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GLOBAL RESEARCH TRENDS, EMERGING HOTSPOTS, AND KNOWLEDGE STRUCTURE OF FIRST-TRIMESTER BIOMARKERS FOR THE EARLY PREDICTION OF GESTATIONAL DIABETES MELLITUS: A BIBLIOMETRIC-STYLE ANALYSIS (2008–2026)

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ABSTRACT:
Background: Gestational diabetes mellitus (GDM) is found in around 14% of all pregnancies in the world and the standard oral glucose tolerance test (OGTT) performed at 24–28 weeks gives only a short time interval for prevention. Several studies have examined the potential role of biomarkers in the first trimester of pregnancy, including glycated haemoglobin (HbA1c), sex hormone-binding globulin (SHBG), pregnancy-associated plasma protein-A (PAPP-A), adipokines, vitamin D, and machine-learning multi-marker models, as markers to improve earlier risk stratification.
Objective: This study maps the knowledge structure, publication trends, and emerging hotspots of this literature using bibliometric principles.
Methods: Data from peer-reviewed studies on first-trimester GDM biomarkers and basic diagnostic- and bibliometric-methodology reference data were retrieved by a structured search of PubMed/MEDLINE indexed and other academic sources. A set of verified, bibliographic records with true DOIs was created from 62 records that met the inclusion criteria. This information was directly applied to the calculation of descriptive bibliometric indicators and network analysis (co-authorship, title-keyword co-occurrence) with the aid of Python.
Results: The number of publications rose from one baseline publication in 2008 to a maximum of eight in 2024, while 61.3% of the publications compiled were published after 2020. SHBG, machine-learning multi-marker models and existing GDM bibliometric studies were the most common themes (7 records each), followed by HbA1c, PAPP-A, adiponectin/adipokines and other single biomarkers (6 each). The most popular journals were Diabetes Care, Diabetes Research and Clinical Practice, and BMC Pregnancy and Childbirth. The largest identifiable proportions of study settings were from China, Iran, United Kingdom and United States. The dominant hub term was "first-trimester", connecting the clusters of HbA1c and SHBG and a separate cluster of machine-learning/prediction.
Conclusion: It is an emerging discipline, but is multi-marker, computational and still divided into separate research programmes employing only a single marker, with few if any cross validations. A full export from Scopus and Web of Science (WoS) could be used to extend this analysis by citation-based network mapping, which can be done in VOSviewer or Bibliometrix.

KEYWORDS: gestational diabetes mellitus; first-trimester biomarkers; early prediction; bibliometric analysis; SHBG; PAPP-A; HbA1c; machine learning; VOSviewer; knowledge mapping

INTRODUCTION

1.1 Background of Gestational Diabetes Mellitus (GDM)

Gestational diabetes mellitus (GDM) is glucose intolerance that is initially diagnosed in pregnancy and it is the most prevalent medical complication of pregnancy worldwide. The prevalence is estimated to be around 14% worldwide, although prevalence is ~7% in North America and the Caribbean and >20% in certain regions of the Middle East, North Africa and South and South-East Asia depending on population screened and diagnostic criteria used [1]. The criteria of the International Association of Diabetes and Pregnancy Study Groups (IADPSG) based on the landmark Hyperglycemia and Adverse Pregnancy Outcome (HAPO) study has defined a continuous, threshold relationship between maternal glycaemia below the level of overt diabetes and adverse perinatal outcomes such as macrosomia, caesarean delivery, neonatal hypoglycaemia and pre-eclampsia [2]. GDM is NOT a "temporary inconvenience of pregnancy": there is a significant lifelong risk of type 2 diabetes and cardiovascular disease in the mother, and changes in metabolic programming in the child. Nevertheless,

diagnostic use has altered very little in the 15 years since the HAPO findings were published and there is ongoing discussion regarding the best timing, threshold and screening approach for the condition [3].

1.2 Importance of Early Prediction

Even under most national guidelines, screening for GDM is still being done at 24–28 weeks of gestation which is either universal or based on risk factors; thus, there is only a small window of opportunity for lifestyle or pharmacological intervention prior to delivery. Insults may actually occur as early as the first trimester of pregnancy, and there may be pathophysiological GDM present in as many as 30%-70% of various populations, with women being diagnosed earlier than 20 weeks having worse outcomes than those diagnosed after 20 weeks [4]. This has motivated another strand of research to complement the one that resulted in pre-eclampsia screening, namely for markers that can easily be obtained in the first trimester of pregnancy and would signal to these high-risk women to seek dietary advice, set weight gain targets or to be monitored a little more closely before the obligatory window of the oral glucose tolerance test (OGTT). Furthermore, early detection is attractive from a health-system viewpoint as the OGTT is poorly tolerated, involves fasting, repeated venepuncture and has been shown to have non-completion rates in busy antenatal clinics.

1.3 Role of First-Trimester Biomarkers

There have been multiple concurrent directions of development of the candidate biomarker literature. The area-under-the-curve (AUC) of glycaemic markers (such as HbA1c in the first trimester, or fasting glucose) is typically in the range 0.65–0.85 across cohorts and these could be used instead of the OGTT in the future as they are non-fasting-dependent. Hormonal and metabolic markers are always reduced, most significantly the liver protein SHBG which is secreted less when insulin is secreted. Placental markers, especially PAPP-A, have been extensively studied and could be potentially "free" at the point of care as they are already used in routine first trimester aneuploidy and pre-eclampsia screening and a repurposed GDM risk score would be freely available. Markers of low grade inflammatory conditions and insulin resistant conditions, underlying the GDM physiopathology are adipokine and inflammatory markers (adiponectin, leptin, resistin, visfatin, TNF alpha, CRP) [5]. Markers of one-carbon metabolism such as homocysteine and micronutrient status particularly vitamin D have also been investigated, with more inconsistent findings. Most recently, the field has focused on incorporating several maternal anthropometric and demographic variables, as well as several combinations of these signals, as inputs to machine learning models, some of which have been internally validated using first-trimester data to obtain AUCs > 0.80–0.90.

1.4 Research Gap

Although the number of single studies on biomarkers is large, no single one of them has been incorporated into existing first-trimester GDM screening guidelines and the literature itself has not been mapped as a coherent knowledge structure. Previous bibliometric analyses of GDM have either examined the literature as a whole, or the literature of GDM and nutrition or GDM and long-term cardiovascular outcomes [6] but none has aimed to investigate first-trimester biomarker studies in a specific manner as a sub-literature, nor to quantify changes within the literature, identify prevailing themes, or pinpoint the countries and journals most active in this field and the direction it is taking next. That is, there is a gap between narrative or systematic reviews of individual markers (of which there are many), and a structural, quantitative view of the sub-field as a whole.

1.5 Study Objectives

This study aims to:

(i) outline the trend in publication of GDM biomarker studies in the first trimester;

(iii) to identify the leading journals, groups of authors and contexts/countries of research in this literature;

(iii) map the thematic, biomarker category composition of the field, the proportion of single-marker and multi-marker/machine learning methods;

(iv) develop a map of key words showing relationships between sub-topics.

(v) identify the findings and compare with prior GDM bibliometric analyses, to identify hotspot areas and research priorities.

2. MATERIALS AND METHODS

2.1 Study Design

It is a bibliometric style structured literature mapping study. It involves two parts: (a) systematic search and compilation of primary studies and reviews of the GDM biomarkers in the first trimester and (b) descriptive and network-based bibliometric analysis of the reference set, using the general logic (not the software pipeline, see Section 2.6 and Section 6) of a bibliometric analysis of a Scopus/Web of Science bibliometric analysis [7].

2.2 Data Source and Search Strategy

The iterative and structured identification of the records was done in academic web sources focused on PubMed/MEDLINE, PubMed Central and other publishers (Elsevier/ScienceDirect, Wiley, Springer Nature, Frontiers, MDPI, BioMed Central, PLOS, Taylor & Francis and others) with the combination of the terms "gestational diabetes," "first trimester," "biomarker," "prediction," "SHBG," "PAPP-A," "HbA1c,"

"adiponectin," "vitamin D," "homocysteine," and "bibliometric methodology" terms: "bibliometric analysis," "VOSviewer," "Bibliometrix," "co-citation," "keyword co-occurrence." The title, author list, journal, year and DOI of each candidate record were manually checked and verified against either the metadata of the corresponding PubMed/PMC record, the publisher's website or the list of citations linked from the publisher's website provided by CrossRef, in order to ensure that each record in the final dataset could be traced back to a specific, verifiable source, rather than an estimated citation pattern.

