Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 10 May 2026
Revised 20 June 2026
Accepted 02 July 2026

Natural Resources for Human Health 2026, Vol. 6 (5): 1105–1135

KEYWORDS:
cardio-obstetrics, climate change, preeclampsia, machine learning, environmental exposure, systematic review

Cardio-Obstetrics in a Changing Climate: Environmental Exposures, Artificial Intelligence and Maternal Cardiovascular Risk Prediction

K.G. Abinayasri[1]*, Dr. Darshna Sarvaiya[2], Prof. Shalet Benvin[3], Afreen Amani[4], Prof. Dr. Malvika kandpal[5], Dr. Agestly[6]

[1]*Assistant Professor, Department of Physician Assistant, Dhanalakshmi Srinivasan University, Email ID: abinayasrikg.ahs@dsuniversity.ac.in
[2]Assistant Professor, Department of Community Medicine, Dr.N.D.Desai Faculty of Medical Science and Research, Dharmsinh Desai University, Nadiad,
ORCID ID: 0009-0003-6534-9449 Email ID: drdaarshna@gmail.com
[3]Assistant Professor, Department of Computer Science and Engineering, BGS Institute of Technology, Adichunchanagiri University, BG nagara, Nagamangala, Mandya-571448,
ORCID ID:- 0000-0001-7851-2282, Email id:- shaletbenvin@gmail.com
[4]P G Scholar, Department of Computer Science and Engineering, BGS Institue of Technology, Adichunchanagiri University, BG Nagara, Nagamangala Taluk, Mandya District-57144 Email: afreenamani4@gmail.com
[5]Professor, School of Education, Shri Guru Ram Rai University, Dehradun,
Orcid id - 0009-0001-4646-6899, Email - mskandpal1234@gmail.com
[6]Postgraduate, Physiology, shree balaji medical college and hospital, Chennai Tamilnadu India

ABSTRACT: Climate change is altering pregnant women's exposure to heat, air pollution, wildfire smoke and extreme weather, while artificial intelligence (AI) and machine learning (ML) are increasingly applied to predict maternal cardiovascular complications such as preeclampsia; whether these evidence streams have actually been integrated is unclear. This review synthesizes evidence across three levels: environmental/climate-sensitive exposure and maternal cardiovascular outcomes; AI/ML approaches to maternal cardiovascular prediction; and the extent of environmental-variable incorporation into AI/ML models, then proposes a research agenda. A structured search across four concept groups (maternal population, cardiovascular outcomes, environmental exposures, AI/ML methods) was conducted in PubMed/MEDLINE and peer-reviewed sources following PRISMA 2020 principles; given substantial heterogeneity, findings are reported as narrative synthesis rather than pooled quantitatively. Ambient heat and fine particulate matter were associated with gestational hypertension, preeclampsia and eclampsia (odds ratios generally 1.1–1.6), with larger increases for wildfire-sourced than urban-source particulate matter. ML models for preeclampsia prediction reported a pooled AUC of 0.91 in a 2026 meta-analysis, reflecting development/internal-validation performance, with extreme heterogeneity and lower pooled sensitivity (0.68) among externally validated models. Two studies incorporated genuine environmental exposure into an AI/ML analysis of a maternal cardiovascular outcome, using chemical biomarkers with a discriminative model in one case and climate-sensitive exposure with causal machine learning in the other, but none combined climate-sensitive exposure with a discriminative model showing demonstrated incremental predictive value. This integration gap is the principal finding; a four-stage research agenda spanning data integration, model development, validation and clinical translation is proposed.

1. INTRODUCTION

Pregnancy is a state of substantial cardiovascular adaptation: blood volume, cardiac output and vascular resistance all change markedly across gestation, and this adaptation can fail in ways that produce gestational hypertension, preeclampsia, eclampsia, peripartum cardiomyopathy or other cardiovascular events. These maternal cardiovascular disorders remain leading contributors to maternal morbidity and mortality worldwide. At the same time, anthropogenic climate change is altering the environmental conditions pregnant women are exposed to: more frequent and intense heat waves, sustained or worsening ambient air pollution in many regions, an expanding wildfire season in several parts of the world, and more frequent extreme weather events. A growing body of environmental epidemiology has examined whether these exposures are associated with maternal cardiovascular outcomes.

