. To comfort the baby and reduce the pain after vaccination, the mother can hold the baby close during and after the shot to make them feel safe and secure. Applying a cool compress or a cloth soaked in cold water to the injection site can help reduce swelling and inflammation.
64	A woman is having shortness of breath and she is in her third trimester. Is this something to worry about?	Yes, this could be a cause for concern. If a pregnant woman is experiencing shortness of breath and her respiratory rate is above 30 breaths per minute, it could indicate severe anaemia, heart disease or other associated medical problems. She should be immediately referred to a medical officer for further investigation and management of any illness that may be present.	It is common for a pregnant women in their third trimester to experience shortness of breath. As the baby grows, it can push up against the diaphragm. This can cause her to experience shortness of breath. But, if the shortness of breath is sudden, severe, or accompanied by chest pain, dizziness, or fainting, it could be a sign of a more serious condition related to heart and blood circulation. If the woman reports any sudden or severe breathing difficulties, she should be referred to the doctor immediately. It is important for everyone around the woman to support her during her pregnancy.

65	This woman just delivered a female baby and she does not feel like feeding her. I noticed she is not treating her the same way when she delivered a baby boy. How can I counsel her so she can be inspired to show gender equality?	You can counsel her by emphasizing the importance of equal care for both genders. Explain that both boys and girls have the same needs and rights, especially for nutrition and care. Encourage her to express her feelings and concerns, and reassure her that it's normal to have different emotions after childbirth. Remind her of the importance of exclusive breastfeeding for the newborn's health, regardless of the baby's gender. Also, involve her family members in the discussion to ensure she receives support at home.	This woman's behavior is considered girl child neglect. It's important to counsel the family. Congratulate her on the birth of her daughter and help her see it as a celebration. Remind her that every child, regardless of gender, is a unique gift and brings their own special joy. It's essential for her baby girl to receive the right nutrition and care from the start, and breastfeeding plays a vital role in this. Breastfeeding will also help in creating a strong bond between mother and child. a female child can be a blessing for the family (give examples to famous and succesful females). You can inspire her by quoting successful females to show gender equality. Counsel her that both male and female children are equal and can be breadwinners and look after the family if they are cared for without any discrimination. It's also important to counsel the rest of the family on "Beti bachao Beti Padhao" and to follow up at least once a week on this mother and child until the situation improves.

66	This woman’s husband is not supporting her after pregnancy and expects her to do all the housework even though she has pain in her stitches. How can I counsel them?	You can counsel them by explaining the importance of shared responsibilities, especially after childbirth. The husband should be made aware of the physical strain and recovery period involved post-pregnancy. He should be encouraged to help with domestic work and childcare. The woman should be advised to take enough rest and eat well for her recovery. It's also important to discuss the potential health risks for the mother and baby if she is overworked during this period.	The husband needs to understand that his role as a father is equally important in pregnancy, delivery, and childcare. It's not solely the mother's duty to take care of the child and the household. The mother needs rest to recover from the energy and hard work her body has put into pregnancy and childbirth. The lack of rest and support can cause her health to deteriorate, which will also negatively impact the baby's well-being. The husband should be made aware of potential complications, such as the risk of infection at the site of the scar from strenuous household work. This could lead to the hospitalization of the woman, altering newborn care and affecting the child's development. Household work should be shared by both the husband and wife, and all family members can contribute to the workload. Other fathers in the community can act as peer educators and motivate her husband by example. Counselling should be done with sensitivity and empathy. Congratulate both the husband and the woman on the birth of their child and remind them that this is a time for family bonding and support. The husband should be reminded that recovery takes time and his wife's body has undergone a lot of changes. Helping her out or sharing household responsibilities can provide her with much-needed support as she is recovering. A healthy mother can care better for the baby, benefiting the entire family. Working together and sharing household as well as parental responsibilities can strengthen their bond as a couple and set a great example for the child. Take the help of husbands family and/or his peer group to counsel the husband too.

67	Why do woman’s legs swell during pregnancy?	Swelling or oedema in the legs during pregnancy can be a normal manifestation. This is often due to the increased pressure from the growing uterus on the veins that return blood from the lower limbs. This swelling usually appears in the evening and disappears in the morning after a full night’s sleep. However, if the swelling is associated with high blood pressure, heart disease, anaemia or proteinuria, it could indicate a problem and the woman should be referred for further investigations.	Swelling in women's legs during pregnancy is a common occurrence due to several factors. The growing uterus puts pressure on the abdomen and affects the blood flow in the legs, leading to increased venous pooling. This pressure, along with the body's natural retention of extra fluid to support the baby, tends to cause fluid accumulation in the lower part of the body, resulting in swelling. Hormonal changes during pregnancy can also contribute to water retention and swelling. This swelling typically appears in the evening and should resolve after a full night's rest. However, if the swelling does not reduce after rest, or if there is swelling in the face, hands, abdominal wall, and vulva, it could indicate other medical issues such as high blood pressure/ heart disease. In such cases, immediate medical attention is required. Pregnant women are advised to rest with their feet raised, drink enough water, and wear comfortable footwear to manage the swelling. If a pregnant woman suddenly notices a lot of swelling in her hands, face, or legs, it's important to consult a doctor.
68	Please remind me what is the proper way to do OGTT testing.	The Oral Glucose Tolerance Test (OGTT) is performed by giving the woman 75g of glucose dissolved in 300ml of water to drink within 10 minutes. After waiting for 2 hours, a blood sample is taken. The blood sample is obtained by puncturing the middle or ring fingers, choosing a different site each time to avoid pain or skin calluses. A test strip is inserted into the test strip port of the meter until it beeps. Then, the blood sample is applied to the narrow end of the test strip until the meter beeps again. A minimum volume of 0.5 microlitre is	The proper way to conduct an OGTT (Oral Glucose Tolerance Test) involves a single step of administering 75g of oral glucose and measuring plasma glucose 2 hours after ingestion. The 75g of glucose should be dissolved in approximately 300ml of water. This can be given to the patient whether they are in a fasting or non-fasting state, irrespective of their last meal. The patient should complete the intake of the solution within 5 minutes. If vomiting occurs within 30 minutes of oral glucose intake, the test should be repeated the next day. However, if vomiting occurs after 30 minutes, the test can continue. A plasma standardised glucometer should be used to evaluate blood glucose 2 hours after the oral glucose load. If the reading is more than 140 mg/dl, the patient should be advised lifestyle changes such as dietary modifications and physical activity for 30 minutes twice daily. After 2 weeks of these lifestyle changes, postprandial glucose should be tested and based on the results, continuation of lifestyle changes or medical treatment should be advised. The threshold plasma glucose level of 140 mg/dL is taken as the cut-off for diagnosis of GDM (Gestational Diabetes Mellitus).

		needed to fill the confirmation window.	
69	Is there any Ayurvedic recommendation for this lady who has gestational diabetes?	I'm sorry, but the documents provided do not contain any information about Ayurvedic recommendations for a lady with gestational diabetes.	An Ayurvedic recommendation for a lady with gestational diabetes should ideally be given by an AYUSH doctor. Lifestyle changes such as a healthy and balanced diet and regular mild exercise like walking are often recommended. The woman can also be encouraged to include fenugreek, green vegetables like bitter gourd (Karela), lettuce leaves, lady finger (bhindi), carrot, soya beans, drumstick, and jamun in her diet and reduce the intake of sweet substances. However, it is not advisable to solely rely on Ayurvedic recommendations. It is better to seek a physician's advice as well.
70	What type of vaginal discharge is normal and what is abnormal during pregnancy?	Normal vaginal discharge during pregnancy is a small amount of discharge or wetness that comes from the vagina. An abnormal vaginal discharge during pregnancy may be indicated by a change in the amount, color, and smell of the discharge. Infections of the reproductive tract in women often present as foul-smelling or bloody-yellow, greenish, or curdy discharge.	Normal vaginal discharge during pregnancy, known as leukorrhea, is thin, white, milky, and mild smelling. This increase in discharge is due to increased vascularity, increased cervical secretion, and a hyper estrogenic state. However, if the vaginal discharge turns green or yellowish, has a strong smell, or is accompanied by redness or itching, it may be a sign of a vaginal infection. Common infections include candidiasis, also known as a yeast infection, and trichomoniasis. These infections require proper treatment. A thick, cheese-like discharge could also indicate a fungal infection. Discharge that is foul smelling, blood stained, causes itching or pain, or appears bloody or brown is also abnormal. In any case of abnormal vaginal discharge, the woman should be referred to a doctor or a primary health care provider immediately.

71	This woman has thyroid problems and is overweight during her pregnancy, what should I tell her as advice?	You should advise her to seek medical attention as she is at risk for hypothyroidism due to her thyroid problems and weight gain. She should be screened for hypothyroidism, especially if she has symptoms like feeling tired, unable to stand cold temperatures, hoarse voice, swelling of the face, constipation, skin and hair changes, hand tingling or pain, slow heart rate, muscle cramps and irregular menstrual periods. She should also increase her intake of food and fluids, take enough rest and sleep, and avoid heavy physical work. Regular intake of IFA and Calcium tablets is also recommended.	The woman should be informed that thyroid problems and obesity can increase the risk of gestational diabetes during pregnancy, which can harm both her and the baby's health and decrease the chances of a normal successful delivery. Uncontrolled hypothyroidism can lead to various complications such as preeclampsia, anaemia, miscarriage, low birth weight, stillbirth, and rarely congestive heart failure. Therefore, it is crucial to maintain normal thyroid function throughout pregnancy. This can be achieved by regularly taking prescribed thyroid medicines and not taking them along with iron or calcium tablets. A 4-hour gap should be maintained between thyroid tablets and iron/calcium tablets. She should also be referred to a Primary Health Centre (PHC) for timely testing and follow-ups. Regular checks on thyroid parameters are essential as the risk of miscarriage is high. In terms of diet, she should aim for a healthy and balanced diet that is rich in protein, minerals, and vitamins. Home-cooked meals with plenty of vegetables, grains, and protein are recommended, while oil, sweets, and fried foods should be avoided. To control weight gain, she should limit her weight gain to 7kgs throughout her pregnancy as excessive weight gain can lead to complications. Regular mild exercise like walking can also be beneficial.
72	This lady,Äôs ultrasound report says she has excess water. What does this mean?	The condition where a woman has excess water or fluid in the womb during pregnancy is known as polyhydramnios. This can be detected through an ultrasound. It can be caused by various factors including multiple pregnancies, gestational diabetes, or abnormalities in the baby. It's important to monitor this condition as it can lead to complications such as preterm birth or placental abruption.	The lady's ultrasound report indicates that she has polyhydramnios, which is the excessive accumulation of amniotic fluid. This is the fluid that surrounds the baby in the uterus during pregnancy. Polyhydramnios occurs in about 1 to 2 percent of pregnancies. Most cases of polyhydramnios are mild, but severe polyhydramnios may cause shortness of breath, preterm labor. Sometimes the levels of this fluid can increase due to various reasons such as gestational diabetes. In most cases, this is not a concern but in some cases, this could cause complications like early delivery. A woman with excess water should be monitored by her doctor regularly and follow the prescribed care.

73	This woman who is 32 weeks is getting contractions every day. Is she at risk of early delivery?	Yes, the woman who is experiencing contractions at 32 weeks is at risk of early delivery. Regular contractions before 37 weeks of pregnancy may be a sign of preterm labor. It is important to monitor the frequency and duration of the contractions and to look out for any emergency signs such as difficulty in breathing, vaginal bleeding, convulsions, and unconsciousness.	The woman experiencing contractions at 32 weeks may or may not be at risk of early delivery. It's important to distinguish between false contractions, and true labor contractions. False contractions are normal and can be very painful, often leading to confusion about whether labor has started. These contractions do not get stronger and do not lead to cervical dilation. They often stop when the woman is resting and drinking water. If this is the case, she is not at risk of preterm delivery as these contractions are a normal part of pregnancy, gradually increasing in the later half and more at term. However, if the contractions continue all the time, it could be a sign of preterm labor or early delivery risk. Regular contractions, especially when accompanied by other signs like bleeding, fluid leak, or pelvic pressure, are concerning, female must be referred to doctor To cope with the discomfort of false labor contractions, the woman can drink lots of water, eat small snacks, watch a movie or TV, listen to music, take a shower or hot bath, alternate walking with rest, and try yoga, deep breathing or meditation. If there is any doubt about whether the contractions are true labor contractions, it's important to consult with a healthcare professional. Sometimes, a vaginal exam is the only way to confirm if true labor has started.

74	This woman is about to deliver twin babies. Is she at any extra risk and what advice can I give her?	Yes, a woman expecting twins is at extra risk and should see a doctor. She may have a larger abdomen size and the babies could be in abnormal positions inside the uterus. She should be advised to take extra rest, avoid heavy manual work, and consume more food for her own health and for the growing fetuses. It's also important to start thinking about family planning methods to use after delivery.	The woman carrying twin babies is indeed at a higher risk of complications compared to those carrying a single fetus. Common complications include preeclampsia, premature labor, preterm birth, diabetes, back pain, sleeping difficulties, heartburn, maternal anemia, and postpartum hemorrhage (bleeding) after delivery. Mostly twins/ triplets are born at less than 37 weeks' gestation. In terms of advice, she should be referred to a 24-hour Primary Health Centre (PHC) for Antenatal Care (ANC) and delivery. Institutional delivery at a PHC or First Referral Unit (FRU) is recommended, and if possible, specialist care at the Community Health Centre (CHC) should be sought. The Accredited Social Health Activist (ASHA) should accompany her to the hospital and hand her over to the specialist for safe delivery. Nutritional counseling is also crucial. A healthy diet containing adequate energy, protein, vitamins, and minerals is necessary. This can be obtained through a variety of foods, including green and orange vegetables, meat/fish, pulses, beans, salads, nuts, whole grains, and seasonal fruits. Extra folic acid tablets are recommended, and she should be prepared for more weight gain due to two babies, two placentas, and more amniotic fluid. She will also need more calories for a twin pregnancy. Lastly, she should be prepared for the possibility of a C-section, as the chances are higher in twin pregnancies. Regular check-ups, possibly twice weekly as the delivery date nears/ in last week ofexpected dateof delivery, are also recommended.

75	How can I support the well-being of this lady now after her abortion?	You can support women in recognizing danger signs during pregnancy by educating them about the various danger signs such as bleeding from the vagina, loss of foetal movement, and symptoms like severe headache, dizziness, or blurred vision. You should also inform them that these signs require immediate referral to a health facility. Additionally, you can educate family members on how to recognize these complications and be prepared for immediate referral.	To support the well-being of a woman after her abortion, it is crucial to provide post-abortion counseling and care. This includes ensuring privacy and confidentiality, maintaining an empathetic attitude, and regularly checking on how she is feeling. It's important to reassure her in case of any problems and inform her about post-procedure care. She should be advised to avoid intercourse until the bleeding stops or to use condoms. Follow-up after abortion is essential, especially if tablets were given for a medical abortion. If the woman experiences any severe abdominal pain, heavy vaginal bleeding, fever, fainting, abdominal distention, severe vomiting, or foul-smelling discharge from the uterus, she should immediately return to the hospital or be referred to the nearest hospital. Counseling can help women seek safe abortions and decrease deaths among pregnant women. Since a woman can become pregnant again within six weeks after an induced abortion, it is advisable to counsel her and her partner about appropriate contraception. In addition to physical health, mental well-being is also important. Counseling can help avoid depression and negative thoughts. The woman should also be advised to maintain a balanced diet and get plenty of rest. It's important to monitor for any danger signs as mentioned above for upto three days after the abortion. If any are present, the woman should be accompanied to the hospital for urgent treatment.

76	Teach me about blood grouping and how it relates to pregnancy.	Blood grouping, including the Rh factor, is an important test during pregnancy, typically conducted during the third antenatal visit between 28 and 34 weeks. This test is crucial as it can help in case the woman suffers from haemorrhage and blood transfusions need to be arranged, thereby saving precious time and potentially the life of the woman. Additionally, it can detect Rh negative pregnancies, which can lead to complications such as Rh disease in the newborn if not properly managed. Therefore, knowing the blood group and Rh factor of a pregnant woman is essential for her health and the health of her baby.	Blood grouping involves the ABO blood group system, which includes blood groups A, B, O, and AB. Each of these groups can have a positive or negative Rhesus (Rh) factor. Knowing your blood group is crucial, especially during pregnancy, as it can affect your baby. If the mother is Rh-negative and the baby is Rh-positive, this can lead to Rh incompatibility, making the pregnancy high risk. This is because if the mother's and baby's blood mix, the mother's body may produce antibodies that can damage the baby's red blood cells. To avoid such risks, if the mother's blood group is negative, the father's blood group should also be checked. If the father's blood group is positive, an Anti D injection may be needed. This is usually determined during the third antenatal visit, between 28 and 34 weeks, when the mother's blood group, including the Rh factor, is tested. This information is also crucial in case of a haemorrhage, as it can help arrange for blood transfusions quickly, potentially saving the life of the mother. Blood grouping is done by obtaining blood through a finger prick.
77	A lady is taking salted beetle nut powder at 32 weeks, it this okay for her?	I'm sorry, but the documents provided do not contain information about the safety or risks of consuming salted beetle nut powder during pregnancy.	No, it is not okay for a lady at 32 weeks of pregnancy to take salted beetle nut powder. Betel nut chewing is harmful for both the mother and the baby as it can cause problems with the baby's breathing and organs. The woman should be advised to refrain from taking alcohol, tobacco in any form or addictive drugs such as opium derivatives during pregnancy as these have adverse effects on the fetus, such as slowing growth in utero and even after delivery. Furthermore, the beetle nut powder contains certain chemicals which is not safe for a pregnant woman. The salted powder will also add to her sodium load and may make her prone to blood pressure issues.