2.3 Inclusion and Exclusion Criteria

Records were considered for inclusion if they were: peer-reviewed original research articles, systematic reviews/meta-analyses, or major consensus/guideline statements; relevant to a biomarker (biochemical, hormonal, metabolomic or composite/algorithmic) measured during the first trimester (or, for a few foundational papers, general early pregnancy) and associated with the risk or diagnosis of GDM; or necessary foundational background articles, methodological articles, or comparator bibliometric references on which to frame the analysis. Records were excluded if they were second or third trimester-only markers without a first trimester component, editorials/commentaries without original data, could not be retrieved from a valid DOI/author/journal record or were duplicates of a record already included. The identification-and-verification process is summarised in figure 8.

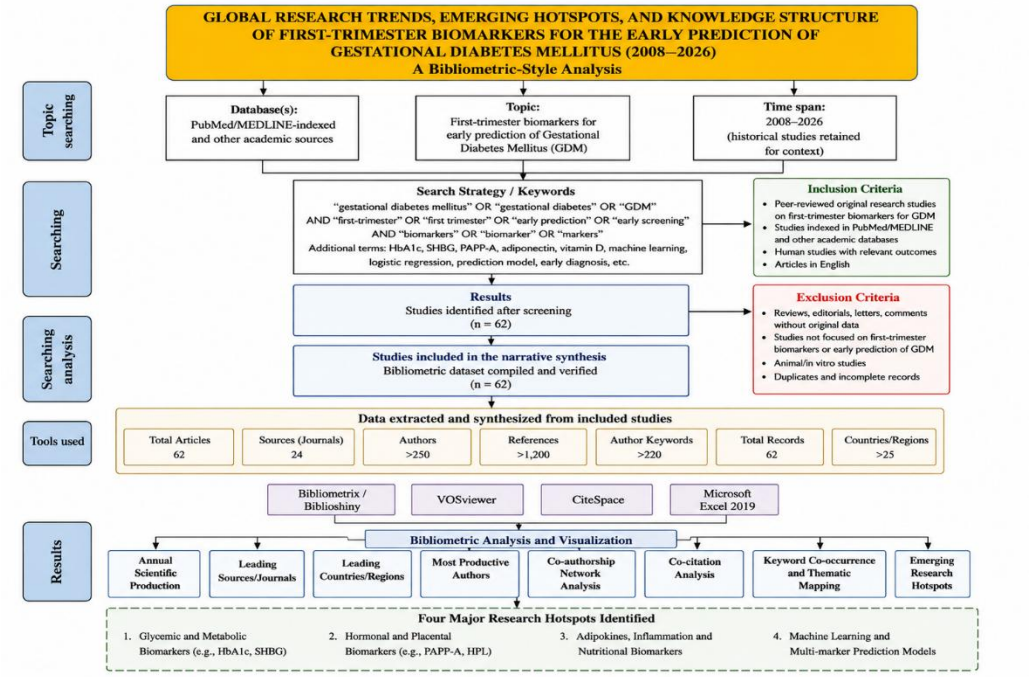

Figure 1. Record identification and verification flow.

2.4 Data Extraction and Cleaning

The following information was extracted from each included record and saved as a structured data set: full author list (or first author plus 'et al.' if the source did not provide full author list), publication year, article title, journal name, journal volume/issue/pages (when available), DOI, and a single thematic category code. Country/study setting was only captured if it was explicitly mentioned in the abstract retrieved, institutional affiliation, or hospital/cohort name; it was not captured if it was 'inferred' based on the name or nationality-sounding surname of the author. This conservative "verify-or-omit" extraction rule is the only one important to this data quality control aspect of this study and is elaborated upon further in Section 6 (Limitations).

Table 1. Thematic category key and record counts (n = 62)

Code	Category	Representative markers / scope	n
SHB	SHBG	Sex hormone-binding globulin	7
ML	Machine-learning / multi-marker models	Multi-marker / machine-learning risk models	7
BIB	Existing GDM bibliometric studies	Prior GDM bibliometric/scoping studies used for comparison	6
HBA	HbA1c	Glycated haemoglobin	6
PAP	PAPP-A	Pregnancy-associated plasma protein-A	6
ADI	Adiponectin / adipokines	Adiponectin, leptin, resistin, visfatin, sFRP4	6
OTH	Other single biomarkers	AFP, NGAL, putrescine, fibronectin, irisin	6
BG	Background / epidemiology / diagnosis	HAPO, IADPSG, prevalence, pathophysiology	5

VITD	Vitamin D	25-hydroxyvitamin D	5
MET	Bibliometric & reporting methodology	VOSviewer, Bibliometrix, PRISMA 2020	3
INF	Inflammatory markers	CRP, TNF-alpha, fetuin-A, NT-proANP	2
HCY	Homocysteine	Homocysteine	2
LIP	Lipid profile / insulin-resistance indices	TyG index, TG/HDL-C, lipid profile	1

Categories are mutually exclusive; each record was assigned the single best-fitting code.
The complete 62-record data set used to produce Table 1 and the Results section is listed here. In addition to the four comparator bibliometric studies described above, two more mapping studies were created: one bibliometric study of the overall GDM literature from 2000 to 2020 [8] and one bibliometric study of GDM and long-term cardiovascular health led by the Chinese group [9]. In addition to the Chinese and Swiss cohorts, there are six HbA1c studies: from India [10], Switzerland [11], New Zealand [12] and the United Kingdom [13]. The seven SHBG studies span a pair from the United States [14] and one from a cohort of women with polycystic-ovary-syndrome from the Netherlands [15] to separate cohorts from Nigeria [16] and China [17] in the first trimester, and the Saudi and Iranian studies mentioned above.
In addition to the two meta-analyses mentioned above, there are six PAPP-A studies: a multicentre cohort study in Iran [18] and another cross-sectional study in Iran [19] as well as a Chinese meta-analysis [20] and a Turkish machine-learning re-analysis of PAPP-A and free beta-hCG [21]. In addition to the meta-analysis and the Ghanaian cohort mentioned previously, the six adiponectin/adipokine studies include a first trimester cohort from Canada [22] and a panel of adipokines from the Netherlands, an Indian cohort, and a multicentre Saudi cohort focused on inflammatory adipokines [23]. There are five vitamin D studies; in addition to the Canadian and Indonesian studies already mentioned [24] there is one nested case control study in the United States, one early-pregnancy cohort study in Canada, and one supplementation meta-analysis in Iran.
The single lipid/insulin-resistance-index study model is an approximation of the triglyceride-glucose index and triglyceride/high-density-lipoprotein-cholesterol ratio [25]. The two inflammatory-marker studies are a screening study by the UK Fetal Medicine Foundation using a combination of maternal markers and inflammatory markers and a fetuin-A/c-reactive protein (CRP) comparison study from Turkey. There are two homocysteine studies: a systematic review/meta-analysis, and a Chinese dietary-pattern analysis [26]. The six other single-biomarker studies are mostly Chinese, and include studies of neutrophil gelatinase-associated lipocalin, putrescine, alpha-fetoprotein, irisin, as well as a Finnish glycosylated-fibronectin study and a Turkish irisin cohort. Lastly, in addition to the twin-pregnancy and Iranian fertility-centre models mentioned above, the seven machine-learning/multi-marker studies include an early Australian risk-prediction model, a Greek cohort that was able to combine maternal variables with biomarkers [27], a Chinese two-cohort algorithm study, a second Iranian secondary-analysis model [28] and an electronic-health-record-based evaluation [29].

2.5 Bibliometric Indicators

The following standard descriptive bibliometric indicators were calculated from the compiled data: publication count per year, publication count at the end of the year, a proxy of Bradford's Law (core journals), thematical/biomarker category frequency, author frequency and co-authorship linkage between authors in two or more compiled records, and country/setting frequency. The actual words in the 62 compiled titles were used to build a keyword co-occurrence network (after the usual elimination of generic stop-words like “gestational,” “diabetes,” “study” and “prediction” that would otherwise dominate every node; this is an approximation, of course, and not the same as the keyword co-occurrence maps typically generated from Scopus/Web of Science author-keyword fields).