Separately, and largely on a different research trajectory, artificial intelligence and machine learning methods — ensemble tree methods, gradient boosting, neural networks and, increasingly, explainable AI techniques such as SHapley Additive exPlanations (SHAP) — have been applied with growing frequency to predict maternal cardiovascular complications, most often preeclampsia, from clinical, demographic and biochemical data available earlier in pregnancy than a clinical diagnosis would otherwise permit.

These two literatures — environmental exposure epidemiology and AI/ML prediction modelling — have developed largely in parallel. It is not obvious, and has not to our knowledge been systematically established, whether AI/ML models predicting maternal cardiovascular risk have actually incorporated environmental or climate-related exposure variables, as opposed to only clinical, demographic, biochemical and genetic predictors. This distinction matters: a model can achieve strong discriminative performance while omitting a modifiable, geographically and temporally variable risk factor that is itself becoming more prevalent under climate change. Conflating "evidence that heat or air pollution is associated with a cardiovascular outcome" with "evidence that heat or air pollution has been built into a predictive model" would overstate how far the field has actually progressed toward climate-informed clinical risk prediction.

This review therefore addresses four questions, structured around three evidence levels:

1. Question 1 — What environmental/climate exposures are associated with maternal cardiovascular complications? (Level 1)
2. Question 2 — What AI/ML approaches currently exist for maternal cardiovascular risk prediction? (Level 2)
3. Question 3 — To what extent are environmental exposures integrated into these AI/ML prediction approaches? (Level 3)
4. Question 4 — What methodological, data, validation, ethical and clinical gaps must be addressed before climate-informed AI prediction can become clinically useful?

The remainder of this manuscript presents a conceptual framework linking these three levels (Section 2), the methods used to identify and synthesize the evidence (Section 3), the synthesized results organized by evidence level together with their interpretation (Section 4), a concrete research agenda (Section 5), a proposed — explicitly not yet validated — framework for climate-informed cardio-obstetric AI (Section 6), the limitations of this review (Section 7), and conclusions (Section 8).

2. CONCEPTUAL FRAMEWORK

Figure 1 sets out the pathway this review uses to organize the evidence: from climate change and environmental exposure, through exposure intensity/timing/duration, maternal physiological response, a cardiovascular pathway, a diagnosed maternal cardiovascular complication, AI/ML-based risk prediction, and finally proposed (not yet validated) risk stratification or clinical decision support. The first five steps of this pathway are supported, to varying degrees, by the Level 1 evidence reviewed in Section 4.2. The step from complication to AI/ML prediction is supported by the Level 2 evidence in Section 4.3. The step that would connect environmental exposure directly into the AI/ML layer — shown as the dashed integration point in Figure 2 below — is the Level 3 question this review treats as its central concern, and the evidence base addressing it directly is characterized in Sections 4.4 and 4.5.