78	This woman delivered her baby at 36 weeks. What advice can I give her?	You can advise her to rest, especially if she is feeling tired. She should use disposable sanitary napkins, if available, or change the cloth/pad every 4–6 hours. The cloth should be washed with soap and water and dried in the sun. She should wash the perineum daily with soap and water and avoid sexual intercourse until the bleeding stops. Also, she should be informed about family planning methods and that she can conceive soon after the delivery if she resumes sexual intercourse, unless she uses a contraceptive.	A baby born at 36 weeks is considered late preterm and may face risks such as breathing issues, intestinal problems, and bleeding in their brains. Long-term problems may include developmental delay. It is crucial that the mother and newborn remain together from birth unless the baby is critically ill. The baby will need extra warmth and support for feeding. Kangaroo Mother Care, a technique where the baby is placed in an upright position on the mother, bare chest. This method has been shown to help with body temperature regulation, breastfeeding, weight gain, and bonding. Breastfeeding should be initiated as soon as possible after birth as breast milk is the best nutrition for preterm babies. If the baby is unable to coordinate the suck and swallow reflex, the mother can give expressed breast milk by cup and spoon. In addition, the mother should be advised to prevent hypothermia, delay bathing for the baby, and schedule regular follow-up check-ups. If she has any doubts, she should consult with a healthcare provider.
79	A woman does not feel like eating in her first trimester. What advice can I give her?	You can advise her to eat dry foods, such as roti/paratha, biscuits or toast, after waking up in the morning. It's important to note that each person's morning sickness differs, and some people may have morning sickness that is unrelated to the food they eat. Their morning sickness might get triggered by smell, so they should avoid perfumes and smoke.	During the first trimester, it's common for a woman to experience nausea and vomiting, often referred to as morning sickness. This can lead to a general disinterest in all foods or a lack of desire to eat. It's important to counsel her to take frequent small meals in a day instead of having two or three heavy meals. She should try to avoid fatty or spicy foods, drink fluids. She may find it easier to tolerate dry, salty snacks and bland food. There are a few foods she can prioritize even if she doesn't feel like eating whole meals. These will help ensure adequate nutrient intake for both her and her baby. These include protein-rich snacks like boiled eggs, yogurt, roasted chickpeas, and chicken; veggies like sweet potatoes, green beans, carrots, spinach, fresh berries,dried fruit, and dairy products like paneer; and baked or mashed potato; soups and liquids like juices and milkshakes. she should take banana in the morning which helps in morning sickness.

			Home remedies such as eating citrus fruits, consuming vitamin C, and taking light foods without much spices and oil can also be beneficial as they can help to reduce bloating. It's also worth noting that certain mental health conditions, including anxiety and depression, as well as certain medications taken during pregnancy, can affect appetite.
80	How can I identify complications during delivery?	Complications during delivery can be identified by observing certain signs. These include bleeding from the vagina, loss of foetal movement or severe abdominal pain, and severe headache with blurred vision or spots before the eyes. During the delivery process, it's also important to note the time of birth, place the baby on the mother's abdomen, look for meconium, and ensure the baby is dried and wrapped in a clean, warm towel. If the baby remains wet, it can lead to heat loss.	Complications during delivery can be identified through various symptoms and signs. If the baby's position is anything other than longitudinal with a cephalic presentation (meaning a vertically aligned body with head towards the lower side of the belly), this is abnormal and the woman should be referred to a facility where emergency obstetric services and a caesarean section are available. Foetal distress can be indicated by a heart rate of less than 120 beats per minute or more than 160 beats per minute. If the woman has a haemoglobin level of less than 7 or experiences palpitations or breathlessness at rest, diastolic blood pressure of 110 mmHg or higher, proteinuria, fever with or without rashes, convulsions or fits, severe headache, blurring of vision, severe pain abdomen. Previous obstetric history can also provide clues to potential complications. This includes stillbirth or neonatal loss, three or more consecutive spontaneous abortions, obstructed labour, premature births, twins or multiple pregnancies, a previous baby weighing less than 2500 g or more than 4500 g, admission for hypertension or pre-eclampsia/eclampsia in a previous pregnancy, surgery on the reproductive tract, congenital anomaly, treatment for infertility, spinal deformities, and Rh negativity. Past systemic illnesses such as hypertension, diabetes, HIV, and a history of thalassemia can also indicate potential complications. Other complications include excessive bleeding, the membrane breaking but labour not starting within 24 hours or less, prolonged labour of more than 12 hours, fever, fits. Danger signs that can occur at any time include bleeding, a swollen face and hands, the baby lying sideways and the colour of the water being green or brown.

81	How can I support women in recognizing danger signs during pregnancy?	You can support women in recognizing danger signs during pregnancy by educating them about the various danger signs such as bleeding from the vagina, loss of foetal movement, and symptoms like severe headache, dizziness, or blurred vision. You should also inform them that these signs require immediate referral to a health facility. Additionally, you can educate family members on how to recognize these complications and be prepared for immediate referral.	To support women in recognizing danger signs during pregnancy, it is crucial to provide awareness and health education to both the pregnant woman and her family members. This includes advising them about potential danger signs during pregnancy, delivery, and the post-partum period. Some of these danger signs include generalized weakness, severe headaches, giddiness, blurred vision, convulsions, severe abdominal pain, any vaginal bleeding, fever, difficulty in breathing, and the absence of fetal movements. Other specific signs include labor pains lasting more than 12 hours, labor pains before eight months or 32-36 weeks of pregnancy, premature rupture of the bag of waters or leakage of water from uterus membranes, and failure of the placenta to come out within 30 minutes after delivery. If any of these signs are observed, the woman should be taken immediately to the nearest functional health facility.
82	How can I find out if a woman is pregnant as early as possible?	The earliest way to find out if a woman is pregnant is after the first missed period. There are two ways to diagnose pregnancy early: missed periods and pregnancy testing. Pregnancy testing can be done through the use of the Nischay home pregnancy test card. The test can be done immediately after the missed period. A positive test means that the woman is pregnant.	A woman in her reproductive age can find out if she is pregnant as early as possible by noting a missed period and then conducting a urine pregnancy test after one week of missed date. The simplest way to confirm pregnancy in the first trimester is to use a pregnancy test kit, such as the ,nischay pregnancy test kit, which is widely available. The test can be performed soon after a missed period and requires just five minutes and two drops of the woman's urine. It is also important to register every pregnancy within 12 weeks and to utilize opportunities such as the Village Health and Nutrition Day for early registration and antenatal check-ups. Community members, such as ASHAs, Anganwadi Workers, members of Mahila Mandals, Self-Help Groups, NGOs, panchayat and village health committees, school teachers, and other important people in the village can also be helpful in identifying pregnant women.

83	How do I calculate the Expected Date of Delivery (EDD) for a pregnant woman?	To calculate the Expected Date of Delivery (EDD) for a pregnant woman, you need to find out the date of the first day of her last menstrual period (LMP). Then, count nine months after that date and add seven days to that date. For example, if the first day of the LMP is 10th Dec. 2009, nine months later is 10th Sept. 2010. Adding seven days gives you 17th Sept. 2010. Therefore, the expected date of delivery is 17th September 2010. Please note that this method only gives an approximate date of delivery, and the baby may be born anytime during 15 days before or after the EDD.	To calculate the Expected Date of Delivery (EDD) for a pregnant woman, you need to add 9 months and 7 days to the date of her last menstrual period (LMP). It's important to note that the LMP refers to the first day of the woman's last menstrual period, not the date of the first missed period, as this could lead to a miscalculation of the gestational age and EDD by about four weeks. If the woman is unable to remember the exact date, encourage her to remember some major event, festival or occurrence which she might link with her LMP. If the exact date of the LMP is not known and it is late in the pregnancy, ask for the date when the foetal movements were first felt, known as quickening which is felt at around 20 weeks of pregnancy. This information would give a rough idea about the period of gestation, which needs to be correlated with the fundal height to estimate the gestational age. If the woman has undergone a test to confirm the pregnancy, ask her the approximate date of the test and also, after how many days of missed period it was conducted. This will also assist you in estimating her LMP. The LMP is used to calculate the gestational age at the time of check-up and the EDD.
84	How often should a pregnant woman's weight be checked?	A pregnant woman's weight should be checked at each visit during her pregnancy.	A pregnant woman's weight should be checked at every antenatal care visit. A minimum of four antenatal care visits are recommended during the pregnancy period. This is to ensure that the woman is gaining adequate weight during her pregnancy, which is crucial for her own health, the growing fetus, and for effective breastfeeding later on. The woman's family and community play a key role in ensuring she gets adequate food during pregnancy. A nutritious diet rich in iron, calcium, and protein is required, and a pregnant woman should not fast. Overweight pregnant women may need to adjust their diet and should consult a doctor.

85	Why is a blood test for anaemia essential during pregnancy?	A blood test for anaemia during pregnancy is essential because anaemia can lead to the woman feeling tired, short of breath, and weak. This can impact her ability to take care of her baby and her ability to breastfeed. Anaemia can also increase the woman's risk of infections. If left undetected and untreated, anaemia can cause complications during pregnancy and delivery, including the need for blood transfusions. Therefore, early detection and management of anaemia can help ensure the health and well-being of both the mother and the baby.	A blood test for anaemia is essential during pregnancy to identify if the woman is anaemic and to determine the severity of the condition. Anaemia, or a lack of blood in the body, is common and can lead to complications for both the mother and the fetus. Symptoms of anaemia in a pregnant woman may include paleness, fatigue, breathlessness during routine work, and possible swelling of the face and body. Severe anaemia can lead to complications during delivery, potentially resulting in the death of the mother and/or baby. Prompt treatment, which may include iron tablets, can help prevent complications during pregnancy, delivery, and post-delivery. Therefore, it is important for pregnant women to follow the advice of their healthcare provider to prevent and treat anaemia.
86	Why are mothers over 40 years of age considered at higher risk during delivery?	Mothers over 40 years of age are considered at higher risk during delivery due to increased chances of pregnancy-related complications. These complications can occur at any stage of the pregnancy and can include risks like stillbirth, birth injuries during vaginal delivery, and gestational diabetes. Therefore, it is recommended that these pregnancies be treated as high-risk and the mothers should deliver their babies at a hospital with facilities for C-Section and special care for the baby.	Mothers over 40 years of age are considered at higher risk during delivery due to a variety of factors. The chances of stillbirths, multiple births, pregnancy complications such as high blood pressure, gestational diabetes mellitus, and birth defects are higher in these pregnant mothers. Additionally, there is an increased risk of obstetrical complications like malpresentation, instrumental deliveries, antepartum and postpartum hemorrhage, hypertension, cephalopelvic disproportion and diabetes mellitus. This results in an increased rate of caesarean sections. The increased incidence of underlying medical diseases, decreased cardiovascular reserve and diminished ability to adapt to physical stress that may accompany aging also contribute to the increased risk. Furthermore, there are higher chances of abortions and fetal abnormalities.

87	At what age should a woman be concerned about their delivery?	Women should be specially counseled for delivery if they are adolescent girls below 19 years of age or women who are over 40 years of age. These age groups are at a higher risk of developing complications during delivery.	A woman should be concerned about their delivery if they are in the teenage years or over the age of 35. These age groups are considered high-risk pregnancies due to increased chances of complications such as stillbirths, abortions, and other health risks. Pregnant teenagers are more likely to be under-nourished and suffer problems during delivery, including higher risks of hypertension, systemic infections, and their babies face higher risks of low birth weight, preterm birth. Women aged 35 and above, are often associated with obstetrical complications like malpresentation, instrumental deliveries, antepartum and postpartum hemorrhage, hypertension, cephalopelvic disproportion and diabetes mellitus. The ideal age group for a healthy pregnancy is considered to be 20 to 29.
88	A woman already has 3 children. Should she be concerned during her delivery?	Yes, she should be concerned. Women who have had four or more pregnancies, known as grand multiparas, are at a higher risk of developing complications during pregnancy and labour. Therefore, every pregnancy needs to be cared for by a Skilled Birth Attendant (SBA) during pregnancy.	Yes, a woman who already has three children should be (a little) concerned during her delivery. As a multipara woman, she is considered to have a high-risk pregnancy. There are increased chances of complications such as antepartum hemorrhage, premature births, and postpartum hemorrhage. Additionally, she may also be at a higher risk of obstetric complications such as gestational diabetes, gestational hypertensive disorders, maternal anemia, congenital malformations, perinatal mortality, and even uterus rupture. Therefore, it is important for the family to be counseled about family planning methods after delivery.

89	How does too much weight gain impact pregnancy?	Excessive weight gain during pregnancy (more than 3 kg in a month) can raise suspicion of pre-eclampsia, twins (multiple pregnancy), or diabetes. It is important to monitor the woman's blood pressure in such cases.	Excessive weight gain during pregnancy can lead to a variety of maternal complications. These include an increased risk of gestational diabetes mellitus, which is characterized by high levels of glucose (blood sugar) during pregnancy. This condition can increase the risk of having a very large size baby or overweight baby which may cause obstructed labor, resulting in a cesarean section. In addition to gestational diabetes, excessive weight gain can also lead to gestational hypertension or high blood pressure, and a serious form of gestational hypertension known as preeclampsia. These conditions can lead to a medically indicated preterm birth, which carries its own set of risks for the baby. Obesity during pregnancy can also cause obstructive sleep apnea, a condition in which a person stops breathing for short periods during sleep. This can cause fatigue and increase the risk of high blood pressure, preeclampsia, and heart and lung problems. For the baby, excessive maternal weight gain can increase the risk of birth defects, such as heart defects and neural tube defects. It can also make certain diagnostic tests more difficult, such as checking the fetus's heart rate during labor or seeing certain problems on an ultrasound. There is also a higher risk of stillbirth. Furthermore, babies born to obese mothers have a greater chance of having obesity later in life.
90	Should nuts in included in the diet of a woman with Anaemia?	Yes, nuts should be included in the diet of a woman with Anaemia. They are rich in iron, calcium, vitamins and minerals which are beneficial for anemic patients.	Nuts should be included in the diet of a woman with anemia as they are good sources of iron, magnesium, and zinc, which play a crucial role in improving anemia status. Specific nuts and legumes beneficial for anemia prevention and treatment include beans (white beans, kidney beans, chickpeas beans), lentils, dried peas, cashews, pistachios, and pumpkin seeds. However, the inclusion of nuts in the diet may depend on the socioeconomic status of the family as nuts can be costly. Alternatively, green leafy vegetables such as spinach, and mustard leaves are also rich sources of iron and are more affordable.

91	How can I help a pregnant mother and her family prepare for a safe and comfortable delivery?	To help a pregnant mother and her family prepare for a safe and comfortable delivery, you should use simple language and basic communication techniques to establish a trusting relationship. Ensure that the woman has a companion of her choice throughout labour and delivery. Advise the mother to take enough rest and sleep, and increase her intake of food and fluids. Encourage her to refrain from observing taboos against nutritionally healthy foods. Talk to the woman's family members to ensure that she eats enough and avoids heavy physical work. Advise on regular intake of IFA and Calcium tablets. Also, advise the couple on birth spacing or limiting the size of the family and to abstain from sexual intercourse for about 6 weeks post-partum, or till the perineal wounds heal.	To help a pregnant mother and her family prepare for a safe and comfortable delivery, it is important to provide counseling and education on birth preparedness. This involves planning in advance for the delivery and post-delivery care. This includes: 1. Registration of pregnancy: During the first antenatal visit, the MPW will fill up the MCP card and the RCH register, informing her of the dates of her subsequent antenatal visits. 2. Identifying the appropriate health facility for the delivery: All pregnant women must be encouraged to opt for an institutional delivery. If the mother and family insist on delivering at home, despite counseling, a delivery SBA trained ANM should be arranged. 3. Recognising the signs of labour: The woman should be advised to go to the health facility or inform the ASHA to contact the ANM if she has any signs of labour. 4. Arrangement for referral transport: The woman should be provided with the contact details of 108 and other government referral transport to ensure that a vehicle is available to transport her to the health facility whenever required. 5. Finances: The woman and her family should be assisted in calculating an estimate of expenses of the delivery and related aspects, and advised to keep an emergency fund or have a source for emergency funding in case of complications. They should also be helped to access various schemes that are available for assisting women with transportation facilities or providing funds for maternal health. In addition, the family should be counseled to keep all the antenatal check-up records in one place and prepare a few things to carry while going for delivery, such as clothes, baby towel, and utensils for meals.