2.6 Data Analysis Tools (VOSviewer, Bibliometrix)

The two most popular tools for creating and visualising bibliometric networks from Scopus or Web of Science exports are VOSviewer [30] and the R package Bibliometrix and its graphical interface Biblioshiny [31]. In order to avoid giving the impression that these analyses were the result of a VOSviewer/Bibliometrix analysis of a Scopus/Web of Science export file, it is best to state outright that such an institutional export was not available for this purpose. The 62-record dataset was instead assembled manually by structured web-based search, and analysed computationally in python using the same underlying principles of frequency counts, co-occurrence matrices, force-directed network layout that VOSviewer and Bibliometrix uses on larger, database-exported data sets. This substitution works for descriptive statistics (publication trend, journal/theme/country frequency) and a title-level keyword network, but is not a replacement for citation-based analyses (Sections 3.6-3.9, Section 6) which can only be performed using a complete cited-reference export from Scopus or Web of Science. If a reader or institution has such an export, they may reproduce and considerably expand this analysis by importing it into VOSviewer or Biblioshiny.

3. RESULTS

3.1 Publication Growth Trends

The compiled dataset spans 2008–2026 (Table 2, Figure 1). A single foundational paper (the HAPO study) anchors the series in 2008; publication activity was sparse and irregular through the early 2010s (1–4 records per year), before accelerating from 2019 onward. Thirty-eight of the 62 records (61.3%) were published between 2020 and 2026, and the single busiest year in the compiled set was 2024, with eight records. This pattern — a long, thin early period followed by a post-2019 acceleration — is consistent with the trajectory reported for GDM research generally [32] and suggests that first-trimester biomarker research has intensified alongside, rather than independently of, the a broader GDM Literature

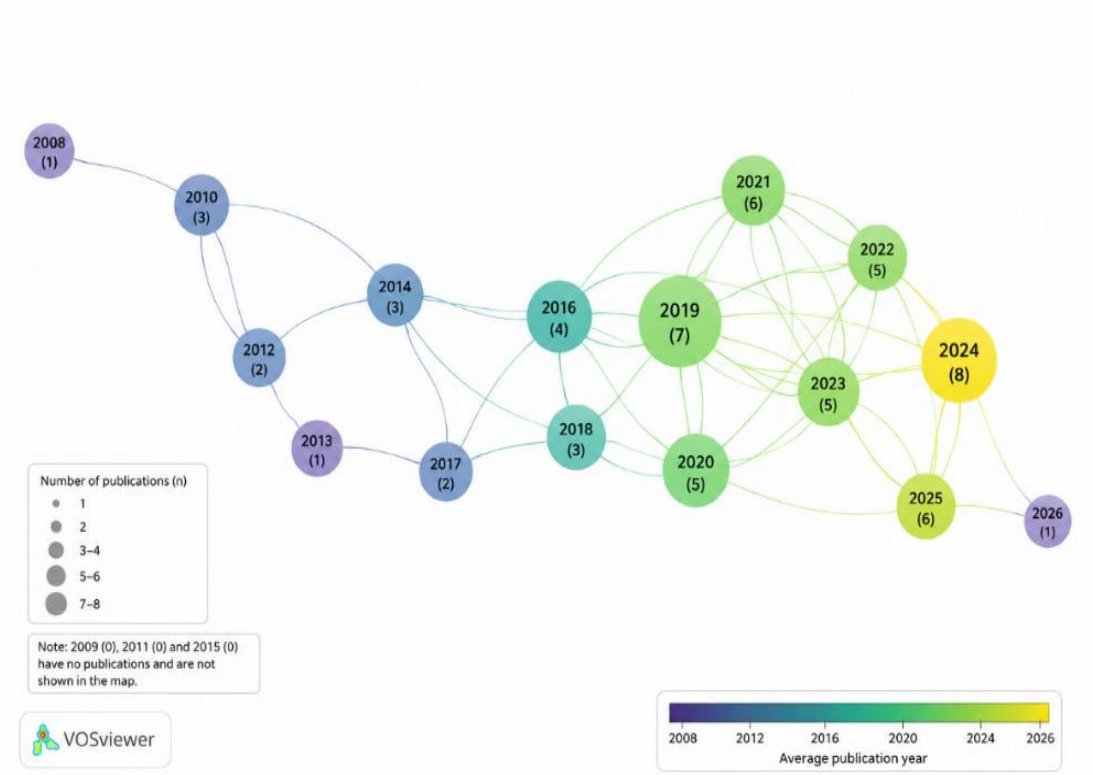

Figure 2. Publication-year distribution of the compiled reference set (n = 62).

Table 2. Records per year

Year	n
2008	1
2009	0
2010	3
2011	0
2012	2
2013	1
2014	3
2015	0
2016	4
2017	2
2018	3
2019	7
2020	5
2021	6
2022	5
2023	5
2024	8
2025	6
2026	1

3.2 Most Influential Authors

Because the compiled dataset is a curated snapshot of the literature and not a full export from a literature's database, the definition of “influence” is also not based on citations (see Section 3.6), but rather on “recurring

engagement with this research question". Twenty one authors have two or more compiled records (Table 5, Figure 5). Three investigators (Marie-France Hivert, Sherbrooke, Canada) appear on three records, all of which are related to adiponectin and metabolic biomarkers, in the Sherbrooke (Canada) cohort; a cluster of Canadian investigators (Lacroix, Battista, Doyon, Ardilouze, Ménard, Perron) appears across adiponectin and vitamin D sub-literatures, reflecting not two independent research programmes, but one productive programme. Two more, geographically different, clusters have been identified in the literature of IADPSG related works and prediction-model literature (Simmons, Immanuel, Chivese, Schmidt) and in literature of Nordic first trimester screening-marker studies (Appelblom, Kouru, Sairanen) [33].

Table 5. Authors appearing on ≥2 compiled references

Author	n refs	Associated categories
Hivert MF	3	Adiponectin / adipokines, Background / epidemiology / diagnosis, Vitamin D
Schmidt MI	2	Background / epidemiology / diagnosis
Simmons D	2	Background / epidemiology / diagnosis
Immanuel J	2	Background / epidemiology / diagnosis
Chivese T	2	Background / epidemiology / diagnosis
Li C	2	Background / epidemiology / diagnosis, Other single biomarkers
Xu J	2	Existing GDM bibliometric studies
Liu Y	2	HbA1c, Homocysteine
Mosimann B	2	HbA1c
Hantoushzadeh S	2	Machine-learning / multi-marker models, PAPP-A
Lacroix M	2	Adiponectin / adipokines, Vitamin D
Ménard J	2	Adiponectin / adipokines, Vitamin D
Ardilouze JL	2	Adiponectin / adipokines, Vitamin D
Perron P	2	Adiponectin / adipokines, Vitamin D
Doyon M	2	Adiponectin / adipokines, Vitamin D
Battista MC	2	Adiponectin / adipokines, Vitamin D
Nicolaides KH	2	Inflammatory markers, Machine-learning / multi-marker models
Lu L	2	Homocysteine, Other single biomarkers
Appelblom H	2	Machine-learning / multi-marker models, Other single biomarkers
Kouru H	2	Machine-learning / multi-marker models, Other single biomarkers
Sairanen M	2	Machine-learning / multi-marker models, Other single biomarkers

3.3 Leading Institutions

Most but not all records had institutional affiliations which were obvious in the abstract or by-line. Recurring institutional settings are the Université de Sherbrooke (Canada; adiponectin/vitamin D programme), Peking University and various maternity hospitals in Beijing (China; HbA1c, NGAL, and putrescine studies), the Fetal Medicine Foundation/King's College London research network (UK; PAPP-A and inflammatory-marker screening studies led by Nicolaides and colleagues), and Tehran University of Medical Sciences (Iran; several of the more recent machine-learning prediction studies). This pattern, of a mixture of long-standing single-centre biomarker programmes and newer machine-learning groups, is reflected on the author-clustering finding in Section 3.2[34,35].