Natural Resources for Human Health
eISSN: 2583-1194

Figure 1. Conceptual Framework

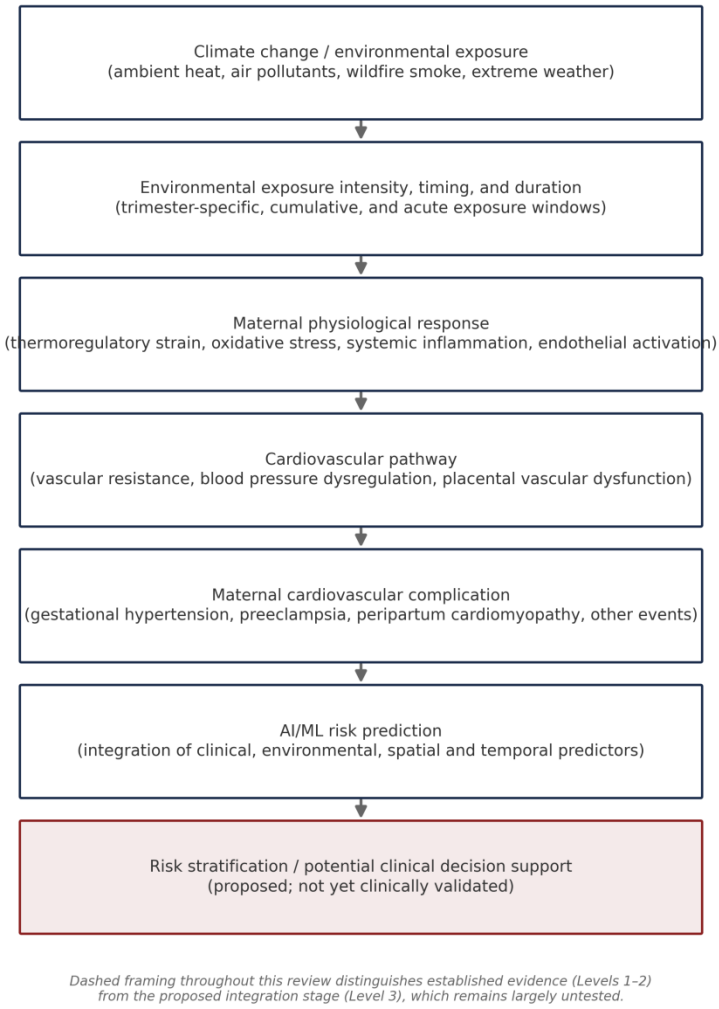

Figure 1. Conceptual framework linking climate/environmental exposure, maternal physiology, cardiovascular outcome and AI/ML-based prediction. Boxes shaded in red indicate stages that remain proposed rather than clinically established.

3. MATERIALS AND METHODS

3.1 Protocol and Reporting Framework

This review followed the PRISMA 2020 statement (Page et al., 2021) as its reporting framework. The review question and eligibility criteria were defined prospectively around the three-level evidence structure set out in Section 2 and Section 3.7. The review has not been registered on PROSPERO at the time of this draft.

3.2 Search Strategy

The search was structured around three complementary streams, corresponding to the three evidence levels in Section 3.7, each combining a population concept group with an outcome concept group and one or both of the exposure/method concept groups below (Boolean structure: Group 1 AND Group 2 AND (Group 3 OR Group 4)):

5. Group 1 (population): pregnancy; pregnant women; maternal health; obstetric; cardio-obstetrics
6. Group 2 (cardiovascular outcome): preeclampsia; gestational hypertension; eclampsia; hypertensive disorders of

pregnancy; peripartum cardiomyopathy; heart failure; arrhythmia; chronic hypertension

7. Group 3 (environmental/climate exposure): climate change; heat; ambient temperature; extreme temperature; heat wave; heat stress; air pollution; PM2.5; PM10; particulate matter; nitrogen dioxide; NOx; ozone; SO2; CO; wildfire smoke; extreme weather; environmental chemical biomarkers; exposome

8. Group 4 (AI/prediction): artificial intelligence; machine learning; deep learning; predictive model; risk prediction; neural network; random forest; gradient boosting; XGBoost; support vector machine; ensemble model; explainable AI; SHAP; double machine learning; causal machine learning

Search A (Group 1 AND Group 2 AND Group 3) targeted environmental/climate exposure and maternal cardiovascular outcomes (Section 4.2). Search B (Group 1 AND Group 2 AND Group 4) targeted AI/ML approaches to maternal cardiovascular prediction (Section 4.3). Search C (Group 1 AND Group 2 AND Group 3 AND Group 4) targeted the integration of the two (Section 4.4) and was run with specific combined terms in addition to the general four-group structure, including: ambient temperature + machine learning + preeclampsia; heat exposure + AI + pregnancy hypertension; PM2.5 + machine learning + preeclampsia; air pollution + machine learning + hypertensive disorders of pregnancy; wildfire smoke + AI + pregnancy hypertension; geospatial exposure + maternal cardiovascular prediction; meteorological variables + pregnancy hypertension prediction; environmental biomarkers + maternal cardiovascular prediction; and exposome + machine learning + hypertensive disorders of pregnancy. Reference lists and citing-article lists of key Level 2 and Level 3 sources (including Ranjbar et al. (2024), Malik et al. (2024), Mohamed Dkeen et al. (2025), Wang et al. (2026) and Liu et al. (2026)) were also examined for additional eligible studies not returned directly by the term-based searches.