92	Why is it important to measure a pregnant woman's blood pressure regularly?	Measuring a pregnant woman's blood pressure regularly is important to rule out hypertensive disorders of pregnancy. High blood pressure during pregnancy may signify Pregnancy-Induced Hypertension (PIH) and/or chronic hypertension. If left unchecked, these conditions can lead to serious complications such as pre-eclampsia or eclampsia. Furthermore, high blood pressure and diabetes are major risk factors for heart disease, the most common cause of death in women in India. Early detection during pregnancy can help identify women at risk and take preventive measures.	Regular measurement of a pregnant woman's blood pressure is crucial to rule out pregnancy-induced hypertension and to monitor for early signs of hypertensive disorders of pregnancy. If blood pressure readings are consistently high, equal to or exceeding 140/90 mmHg, it can lead to conditions such as pre-eclampsia and pre-term labor. Specific symptoms such as a puffy face, swelling of the whole body, proteinuria, severe headache, blurred vision, pain abdomen, and reduced urine output can indicate pre-eclampsia, which can escalate to eclampsia, characterized by convulsions or fits. These conditions can cause severe complications for both the mother and the baby, and in extreme cases, can even lead to fetal loss. Therefore, blood pressure should be monitored at every antenatal visit for early identification and management of these potential issues.
93	How much extra food should a woman eat in the second trimester?	A pregnant woman should eat more than her normal diet throughout her pregnancy. Specifically, she needs about 300 kcal extra per day, over and above her usual diet. This is to maintain her health as a mother and meet the needs of the growing fetus.	During the second trimester, a pregnant woman should add two to three more servings to her regular diet, which equates to consuming an extra 300 to 350 calories per day. This increase in energy requirements can be met by including a balanced diet with small but frequent meals. Essential ingredients to consider are cereals and pulses, with an extra 35 grams and 15 grams respectively, along with a 100ml glass of milk and a teaspoon of sugar. This will provide the necessary calories for her pregnancy. It's important to note that while pregnant women can have cravings, these should not be the sole indicator of nutritional needs. Regular consumption of healthy foods, plenty of water, regular exercise, and avoidance of excess sugar and fat can significantly reduce uncomfortable pregnancy symptoms like nausea, acidity, and constipation. Gaining enough weight during pregnancy is crucial as it reduces the risk of severe complications such as premature birth, which can cause lung and heart problems. A healthy pregnancy also includes fat storage, which the body uses as energy during labor and breastfeeding.

94	How soon after a delivery can a woman return to usual housework?	A woman can start breastfeeding as soon as the baby is able to suckle. However, for babies less than 1500 gm, they may not be able to breastfeed in the beginning. In such cases, the mother can express milk every 2-3 hours to keep the milk supply up and feed the baby with a spoon until the baby is able to get its milk requirements directly from the breast.	After delivery she can start moving about as early as the 2nd or 3rd day because early ambulation/movement helps to prevent thromboembolic/clotting disorders. It is recommended waiting for about two weeks or even up to six weeks after delivery to return to the pre-pregnancy state of working. During this recovery period, she can still perform her activities of daily living such as bathing and eating. Ultimately, the timing is subjective and depends on the individual's health and recovery.
95	What are the risks to a woman if she develops high blood pressure during pregnancy?	A woman who develops high blood pressure during pregnancy may face several risks including the development of Eclampsia, which are fits. She may also experience a risk of the placenta separating from the womb, known as placental abruption. Other risks include stroke, liver failure (HELLP syndrome), kidney failure, blood clotting problems, and even maternal death. Additionally, she may have an increased risk of developing persistent high BP within 5 –10 years and a higher risk of developing heart disease & stroke in the future.	High blood pressure during pregnancy can manifest in two forms: Pre-eclampsia and Eclampsia. Pre-eclampsia is characterized by increased blood pressure and proteinuria. If left untreated, it can progress to Eclampsia, which causes seizures and increases the risk of preterm and stillbirth. Other risks to the woman include Antepartum hemorrhage, cardiovascular diseases, Disseminated Intravascular Coagulation (DIC), and convulsions during delivery. There is also a risk of miscarriage and maternal death. For the fetus, high maternal blood pressure can lead to intrauterine growth retardation, prematurity, and intrauterine death. Furthermore, women diagnosed with high blood pressure during pregnancy are at risk for cardiovascular complications, cerebrovascular complications, renal disease, and other complications.

96	How should a woman be sitting when I measure her blood pressure?	The woman should be sitting comfortably with her back supported and both feet on the floor. Her arm should be rested on a flat surface.	When measuring a woman's blood pressure, she should be sitting in an upright position with her back supported, ideally in a chair. Her feet should be flat on the floor without crossing her legs. Her arm should be resting on the chair or another support, positioned at the level of the heart. The cuff should be accurately tied on the upper arm region. It's important that she is relaxed and has rested for at least 2-3 minutes before taking the blood pressure, ideally undisturbed and at rest for at least 5 minutes in a quiet room, if possible. The blood pressure should be measured consistently using either the right or left arm. If the blood pressure is consistently higher in one arm, the arm with the higher values should be used for all the blood pressure measurements.
97	Is there any food a woman should avoid eating before I measure her blood pressure?	The document does not provide specific information on foods a woman should avoid eating before having her blood pressure measured.	Before measuring a woman's blood pressure, it is advisable that she avoids consuming any food for at least half an hour prior to the measurement. Specifically, salty foods, sugary and processed foods, and drinks, including tea and coffee, should be avoided. Caffeine and tobacco should also be avoided for at least 30 minutes prior to the measurement. It is also important to note that automated machines should be avoided for measuring blood pressure as they need to be calibrated at regular intervals and may under- or overestimate the readings if not properly validated or used.
98	Are there any risks to the baby if a woman has high blood pressure?	Yes, there are several risks to the baby if a woman has high blood pressure during pregnancy. These include the baby not growing to full size within the womb (growth restriction), the baby being born early or with low birth weight, and stillbirth. Additionally, babies who suffered from growth restriction are more likely to develop heart disease, diabetes, and high blood pressure in their adult life.	Yes, there are several risks to the baby if a woman has high blood pressure during pregnancy. These risks include intrauterine growth retardation (IUGR), which is a condition where the baby doesn't grow as expected in the womb. There is also an increased chance of premature birth, stillbirth or intrauterine death. Additionally, the baby may be at risk of having a low birth weight. In cases where the woman has chronic hypertension and preeclampsia (PE), the risks of fetal growth restriction (FGR), premature birth, and perinatal death are even higher.

99	How can a mother keep the baby warm at home after delivery?	A mother can keep the baby warm at home after delivery by providing skin-to-skin contact, known as Kangaroo Mother Care (KMC). This involves undressing the baby (but keeping the cap, nappy, and socks on) and placing the baby prone on the mother's chest in skin-to-skin contact. The baby should be covered with the mother's blouse, 'pallu', or gown, and both should be wrapped with a blanket or shawl. The mother should breastfeed the baby frequently. If possible, the room should be warmed with a heating device. If skin-to-skin contact is not possible, the baby should be clothed in 1-2 layers in summer and 3-4 layers in winter.	To keep a baby warm at home after delivery, a mother can use several methods. One of the most effective is Kangaroo Mother Care (KMC), which involves skin-to-skin contact on the mother's chest. The baby should also be completely covered with proper clothes and a blanket, including a cap for the head and baby socks to cover the feet. Before delivery, the room should be warmed up to a comfortable temperature. Immediately after delivery, the baby should be dried, a cap should be put on its head to prevent heat loss, and it should be placed in skin-to-skin contact with the mother. The baby should then be covered or dressed, wrapped up with a clean cloth, and placed close to the mother. Early breastfeeding should also be initiated. The use of a heater ifrequired can also help maintain a warm environment.
100	How does a woman know that she is going into labour?	A woman may know that she is going into labour if she experiences any one of the following signs: a bloody, sticky discharge from the vagina (also known as 'show'), or painful uterine contractions that increase in duration, frequency, and intensity over time.	A woman can know she is going into labour by experiencing periodic pains that gradually increase. These pains are due to regular contractions which increase in time duration and intensity. However, the time between two successive contractions decreases as labour progresses. In other words, the contraction time duration increases but the interval between two successive contractions gets shorter during the progression of labour. These strong and regular contractions are often referred to as labour pains. the pain do not subsides with painkillers also.
101	How much movement should a woman feel from her baby at 16-20 weeks of pregnancy?	A woman should start to feel her baby's movements around 18-22 weeks of pregnancy. The number of movements can vary, but normally 10-	Between 16 to 20 weeks of pregnancy, a woman should be able to feel her baby's movements, although they may be subtle and not too pronounced. The movements may feel like a twitch or a flutter and can be described as bubbles popping or light tapping. It's normal for these sensations to be confusing, especially for first-time mothers.

		12 fetal movements should be felt by the pregnant woman in a day.	
102	I have noticed a woman's husband is not treating her well during her pregnancy. What should I do?	You can counsel them by explaining the importance of shared responsibilities, especially after childbirth. The husband should be made aware of the physical strain and recovery period involved post-pregnancy. He should be encouraged to help with domestic work and childcare. The woman should be advised to take enough rest and eat well for her recovery. It's also important to discuss the potential health risks for the mother and baby if she is overworked during this period.	The best course of action in this situation is to counsel both the husband and the wife. It's important to advise the husband that during pregnancy, his wife needs rest for the health of both her and their child. He should be involved in antenatal check-up visits at the healthcare facility and take care of her nutrition for healthy outcomes for their child and his wife. If necessary, it may be beneficial to suggest that she stay at her mother's house, as stress and anxiety can adversely affect the outcome of the pregnancy. Also try to involve the whole family in your counselling so they can feel responsible as well.
103	How much water can a woman drink during pregnancy?	The document does not provide specific information on how much water a woman should drink during pregnancy.	A woman can drink between 2 to 5 litres of water per day during pregnancy. This can also be measured as 8-10 glasses of water each day. The exact amount can vary, but it's important to stay hydrated. Other than normal water she can also consume juices, soups etc as per local recipes in the village.
104	How should a woman sleep during the last part of her pregnancy?	A woman should aim to have 8 hours of sleep at night and at least 2 hours rest during the day. It is recommended to lie on the left side as it increases the blood supply to the fetus. She should avoid hard work such as lifting heavy weight and not overexert herself.	During the last part of her pregnancy, a woman should preferably sleep in the left lateral position for good blood supply. This position involves lying on her left side with her legs slightly tucked up towards her chin and her knees bent. Additionally, she should aim to have 8 hours of sleep at night and at least 2 hours of rest during the day.

105	How can a woman manage the craving to eat too much food during pregnancy?	A woman can manage the craving to eat too much food during pregnancy by incorporating a balanced diet with whole grains, dalia, soyabean, peanuts, fresh fish, meat, milk or other foods that are high in protein. These foods not only provide necessary nutrients but also help in getting rid of any extra water, making the belly feel less full and light. It's also advisable to avoid caffeine. However, it's important to remember that a pregnant woman needs about 300 kcal extra per day, over and above her usual diet, to maintain her health and meet the needs of the growing fetus.	A woman can manage the craving to eat too much food during pregnancy through a combination of self-motivation, awareness of the harmful effects of overeating, and understanding the impact of gestational diabetes on the baby. It's important to maintain a balanced and healthy diet, which can be achieved by having frequent mini meals, staying hydrated, and incorporating seasonal vegetables and fruits. While it's okay to occasionally give in to food cravings, it's crucial not to over-indulge, especially in unhealthy foods like sweets or chocolate, as excessive sugar can lead to excessive weight gain and dental problems. The unhealthy food items/fast foods should be kept out of usual field of vision in the kitchen and in the refrigerator and the healthy alternatives should be kept at a place of good vivibility to the pregnant eoman. This will also help curb consumption of unhealthy food.
106	What can a woman do for swollen feet during pregnancy?	Swollen feet during pregnancy, also known as oedema, can be a normal manifestation of pregnancy. However, if the swelling is also present in the face, hands, abdominal wall, and vulva, it is considered abnormal and the woman should be referred to a healthcare professional. If the swelling is associated with high blood pressure, heart disease, anaemia or proteinuria, immediate medical attention is required. Non-pitting oedema could indicate hypothyroidism or filariasis and also requires immediate referral to a healthcare professional.	To alleviate swollen feet during pregnancy, a woman should elevate her feet using pillows and rest as much as possible, ideally with her feet raised. Walking for at least half an hour daily can also be beneficial. It's important to avoid standing for long periods and to wear loose, comfortable clothing and shoes without tight straps. Waist-high compression stockings can also be helpful. Hydration is key, so increasing fluid intake can help the body get rid of excess water. Reducing sodium intake in form of salt restrictions can also help reduce swelling. Additionally, reducing caffeine intake and staying cool can be beneficial.

107	Can a woman with anaemia drink tea during pregnancy?	A woman with anaemia should avoid drinking tea during pregnancy, especially with or immediately before or after meals. This is because tannins in tea can reduce iron absorption, which is crucial for managing anaemia.	A woman with anaemia can drink tea during pregnancy, but it should be in limited quantities and not with meals. This is because tea can interfere with iron absorption, which is crucial for an anaemic woman. Excessive drinking of tea is not recommended as it can decrease iron absorption by 50% or more, potentially increasing the chances of iron deficiency. However, it's important to note that while tea reduces iron absorption, it does not influence iron status in people with adequate iron stores. Therefore, it's better for pregnant women with anaemia to avoid or limit their intake of tea to ensure optimal iron absorption. She can switch tea with health alternatives like juices or soups also to set in a healthy food habit.
108	How does a woman know if she is having twins in her pregnancy?	The suspicion of multiple pregnancies, such as twins, is usually suspected by a health professional like an ANM or a doctor after an abdominal examination. This suspicion can be confirmed through an ultrasound examination.	A woman can determine if she is having twins in her pregnancy through several indicators. The most reliable method is through prenatal ultrasonography, also known as an early USG scan or an ultrasound of the abdomen. This can confirm the presence of twins. Additionally, physical symptoms such as severe morning sickness, including nausea and vomiting (a condition known as hyperemesis gravidarum), can suggest a twin pregnancy. Excessive weight gain and feeling fetal movements in more than one area are also potential signs of a twin pregnancy. Twin pregnancy is generally more common among women undergoing IVF or any fertility related procedures and medicines or in women with family history of twin births.
109	How much sleep should a woman get during pregnancy?	A woman should get 8 hours of sleep at night and at least 2 hours rest during the day during pregnancy.	During pregnancy, a woman should aim to get a minimum of 7-9 hours of sleep per night. It is also beneficial to have an additional 2 hours of rest during the day. Therefore, the total sleep and rest time can range from 8 to 10 hours. This includes both nighttime sleep and afternoon rest.
110	A woman is having increased watery discharge in her third trimester. How do I know if this is normal?	You can provide supportive companionship to the woman, enabling her to face fear and anxiety. Encourage her to express her feelings and reassure her that it's normal to feel this way during pregnancy. You can also focus on talking to her and caring for her emotional needs. If possible, provide as much privacy as possible to	To determine if the increased watery discharge in the third trimester is normal, a few factors need to be considered. The discharge should be thin, clear or milky white in color, which is a normal part of pregnancy. If the discharge is reddish or has a foul smell, it is not normal. A Per-Vaginal (PV) examination can be conducted under supervision to ensure there is no Pre-mature Rupture of Membranes (PROM). It is also advisable to consult the nearest health facility for a professional evaluation.

		the woman. If she is non-cooperative or argumentative, sympathise with her and be friendly; do not get angry. Spend more time in listening to her.	
111	Women who have had an abortion often seek answers to why it occurred.	The document does not provide information on why abortions occur.	Some women may be worried about future pregnancies and also they face pressure for conceiving again as soon as possible. They should be told that spontaneous abortion are not uncommon. The reasons for an abortion are multifactorial and can be diagnosed by a doctor, so it is recommended that they be referred to the doctor. Women may also seek answers from their local health facility. The reasons for seeking an abortion include socioeconomic status, age, health, parity, marital status, or any other issues. These factors cumulatively contribute to their decision to terminate their pregnancies.
112	What steps should you take if you are diagnosed with GDM?	If you are diagnosed with Gestational Diabetes Mellitus (GDM), you should follow a medical nutrition therapy, plan your meals carefully, and engage in regular exercise during pregnancy. If these measures do not help reduce blood sugar levels, further medical intervention may be required. It's also important to monitor for low blood sugar (hypoglycaemia) and know how to detect it. After pregnancy, you should be tested to see if diabetes persists. Always consult with your healthcare provider for personalized advice and treatment.	If you are diagnosed with GDM, it is crucial to consult your gynecologist/medical officer regularly and follow their advice. This may include making dietary changes such as eating more vegetables and making healthy food choices. Regular exercise or walking can help manage excess weight gain during pregnancy. It's also important to monitor your blood sugar levels regularly and take any prescribed medicines or insulin as directed by your healthcare provider. You should also be vigilant in monitoring fetal movements and be alert for warning signs of low blood sugar levels, which can include excessive sweating, fainting, excessive tiredness, shakiness, sleepiness, blurred vision, headache, irritability, and confusion. Regular check-ups are essential to ensure that your blood glucose levels are under control. While prevention of GDM is not guaranteed, adopting healthy diet habits before and during pregnancy may reduce the risk. More frequent doctor check-ups, especially in the last three months of pregnancy, are necessary as your healthcare provider will monitor both your blood sugar levels and your baby's health condition.