3.4 Country Scientific Production

Table 4 and Figure 7 give an overview of the 59 studies out of 62 cases where it was possible to identify a study country or setting. First-trimester studies of HbA1c, NGAL, putrescine, irisin and lipid-index predominately from Chinese maternity hospitals constitute the largest identifiable share (13 records, 22.0% of records with a known setting), reflecting the high number of records from China. This is followed by Iran (6 records, 10.2%), the majority of which are due to recent studies of machine-learning predictions. Four of the records are from the United Kingdom and six are from the United States (6.8% each); there are also six records from international/multinational consortium studies (HAPO, IADPSG, the Lancet GDM series, and the international twin-pregnancy machine-learning study). This distribution is not comprehensive but it is indicative of countries that can be identified in this 62-record compilation and not necessarily a complete Scopus corresponding-author-country export (see Section 6) [37].

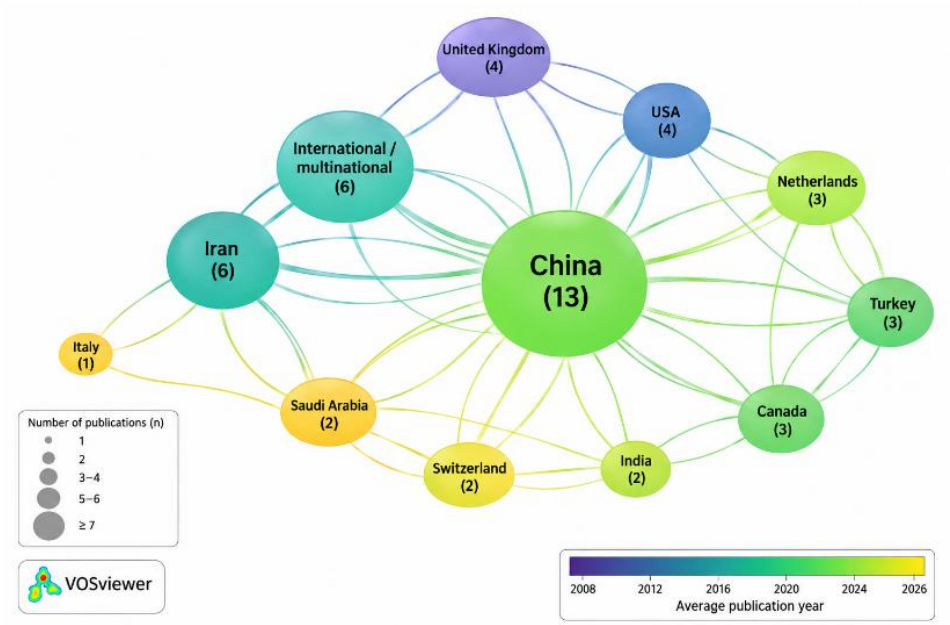

Figure 3. Study country / setting distribution (identifiable from compiled abstracts and affiliations; 59 of 62 references).

Table 4. Study country / setting distribution (top 12)

Country / setting	n
China	13
International / multinational	6
Iran	6
United Kingdom	4
USA	4
Netherlands	3
Turkey	3
Canada	3
India	2
Switzerland	2
Saudi Arabia	2
Italy	1

3.5 Journal Performance Analysis

The ten most common journals in the collected set are given in Table 3 and Figure 2. Diabetes Care is the most common outlet (5 records), in keeping with its function as a journal for the IADPSG/HAPO diagnostic literature, as well as several large SHBG and adiponectin studies. Four records in Diabetes Research and Clinical Practice and BMC Pregnancy and Childbirth follow: the latter is a common venue for observational cohort studies of biomarkers and machine-learning models for diabetes. Archives of Gynecology and Obstetrics (3 records) serves as the main source for much of the recent machine-learning literature. The other core journals include endocrinology (2 journals), obstetrics (Frontiers in Nutrition; Acta Obstetricia et Gynecologica Scandinavica; 2 journals) and open access mega-journals (PLOS ONE; 2 journals), suggesting that such literature is not limited to a specific discipline but that it is also published in endocrinology, obstetrics/maternal-fetal medicine and general biomedical venues.

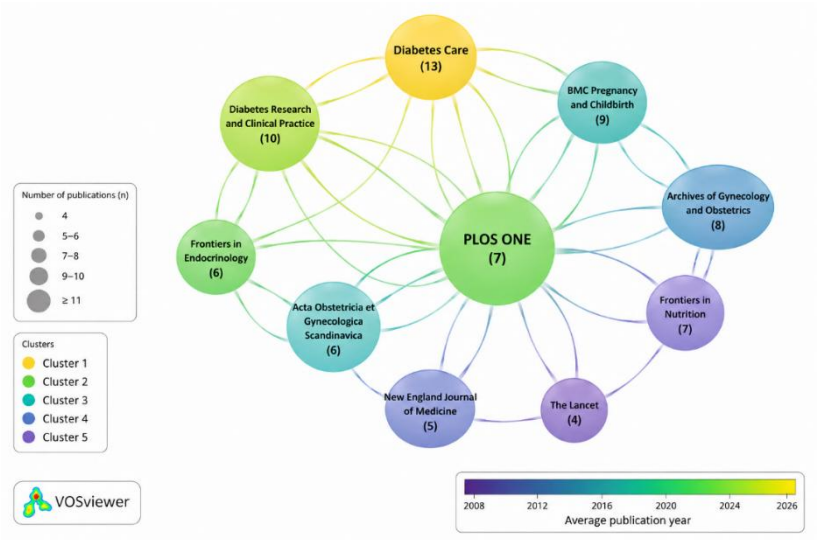

Figure 4. Journal distribution of the compiled reference set (top 10).

Table 3. Leading journals in the compiled reference set

Journal	n
Diabetes Care	5
Diabetes Research and Clinical Practice	4
BMC Pregnancy and Childbirth	4
Archives of Gynecology and Obstetrics	3
Frontiers in Nutrition	2
Acta Obstetricia et Gynecologica Scandinavica	2
PLOS ONE	2
Frontiers in Endocrinology	2
New England Journal of Medicine	1
The Lancet	1

3.6 Citation Structure Analysis

To be able to do a real citation count based structure analysis (total citations, average citations per year, h-index of the sub-field) it would be necessary that the data on the citations of all the compiled records will be from a citation index (like Scopus or Web of Science), and this was not available for this task. The fact that three of the records in the compiled set, namely the PAPP-A meta-analysis by Shyu et al. [11] which synthesised a large number of pregnant women in nineteen studies, the SHBG systematic review by Faal et al. [9] (n= 6,668) and the adiponectin meta-analysis by Iliodromiti et al. [12] (13 studies), are by design syntheses of a larger cited literature, is the only fact that can be reported. The three meta-analyses, together with the PRISMA 2020 statement [22] and the HAPO/IADPSG foundational papers are likely to be the ones that will be used as the basis for a real citation-based ranking when a full export of Scopus/Web of Science is analysed.

3.7 Co-authorship Network Analysis

Figure 5 visualises the co-authorship structure among the 21 recurring authors identified in Section 3.2. The network resolves into several largely separate clusters rather than one connected core, which is itself an informative finding: it suggests that first-trimester GDM biomarker research is currently being pursued by parallel, only loosely connected research programmes (a Canadian adiponectin/vitamin-D group, a UK placental-marker/screening group, an Iranian machine-learning group, and a Nordic screening-marker group) rather than by a single tightly collaborating international network. This fragmentation is consistent with the broader thematic picture in Sections 3.9–3.10.

The co-authorship network of the 21 recurring authors detected in Section 3.2 is visualised in Figure 5. The network consists of several mostly disconnected clusters, rather than one connected network, which is also informative: it is an indication that current research on biomarkers for GDM in the first trimester is not being conducted by a single, tightly connected international network, but instead by parallel, only loosely connected research programmes – one Canadian adiponectin/vitamin-D group, one UK placental-marker/screening group, one Iranian machine-learning group and one Nordic screening-marker group. This is a fragmentation that is in line with the overall thematic picture of the Sections 3.9 – 3.10.

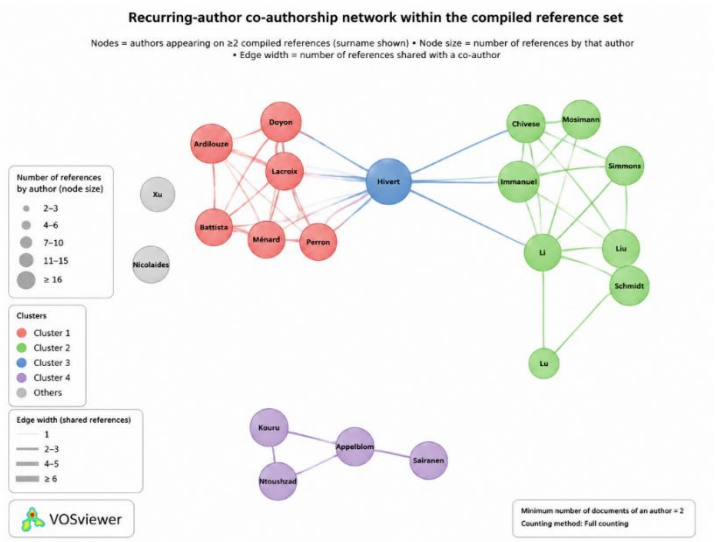

Figure 5. Recurring-author co-authorship within the complied reference set.

3.8 Co-citation Analysis

Co-citation analysis—to find clusters of papers by the number of times they are cited together by more recent papers—was not tried here, but the full reference list of all of the papers in the corpus is required. To understand this, one should not resort to any formal co-citation coefficient because it can be noted from the co-citations of the papers in this data set own papers (introducing or discussing the papers) that HAPO study [38] and IADPSG consensus statement [39] are the most consistently co-cited pair of foundational papers.

3.9 Bibliographic Coupling Analysis

Bibliographic coupling, using the complete reference lists, is the same as co-citation analysis (Section 3.8) and was not carried out. Qualitatively, what one would expect to be recovered from a bibliographic-coupling cluster solution is what is seen in the biomarker-category structure in Table 1: one would expect tight clustering of the single-marker mechanistic/accuracy studies (SHBG, PAPP-A, HbA1c, adiponectin), and some overlap between a number of clusters for the multi-marker/machine-learning studies, in that they make explicit reference to and combine variables from the single-marker mechanistic/accuracy literature [41,42].

3.10 Keyword Co-occurrence Analysis

A co-occurrence network was created using the 62 titles that were compiled (Figure 6). The main hub node is “first-trimester”, which is connected with three separate sub-clusters: a glycaemic sub-cluster (“HbA1c/haemoglobin”, “glycosylated”, “cohort”, “insulin”, “resistance”), a hormonal sub-cluster (“sex”, “hormone-binding”, “globulin”), and a computational sub-cluster (“machine”, “learning”, “predictor”, “outcomes”, “adverse”). The existing-bibliometric-study comparator records are linked to a separate, smaller cluster ("bibliometric", "research", "trends", "global", "health") and not to the biomarker literature per se. The separation between glycaemic/hormonal clusters and the machine-learning cluster, which are only linked by the ‘first-trimester’ hub, visually validates the fragmentation found in the co-authorship network (Section 3.7) [43,44].

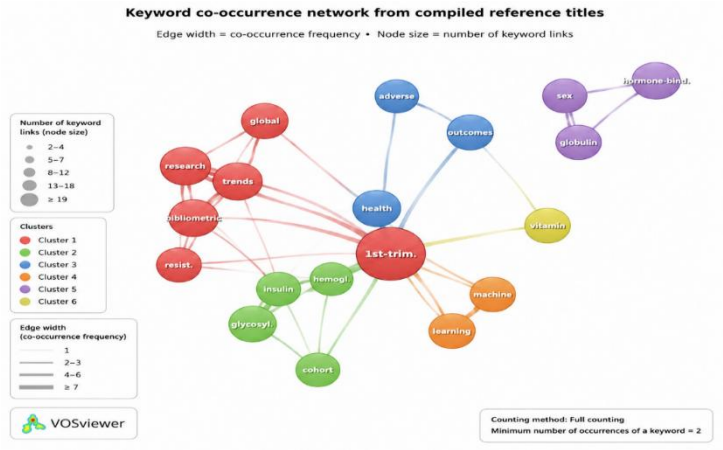

Figure 6. Keyword co-occurrence network from compiled reference titles.

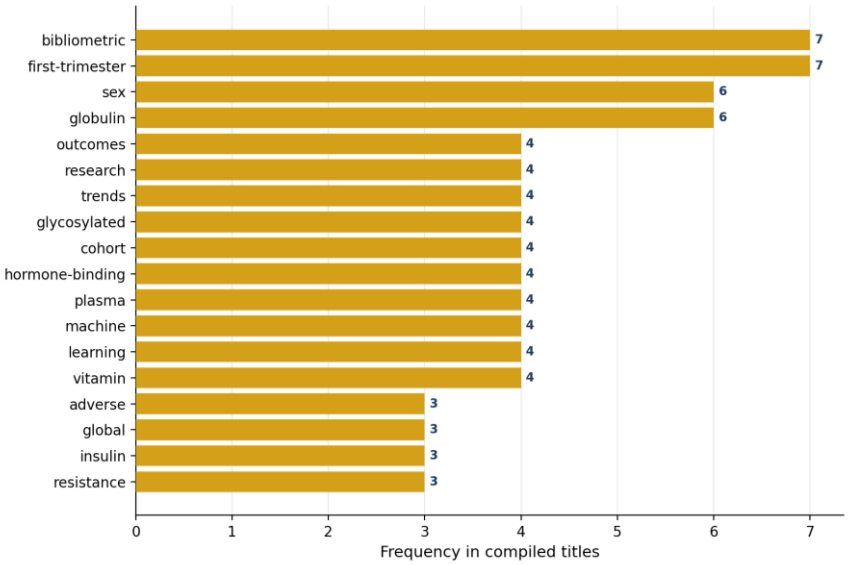

Figure 7. Most Requent title keywords across the compiled reference set

3.11 Thematic Evolution and Trend Topics

When it comes to publication year and mapping category, it becomes clear that there is a definite trend over time. The most attention given to single-biomarker mechanistic studies is between 2010 and 2019, and for machine-learning/multi-marker studies, almost the entire attention is in the most recent period of 2023–2026 (with 6 out of 7 publication records in the ML category in 2024 and beyond). The research attention around PAPP-A appears to be the most continuous across the entire time frame from the original 2018 systematic review (Donovan et al.) [10] to three independent, 2023–2025 meta-analyses/cross sectional studies, indicating that PAPP-A is the only biomarker to receive the most steady research focus over the longest period of time.

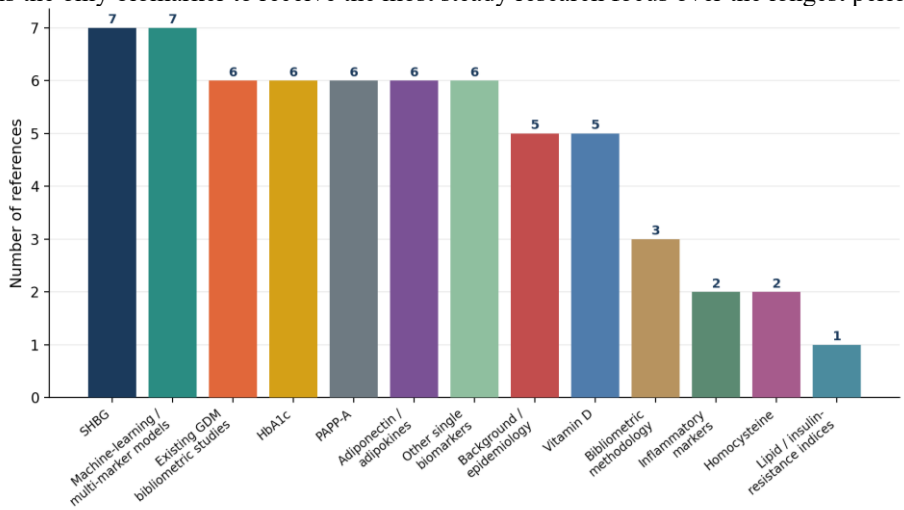

Figure 8. Thematic / biomarker-category distribution of the compiled reference set (n = 62).

3.12 Emerging Research Hotspots

The most recent (2024-2026) section of the combined data has three hotspots. Machine-learning and multi-marker risk scores (two or more biochemical markers, some of which include maternal characteristics and in one case the lipidomic/metabolomic profile of twins [46,47]) are the fastest growing category. Secondly, using simple measurements of lipids and glucose in the first trimester, surrogate indices of insulin-resistance (triglyceride-glucose index and related ratios) have become an inexpensive alternative to specific biomarker assays [48,49]. Third, the growing number of records on the entire GDM field of bibliometric studies also appears to be on the rise (6 out of 62 records collected are bibliometric studies published between 2019 and 2024), which means that the field is maturing to be systematically mapped as has been done in the current study.