113	What are the concerns when one has high-risk pregnancy?	A high-risk pregnancy can lead to various concerns for both the mother and the baby. For the baby, the risks include stillbirth, birth injuries during vaginal delivery, trouble breathing, low blood sugar after birth (hypoglycaemia), jaundice, higher risk of being overweight as a child, and higher risk of developing Type 2 diabetes as an adult. For the woman, there are risks associated with the need for a C-section and the need for special care of the baby. Additionally, there can be psychological stress due to the potential complications and the need for more intensive medical monitoring.	High-risk pregnancy can lead to several concerns for both the mother and the developing fetus. These concerns include the risk of Intra Uterine Growth Retardation, preterm and still birth of the fetus, and maternal mortality. The mother's health should be of utmost priority. Danger signs such as bleeding, excessive headache, dizziness, blurred vision, loss of fetal movement, swollen face or hands, convulsions, and water break should be closely monitored. If any of these signs are experienced, the woman should be immediately referred to the nearest health facility. Family members should also be educated on how to recognize these complications. Screening for high-risk pregnancy types such as elderly primi, multi gravida, previous abortion, previous cesarean section, multiple fetus, breech lie, transverse lie, and diseases such as high blood pressure, severe anemia, less than 10 gm Hb, eclampsia condition, bleeding in pregnancy, diabetes hypothyroidism, fetal distress, HIV positive, high fever is crucial. These patients should be identified and referred to the First Refferal Unit at the earliest to reduce the impact of disease on safe delivery. The nearest institution with skilled staff and equipment to provide Emergency Obstetric and Newborn Care should be identified, and the mother and family should be counseled to go there timely.
114	What steps should be taken when there is reduced amniotic fluid, and it is impacting the baby's growth?	I'm sorry, but the documents provided do not contain information on what steps should be taken when there is reduced amniotic fluid, and it is impacting the baby's growth.	When there is reduced amniotic fluid, it can impact the baby's growth and lead to complications such as preterm birth, early labor, miscarriage, stillbirth, intrauterine growth retardation, cord compression, and the passage of stool in the mother's womb indicative of fetal stress. This condition requires immediate attention and intervention. The steps to be taken include maintaining maternal rehydration by increasing fluid intake to 3-4 liters of water per day, consuming fruits and vegetables with high water content like watermelon and cucumber, and drinking lemon water and coconut water. The mother should also rest in the left lateral position and reduce physical activity or even bed rest if the amniotic fluid is very low. It's important to monitor fetal movement and consult a healthcare professional immediately if there are any danger signs like reduced or no fetal movement. Regular visits to the gynecologist are also advised for proper monitoring and guidance. In addition, the woman should contact the ASHA worker who can refer the patient to the nearest health center for an ultrasound and further assessment by an obstetrician.

115	What might be the gender of the child?	The gender of the child is determined by whether a boy-sperm (XY) or girl-sperm (XX) meet with the egg. This happens completely by chance inside the woman's body. It is not mentioned in the provided text.	The gender of the child should not be revealed by any means, as it is illegal and punishable under the PCPNDT Act of 1994. This law prohibits prenatal testing to identify the gender of a fetus, and any healthcare worker or doctor found committing such illegal activities can face penalties including a fine ranging from Rs.50,000 to Rs.1 lakh, imprisonment up to 5 years, and potential cancellation of their license. The gender of the baby depends on the father's genes, not the mother's. The focus should be on the well-being of the child and mother, rather than the gender of the fetus. All children, regardless of gender, should be given equal rights, love, care, affection, and respect.
116	Why do some women have late conception.?	Late conception in women can be due to a variety of factors including age, irregular menstrual cycles, certain medical conditions such as polycystic ovary syndrome (PCOS) or endometriosis, lifestyle factors like smoking or being overweight, and problems with male fertility. Fertility awareness can help in some cases to increase the chances of conception. However, if a woman is having difficulty conceiving, it is advisable to consult a healthcare professional for further advice and treatment.	Late conception in women can occur due to a variety of reasons. One of the main causes can be irregular menstrual cycles, which can be a result of hormonal imbalances or underlying medical conditions such as cysts, PCOD disease, thyroid related diseases, uterine fibroid. Other medical conditions like diabetes, pelvic infections, and obesity can also contribute to late conception. Most of the cases of infertility/delayed conception are due to mixed factors and can be due to health issues with both husband and wife. Hence the pressure of conceiving should not fall only on the woman. You should counsel her and relieve her anxiety. Stress, anxiety, and the side effects of certain drugs taken during the reproductive age can also delay conception. In some cases, late conception can be due to male factors such as male infertility. Another factor that can lead to late conception is infrequent intercourse, especially not engaging in sexual activity near the time of ovulation. It is advised for couples trying to conceive to have regular intercourse around the 14th day of the menstrual cycle, which is typically when ovulation occurs. Breastfeeding and old age can also be contributing factors to late conception.
117	Why did hypertension develop for the first time¬†after delivery?	The document does not provide information on why hypertension might develop for the first time after delivery.	Hypertension can develop for the first time after delivery due to a variety of factors. Blood pressure normally peaks three to six days after delivery in women, which can be attributed to pain, anxiety, the use of certain drugs such as nonsteroidal anti-inflammatory drugs (NSAIDs), and excessive fluid administration at the time of delivery. Other factors

			include the accumulation of salt and water during pregnancy, and other bodily changes leading to narrowing of blood vessels and high blood pressure. This condition may subside after the termination of pregnancy, but in some cases, it may persist and result in hypertension. It's also possible that the individual may not have taken note of their blood pressure during pregnancy and only noticed it for the first time after delivery. An abnormal unhealthy diet and a sedentary lifestyle during pregnancy can also contribute to the development of hypertension. It's important to manage this condition properly as it can lead to life-threatening complications such as bleeding in the brain, fits, convulsions, stroke, or paralysis.
118	What is the expected daily pad usage post delivery?	The expected daily pad usage post delivery should be less than 5 per day.	The expected daily pad usage post delivery varies depending on the flow of the blood. On the day of delivery, it is normal to use one pad every hour or two, which reduces to one pad every three hours from the second day onwards. Initially after delivery, for about 10-15 days, blood loss with some clots is normal and using 3-5 pads a day is typical. it is normal to use 4-5 pads. Excessive bleeding is when one pad becomes bloody within 15 minutes or if more than 5 pads are used in a day. It is advised to use pads instead of tampons as tampons are more prone to infection. Normal cotton pads are preferred to sanitary pads as they are more absorbent and have a cotton instead of plastic covering, which may be soothing to the stitches and less irritating.
119	Why I am feeling shortness of breath when walk a little?	The shortness of breath you're experiencing when walking could be due to a number of health conditions. It could be a sign of heart conditions such as irregular heartbeats or palpitations, or it could be due to lung conditions. Weakness and decreased ability to exercise could also contribute to this symptom. It's important to consult with a healthcare professional to get a proper diagnosis and treatment.	Shortness of breath, or dyspnoea, can be caused by a variety of factors. One common cause is anemia, which can lead to shortness of breath even after walking a short distance. Heart conditions, such as impending congestive heart failure, can also result in shortness of breath. In addition, certain lung disorders like chronic obstructive pulmonary disease or asthma can cause this symptom. Obesity can also contribute to shortness of breath. In pregnant women, shortness of breath is common, affecting around 70% of healthy pregnant females, especially in the early stages of pregnancy. This is due to the expanding uterus and growing baby decreasing space for breathing, as well as hormonal changes. If shortness of breath is severe and affecting daily activities, it is recommended to consult a medical professional to exclude any heart or lung disorders.

120	why does eating a little make me feel tired.	Eating too little can make you feel tired because your body is not receiving enough nutrients and energy it needs to function properly. This can lead to malnutrition, weakness, and fatigue. It's important to maintain a balanced diet to ensure your body gets the necessary nutrients.	Feeling tired after eating a small amount can be attributed to several factors. One reason could be due to the body working extra to digest the food, especially during pregnancy. The movement of the gut slows down and most of the blood moves to the gut area for digestion, causing other limbs to experience fatigue. As the baby grows, more blood is diverted to the baby and the uterus pushes against the stomach, leaving less space to hold food and causing you to feel full after eating just a small meal. Another reason could be a diet rich in carbohydrates, which can cause postprandial somnolence. Eating to the point of fullness can also cause tiredness. Additionally, improper sleep at night or decreased insulin levels can lead to fatigue after eating. Severe anemia can also cause tiredness after eating as it puts a lot of stress on the heart. Therefore, it is important to take a balanced diet and get evaluated for conditions like anemia if symptoms persist. Proper rest after meals, especially during pregnancy, is also recommended.
121	Why is my vomiting increasing?	Your vomiting could be increasing due to a variety of reasons. It could be due to morning sickness, especially if you are in the early stages of pregnancy. If the vomiting is excessive and continues after the first trimester, it could be a condition called hyperemesis gravidarum. Other causes could be related to certain health conditions like sickle cell anemia or hypertensive disorders of pregnancy. It's important to seek medical attention if the vomiting is severe or persistent.	Your increasing vomiting could be due to several factors related to pregnancy. Vomiting is a common symptom of pregnancy, experienced by around 70% of pregnant women, particularly during the initial phase. This can be due to hormonal changes that occur during pregnancy, which can trigger morning sickness. If you are having a multiple pregnancy, such as twins, the levels of these hormones might be higher, leading to increased vomiting, a condition known as hyperemesis gravidarum. A history of nausea and vomiting in previous pregnancies or a family history of severe nausea and vomiting during pregnancy can also contribute to this. As the pregnancy progresses, these hormones can continue to influence the vomiting center, leading to an increase in vomiting. It's important to monitor this closely, especially in cases of twin pregnancies. If your vomiting continues to increase, it would be advisable to contact your local health facility.

122	Why is my haemoglobin not increasing even after having good food?	There could be several reasons why your haemoglobin is not increasing even after having good food. One possibility is that your body is not absorbing the nutrients from the food properly. Another possibility is that you have a condition such as anemia that is affecting your body's ability to produce haemoglobin. It's also possible that you're not getting enough of certain nutrients, like iron, that are needed to produce haemoglobin. You should consult with a healthcare provider for a proper diagnosis and treatment plan.	Your haemoglobin may not be increasing even after having good food due to several reasons. One reason could be anemia or low haemoglobin, which is common during pregnancy due to hormonal changes and an increase in blood plasma. The body's iron demand increases during this time and cannot be met solely by a good diet. It needs to be supplemented with extra iron intake in the form of iron folic acid tablets. Another reason could be malabsorption of iron, which can prevent an improvement in Hb levels. Certain medical conditions like peptic ulcers can also lead to a loss of blood in stools, which you might not notice until later. Furthermore, even if you're eating good food, it may be deficient in micronutrients such as iron, folic acid, and vitamin B12. Consuming foods rich in these nutrients, such as jaggery, beetroot, pomegranate, pista, dates, green leafy vegetables, yogurt, asparagus, and mushrooms, may help increase your haemoglobin levels. Supplementation of micronutrients in tablet form can also help increase haemoglobin if no other disease, such as sickle cell anemia or thalassemia, is present. Lastly, consuming tea or milk with food could also be affecting your haemoglobin levels.
123	what is the reason for not getting proper sleep?	The document does not provide specific reasons for not getting proper sleep.	The reasons for not getting proper sleep can be numerous and varied. They can include hormonal changes, stress, anxiety, anemia, reflux disease, and heart failure. In particular, hormonal changes and anxiety are common in pregnant women, along with the discomfort of a growing baby bump and an elevated perception of pain. Other factors that can contribute to sleep disturbances are lack of physical activity and improper diet. Consuming caffeine in the evening, such as in tea, coffee, or cola drinks, can also make it harder to fall asleep. To improve sleep, it is recommended to avoid eating before going to bed to reduce the chance of reflux, take short naps, engage in physical activities like yoga to reduce stress and anxiety, and consider natural remedies like taking jaiphal at night with milk.
124	what is the cause for leg swelling?	Leg swelling can be caused by several factors including standing or sitting for long periods, being overweight, aging, or it could be a normal manifestation of pregnancy. It can also be a	Leg swelling, also known as edema, can be caused by a variety of factors. During pregnancy, the extra fluid in the body, the pressure from the growing uterus, and prolonged standing or walking can lead to swelling in the legs. This can be exacerbated by excessive salt intake. The developing fetus pressing on leg veins can also contribute to this swelling. Hypertension, both generally and specifically pregnancy-induced, can cause

		symptom of serious conditions such as heart disease, hypothyroidism, filariasis, or proteinuria. If there is leg swelling in association with these conditions, immediate medical attention is required.	leg swelling, as can hypothyroidism and kidney disorders. Certain medications, such as amlodipine, may also lead to edema. Additionally, loss of proteins can lead to swelling of the feet, and anemia is a common cause of leg swelling. Regular health check-ups, including hemoglobin monitoring and urine tests for proteinuria, can help reduce the chance of complications during pregnancy.
125	At 3 Months pregnancy what kind of food should be taken to reduce vomiting	At 3 months of pregnancy, to reduce vomiting, the woman should eat small frequent meals, avoid greasy food, eat lots of green vegetables, and drink plenty of fluids. If vomiting is excessive in the morning, she should eat dry foods, such as roti/paratha, biscuits, or toast, after waking up in the morning.	Vomiting is a common symptom during pregnancy, experienced by around 70% of pregnant women, and can last throughout the pregnancy. To reduce vomiting, small frequent meals should be taken instead of heavy meals. Foods that are easily digestible, non-spicy, and bland should be consumed. This includes fruits such as bananas, oranges, lemons, watermelons, berries, and other foods with high citrus content like tangerines (fruit like orange) and sweet lemons. These are known to help control vomiting. Additionally, foods like rice that are easy to digest can also be beneficial. It's also recommended to avoid foods that induce nausea. Ginger and herbal tea can also be helpful in reducing vomiting.
126	At 3 Months pregnancy - why, I feel fatigue and uneasyness?	Feeling fatigue and uneasiness during the first trimester of pregnancy can be due to several reasons. Hormonal changes can make you feel tired. Also, your body is working hard to support the growing fetus which can cause tiredness. Dehydration can also cause fatigue. If your fatigue is severe or you're feeling breathless at rest, it could be a sign of severe anaemia and you should seek medical attention.	At 3 months of pregnancy, you may feel fatigue and uneasiness due to several factors. There are numerous hormonal changes occurring in your body, which can cause morning sickness. These hormonal changes, along with changes in blood sugar and blood pressure levels, can contribute to feelings of exhaustion and unease. Anxiety about motherhood, worry about the baby's health, and stress can also play a part. Physically, you are carrying extra weight and may be dealing with frequent urination and trouble sleeping. The fetus can put pressure on your digestive tract, leading to uneasiness and digestion problems. Additionally, you may be experiencing anemia, a condition characterized by reduced hemoglobin in the blood. The pregnancy-induced dilution of blood can put an extra burden on your heart, leading to feelings of fatigue and weakness. It's important to rest and take care of yourself during this time.

127	3 Months pregnancy/mother - how to know baby boy or girl during pregnancy	The sex of the baby is determined by whether a boy-sperm (XY) or girl-sperm (XX) meets with the egg. This happens completely by chance inside the woman's body. It is not possible to determine the sex of the baby during pregnancy without medical procedures such as an ultrasound. However, it is important to note that in many places, including India, it is illegal to use these methods to determine the sex of a baby due to issues of gender bias and sex-selective abortions.	Determining the gender of a baby during pregnancy is illegal and punishable under the PCPNDT act. This includes ultrasonography done to reveal the gender. Both the doctor and the family involved can be punished with a fine ranging from Rs.50,000 to Rs.1 lakh and imprisonment up to 5 years. This law also applies to anyone who facilitates in the detection of the unborn child's sex leading to the abortion of fetuses. It's important to note that the gender of the baby depends on the father's genes, not the mother's, and every child, regardless of gender, should be given equal rights, love, care, affection, and respect.
128	What kind of food should be taken to increase breast milk	During pregnancy, a balanced diet rich in proteins and vitamins is important for the preparation of breast milk. Foods such as milk and milk products, eggs, chicken, fish, meat, fruits, and vegetables should be consumed every day. At least 3 main meals and 2 nutritious snacks should be consumed, second trimester onwards. Supplementary nutrition provided by the Anganwadi centre should be consumed regularly along with the daily diet. Consumption of iron-folic acid (red coloured) tablet prevents anemia and facilitates absorption of iron when consumed with vitamin C rich foods like lemon, guava, orange, and amla.	To increase breast milk production, a balanced diet should be maintained. This includes proper hydration and consumption of a variety of foods. Protein-rich foods like chicken, fish, paneer, and pulses such as masoor and moong dal are beneficial. Cereals, oats, fenugreek, fennel seeds, garlic, almonds, sesame seeds, and chickpeas can also enhance milk production. Green leafy vegetables, carrots, and fruits should be included in the diet. Foods like shatavari and yeast, which have properties of secreting milk, may be consumed. Additionally, plenty of fluids and milk should be taken.

129	A woman is developing an allergy after taking iron tablets. She is getting swelling in her feet. She has tried tablets both from the market and the doctor. She still has swelling in her feet and has pain in her stomach and they told her she has an infection. She has tried everything but is not getting better. The doctor told her that she will only get better after she delivers. What could be the reason for this? Could it be due to the iron tablets or is there another reason?	The woman's symptoms could be due to a number of factors. It's possible that she is experiencing side effects from the iron tablets, which can include nausea, occasional vomiting, and mild diarrhea. However, the swelling in her feet and stomach pain could also be symptoms of other conditions, such as heart disease or an infection. It's also possible that these symptoms are related to her pregnancy. It's important that she consults with a healthcare professional to determine the exact cause of her symptoms.	The woman's symptoms are less likely to be due to an allergy to iron tablets. The swelling in her feet could be due to various reasons, including high blood pressure, severe anemia, heart disease, clots in the leg, or renal disease. It could also be a normal manifestation of pregnancy due to extra fluid in the body and pressure from the growing fetus in the uterus. If the swelling is associated with high blood pressure, heart disease, anemia, or proteinuria, she should be referred to a medical officer. Non-pitting edema could indicate hypothyroidism or filariasis and requires immediate referral for investigations. The pain in her abdomen could be due to gastritis, worm infestation, high blood pressure, or different types of anemia like sickle cell anemia. It could also be due to iron consumption as constipation is a common side effect of iron intake. To prevent constipation, she can add iron-rich foods that also provide fiber to her diet, such as fruits, vegetables, and whole grains/fortified cereals, and drink plenty of fluids. Another possibility is that she may have pregnancy-induced hypertension or the gravid uterus pressing on the leg veins, causing the swelling of the feet. Both of these conditions will subside after delivery. Therefore, the doctor's advice that she will only get better after she delivers seems to be accurate.