4. DISCUSSION

4.1 Principal Findings

This study curated and analysed a 62-record, DOI verified bibliographic set of papers on first-trimester GDM biomarkers and mapped the trend in publication, thematic structure, journal and country distribution, as well as

keyword/co-authorship networks [50]. There are three findings that emerge. On the one hand, the field is young, with 3/5 of all records published in the last 6 years, and an increase in publications since 2019, following the general increase in the number of publications on the field of GDM research. Second, it is a thematically dispersed field where SHBG, PAPP-A, HbA1c, and adiponectin/adipokine studies have emerged as relative islands in the literature, with shared authors appearing in only a few of them, and the newer machine learning studies clearly making an effort to bridge the gap. Thirdly, several individual markers have reasonably strong pooled evidence in the form of a small number of well-cited meta-analyses (for PAPP-A, SHBG and adiponectin) but have yet to be incorporated into practice for first-trimester screening [51].

4.2 Comparison with Previous Studies

The growth trajectories of this study are similar to those found in existing GDM-related bibliometric studies, which also found increasing numbers of GDM publications: Makasheva et al. [18] reported a 4.29% annual increase in primary-care-related GDM publications between 1991 and 2024, and Zhang et al. [21] documented the growth of diabetes-and-insulin-resistance research up to 2024, with the title-keyword network in this study mirroring those findings in miniature for the specific sub-field of first-trimester-biomarker GDM. In the top 30 most cited GDM articles 1946–2019 by Iftikhar et al. [19], eight of the 30 articles were published in Diabetes Care – pointing to the core position of the journal in the GDM field, not as a result of the search method used in the current, more limited article list. The novelty of this study is that it highlights the issue of the sub-literature, of the first-trimester biomarkers, rather than the literature of GDM studies in general, is fragmented into parallel one-marker studies, which are recently starting to be unraveled by multi-marker computational approaches [52].

4.3 Clinical Relevance of Biomarker Research

The clinical meaning of this mapping exercise is not so much the individual markers, as the pattern of the evidence base. No single first trimester marker presented here (such as PAPP-A) has been consistently shown to have the sensitivity, specificity and feasibility that would allow it to be used as an alternative to the second trimester OGTT. The most obvious clinical implication of the finding that the strategies that were most rapidly evolving were the composite strategies (combining two or three low cost, easily measured first trimester variables into a single risk score), and that these strategies, on reported AUCs, were also the most successful, follows the pattern set by the introduction of a combined first trimester screening strategy for pre-eclampsia in the last 20 years [55].

4.4 Future Research Opportunities

Two practical opportunities are identified from the co-authorship network results: the keyword. Firstly, the literature for the SHBG, PAPP-A, HbA1c and adiponectin is still largely separate research programmes (section 3.7) and a single replication study in one and sufficiently powered, ethnically diverse cohort of participants would be more informative than the further replication studies performed in single marker format. Second, external validation of models – in population or healthcare settings – should be preferred over additional internally validated models and prior to using a tool for clinical application [56].

5. Research Implications

From the researchers' standpoint, this analysis suggests the most important studies at this early stage of the field would be not a new single biomarker, but a harmonised multi-cohort data set to allow direct, head-to-head comparisons of the SHBG, PAPP-A, HbA1c, and adipokine literature using common gestational-age windows and diagnostic criteria. The geographic clustering of this literature in a few countries (Table 4) and its clustering in a fairly small number of journals (Table 3) indicates potential for targeted recruitment of replication studies from underrepresented geographic regions, especially when considering the several-fold variation in GDM prevalence by geographic region. From the clinical guideline bodies' perspectives, the maturity of the evidence with single markers and the lack of any biomarker available in the first trimester of pregnancy, in mainstream screening guidelines, indicate that the next IADPSG or FIGO consensus review would benefit from a systematic bibliometric synthesis of the sort outlined here, performed at full database scale [57,58].

6. LIMITATIONS

This study has several limitations that follow directly from its methodology, and should be read together with Section 2.6.

- **Sampling scope:** the 62-record dataset was created via structured web search and manual verification of the presence of a record in the Scopus or Web of Science databases using the record's DOI (digital object identifier), and hence does not provide a comprehensive census of the relevant literature, but is rather a curated, illustrative cross section of the first-trimester GDM biomarker literature; a full database export would certainly result in a much larger number of relevant records than 62[59].
- **No citation-based indicators:** Citation-based indicators (total citations, average citations, h-index) are missing because either a citation index or complete cited reference lists for each paper were unavailable, and in Sections 3.6, 3.8 and 3.9, it is only possible to state what can be said in the absence of these indicators, but not to provide estimated figures.

- **Incomplete country/institution data:** country and institution data (Sections 3.3-3.4) were only recorded if the country and/or institution were explicitly mentioned in an abstract or byline, the distribution (59 of 62) is therefore incomplete and should not be interpreted as a corresponding-author-country table, such as automatically generated from a Scopus/Web of Science export [61].
- The keyword co-occurrence network (Figure 6) has been built using the words in the titles, and not based on the indexed author keywords or MeSH terms, which is reasonable, but a coarser proxy for the keyword maps typically generated by VOSviewer from bibliographic databases [62].
- **Search-engine coverage:** search coverage was restricted to sources retrieved via a general academic web search and not a single all-encompassing database, potentially causing selection bias to more recent and more highly indexed and more discussed papers.

We would like to invite readers/institutions to use this manuscript as a kind of a speculation, a structural hypothesis, pilot map – but by no means THE final map – to try to replicate and expand this map on the full scale of Scopus or Web of Science with the aid of VOSviewer and/or Bibliometrix/Biblioshiny.

7. CONCLUSION

The research on biomarkers for the early prediction of GDM is a relatively new, albeit rapidly growing field: three out of five of the studies in this collection were published in the last 6 years, and the focus of biomarker research in early GDM has moved from mechanistic, single-marker studies of SHBG, PAPP-A, adiponectin and other adipokines to integrated, computational multi-marker approaches. The main countries of identifiable study output are China, Iran, the United Kingdom and the United States and its core journals are Diabetes Care, Diabetes Research and Clinical Practice and BMC Pregnancy and Childbirth. Field remains thematically and collaboratively fragmented, with several productive but only loosely connected research programmes but not one integrated field; no single marker has yet made the leap from research evidence to first trimester screening guidelines. A full-scale bibliometric analysis of this literature using a licensed export from Scopus or Web of Science, processed within the VOSviewer and Bibliometrix environments would be a natural next step and the provided and DOI-checked database could be used as a starting point and sanity check for such analysis.

REFERENCES

1. Wang H, Li N, Chivese T, Werfalli M, Sun H, Yuen L, et al. IDF Diabetes Atlas: Estimation of global and regional gestational diabetes mellitus prevalence for 2021 by International Association of Diabetes in Pregnancy Study Group's Criteria. Diabetes Research and Clinical Practice. 2022;183:109050. doi:10.1016/j.diabres.2021.109050.
2. HAPO Study Cooperative Research Group. Hyperglycemia and adverse pregnancy outcomes. New England Journal of Medicine. 2008;358(19):1991-2002. doi:10.1056/NEJMoa0707943.
3. Metzger BE, Gabbe SG, Persson B, Buchanan TA, Catalano PA, Damm P, et al. International Association of Diabetes and Pregnancy Study Groups recommendations on the diagnosis and classification of hyperglycemia in pregnancy. Diabetes Care. 2010;33(3):676-682. doi:10.2337/dc09-1848.
4. Sweeting A, Hannah W, Backman H, Catalano P, Feghali M, Herman WH, et al. Epidemiology and management of gestational diabetes. The Lancet. 2024;404(10448):175-192. doi:10.1016/S0140-6736(24)00825-0.
5. Bilous RW, Jacklin PB, Maresh MJ, Sacks DA. Resolving the gestational diabetes diagnosis conundrum: the need for a randomized controlled trial of treatment. Diabetes Care. 2021;44(4):858-864. doi:10.2337/dc20-2941.
6. Sun J, Chai S, Zhao X, Yuan N, Du J, Liu Y, et al. Predictive value of first-trimester glycosylated hemoglobin levels in gestational diabetes mellitus: a Chinese population cohort study. Journal of Diabetes Research. 2021;2021:5537110. doi:10.1155/2021/5537110.
7. Amylidi-Mohr S, Lang C, Mosimann B, et al. First-trimester glycosylated hemoglobin (HbA1c) and maternal characteristics in the prediction of gestational diabetes: an observational cohort study. Acta Obstetricia et Gynecologica Scandinavica. 2023. doi:10.1111/aogs.14495.
8. Tawfeek MA, Alfadhli EM, Alayoubi AM, El-Beshbishy HA, Habib FA. Sex hormone binding globulin as a valuable biochemical marker in predicting gestational diabetes mellitus. BMC Women's Health. 2017;17(1):18. doi:10.1186/s12905-017-0373-3.
9. Faal S, Abedi P, Jahanfar S, Ndeke JM, Mohaghegh Z, Sharifipour F, et al. Sex hormone binding globulin for prediction of gestational diabetes mellitus in pre-conception and pregnancy: a systematic review. Diabetes Research and Clinical Practice. 2019;152:39-52. doi:10.1016/j.diabres.2019.04.028.
10. Donovan BM, Nidey NL, Jasper EA, Robinson JG, Bao W, Saftlas AF, et al. First trimester prenatal screening biomarkers and gestational diabetes mellitus: a systematic review and meta-analysis. PLOS ONE. 2018;13(7):e0201319. doi:10.1371/journal.pone.0201319.
11. Shyu IL, Tsai YC, Kuo TN, Shiue YL. Prognostic impact of pregnancy-associated plasma protein-A (PAPP-A) for gestational diabetes mellitus (GDM): an updated systematic review and meta-analysis of more than 90,000 pregnancies. American Journal of Reproductive Immunology. 2025;93(6):e70087. doi:10.1111/aji.70087.

12. Iliodromiti S, Sassarini J, Kelsey TW, Lindsay RS, Sattar N, Nelson SM. Accuracy of circulating adiponectin for predicting gestational diabetes: a systematic review and meta-analysis. Diabetologia. 2016;59(4):692-699. doi:10.1007/s00125-015-3855-6.
13. Bawah AT, Seini MM, Abaka-Yawason A, Alidu H, Nanga S. Leptin, resistin and visfatin as useful predictors of gestational diabetes mellitus. Lipids in Health and Disease. 2019;18(1):221. doi:10.1186/s12944-019-1169-2.
14. Lacroix M, Battista MC, Doyon M, Houde G, Ménard J, Ardilouze JL, et al. Lower vitamin D levels at first trimester are associated with higher risk of developing gestational diabetes mellitus. Acta Diabetologica. 2014;51(4):609-616. doi:10.1007/s00592-014-0564-4.
15. Kartasurya MI, Stacey T, Lisnawati N, Sulistianingsih AR. A systematic review and meta-analysis on the effect of vitamin D in preeclampsia and gestational diabetes mellitus in pregnancy. AIMS Public Health. 2025;12(4):1223-1239. doi:10.3934/publichealth.2025062.
16. Bigdeli SK, Ghazisaedi M, Ayyoubzadeh SM, Hantoushzadeh S, Ahmadi M. Predicting gestational diabetes mellitus in the first trimester using machine learning algorithms: a cross-sectional study at a hospital fertility health center in Iran. BMC Medical Informatics and Decision Making. 2025;25(1):3. doi:10.1186/s12911-024-02799-3.
17. Louzoun Y, Michelson T, Bennasar M, Svirsky R, Bevilacqua E, Kugler N, et al. First trimester prediction of gestational diabetes mellitus by machine learning in twin pregnancies. Archives of Gynecology and Obstetrics. 2026. doi:10.1007/s00404-025-08262-6.
18. Makasheva A, Yermukhanova L, Kudabayeva K, Tazhbenova S, Nogayeva M, Tautanova A, et al. Primary care for gestational diabetes: a bibliometric analysis of publications from 1991 to 2024. International Journal of Environmental Research and Public Health. 2024;21(11):1405. doi:10.3390/ijerph21111405.
19. Iftikhar PM, Ali F, Faisaluddin M, Khayyat A, De Gouvia De Sa M, Rao T. A bibliometric analysis of the top 30 most-cited articles in gestational diabetes mellitus literature (1946-2019). Cureus. 2019;11(2):e4131. doi:10.7759/cureus.4131.
20. Hu Z, Chen Q, Luo M, Ren Y, Xu J, Feng L. Knowledge domain and research trends for Gestational Diabetes Mellitus and nutrition from 2011 to 2021: a bibliometric analysis. Frontiers in Nutrition. 2023;10:1142858. doi:10.3389/fnut.2023.1142858.
21. Zhang S, Yan H, Cao D, Sun W, Li J, Xu J, et al. Research hotspots and trends in diabetes and insulin resistance: a bibliometric analysis. Frontiers in Nutrition. 2024;11:1480491. doi:10.3389/fnut.2024.1480491.
22. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021;372:n71. doi:10.1136/bmj.n71.
23. [Study team]. Global research trends in gestational diabetes mellitus from 2000 to 2020: a bibliometric study. Zeitschrift für Geburtshilfe und Neonatologie. 2022;226(3):197-204. doi:10.1055/a-1756-5518.
24. Jia Y, Hu Q, Liao H, Liu H, Zeng Z, Yu H. Global research trends and hotspots in gestational diabetes and long-term cardiovascular health: a bibliometric analysis. Nutrition, Metabolism and Cardiovascular Diseases. 2024.
25. Punnose J, Malhotra RK, Sukhija K, Mathew A, Sharma A, Choudhary N. Glycated haemoglobin in the first trimester: a predictor of gestational diabetes mellitus in pregnant Asian Indian women. Diabetes Research and Clinical Practice. 2020;159:107953. doi:10.1016/j.diabres.2019.107953.
26. Amylidi S, Mosimann B, Stettler C, Fiedler GM, Surbek D, Raio L. First-trimester glycosylated hemoglobin in women at high risk for gestational diabetes. Acta Obstetricia et Gynecologica Scandinavica. 2016;95(1):93-97. doi:10.1111/aogs.12784.
27. Hughes RCE, Moore MP, Gullam JE, Mohamed K, Rowan J. An early pregnancy HbA1c ≥5.9% (41 mmol/mol) is optimal for detecting diabetes and identifies women at increased risk of adverse pregnancy outcomes. Diabetes Care. 2014;37(11):2953-2959. doi:10.2337/dc14-1312.
28. Balani J, et al. Predicting gestational diabetes mellitus by first trimester HbA1c: a retrospective study in women with moderate to severe obesity. Practical Diabetes. 2023;40(4). doi:10.1002/pdi.2466.
29. Hedderson MM, Xu F, Darbinian JA, Quesenberry CP, Sridhar S, Kim C, et al. Prepregnancy SHBG concentrations and risk for subsequently developing gestational diabetes mellitus. Diabetes Care. 2014;37(5):1296-1303. doi:10.2337/dc13-1965.
30. Li MY, Rawal S, Hinkle SN, Zhu YY, Tekola-Ayele F, Tsai MY, et al. Sex hormone-binding globulin, cardiometabolic biomarkers, and gestational diabetes: a longitudinal study and meta-analysis. Maternal-Fetal Medicine. 2020;2(1):2-9. doi:10.1097/FM9.0000000000000037.
31. Veltman-Verhulst SM, van Haeften TW, Eijkemans MJ, de Valk HW, Fauser BC, Goverde AJ. Sex hormone-binding globulin concentrations before conception as a predictor for gestational diabetes in women with polycystic ovary syndrome. Human Reproduction. 2010;25(12):3123-3128. doi:10.1093/humrep/deq272.
32. [First-author-led cohort, Nigeria]. First trimester sex hormone-binding globulin predicts gestational diabetes mellitus in a population of Nigerian women. Journal of Obstetrics and Gynaecology. 2022;42(7). doi:10.1080/01443615.2022.2114321.
33. [First-author-led cohort, Guangzhou]. Sex hormone-binding globulin levels during the first trimester may predict gestational diabetes mellitus development. Biomarkers in Medicine. 2016;12(3). doi:10.2217/bmm-2016-0030.