130	Why are some women not able to produce breastmilk? Some women make less breastmilk and some women make more.	The document does not provide specific reasons why some women are not able to produce breast milk or why some women produce less or more breast milk.	Some women may not be able to produce breast milk or may produce less than others due to various factors that can affect lactation. These factors include infrequent breastfeeding, giving formula milk to the baby, the baby not sucking the breast properly due to premature birth, jaundice, or infection, or the woman being under stress. Other factors that influence breastmilk production include the nutrition and hydration of the mother, correct latch and positioning, early initiation of breastfeeding, skin to skin contact, and exclusive breastfeeding. Feeding more often can help in the production of more milk, as the more the baby sucks, the more milk is produced. A balanced diet, along with iron and calcium supplements, can also aid in milk production. It's important for the mother and baby to spend as much time together as possible, and for the mother to get adequate rest. Family and spouse support is also crucial during this period. The baby should be fed on demand and 'cues', such as suckling movements and sounds, should be identified before the baby cries. The best way to assess milk supply is by monitoring the infant's weight through test weighing and measuring stool output during wellness visits. If the baby passes urine 4-6 times a day and is gaining sufficient weight (after 1 week of birth, 150-200 gm per week), there is likely enough milk for the baby. If a woman is having less milk, she should consult a medical officer for advice.
131	What does the word Thalassemia mean?	I'm sorry, but the provided context does not contain information on what the word Thalassemia means.	Thalassemia is an inherited blood disorder present since birth that causes the body to produce abnormal hemoglobin and have less hemoglobin than normal. This abnormal structure of hemoglobin results in red blood cells that cannot function properly and last shorter periods of time in the blood circulation, leading to anemia due to defective circulating red cells. Red blood cells carry oxygen, which is required for all the cells of the body to function well. It is important to diagnose whether you carry genes for thalassemia during pregnancy, as it can be transmitted to the baby, especially if both parents carry the genes for the disorder.

132	A woman has taken Iron tablets and she has also received iron sucrose injections, but her Hb is not rising. What is the reason for this?	The feeling of nausea or vomiting after taking iron tablets can be a side effect of the medication. It can be reduced by taking the tablet after meals.	There are several possible reasons why a woman's hemoglobin (Hb) level is not rising despite taking iron tablets and receiving iron sucrose injections. One possibility is that her anemia is not due to iron deficiency. In such cases, her Hb will not rise after giving iron tablet and iron sucrose injection. She may have a deficiency of other nutrients that are needed for red blood cell production, such as vitamin B12, folate, or copper. Another possibility is that she may have a condition that causes chronic inflammation, infection, or autoimmune disease, which can suppress the bone marrow's response to iron therapy. She could also have other blood disorders which are not responsive to iron therapy. In these cases, she should be referred to a tertiary care center for further investigation. Another potential cause could be thalassemia, a type of hemoglobinopathy. Other conditions leading to non-nutritional anemia, such as soil transmitted helminths inflammation, fluorosis, malaria, and chronic diseases such as tuberculosis should also be considered.
133	What lifestyle advice can be given to a pregnant woman ? How much physically active should a pregnant woman be ? Can she be allowed to lift heavy weight?	A pregnant woman should get adequate rest, with 2 hours of rest in the day and 8 hours of sleep at night. She should also engage in at least thirty minutes of brisk walking or light exercise daily. However, she should not lift heavy objects. Consumption of alcohol, beedi, cigarette, gutkha, tobacco should be avoided. She should also maintain a healthy diet to ensure proper weight gain during pregnancy.	A pregnant woman should maintain a healthy lifestyle, which includes a balanced diet of fruits, vegetables, whole grains, lean proteins, and healthy fats. This is crucial for the well-being of both the mother and the baby. She should also aim to incorporate 30 minutes of moderate physical activity such as walking or yoga, at least 5 times per week. The level and type of activity can vary depending on the stage of pregnancy, and it's important to consult with a medical professional to determine the most appropriate level of physical activity based on individual circumstances. During the later stages of pregnancy, exercises that put direct pressure on the abdomen should be avoided. It is generally recommended to avoid lifting heavy weights during pregnancy as this can increase the risk of preterm labour. Other precautions include not exercising while lying flat on the back, stopping exercise if contractions are felt or if the heart rate is raised very high (above 140 beats per minute). If the woman is taking insulin and experiences symptoms of low blood sugar, exercise should be stopped and the low blood sugar should be treated immediately. Additionally, the woman should aim for 8-10 hours of sleep and try to decrease stress.

134	How many times a day it is normal to change the pad after delivery ? When should the woman be referred to the first referral unit?	The sanitary pads must be changed every 4-6 hours or more frequently if there is heavy lochia. A woman should be referred to the first referral unit if she has any complaints regarding the condition of her breasts.	After delivery blood/ other secretions (lochia) are normally seen for 3-6 weeks which gradually decreases and changes color from reddish to yellow to creamy white (in about 2 weeks). It is normal for a woman to change her pad 3-5 times a day after delivery, depending on the absorbency of the pad. This frequency can be translated to changing the pad every 4-6 hours. The sanitary pads must be changed frequently to ensure that the woman does not contract any infection. If the woman is using more than five pads in a day, she is having heavy bleeding. If the woman experiences heavy bleeding of more than one pad per hour, feels dizzy, experiences abdominal cramping, or has a foul-smelling per vaginal discharge, she should be referred to the first referral unit or an institution which manages complications. It is also recommended that a woman should have someone near her for the first 24 hours to take care of her and the baby.
135	What are the risks of anemia during pregnancy?	The risks of anemia during pregnancy for the woman include increased blood loss, low mood after childbirth, poor maternal/infant interaction, impaired breastfeeding, and maternal death. For the baby, the risks include growth restriction in the womb, being smaller than normal, being born early, stillbirth, and long-term problems with brain function.	Anemia during pregnancy can lead to several risks for both the mother and the baby. For the mother, anemia can increase the risk of excessive blood loss, low mood after childbirth, poor maternal/infant interaction, impaired breastfeeding, and even maternal death. It can also lead to complications such as preeclampsia, antepartum/ postpartum hemorrhage, shock, and cardiac failure. For the baby, anemia in the mother can cause growth retardation, resulting in the baby not growing to full size within the womb. This can lead to low birth weight, premature birth, and even stillbirth. The baby's mind and organs may not fully develop, which could result in long-term problems with brain function. Even after birth, the chances of diseases and infections will be high in such babies.
136	How can severe Anaemia be treated in pregnant woman?	The document does not provide specific information on how severe anaemia is treated in pregnant women.	Severe anaemia in pregnant women, characterized by a hemoglobin (Hb) level less than 7g/dL, requires immediate medical attention. The woman should be referred to the nearest primary health care center, community health center, or district hospital for further treatment. The treatment approach depends on the duration of pregnancy and the severity of the anaemia. If the woman is less than 30 weeks pregnant, oral iron therapy with ferrous sulfate is recommended, with one tablet taken three times daily until the Hb level normalizes. A maintenance dose of one tablet daily is then continued for 100 days post-delivery. If the woman is between 30-36 weeks pregnant, parenteral iron therapy with iron sucrose is administered daily for 10 days. If the woman is more than 36 weeks pregnant or

			if her Hb level is extremely low (less than 5 g/dL), or if she is unwell or severely short of breath, a blood transfusion is the treatment of choice. The woman should be admitted to a hospital with blood transfusion facilities and 24-hour specialist care.
137	Why do pregnant women get Anaemia?	Pregnant women get anaemia due to the body's increased need for iron during pregnancy. Other contributing factors include short intervals between pregnancies, repeated pregnancies, and not taking the iron folate medicine.	Pregnant women are susceptible to anaemia due to a variety of factors. During pregnancy, the volume of blood in the body increases, which requires more iron and vitamins to produce additional red blood cells. This increased demand for iron can lead to a deficiency if the body does not have enough iron stores, which is the most common cause of anaemia. Other nutritional deficiencies that can lead to anaemia include lack of zinc, copper, B12, B6, and folic acid. In addition to nutritional deficiencies, anaemia can also be caused by increased red cell destruction due to conditions like fevers or inherited blood disorders such as sickle cell anaemia and thalassemia. Hemodilution, a condition where there is an increased amount of plasma in the blood, can also contribute to anaemia in pregnant women. Certain other factors can increase the risk of anaemia during pregnancy, such as carrying multiple babies, having a short interval between pregnancies, experiencing heavy menstrual flow before pregnancy, or having a low iron intake. Other factors include diminished intake of iron due to loss of appetite or vomiting, and depleted iron stores due to previous pregnancies.

138	How can we test for worm infections in a pregnant woman?	We can test for worm infections in a pregnant woman by taking a stool sample.	To test for worm infections in a pregnant woman, clinical assessments and stool tests are typically conducted. A stool sample from the woman is analyzed in a lab for signs of worms or their eggs. This examination of the stool for ova and cysts can help confirm the presence of a worm infection. In terms of prevention, good hygiene practices such as handwashing before cooking and eating food, after defecating or dealing with children's stools, avoiding open defecation, and not walking barefoot in open grounds are recommended. If a worm infestation is detected, deworming can be done with one dose of 400 mg albendazole (1 tablet), preferably during the second trimester, but only after the first trimester.
139	How common is Anaemia in India?	I'm sorry, but the document provided does not contain information on the prevalence of Anaemia in India.	Anaemia is quite common in India, especially among women and children. According to the National Family Health Survey 5 (2019-21), 57% of women in the age group of 15-49 years were found to be anemic. The prevalence of anaemia in pregnant women is 52.2%, and this figure is consistent across most Indian states. Additionally, the prevalence of anaemia is also high in children aged 6-59 months, with a rate of 58.6%. Therefore, the prevalence of anaemia among the reproductive age group women and children in India is significantly high.
140	A woman is feeling tired and weak during the third trimester of pregnancy. Could she have severe Anaemia?	Yes, the woman could have severe anaemia. Symptoms of severe anaemia include fatigue, weakness, palpitations, shortness of breath, and chest pain. If her hemoglobin (Hb) level is less than 7g/dL, it is indicative of severe anaemia. It is recommended to refer her to a medical officer for further management and advise her to have a hospital delivery.	Yes, it is possible that a woman feeling tired and weak during the third trimester of pregnancy could have severe anaemia. Symptoms of severe anaemia include feeling very weak, always being exhausted, irritability, panting even on slight effort, lethargy, breathlessness, giddiness, and getting tired easily. However, there could be multiple reasons for these symptoms during the third trimester of pregnancy, such as carrying a growing baby, multiple bathroom trips disrupting sleep, and difficulty sleeping due to an inability to find a comfortable position. To cope with pregnancy fatigue, it is recommended to practice good sleep hygiene, drink plenty of water, get some exercise like walking, and eat small, regular meals. It is important to check her Hb levels to ensure her symptoms are not related to Anaemia. Other signs of severe anaemia include paleness and low blood pressure. If anaemia is suspected, it is important to consult with a medical officer for proper evaluation and diagnosis. The severity of anaemia can be assessed by a medical officer or after doing a hemoglobin test. If the hemoglobin level is less than 7, then it is considered severe anaemia.

141	What are the side effects of taking iron tablets for pregnant women?	The side effects of taking iron tablets for pregnant women can include nausea or occasional vomiting, which can be prevented by taking the tablet after meals. Another side effect is constipation, which can be managed by drinking more water and eating fruits. Other possible side effects include black stools or mild diarrhoea. It's also important to note that iron tablets should not be taken along with tea as that reduces its absorption.	Taking iron tablets during pregnancy can lead to several side effects, primarily affecting the gastrointestinal system. These include stomach upset, bloating, nausea, and vomiting. Constipation and diarrhea are also common, as well as a metallic taste in the mouth. Some women may experience gastric irritation, epigastric pain, and dark stools. Other side effects can include heartburn, dizziness, and headache. To minimize these side effects, it is often recommended that pregnant women take iron tablets after food and just before sleeping. If the symptoms become severe or persistent, it is advised to seek medical attention. It is important to always follow the prescribed dose.
142	What foods should a vegetarian woman avoid if she has Anaemia?	A vegetarian woman with anaemia should avoid consuming tea and coffee with meals, as these can inhibit iron absorption. She should also limit intake of foods high in phytic acid like whole grains and legumes, or consume them in a way that reduces their phytic acid content, such as by soaking, sprouting or fermenting them. Phytic acid can also inhibit iron absorption.	A vegetarian woman with anaemia should avoid certain foods and beverages that can interfere with the absorption of iron. These include tea and coffee, which should not be consumed with meals or iron folic acid (IFA) tablets. Dairy products such as milk, cheese, and yoghurt, as well as foods containing tannins like corn, grapes, and sorghum, can also reduce iron absorption when consumed with iron-rich foods. It's important to note that there are no specific dietary restrictions for anemia, but it's beneficial to pair iron-rich foods with sources of vitamin C, like lemon and amla, to enhance iron absorption.

143	What can go wrong if a woman gets Anaemia after delivery?	If a woman gets anaemia after delivery, it can lead to tiredness, inability to breastfeed, and bonding problems with the baby.	If a woman gets anemia after delivery, she may face difficulty in recovering from the physical stress of delivery and may have problems taking proper care and feeding of her baby. This condition can lead to depression, fatigue, impaired cognition, and altered maternal-infant bonding. It can also result in an impaired quality of life, reduced cognitive abilities, emotional instability, and increased irritability due to low energy. Furthermore, it can lead to increased risk of puerperal sepsis, subinvolution, poor lactation, puerperal venous thrombosis, pulmonary embolism, poor wound healing, and congestive cardiac failure. In extreme cases, it could affect her ability to produce breast milk or even cause heart problems. To avoid anemia after delivery, it is recommended to continue taking one iron and folic acid tablet daily for 180 days postpartum and to consume iron-rich foods. Inclusion of vitamin C rich foods can also help in improving iron absorption. It is important for the woman's family to monitor and support her after her delivery, and for her to have regular follow-ups with a healthcare professional if she has moderate or severe anemia.
144	When should I refer a pregnant woman with Anaemia to the first referral Unit?	A pregnant woman with anaemia should be referred to the first referral unit if her haemoglobin level has not increased after one month of starting her on a therapeutic dose of IFA. This referral should be made to a higher facility with a good laboratory infrastructure and trained personnel so that the cause of the anaemia can be determined and the requisite treatment started.	A pregnant woman with anaemia should be referred to the first referral unit (FRU) under certain conditions. If the woman has severe anaemia, indicated by a haemoglobin level of less than 7mg/dl, she should be immediately referred to the FRU. This also applies if there is no improvement in her haemoglobin level after undergoing oral iron folic acid therapy for the recommended duration. Women with moderate to severe anaemia should also be referred to the FRU for further treatment, which may include injections or blood transfusions. The husband and family play an important role in caring for the woman during this time.

145	What food should a vegetarian woman with Anaemia eat during pregnancy?	A vegetarian woman with anaemia during pregnancy should eat a well-balanced diet consisting of a variety of foods. She should consume milk and dairy products like curd, buttermilk, and paneer as they are rich in calcium, proteins, and vitamins. Fresh/seasonal fruits and vegetables should be included as they provide vitamins and iron. Cereals, whole grains, and pulses are good sources of proteins. Green leafy vegetables are a rich source of iron and folic acid. A handful (45 grams) of nuts and at least two cups of daal can provide the daily requirement of proteins.	A vegetarian woman with Anaemia during pregnancy should consume a diet rich in iron and vitamin C. Iron-rich foods include green leafy vegetables such as spinach, fenugreek (methi), bathua, amaranth leaves, and radish leaves. Whole pulses like Bengal gram and horse gram, cereals like whole wheat flour, bajra, ragi, jowar, and other foods like jaggery, lentils, chickpeas, pomegranates, apples, almonds, green peas, figs, beans, and onion stalks are also beneficial. Vitamin C rich foods like fruits (gooseberry, guava, lemon, orange, raw mango), vegetables (drumstick leaves, amaranth leaves, capsicum) and sprouts help in improving iron absorption. This helps in prevention of anemia. Foods like oranges and tomatoes can also be added to help her body absorb iron better. She can also cook meals using these ingredients such as saag made from mustard greens or spinach, dal, chana masala, and rajma. She can also cook poha with added veggies, upma, and rotis made from whole wheat. She can also have amla (Indian gooseberry) chutney or fresh orange juice to add Vitamin C to her diet. An IFA supplement should be consumed along with foods rich in vitamin C such as lemon in the form of nimbu-paani, amla (Indian gooseberry) etc. for improving the absorption of iron. Drinking of tea or coffee within an hour of consuming IFA should be discouraged, as it may reduce the iron absorption. Iron and calcium tablets should not be consumed together, as calcium interferes in iron absorption. At least two hours of interval should be there between calcium and iron tablet consumption. Cooking in iron utensils is also encouraged to increase iron intake.

146	A woman with mild anaemia is taking her tablets for two weeks and she is not feeling better, she is still tired. Is this normal?	Yes, this can be normal. Anaemia can cause feelings of tiredness and weakness, and while taking iron supplements can help to increase the body's iron levels, it may take a few weeks to several months for the body to replenish its iron stores and for symptoms to improve. It's important for the woman to continue taking her medication as prescribed and to seek medical attention if her symptoms worsen or do not improve after a prolonged period.	It is normal for a woman with mild anemia to not feel better after taking iron tablets for two weeks. Recovery from anemia can take up to one month or even three to six months to restore iron levels completely. The recovery time can depend on many factors, such as the levels of iron when the treatment begins, the causes of the iron deficiency, and how well the body reacts to treatment. After one month of treatment, there is typically an increase of 1gm/dl in Hb levels. The process of red blood cell production, may not yet be completed within two weeks. The body needs time to rebuild its iron stores and produce more red blood cells. If there is no improvement in Hb after one month of treatment with 2 tablets of IFA daily, then she should be referred to a first referral centre. It is also important to check for other factors such as an inadequate or unbalanced diet, inadequate rest, or other health issues if she feels very tired. Consuming iron-rich foods and foods rich in vitamin C can help improve iron absorption. Drinking tea or coffee within an hour of consuming IFA should be discouraged, as it may reduce iron absorption. Iron and calcium tablets should not be consumed together, as calcium interferes with iron absorption. If she doesn't feel better after a month or if her symptoms worsen, she should be referred to a PHC doctor.
147	A woman is having heart palpitations. Is this something to worry about?	Heart palpitations can be a cause for concern as they may indicate a serious heart condition. If a woman is experiencing heart palpitations along with other symptoms such as shortness of breath, chest pain, dizziness, and weakness, it is recommended that she be taken to the hospital for an urgent review. The SMARThealth device can be used to monitor her condition. If the readings indicate possible or severe pre-eclampsia, immediate medical attention is required.	Heart palpitations, characterized by feelings of a fast-beating, fluttering, or pounding heart, can occur in women due to various reasons such as overexertion, stress, consumption of caffeine, alcohol, tobacco, or diet pills, thyroid-related diseases, hormone changes associated with menstruation, pregnancy, or menopause, low blood pressure, heart disease or abnormal heart valves, and side effects of certain medications. Sometimes, these palpitations can be a sign of a more serious heart problem, such as an irregular heartbeat, severe anemia, or even congestive heart failure, which might require medical attention. In the case of pregnancy, occasional sensations of heart palpitations can happen due to increased blood volume and hormonal changes. However, persistent or severe palpitations can be a cause for concern. Therefore, it is necessary for a woman experiencing heart palpitations to consult a doctor to determine the cause and address it timely. If a pregnant woman reports such symptoms, it is always better to be safe and get any unusual symptoms checked by the doctor.

148	A pregnant lady is looking very tired and she has white spots on her nails. What does this mean during her pregnancy?	The symptoms described, such as fatigue and white spots on nails, could suggest a deficiency in certain nutrients, possibly iron, indicating anemia. However, a proper diagnosis can only be made by a healthcare professional. It is recommended to refer the woman to a Primary Health Centre or District Hospital for a thorough check-up.	The pregnant lady's fatigue and white spots on her nails could be indicative of several conditions. Fatigue is a common symptom of early pregnancy, often starting as early as week five and lasting through the first trimester. This is due to major changes in the body such as an increase in certain hormones , an increase in blood volume to support the developing baby and placenta, low blood sugar, low blood pressure, sleep disturbances, and nausea. Fatigue can also occur in the third trimester due to the physical demands of carrying a growing baby, frequent bathroom trips disrupting sleep, and difficulty finding a comfortable sleeping position. The white spots on her nails could be due to a deficiency in vitamins and minerals, including calcium, zinc, or iron, which could also be causing her fatigue. One out of four pregnant women develop such spots, and they are usually not a cause for concern. However, they could also be a sign of anemia, a condition that is common during pregnancy as the body needs more iron. To manage her fatigue, the woman should practice good sleep hygiene, drink plenty of water, get some exercise like walking, and eat small, regular meals. She should also consult a doctor to rule out anemia or any other deficiencies. If she is found to be anemic, she should be counseled on a balanced diet and adequate rest during pregnancy. A finger prick blood test can be performed to confirm if she is anemic and appropriate recommendations can be made based on her test results.

149	Are there any tips I can give this woman for reducing back pain? She is 36 weeks pregnant	Yes, there are several tips you can give to a pregnant woman for reducing back pain. Encourage her to change positions frequently as no position is comfortable for a long period of time. She can also try non-pharmacological methods of relieving pain like practicing relaxation techniques, such as deep breathing exercises. A back massage can also help relieve the pain. Assisting her in voiding urine and changing her position will make her more comfortable.	Back pain is a common issue during pregnancy, particularly in the later stages due to the extra stress on the back from the expanding uterus and the growing baby's weight. Here are some tips to help reduce back pain: 1. Maintain good posture: As the baby grows, the center of gravity shifts forward, which can cause the woman to lean back and strain the lower back muscles. To avoid this, she should stand up straight and tall, keep her shoulders back and relaxed. When sitting, she should choose a chair that supports her back or use a small pillow behind her lower back. 2. Rest and sleep: She should take proper rest, ideally 2 hours during the day and 8 hours at night. It's recommended to sleep on her side, preferably the left, and keep one or both knees bent. Placing a pillow between her knees and another under her belly can also help. 3. Use heat or cold: A heating pad or warm water bottle can be used for painful back muscles. Wrap the heating pad or warm water bottle in a towel to help prevent burns. Cold compresses can also help ease pain. Limit the time you use heat or cold. 4. Wear comfortable footwear: She should wear low-heeled shoes with good arch support or flat shoes and avoid high heels, which can further shift the balance forward and cause falls. 5. Avoid heavy lifting: If she must lift something, she should squat down, bend her knees, and keep her back straight. She should not bend at the waist to pick up things. 6. Gentle exercise: Gentle walking within the house or village can be beneficial. 7. Hydrate: Drinking enough water throughout the day is important. 8. Seek help: If there is severe back pain, or if the pain goes on for more than two weeks, she should contact a doctor. A light massage from a family member can also provide relief. If the pain becomes too much, she should be referred to the ANM or PHC doctor.

150	How much walking should this lady do during this pregnancy in the third trimester?	The document does not provide specific information on how much walking a pregnant woman should do during her third trimester.	Walking is considered a safe and beneficial activity during pregnancy, particularly in the third trimester, as it is good for heart. It can help reduce the risk of excessive weight gain and gestational diabetes, and keep the heart and lungs healthy. If the pregnant woman is generally healthy, she can walk for 30 minutes, five days a week. However, if she is a beginner, she should start with 10 minutes of walking for four to five days a week, walking slowly and taking regular breaks to avoid panting. If walking for 30 minutes at a time is too strenuous, she can break it up into shorter sessions of 10 minutes two or three times a day. Walking should be done cautiously, especially as she nears delivery in the 9th month. It's important for her to listen to her body and rest if she feels pain or is too tired. She should wear comfortable footwear, walk on flat paths, and stay hydrated. However, if she is a high-risk pregnancy, she should consult a doctor before starting any walking regimen.
151	This lady is 19 week pregnant and she can not feel her baby move. Is this normal?	Yes, this is normal. Foetal movements, also known as 'quickening', typically begin to be felt around 18-22 weeks of pregnancy. They are usually felt earlier in women who have been pregnant before (multigravida) and later in women who are pregnant for the first time (primigravida).	It is normal for some women, particularly those in their first pregnancy, to not feel their baby move at 19 weeks. The first detection of movement, also known as quickening, can range from 13-25 weeks, with some women not feeling anything until 20 to 22 weeks. The movements at this stage often feel like flutters or butterflies, and can be mistaken for a gassy tummy. Factors such as the position of the placenta, which can cushion some of the baby's movements, can also affect when and how movements are felt. It is not worrisome at this stage if she is not able to clearly feel the baby's movements, particularly if she is otherwise healthy. However, if she does not feel anything in the next 2-3 weeks, it should be reported to a healthcare professional. In case of doubt, a USG scan or a fetal doppler can be done to confirm heartbeat and fetal well-being.

152	A lady who is 18 weeks pregnant has gained only 2 kg during this pregnancy. Is this normal?	Yes, this is normal. Ideally, after the first trimester, a pregnant woman gains around 2 kg every month. Therefore, if a woman who is 18 weeks pregnant has gained only 2 kg, it is within the normal range. However, if her weight gain is consistently less than 2 kg per month, it might indicate inadequate dietary intake and she may need food supplementation.	The weight gain of a woman who is 18 weeks pregnant and has gained only 2 kg may or may not be within the normal range, depending on her individual situation. Factors such as starting weight, diet, physical activity, and whether it's a first pregnancy can influence weight gain. For example, if she was overweight initially, she may need to gain less weight. Additionally, symptoms like nausea and vomiting, especially in the first trimester, can affect weight gain. In general, a weight gain of 1 to 1.5 kg per month in the first trimester and 1.5 to 2 kg every month in the 2nd and 3rd trimesters is recommended. However, every pregnancy is different and there is no one-size-fits-all approach to pregnancy weight gain. The most significant weight gain usually happens in the second half of pregnancy. It's important for the woman to focus on her own health and well-being and that of her baby, rather than comparing herself with others. A healthy diet during pregnancy includes milk, eggs, lentils, peas, beans, sweet potatoes, nuts, and leafy vegetables. If she experiences any concerning symptoms such as constant lack of appetite, reduction in weight, fatigue, or continuous nausea, she should inform her healthcare provider. The best way to determine if the weight gain is normal is to consult her doctor, who can monitor her weight and measure her baby's growth through regular prenatal checkups. The healthcare provider can also offer guidance on nutrition, physical activity, and strategies to manage weight gain throughout pregnancy.

153	How much weight can a pregnant woman who is 16 weeks lift at one time?	The document does not provide information on how much weight a pregnant woman who is 16 weeks can lift at one time.	The amount of weight a pregnant woman who is 16 weeks along can lift at one time depends on several factors. These include the number of weeks of pregnancy, the duration and frequency of lifting, pre-pregnancy weight, fitness level, health conditions, and the type of lifting. Generally, a woman in her second trimester should not lift more than 5kg. It's important that she avoids stooping, bending, or squatting often, lifting heavy objects from the floor, and standing for 3 hours or more. She should also avoid strenuous weight lifting and stick to weights associated with normal routine activities. If she must lift something, she should squat down, bend her knees, and keep her back straight, avoiding bending at the waist. The advice may differ based on whether the pregnancy is normal or high risk, so it's recommended to consult a doctor for more details. Each woman's ability to lift weight during pregnancy is different and depends on various factors such as her work routine before she was pregnant, her age, muscle mass and medical history. If she has family or others to help her lift weight during this time, they should be encouraged to support her. If a woman is unsure about lifting weight or is uncomfortable, she should avoid doing so.

154	I am not getting a clear blood pressure reading. What can I do?	The document does not provide information on troubleshooting issues with blood pressure readings.	If you're not getting a clear blood pressure reading, there could be several reasons for this. It could be patient-related, such as the patient not resting comfortably in a quiet environment atleast for five minutes prior to the measurement. The patient should also have an empty bladder and should not have eaten, ingested caffeine, smoked, or engaged in physical activity at least 30 minutes before the measurement. Procedure-related errors could also be the cause. Make sure the patient's arm is at heart level during the reading, and that the patient's legs are not crossed at the knees. Also, ensure that no talking occurs during the measurement. Equipment-related issues could also be a factor. Check if the cuff is too small or too large, as this can cause errors in measurement. The blood pressure monitor should be checked regularly for any signs of damage or malfunction. Make sure the cuff is not too tight or too loose, and that it is positioned correctly on the patient's bare arm. Health worker-related errors can also occur, such as failing to include a five-minute rest period, talking during the measurement procedure, using an incorrect cuff size, and failing to take multiple measurements. If you're still unable to get a clear reading, try again at another time of the day or with a different blood pressure apparatus. If the problem persists, refer the patient to a medical officer or first referral unit. Also, ensure that the patient is not talking or moving during the reading, and that both her feet are flat on the ground. If you are still not able to get a reading, consult a senior such as an ANM or field supervisor.

155	This lady with a 14 weeks pregnancy is having some spotting. What advice can I give her?	You can advise her to rest for a few days, especially if she is feeling tired. She should use disposable sanitary napkins, if available, or change the cloth/pad every 4–6 hours. The cloth should be washed with soap and water and dried in the sun. She should wash the perineum daily with soap and water. She should avoid sexual intercourse until the bleeding stops. If the bleeding decreases or stops, reassure her and advise her to go home after you have checked her vital signs. Advise her to return to you or the MO if the bleeding recurs.	Spotting, or light bleeding, during pregnancy is common, especially during the first trimester. It is often mistaken for a pending period and is not always a cause for concern. However, any spotting or bleeding, particularly in the second or third trimesters, should be reported to a healthcare provider immediately. It's important to note the color, amount, and frequency of the bleeding. While light spotting is not necessarily concerning, it can be a symptom of complications such as miscarriage, ectopic pregnancy, or placenta previa. Therefore, it is crucial to consult a medical officer if there's any bleeding or spotting during pregnancy. In this case, the woman should be referred to a medical officer or first referral unit (FRU) for further investigation. While waiting to see a doctor, she may be advised to avoid sexual intercourse and heavy physical activity. Bed rest may also be recommended as she could be at risk of a threatened abortion. It is important for her husband and family to support her and help her stay calm as she seeks medical advice.
156	Is it normal to have heavy bleeding if a pregnant woman is 8 weeks pregnant?	No, it is not normal to have heavy bleeding at 8 weeks of pregnancy. Any bleeding during pregnancy should be considered serious and the individual should seek immediate medical attention. It could indicate various complications such as a miscarriage or an ectopic pregnancy.	No, it is not normal for a pregnant woman to experience heavy bleeding at 8 weeks. This could indicate a high risk of miscarriage or other serious problems such as an ectopic pregnancy, molar pregnancy, or issues with the placenta or cervix. While light spotting can be common during the first trimester, heavy bleeding at any stage of pregnancy is not normal. The woman should be referred immediately to a Health professional, Medical Officer, or the nearest civil hospital. She should also be advised to avoid any activity that causes strain.

157	This mother delivered 2 weeks ago and she has stopped producing milk. What food can she eat to help?	The mother can eat foods rich in calories, proteins, iron, vitamins and other micro-nutrients to help with milk production. These include milk and milk products like curd and cottage cheese, green leafy vegetables and other seasonal vegetables, pulses, eggs, meat including fish and poultry, groundnuts, ragi, jaggery, and fruits such as mango, guava, orange, sweet lime and watermelon.	The mother can increase her milk production by maintaining a balanced diet, which includes iron and calcium supplements, and spending as much time as possible with her baby. She should feed her baby on demand and identify 'cues' such as suckling movements and sounds before the baby cries. It's recommended that the newborn suckle from only one breast at each feed and continue at that breast until they finish by themselves, so that they get an adequate amount of fat-rich hindmilk. The other breast can be used for the next feed. In addition to this, the mother should nurse or pump often and empty the breasts completely at each feeding. She should also drink plenty of water and other fluids to stay hydrated and support milk production. Her diet should include plenty of fluids, green leafy vegetables, pulses, jaggery, milk and milk products. Specific foods that can help increase milk production include fenugreek (methi), which can be included in meals or soaked in warm water and drunk, fennel seeds (saunf), which can be chewed or made into a tea, and garlic (lahsun), which can be added to daily dishes. Dishes made with spinach (palak) and carrots can also be helpful. Drinking barley (jau) water, having almonds (badam), cumin seeds (jeera), sesame seeds (til), and dill leaves (suva bhaji) can also support milk production. However, there can be many reasons why she might not be producing milk and she should consult a doctor for further investigations if her milk production has stopped.

158	Can you explain to this pregnant lady, what is the proper way to breastfeed her baby?	The proper way to breastfeed a baby involves correct positioning. The mother’s hand should support the baby’s bottom, not just the head or shoulders. The baby’s face should face the breast, with the nose opposite the nipple, chin touching the breast, mouth wide open and the lips upturned. The baby should be held in the correct position and be put correctly to the breast. The mother should be comfortable, either sitting or reclining. The baby should be breastfed frequently.	The proper way to breastfeed a baby involves several steps. First, the baby should be fed on demand and cues such as suckling movements and sounds should be identified before the baby cries. The newborn should suckle from only one breast at each feed and continue at that breast until they finish by themselves, so that they get an adequate amount of fat-rich hindmilk. The other breast should be used during the next feed. The baby should not be given water or any liquid other than breastmilk unless medically indicated. Breastfeeding should be frequent, at least 6-8 times during the day and 2-3 times during the night. The mother should hold the baby in the correct position, supporting the baby's bottom, not just the head or shoulders. The baby's face should be facing the breast, with the nose opposite the nipple. The baby's chin should touch the breast, the mouth should be wide open, and the baby's lower lip should be turned outside. The mother should find a comfortable place and hold her baby close, with the baby's chest against hers. She should touch the baby's lips with her nipple to help the baby open their mouth wide. When the baby's lips open up, the baby should latch onto as much of the dark area around the nipple, not just the tip. Their lips should be flared out, not tucked in. If it hurts or feels wrong, the mother should gently stop by putting a finger in the corner of the baby's mouth and try again. The mother should remember to switch sides during feeding and make the baby lie down after breastfeeding only after the baby has burped once. If there are any problems with breastfeeding, the mother should contact a health worker. Exclusive breastfeeding (not even water) should be practiced for the first 6 months and then along with other food, breastfeeding should continue till the child is at least 2 years old. During loose motions/loose stools, the frequency of breastfeeding should be increased and breastfeeding should not be stopped.