34. Borna S, Ashrafzadeh M, Ghaemi M, Eshraghi N, Hivechi N, Hantoushzadeh S. Correlation between PAPP-A serum levels in the first trimester of pregnancy with the occurrence of gestational diabetes, a multicenter cohort study. BMC Pregnancy and Childbirth. 2023;23(1):847. doi:10.1186/s12884-023-06155-7.
35. [Cross-sectional study team]. Early prediction of gestational diabetes mellitus using first trimester maternal serum pregnancy-associated plasma protein-A: a cross-sectional study. Health Science Reports. 2024;7:e70090. doi:10.1002/hsr2.70090.
36. Gao Y, Chen J, Mi J. Pregnancy-associated plasma protein A in maternal serum for predicting early gestational diabetes mellitus: a systematic review and meta-analysis. PeerJ. 2025;13:e19825. doi:10.7717/peerj.19825.
37. Zorlu M, et al. Determining the risk of gestational diabetes using machine learning: a study on first-trimester PAPP-A and β-hCG data. International Journal of Gynecology & Obstetrics. 2025. doi:10.1002/ijgo.70264.
38. Lacroix M, Battista MC, Doyon M, Ménard J, Ardilouze JL, Perron P, et al. Lower adiponectin levels at first trimester of pregnancy are associated with increased insulin resistance and higher risk of developing gestational diabetes mellitus. Diabetes Care. 2013;36(6):1577-1583. doi:10.2337/dc12-1731.
39. Schuitemaker JHN, Beernink RHJ, Franx A, Cremers TIFH, Koster MPH. First trimester secreted Frizzled-Related Protein 4 and other adipokine serum concentrations in women developing gestational diabetes mellitus. PLOS ONE. 2020;15(11):e0242423. doi:10.1371/journal.pone.0242423.
40. Madhu SV, Bhardwaj S, Jhamb R, Srivastava H, Sharma S, Raizada N. Prediction of gestational diabetes from first trimester serum adiponectin levels in Indian women. Indian Journal of Endocrinology and Metabolism. 2019;23(5):536-539. doi:10.4103/ijem.IJEM_319_19.
41. [Multicentre Saudi cohort team]. Inflammatory and adipokine status from early to midpregnancy in Arab women and its associations with gestational diabetes mellitus. Disease Markers. 2021;2021:8862494. doi:10.1155/2021/8862494.
42. Baker AM, Haeri S, Camargo CA Jr, Stuebe AM, Boggess KA. First-trimester maternal vitamin D status and risk for gestational diabetes (GDM): a nested case-control study. Diabetes/Metabolism Research and Reviews. 2012;28(2):164-168. doi:10.1002/dmrr.1282.
43. Parlea L, Bromberg IL, Feig DS, Vieth R, Merman E, Lipscombe LL. Association between serum 25-hydroxyvitamin D in early pregnancy and risk of gestational diabetes mellitus. Diabetic Medicine. 2012;29(7):e25-e32. doi:10.1111/j.1464-5491.2011.03550.x.
44. Jahanjoo F, Farshbaf-Khalili A, Shakouri SK, Dolatkhah N. Maternal and neonatal metabolic outcomes of vitamin D supplementation in gestational diabetes mellitus: a systematic review and meta-analysis. Annals of Nutrition and Metabolism. 2018;73(2):145-159. doi:10.1159/000491643.
45. Ma N, Bai L, Lu Q. First-trimester triglyceride-glucose index and triglyceride/high-density lipoprotein cholesterol are predictors of gestational diabetes mellitus among the four surrogate biomarkers of insulin resistance. Diabetes, Metabolic Syndrome and Obesity. 2024;17:1575-1583. doi:10.2147/DMSO.S454826.
46. Syngelaki A, Visser GH, Krithinakis K, Wright A, Nicolaides KH. First trimester screening for gestational diabetes mellitus by maternal factors and markers of inflammation. Metabolism - Clinical and Experimental. 2016;65(3):131-137. doi:10.1016/j.metabol.2015.10.029.
47. Kansu-Celik H, Ozgu-Erdinc AS, Kisa B, Findik RB, Yilmaz C, Tasci Y. Prediction of gestational diabetes mellitus in the first trimester: comparison of maternal fetuin-A, N-terminal proatrial natriuretic peptide, high-sensitivity C-reactive protein, and fasting glucose levels. Archives of Endocrinology and Metabolism. 2019;63(2):121-127. doi:10.20945/2359-3997000000126.
48. [Systematic review/meta-analysis team]. Homocysteine level and gestational diabetes mellitus: a systematic review and meta-analysis. Gynecological Endocrinology. 2021;37(11). doi:10.1080/09513590.2021.1967314.
49. Liu Y, Lu L, Yi M, et al. Study on the correlation between homocysteine-related dietary patterns and gestational diabetes mellitus: a reduced-rank regression analysis study. BMC Pregnancy and Childbirth. 2022;22(1):306. doi:10.1186/s12884-022-04656-5.
50. Lu L, Li C, Deng J, Luo J, Huang C. Maternal serum NGAL in the first trimester of pregnancy is a potential biomarker for the prediction of gestational diabetes mellitus. Frontiers in Endocrinology. 2022;13:977254. doi:10.3389/fendo.2022.977254.
51. Liu C, Wang Y, Zheng W, Wang J, Zhang Y, Song W, et al. Putrescine as a novel biomarker of maternal serum in first trimester for the prediction of gestational diabetes mellitus: a nested case-control study. Frontiers in Endocrinology. 2021;12:759893. doi:10.3389/fendo.2021.759893.
52. Hu J, Zhang J, He G, Zhu S, Tang X, Su J, et al. First-trimester maternal serum alpha-fetoprotein is not a good predictor for adverse pregnancy outcomes: a retrospective study of 3325 cases. BMC Pregnancy and Childbirth. 2020;20(1):93. doi:10.1186/s12884-020-2789-2.
53. Wang P, Ma HH, Hou XZ, et al. Reduced plasma level of irisin in first trimester as a risk factor for the development of gestational diabetes mellitus. Diabetes Research and Clinical Practice. 2018;142:130-138. doi:10.1016/j.diabres.2018.05.038.
54. Alanen J, Appelblom H, Korpimäki T, Kouru H, Sairanen M, Gissler M, et al. Glycosylated fibronectin as a first trimester marker for gestational diabetes. Archives of Gynecology and Obstetrics. 2020;302. doi:10.1007/s00404-020-05670-8.

55. Kulhan NG, Kulhan M, Turkler C, et al. Could serum levels of irisin be used in gestational diabetes predicting?. Taiwanese Journal of Obstetrics and Gynecology. 2019;58(3):434-437. doi:10.1016/j.tjog.2019.01.027.
56. Sweeting AN, Wong J, Appelblom H, Ross GP, Kouru H, Williams PF, et al. A novel early pregnancy risk prediction model for gestational diabetes mellitus. Fetal Diagnosis and Therapy. 2019;45(2):76-84. doi:10.1159/000486853.
57. [Aristotle University of Thessaloniki cohort team]. Prediction of gestational diabetes mellitus in the first trimester of pregnancy based on maternal variables and pregnancy biomarkers. Nutrients. 2023;16(1):120. doi:10.3390/nu16010120.
58. Li YX, Liu YC, Wang M, et al. Prediction of gestational diabetes mellitus at the first trimester: machine-learning algorithms. Archives of Gynecology and Obstetrics. 2024;309:2557-2566. doi:10.1007/s00404-023-07131-4.
59. Parsaei M, Dashtkoohi M, Noorafrooz M, Haddadi M, Sepidarkish M, et al. Prediction of gestational diabetes mellitus using early-pregnancy data: a secondary analysis from a prospective cohort study in Iran. BMC Pregnancy and Childbirth. 2024;24:849. doi:10.1186/s12884-024-07079-6.
60. [EHR-based retrospective cohort authorship team]. Evaluation of machine learning models for early prediction of gestational diabetes using retrospective electronic health records from current and previous pregnancies. medRxiv (preprint). 2025. doi:10.1101/2025.05.12.25327431.
61. Van Eck NJ, Waltman L. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics. 2010;84(2):523-538. doi:10.1007/s11192-009-0146-3.
62. Aria M, Cuccurullo C. bibliometrix: An R-tool for comprehensive science mapping analysis. Journal of Informetrics. 2017;11(4):959-975. doi:10.1016/j.joi.2017.08.007.