159	This lady is having some pain in the right part of her C-Section scar. She had her C-section 1 month ago and this is the first time she has pain. What advice should I give her?	You should advise her to seek immediate medical attention. Pain in the C-section scar could be a sign of a surgical site infection, especially if it is accompanied by other symptoms such as fever, pus discharge from the wound, evidence of an abscess, reopening of the surgical wound, or painful, spreading redness surrounding the surgical site. It's important to get this checked out by a medical professional as soon as possible.	The lady should be informed to check for any signs of infection at the scar site such as redness, pus formation, bad smell, swelling, fever or discharge. If any of these signs are present, she should immediately inform the health care worker. Pain in the right part of the C-section scar may be caused by infection or inflammation. Normally, nerve damage after a C-section improves in the months following delivery and pain slowly subsides. However, if the pain is severe or has other symptoms, she should be referred to a medical officer or FRU for a proper medical assessment. To ease the pain, she can apply a heating pad to the abdomen in 15 minute intervals or a warm compress. She can also take pain relieving medications like paracetamol or ibuprofen after consulting Medical officer. She should wear loose clothes, avoid lifting heavy things, and keep the scar clean and dry to prevent further irritation or infection.
160	How much food is okay to eat after delivery? She feels very hungry all the time	There is no specific limit to how much food a new mother can eat after delivery, especially if she is breastfeeding. She should listen to her body's hunger cues and eat accordingly. It's important that she consumes a balanced diet rich in calories, proteins, iron, vitamins and other micro-nutrients. Foods like milk and milk products, green leafy vegetables, pulses, eggs, meat, groundnuts, ragi, jaggery, and fruits are recommended.	After delivery, it is normal for a woman to feel hungry, especially if she is breastfeeding, as it demands more energy than pregnancy. She should eat more than her normal diet throughout her pregnancy and lactation, as she needs these extra calories to maintain her health and meet the needs of the growing baby and for successful lactation. In general, she should consume about 500-600 more calories per day than she did before she was pregnant if she is breastfeeding. The quality of food she eats is also important. She should eat a balanced diet that includes a variety of foods from all the food groups: fruits, vegetables, grains, protein, and dairy. Some of the recommended dietary items are cereals, milk and milk products (such as curd and paneer), green leafy vegetables and other vegetables, pulses, eggs, meat (including fish and poultry), groundnuts, ragi, jaggery and fruits (like mango, guava, orange, sweet lime and watermelon). A diet rich in iron, calcium, vitamins and proteins should be preferred. Instead of large meals, she can have smaller, frequent meals and snacks throughout the day depending on her hunger. It is important for her to listen to her body and eat when she's hungry. She should also drink plenty of water and stay hydrated.

161	What are the signs of high blood pressure during pregnancy?	The signs and symptoms of severe anemia in a pregnant woman include appearing pale, heart racing, weakness or inability to stand up, signs of bleeding, and low blood pressure. Other features of severe anemia are decreased conscious level, palpitations, shortness of breath, and chest pain. There may also be generalized weakness, easy fatigability, breathlessness, severe pain in the abdomen, excessive swelling in legs, bleeding, fever, and convulsions	The signs of high blood pressure during pregnancy include headaches, blurring of vision, and feelings of dizziness or giddiness. There may also be swelling on the face and limbs, particularly the feet, which does not resolve even after a full night's rest. Some women may experience pain in the upper abdominal region and shortness of breath. Additionally, proteinuria, which is the presence of excess proteins in the urine, may be present along with increased blood pressure and edema.
162	What kind of food should a woman eat while she is breastfeeding?	A woman who is breastfeeding should eat foods rich in calories, proteins, iron, vitamins and other micro-nutrients. This includes milk and milk products like curd and cottage cheese, green leafy vegetables and other seasonal vegetables, pulses, eggs, meat including fish and poultry, groundnuts, ragi, jaggery, and fruits such as mango, guava, orange, sweet lime and watermelon.	A woman who is breastfeeding should consume a balanced diet that includes iron-rich foods such as leafy vegetables like spinach and beetroot, anjeer, raisins, fruits, liver, and meat including fish, chicken, and mutton. She should also consume cereals, pulses, and other iron-rich foods. Calcium-rich foods like ragi, black gram, Bengal gram, whole green gram, and green leafy vegetables are also important. Protein-rich foods like dairy products including milk, paneer, and curd, as well as beans, grains like sprouts, and green dried peas should be included in the diet. Regular intake of milk and eggs is also recommended, as per cultural norms. In addition to these, she can also consume mashed roti, rice, bread, or biscuit mixed in sweetened undiluted milk, or mixed in thick dal with added ghee or oil. Khichdi with added oil or ghee, and cooked vegetables such as potatoes, carrots, green leafy vegetables, and yellow pumpkins can also be included in the servings. Other options include sevaiyan, dalia, halwa, kheer prepared in milk, or any cereal porridge cooked in milk. Mashed boiled or fried potatoes, seasonal fruits like banana, cheeku, mango, or meat, fish, and egg can also be consumed.

			She should also have multiple frequent meals instead of two or three heavy meals, and ensure adequate fluid intake for hydration. The variety in the diet should be increased by including family foods in the diet of the child.
163	What should I do if a woman has very low blood pressure?	If a woman has very low blood pressure, you should raise the foot end of the bed so that her head is lower than her body. This will help increase the flow of blood to the heart. Keep the woman warm and covered with a blanket. If she is in shock, she might feel cold even in warm weather. If the condition persists, make arrangements for transporting the woman to the nearest health facility where appropriate care is available.	If a woman has very low blood pressure, she should be referred to the nearest health care center. An immediate ORS solution could be given. She should also maintain a balanced diet, including cereals, pulses, fats, vitamins, and minerals, and take small proportions of meals throughout the day. Increasing her fluid intake in the form of milk, lassi, lemonade, soup, juice, etc. can also help. If she needs to increase her salt intake after counselling from a medical officer. She should avoid getting up quickly when seated or lying down, and avoid standing for long periods of time. She should also avoid taking very hot baths or showers. Lying down and raising her legs can also help, as can wearing loose clothing.
164	A woman had diabetes during her previous pregnancy? Could she get diabetes again in this pregnancy?	Yes, a woman who had diabetes during her previous pregnancy could get diabetes again in this pregnancy. She is at risk of having diabetes in the future, especially if her blood sugar was raised during her previous pregnancy. It is important for her to have a repeat blood sugar test 6 -12 weeks after her pregnancy and receive long-term follow-up care.	Yes, if a woman had diabetes during her previous pregnancy, there is a chance of getting diabetes again in the current pregnancy. Having a past medical history of gestational diabetes in a previous pregnancy increases the risk of developing diabetes in subsequent pregnancies. Therefore, it is recommended that she should be checked with an Oral Glucose Tolerance Test (OGTT) and maintain a balanced diet and mild exercise routine, such as walking everyday.

165	How soon after a delivery can a woman start breastfeeding?	The document does not provide information on how soon after a delivery a woman can return to usual housework.	A woman can start breastfeeding immediately after delivery, within half an hour. As soon as she is able to, she should begin breastfeeding the baby. The first semi-solid yellowish colored milk, known as colostrum, is extremely nutritious for a newborn. It boosts the baby's immunity and provides protection from many diseases. Therefore, it is beneficial to start as early as possible.
166	How can you make anemia better and what foods can you eat to raise your hemoglobin?	To improve anemia, it is important to consume iron-rich foods such as meat, fish, eggs, poultry, green leafy vegetables (like mustard, fenugreek, bathua, amaranth leaves, radish leaves), whole pulses (like Bengal gram whole, horse gram whole), and cereals (like whole wheat flour, bajra, ragi, jowar). Including vitamin C rich foods like fruits (gooseberry, guava, lemon, orange, raw mango), vegetables (drumstick leaves, amaranth leaves, capsicum) and sprouts can help in improving iron absorption, which in turn can raise your hemoglobin levels.	To improve anemia, it is recommended to take one iron and folic acid tablet daily starting from the fourth month of pregnancy and continuing throughout the pregnancy. In cases of mild to moderate anemia, two tablets of iron and folic acid daily may be consumed. If there is no improvement in hemoglobin levels, consult a doctor for possible iron infusion. It is also beneficial to take one dose of albendazole after the first three months of pregnancy. Diet plays a crucial role in managing anemia. Iron-rich foods such as meat, fish, eggs, poultry, green leafy vegetables (like mustard, fenugreek, bathua, amaranth leaves, radish leaves), whole pulses (like Bengal gram whole, horse gram whole), and cereals (like whole wheat flour, bajra, ragi, jowar) should be included in the diet. Other foods that can increase hemoglobin levels include jaggery, whole grains, nuts, oilseeds, liver, and dry fruits like anjeer. Fruits and vegetables rich in vitamin C, such as gooseberry, guava, lemon, orange, raw mango, drumstick leaves, amaranth leaves, capsicum, sprouts, lemons, tomatoes, and amlas, help in improving iron absorption. Cooking in iron utensils and adding lime and Indian gooseberry to food can also aid in iron absorption. Avoid taking milk and tea with food as they can inhibit iron absorption. Regular deworming, at least twice yearly, is also recommended. If anemia is mild, foods such as spinach, broccoli, groundnut, and jaggery can be of great help.

167	If a pregnant woman has gestational diabetes, what are the signs she should watch for? When should she contact the doctor right away?	The document does not provide specific signs that a pregnant woman with gestational diabetes should watch for or when she should contact the doctor right away.	A pregnant woman with gestational diabetes should watch for signs such as fatigue, excessive urination, excessive thirst, irritation, increased mood swings, blurred vision, headaches, nausea, vomiting, dizziness, and recurrent urinary infections. Other signs include excessive amniotic fluid, and being overweight or obese. However, some women with gestational diabetes may not exhibit any physical signs of this condition. In terms of blood glucose levels, a fasting blood glucose level greater than 200mg/dL with or without insulin, or a fasting blood glucose level greater than 150 mg/dL or post breakfast level greater than 250 mg/dL even after giving insulin, could be indicative of gestational diabetes. Hypoglycemia, or low blood sugar, can also be a sign. Early symptoms of hypoglycemia include tremors of hands, sweating, palpitations, hunger, easy fatigability, headache, mood changes, irritability, low attentiveness, tingling sensation around the mouth/lips or any other abnormal feeling. Severe symptoms include confusion, abnormal behaviour or both, visual disturbances, nervousness or anxiety, abnormal behaviour, seizures and loss of consciousness. A pregnant woman should contact her doctor right away if she experiences any of these signs, or if her OGTT test is abnormal, if there are decreased fetal movements, bleeding, abdominal pain, severe headaches or dizziness. It is also important to contact the doctor if the total dose of insulin (combined morning and evening dose) on each day exceeds 20 units, or if the woman develops low blood glucose (hypoglycaemia) more than once in a day. Other danger signs include vaginal bleeding, regular contractions and decreased or absent fetal movement.

168	What can happen to the baby if a mother has gestational diabetes? What advice can be given to the mothers to reduce these risks ?	If a mother has gestational diabetes, the baby may face risks such as birth injuries during vaginal delivery, trouble breathing, low blood sugar after birth (hypoglycaemia), jaundice, a higher risk of being overweight as a child, and a higher risk of developing Type 2 diabetes as an adult. To reduce these risks, mothers should treat their condition as a high-risk pregnancy with regular review. They should modify their diet, avoiding sweets at all times during pregnancy. If they are taking insulin, they should always keep glucose, sugar with them. Blood glucose should be properly monitored to ensure the safety of both mother and baby. Delivery should be at a health facility to manage any potential complications.	If a mother has gestational diabetes, there are several risks to the baby. These risks can include the baby growing too large, which can lead to complications during vaginal delivery. The baby may also have difficulty breathing, low blood sugar levels at birth, and there is an increased risk of stillbirth. Other potential complications include spontaneous abortion, intra-uterine death, congenital malformations, shoulder dystocia, birth injuries, neonatal hypoglycaemia, and infant respiratory distress syndrome. To reduce these risks, mothers with gestational diabetes are advised to follow a healthy balanced diet, which should consist of complex carbohydrates such as whole cereals, pulses, fruits, and vegetables. Refined cereals like maida and fast food/ packaged food items should be avoided, and proteins should be incorporated in every meal and snack. A meal pattern of three major meals interspaced by three small snacks is recommended. Regular exercise is also encouraged, as well as monitoring blood sugar levels and regular antenatal checkups. In some cases, medication may be prescribed. It is important for mothers to adhere strictly to their medication regimen and to avoid a sedentary lifestyle. Regular follow-ups with healthcare providers are crucial, and mothers should monitor their body weight. Daily fetal activity assessment is also recommended. If fewer than 10 fetal kicks are felt in a 2-hour duration, a healthcare worker should be consulted immediately. It is important for mothers with gestational diabetes to consult with their healthcare provider for personalized advice and guidance based on their specific situation.
169	Is it normal for a pregnant woman to have swelling of feet after a night's sleep ?Swelling of which part of the body be considered abnormal ? When should she be	Swelling (oedema) that appears in the evening and disappears in the morning after a full night’s sleep can be a normal manifestation of pregnancy. However, any oedema of the face, hands, abdominal wall, and vulva is considered abnormal. A woman should be referred immediately for	Mild swelling of the feet and ankles is common in the third trimester of pregnancy. But it is not normal for a pregnant woman to have swelling of the feet after a night's sleep because redistribution of body fluids occurs during the night due to the resting position of pregnant women, and swelling typically subsides in the morning. If the swelling does not subside after rest, or if the woman experiences swelling in only one leg, severe swelling in both legs, or sudden swelling of any other area such as her hands, face, abdominal wall, or vulva, this is considered abnormal. Additionally, if the swelling is associated with high blood pressure, heart disease, anaemia, or proteinuria, or if the woman has any complaints

	referred to the First Referral Unit ?	further investigations if she complains of abnormal tightening of any rings on her fingers, indicating oedema. Additionally, if there is oedema in association with high blood pressure, heart disease, anaemia, or proteinuria, the woman should be referred to the MO. Non-pitting oedema, which indicates hypothyroidism or filariasis, also requires immediate referral for investigations.	like headache, blurring of vision, nausea, vomiting, pain in the abdomen, or bleeding per vagina, she should be referred to the First Referral Unit (FRU) immediately.
170	What is the proper way to do an OGTT test ? The OGTT test of a GDM mother is 160mg/dL. What is to be done next?	The Oral Glucose Tolerance Test (OGTT) is performed by giving the individual 75g of glucose dissolved in 300ml of water to drink within 10 minutes. After 2 hours, a blood sample is taken to measure the body's ability to absorb sugar. If the 2-hour post-glucose level is above 140 mg/dL, it indicates gestational diabetes. In the case of a GDM mother with a 160mg/dL reading, it is above the threshold value, indicating the presence of gestational diabetes. The management of GDM includes Medical Nutrition Therapy (Diet plan) and if needed, insulin therapy. Regular screenings should continue throughout the pregnancy and postpartum period.	To properly perform an OGTT test, a woman should be given 75g of glucose dissolved in 300ml of water to drink, whether she comes in a fasting or non-fasting state, irrespective of the last meal. The intake of the solution has to be completed within 5 to 10 minutes. After 2 hours, a finger-prick (capillary) blood sample for glucose testing should be taken using a standardised glucometer. If vomiting occurs within 30 minutes of the OGTT being taken, then the test has to be repeated on another day. If vomiting occurs after 30 minutes, then the test can continue. The threshold plasma glucose level of 140 mg/dL is taken as the cut-off for diagnosis of GDM. If the test shows a reading of 160mg/dL, this is an abnormal reading indicating impaired glucose tolerance. The woman should then be referred to her PHC doctor or a higher centre for medical nutrition therapy or medical treatment. After 2 weeks on medical nutrition therapy, a 2 hours post-meal glucose test should be done. If the result is more than or equal to 140 mg/dL, insulin therapy needs to be started, she should also be advised regarding lifestyle changes such as dietary modifications and physical activity for 30 minutes twice daily. Following 2 weeks of lifestyle changes, postprandial glucose has to be tested and based on the results, continuation of lifestyle changes or medical treatment has to be advised.

171	When should a pregnant woman be screened for hypothyroidism ? What are the symptoms for thyroid problems in pregnant women ?	A pregnant woman should be screened for hypothyroidism if she has symptoms of hypothyroidism, a history of hypothyroidism, or with other endocrine system conditions or if she is a high-risk pregnant woman. The symptoms of hypothyroidism include feeling tired, unable to stand cold temperatures, hoarse voice, swelling of the face, weight gain, constipation, skin and hair changes, including dry skin and loss of eyebrows, carpal tunnel syndrome (hand tingling or pain), slow heart rate, muscle cramps and irregular menstrual periods.	A pregnant woman should be screened for hypothyroidism as soon as she comes for her first antenatal care (ANC) visit, ideally in the first trimester itself. This is particularly important if there is a history of this condition in her family, if she has symptoms of hypothyroidism, a history of hypothyroidism, or other endocrine system conditions. High-risk pregnant women should also be screened. Symptoms of thyroid problems in pregnancy can vary depending on whether she has low or high thyroid hormone. If she has hypothyroidism, she might be very tired all the time, unable to stand cold temperatures, have a hoarse voice, swelling of the face, weight gain, constipation, skin and hair changes, including dry skin and loss of eyebrows, carpal tunnel syndrome (hand tingling or pain), slow heart rate, muscle cramps and irregular menstrual periods. If she has hyperthyroidism, she might feel very hot, nervous, shaky or anxious, have sweating, palpitations, heat intolerance, weight loss or failure to gain weight, nausea, tremors, warm extremities, tachycardia, and goiter. Some of these symptoms are common during pregnancy and may not necessarily indicate a thyroid problem. If there are symptoms of thyroid problems, the woman should consult with a doctor for a proper evaluation and diagnosis.
172	How will I know if a woman has moderate Anaemia?	A woman may have moderate anaemia if she exhibits symptoms such as pallor in the eyes, tongue, and lips, tiredness, lack of interest in work, shortness of breath, decreased ability to exercise, delay or difficulty in understanding, dizziness, and heart pounding and beating fast. Additionally, if her respiratory rate is above 30 breaths per minute and pallor is present, it may indicate moderate to severe anaemia. However, the most accurate way to diagnose anaemia is by measuring her haemoglobin level.	A woman with moderate anaemia may present with symptoms such as generalized weakness, exhaustion, irritability, lethargy, breathlessness, giddiness, and fatigue. She may also have pale skin, experience shortness of breath, dizziness, a fast heartbeat, and get tired easily. These symptoms are particularly noticeable in pregnant women. To confirm if a woman has moderate anaemia, a hemoglobin test can be performed. According to the World Health Organization, if the estimated hemoglobin (Hb) level is between 7-9.9 g/dL, it is considered moderate anaemia. This can be assessed through a finger prick test.

173	How should a woman take Iron folic acid tablets?	A woman should take one Iron Folic Acid (IFA) tablet daily starting from the fourth month of pregnancy. If she is anaemic, she should take two IFA tablets daily, one in the morning and one in the evening. The tablets should not be taken with tea, coffee, or milk as these reduce the absorption of iron. Instead, they can be taken with Vitamin C rich sources like lemon water or amla to increase iron absorption. If she is also taking calcium tablets, there should be a minimum of a two-hour gap between the consumption of IFA and calcium tablets.	Iron folic acid (IFA) tablets should be taken regularly, preferably early in the morning on an empty stomach for best absorption. However, if the woman experiences nausea and abdominal pain, she may take the tablets after meals or at night to avoid these symptoms. It's important to consume these tablets with foods rich in Vitamin C, such as lemon and amla, as they aid in the absorption of iron. It's recommended to avoid the consumption of tea, coffee, or milk for at least one hour after taking the IFA tablet, as these can decrease the absorption of iron. There should also be a gap of two hours between iron and calcium tablets. For pregnant women, it's advised to take one IFA tablet every day for at least 100 days, starting after the first trimester, at around 14-16 weeks of gestation, to prevent anaemia. This dosage regimen should be repeated for three months after delivery. Common side effects such as nausea, constipation, and black stools may occur. In case of constipation, the woman should drink more water and add roughage, like green leafy vegetables, to her diet. Passing black stool while consuming IFA is normal and should not be a cause for concern. Despite feeling better, the woman should not stop taking the tablets and must complete the course as advised by the healthcare provider. If there are any problems or side effects, she should consult her healthcare provider. The tablets should be stored in a cool place.

174	A woman had heavy bleeding before she got pregnant. Is there any risk to the baby?	The document does not provide information on whether a woman having heavy bleeding before pregnancy poses any risk to the baby.	Heavy bleeding before pregnancy can potentially pose risks to the baby, but it largely depends on the cause and timing of the bleeding, as well as the health of the mother and the baby. The woman might be suffering from anemia due to heavy bleeding, which could lead to complications such as premature birth, low birth weight, still birth, intrauterine growth retardation, and congenital malformation. If the heavy bleeding was due to heavy periods, it's mostly not an issue in pregnancy other than anemia. However, it's crucial to check for anemia and manage it appropriately. The woman should take iron-rich foods in her diet and get her hemoglobin levels checked regularly. An ultrasound scan can be recommended if she had a history of any problems related to the uterus/womb before getting pregnant. A clotting time and bleeding time test can also be recommended to rule out any bleeding disorders. If the woman had a large fibroid or a bleeding disorder, it could result in difficult labor, although it would not directly impact the baby. Therefore, it's important for her to mention this history to her healthcare provider during her prenatal visits. Regular prenatal care and monitoring throughout pregnancy are essential to ensure the health and well-being of the woman and the baby.
175	How much weight gain is normal during pregnancy?	A woman should normally gain 9–11 kg during her pregnancy. After the first trimester, a pregnant woman ideally gains around 2 kg every month.	The normal weight gain during pregnancy is around 9 to 12 kg.

176	A woman is feeling very sad and anxious during her pregnancy. What can I say to support her?	You can provide supportive companionship to the woman, enabling her to face fear and anxiety. Encourage her to express her feelings and reassure her that it's normal to feel this way during pregnancy. You can also focus on talking to her and caring for her emotional needs. If possible, provide as much privacy as possible to the woman. If she is non-cooperative or argumentative, sympathise with her and be friendly; do not get angry. Spend more time in listening to her.	To support a woman who is feeling very sad and anxious during her pregnancy, it is important to provide her with counseling and probe the reasons for her sadness and anxiety. Assure her that pregnancy is a normal physiological phenomenon and that women all over the world are delivering children. It's crucial to remind her that there is nothing to worry about and that she should be happy about the new life growing in her womb. Encourage her to share her feelings with husband, family and friends, and to engage in light exercise, yoga, and meditation to help manage her emotions. If her symptoms worsen, it might be due to prenatal depression and she should be referred to the Medical Officer . Regular antenatal check-ups are important to ensure everything is moving in the right direction. She should try to remain positive, eat a healthy diet, and follow the advice of health care providers. Pregnancy can be a time of stress or happiness, and it's important for her to manage her stress levels to avoid health disorders like hypertension and diabetes. If there are other pregnant women nearby, encourage her to interact with them and discuss her anxiety issues. She can also engage in activities like knitting for time management and to keep her mind occupied. Lastly, advise her family to provide her with mental/ emotional support and remind her to promptly follow the advice of health care providers.

177	How to reduce fat intake during pregnancy ? How much fat intake is permissible during pregnancy?	To reduce fat intake during pregnancy, use less fat in cooking and avoid frying foods. Opt for low-fat dairy products instead of whole milk or full cream products, choose low fat snacks like fresh fruit over high-fat snacks such as cakes, biscuits, chocolates and pastries, and use lean meat instead of red meat. Saturated fat intake should be less than 10% of total calories and dietary cholesterol should be less than 300mg/d. For obese and overweight patients, a lower-fat diet overall can help slow the rate of weight gain.	To reduce fat intake during pregnancy one can opt for whole foods that naturally contain less fat such as fruits, vegetables, and grains. Reducing the amount of oil used during cooking . High-fat foods such as nuts, high-fat milk, and ghee should be consumed in moderation. Using low-fat dairy products in place of whole milk or full cream products, choosing low fat snacks like fresh fruit instead of high-fat snacks such as cakes, biscuits, chocolates, and pastries, and using lean meat in place of red meat can also help in reducing fat intake. It is also important to maintain a healthy balance of nutrients, including fats. Consuming milk and dairy products like curd, buttermilk, paneer, fresh/seasonal fruits and vegetables, dried fruits, cereals, whole grains, pulses, and green leafy vegetables can provide essential nutrients. The recommended fat intake during pregnancy is approximately 25% to 35% of daily calories. This means that if a woman needs 2,000 calories a day, she should consume about 56 to 78 grams of fat a day. Saturated fat intake (sources - ghee, butter, coconut oil, palm oil, full cream milk etc) should be less than 10 % of total calories and dietary cholesterol should be less than 300mg/d. For a normal pregnant woman, up to 30g oil (20g of vegetable oil and 10g butter or ghee) per day is recommended. For undernourished pregnant women, 35g oil (25g of vegetable oil and 10g butter or ghee) is recommended, and for overweight pregnant women, 20g of oil (15g of vegetable oil and 5g butter or ghee) is recommended.
178	What are the signs and symptoms of severe anemia in a pregnant woman?	The signs and symptoms of severe anemia in a pregnant woman include appearing pale, heart racing, weakness or inability to stand up, signs of bleeding, and low blood pressure. Other features of severe anemia are decreased conscious level, palpitations, shortness of breath, and chest pain. There may also be	If a woman during pregnancy has a hemoglobin level below 11g/dl, she is considered to be suffering from anemia. Severe anemia is a medical emergency and it is important to seek immediate medical attention. The signs and symptoms of severe anemia in a pregnant woman include tiredness, weakness, breathlessness, and a pale face, nails, tongue, and conjunctiva of eyes. She may also experience a lack of concentration, reduced capacity to work, limited learning ability, loss of appetite, and increased vulnerability to infections due to a decrease in immunity. Other symptoms include general swelling in the body, dizziness, rapid heartbeat, headache, and signs of bleeding. The woman may also appear weak or unable to stand up, and her blood pressure may be low.

		generalized weakness, easy fatigability, breathlessness, severe pain in the abdomen, excessive swelling in legs, bleeding, fever, and convulsions	
179	What is gestational diabetes? How and when do we diagnose it in pregnant women?	Gestational diabetes mellitus (GDM) is a condition that occurs in pregnant women who have high blood sugar levels during pregnancy. It is diagnosed through an oral glucose tolerance test (OGTT), which is performed by having the pregnant woman drink a glucose solution and then testing her blood sugar levels at regular intervals. The timing of this test can vary, but it is typically done between the 24th and 28th weeks of pregnancy. However, it's important to note that currently, screening for GDM is not universally done as part of the essential antenatal package in India.	Gestational Diabetes Mellitus (GDM) is a condition where the amount of sugar in a pregnant woman's bloodstream becomes abnormally high. This is due to the body's inability to produce enough insulin, a hormone that controls blood sugar levels, during pregnancy. The hormonal changes during pregnancy make the body harder to process blood sugar efficiently, leading to a rise in blood sugar levels. This condition is more common in women who are overweight, physically inactive, have a family history of diabetes, have been diagnosed with Polycystic Ovarian Disease, or have had gestational diabetes in a previous pregnancy. GDM is usually diagnosed through an Oral Glucose Tolerance Test (OGTT), where the pregnant woman is given 75g of glucose dissolved in approximately 300ml of water. Her blood sugar levels are then measured after 2 hours. If the blood sugar level is more than 140mg/dl, it is diagnosed as gestational diabetes. This test is recommended to be done twice during pregnancy: once at the first antenatal visit as early as possible, and again between 24-28 weeks of gestation. If the woman presents for antenatal care for the first time beyond 28 weeks of pregnancy, only one test is done at the first point of contact. If the OGTT test has not been done during this time, then it can be done any time after 24 weeks of pregnancy. Undiagnosed or inadequately treated GDM can lead to significant maternal and fetal complications, including abortion, intra-uterine death, birth defects, and respiratory problems in the child.

10.1.7. Appendix 7. Supplementary Material for Chapter 7

Supplementary Table 10.17. List of Included Guidelines and Training Data

Document	Source
Abortion	National Health Mission, Government of India
An Update on Water Needs during Pregnancy and Beyond	Kristen S. Montgomery, The Journal of Perinatal Education, Vol. 11, No. 3, 2002
Anatomy and Physiology for Midwives, Fourth Edition, Jane Coad, Kevin Pedley, Melvin Dunstall	Elsevier
Anemia Mukt Bharat Training Tool Kit	National Health Mission, Government of India
Antenatal Care: Counselling	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
Antenatal Care: Laboratory Investigations	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
Antenatal Check Up: Abdominal Examination	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
Antenatal Check up: History Taking	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
ASHA Book No 5	National Rural Health Mission, Government of India
ASHA Module 6 - Skills that Save Lives	National Rural Health Mission, Government of India
ASHA Module 7, Skills that Save Lives	National Rural Health Mission, Government of India
Awareness Modules on Sickle Cell Disease	Ministry of Health & Family Welfare and Ministry for Tribal Affairs, Government of India
Breastfeeding: Common Questions and Answers	American Family Physician, September 15, 2018, Volume 98, Number 6
Care after delivery: Postpartum Care, SBA - Presentation 5 (c)	National Rural Health Mission, Government of India

Clinical Update and Treatment of Lactation Insufficiency	Medical Journal of Islamic World Academy of Sciences 21:1, 19-28, 2013
Comparing the estimation of postpartum hemorrhage using the weighting method and National Guideline with using the weighting method and National Guideline with the postpartum hemorrhage estimation by midwives	Iranian Journal of Nursing and Midwifery Research | July-August 2015 | Vol. 20 | Issue 4
Counselling Modules on Sickle Cell Disease	Ministry of Health & Family Welfare and Ministry for Tribal Affairs, Government of India
DC Dutta's Textbook of Obstetrics	Jaypee
Diagnosis & Management of Gestational Diabetes Mellitus, Technical and Operational Guidelines	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
Diagnosis, management and care of hypertensive disorders of pregnancy (HDP): An Indian Expert Opinion	Pal et al, 2019
Diet Chart for Pregnant Women in North India	National Rural Health Mission, Government of India
Guidelines for Antenatal Care and Skilled Attendance at Birth by ANMs/LHVs/SNs	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
Home Augmented Recipes for Pregnant Women	Lady Irwin College New Delhi
Hypertensive Disorders in Pregnancy (HDP), Good Clinical Practice Recommendations 2019	FOGSI
Hypocalcemia in Pregnancy: A Clinical Review Update	Oman Medical Journal [2018], Vol. 33, No. 6: 453-462
Hypothyroidism in Pregnancy	American Thyroid Association
India Maternal, Infant, and Young Child Community Nutrition, Training Handouts	USAID
Induction Training Module for ASHAs	National Rural Health Mission, Government of India

Infection Prevention	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
Management of Beta Thalassaemia in Pregnancy	RCOG, Green-top Guideline No. 66
Mobilizing for Action on Violence against Women - A Handbook for ASHA	National Health Mission, India, Government of India
Module for ASHA on Non-Communicable Diseases	National Health Mission, Government of India
Module for Multi-Purpose Workers (MPW) - Female/Male on Prevention, Screening and Control of Common Non-Communicable Diseases	National Health Mission, Government of India
My Safe Motherhood, Booklet for expecting mothers	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
National Guidelines for Deworming in Pregnancy	National Health Mission, Government of India
National Guidelines for Diagnosis & Management of Gestational Diabetes Mellitus	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
National Guidelines for Screening of Hypothyroidism during Pregnancy	National Health Mission, Government of India
National Sickle Cell Anaemia Elimination, Training Module for Multi-Purpose Workers (M/F)/ASHAs	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
Nausea and Vomiting of Pregnancy	Gastroenterol Clin North Am. 2011 June ; 40(2): 309–vii. doi:10.1016/j.gtc.2011.03.009.
Park's Textbook of Preventative and Social Science	K.Park
Physical Activity Recommendations for Pregnant and Postpartum Women	CDC
Post Abortion Family Planning, Technical Update	Family Planning Division, Ministry of Health and Family Welfare, Government of India
Pregnancy FAQ	National Institute of Public Cooperation and Child Development

Quality Antenatal Care, SBA - Presentation 2 (a)	Ministry of Health & Family Welfare, Maternal Health Division, Government of India
Reaching the Unreached	National Rural Health Mission, Government of India
Reading Material for ASHA Book 1	National Rural Health Mission, Government of India
Reading Material for ASHA Book 2	National Rural Health Mission, Government of India
Reading Material for ASHA Book 3	National Rural Health Mission, Government of India
Reading Material for ASHA Book 4	National Rural Health Mission, Government of India
Sleep Deprivation during Pregnancy and Maternal and Fetal Outcomes: Is There a Relationship?	Chang et al, 2009
Thalassemia: What Parents Need to Know?	Indian Academy of Pediatrics (IAP)
Thyroid disorders in pregnancy	Indian Journal of Endocrinology and Metabolism / Vol 16 / Supplement 2
Thyroid Update In Pregnancy, Vol 2, 2021	FOGSI
Training manual for ASHAs, Identification and prevention of anaemia, blood pressure in pregnancy and gestational diabetes mellitus using SMARThealth pregnancy application and devices	The George Institute for Global Health
Training Manual on Management of Common Emergencies, Burns and Trauma for ASHA at Ayushman Bharat- Health and Wellness Centres	National Health Mission, Government of India
WHO recommendations on antenatal care for a positive pregnancy experience	WHO

Supplementary Table 10.18. List of Sensitive Topics and Predefined Responses

Category	Response
Desire to Have a Male Child	This topic is outside the scope of what I can help you with. It's important to understand that the desire for a child of a specific gender should not lead to any practices or decisions that discriminate based on gender. Boys and girls are both equally valuable to families and society. The birth of a baby girl and a baby boy should be equally celebrated. The baby's gender should not determine the value placed on their life.There are no medications, food or methods that can guarantee the birth of a child of a specific gender, and attempting to do so is both unethical and illegal. Remember, every child is a blessing.
Reasons for Infertility	This topic is outside the scope of what I can help you with. It is important to remember that conception is related to both the man's health and the woman's health. When thinking about conception, both partners should consider the timing and frequency of sexual intercourse. It's important to consider several aspects: Have you been trying to conceive around the time of ovulation and doing so regularly? Have both partners been tested? Remember, infertility is not merely a woman's issue. Sometimes, both partners can be healthy and there can be no identifiable cause. Together with your partner, please consult a qualified doctor who can help both of understand any underlying health issues and assist with treatment.
Family Disputes	This topic is outside the scope of what I can help you with. When it comes to family disputes or other personal matters, it's essential to approach these matters with sensitivity. An ASHA's role does not extend to providing advice or intervening in personal or marital matters. If there are serious concerns regarding mental health or immediate danger, please contact local authorities to ensure the safety of everyone involved.

Desire to Not Follow National Guidelines (Local Remedies, Religious Decisions)	This topic is outside the scope of what I can help you with. It is important to show respect for everyone's personal beliefs and support individuals in accessing the medical care they need. Please contact your medical officer for more comprehensive support.
Decisions about Pregnancy Termination	This topic is outside the scope of what I can help you with. If you are considering or have questions about termination, it's essential to consult a medical officer or a qualified gynaecologist. These professionals are better equipped to understand your situation and provide you support in a sensitive manner. Additionally, family counselling might be beneficial, involving not just the woman but also her husband, mother-in-law, and other family members who are supporting the couple.
Mental Health Issues (Depression, Anxiety, Suicide)	This topic is outside the scope of what I can help you with. For those experiencing mental health issues, please refer them to the medical officer or nearby Health and Wellness centres. These matters must be handled sensitively and require the advice of a qualified doctor.
Skin Complexion	This topic is outside the scope of what I can help you with. It is important to not discriminate against individuals based on their skin colour. If you are concerned about specific skin conditions, please contact your medical officer.
Unclear	Please try another question.