The search was conducted in PubMed/MEDLINE, supplemented by direct retrieval from publisher platforms (including Nature Portfolio, Elsevier/ScienceDirect, Oxford Academic, Frontiers, BMC, Cureus, JMIR, the American Heart Association journals, BMJ and Annals of Internal Medicine) and cross-checked against PubMed and Crossref records. Embase, Scopus, Web of Science and the Cochrane Library were not directly searchable as platforms in the environment used to prepare this manuscript; this is stated here as a factual limitation of the tools available, not a step that has been completed, and is identified again in Section 7 as outstanding work before external submission. Every candidate record was checked against its original source (PubMed record, publisher page, or both) before being retained; the outcome of that check for each reference is recorded in the Reference Verification Table (Section 11). The search covered literature available through September 2026, with no lower date limit applied; searches were restricted to English-language publications. This is the second iteration of this search: an initial pass identified one Category C study (Wang et al., 2026); Search C was subsequently broadened with the additional term combinations listed above, which identified a second Category C study (Hu et al., 2026) and led to the exclusion of a third candidate (Mizuno et al., 2024) on closer inspection of its full text (Section 4.4). This revision itself is reported as a specific illustration of how extending the search changed a substantive conclusion, consistent with the instruction not to make an absence claim stronger than the search performed actually supports.

3.3 Eligibility Criteria

PICOS element	Included	Excluded
Population	Pregnant or postpartum women (any trimester; up to 12 months postpartum for cardiomyopathy)	Non-pregnant populations; paediatric or neonatal outcomes as the sole focus
Exposure	Ambient/extreme temperature, heat waves; PM2.5/PM10; NO2, O3, SO2, CO; wildfire smoke; extreme weather events	Occupational chemical exposure unrelated to ambient climate/air quality; indoor heat sources (saunas, hot baths) — excluded consistent with (Mao et al., 2023)
Outcome	Gestational hypertension, preeclampsia, eclampsia, peripartum cardiomyopathy, heart failure, arrhythmia, other diagnosed maternal cardiovascular events	Fetal/neonatal-only outcomes (birth weight, preterm birth) unless reported alongside a maternal cardiovascular outcome

PICOS element	Included	Excluded
AI component (Level 2/3 only)	Any ML/DL/ensemble/explainable-AI method used to predict a maternal cardiovascular outcome	Purely mechanistic, non-predictive statistical models (e.g., simple logistic regression used only for association testing, not framed as a prediction model)
Study design	Cohort, case–control, cross-sectional studies; systematic reviews and meta-analyses (for background/synthesis)	Case reports/series; animal or in-vitro studies; conference abstracts without full text; non-English-language sources not independently translatable within this draft

3.4 Study Selection, Data Extraction, and Reference Verification

Sources meeting the eligibility criteria above were organized around the three-level evidence structure introduced in Section 2 and detailed in Section 3.7, spanning environmental/climate exposure epidemiology, AI/ML prediction modelling, and studies integrating the two. Two methodological references (PRISMA 2020 (Page et al., 2021); PROBAST (Wolff et al., 2019)) were used separately to frame the review's own conduct and are not counted among the empirical evidence base. Data extracted from each empirical source included study design, population and setting, exposure or predictor definition, outcome definition, reported effect estimates or model performance metrics, and stated limitations; extracted data are presented in Tables 1–4. For every source, first author, publication year, article title, journal, and DOI (where one exists) were checked against the original publication record; the outcome of that check is recorded in the Reference Verification Table (Section 11), including the small number of instances where a full DOI or complete author list could not be independently confirmed from the sources consulted.

3.5 Risk of Bias Assessment

Risk of bias was assessed using tools appropriate to study design: the Newcastle–Ottawa Scale for observational cohort and case–control studies, and PROBAST (Wolff et al., 2019) for AI/ML prediction-model studies. For primary studies reported within an included systematic review, this review reports the risk-of-bias assessment performed by that review's own authors (for example, the PROBAST ratings reported by Mohamed Dkeen et al. (2025) for their included preeclampsia-prediction studies) rather than independently re-scoring those primary studies; Supplementary Table S2 records, for each source, whether a risk-of-bias or quality rating is available and, where it is, who performed it. An independent, study-by-study risk-of-bias assessment by the present authors, extending beyond what the included reviews themselves report, is identified in Section 7 as a step to be completed before further external submission.

3.6 Data Synthesis Approach

Quantitative pooling (meta-analysis) across the included sources was not attempted. The sources span markedly different exposure metrics (categorical heat-wave definitions versus continuous temperature; total PM2.5 mass versus source-apportioned PM2.5 components), outcome definitions (combined hypertensive disorders of pregnancy versus preeclampsia alone versus eclampsia alone), populations (China, the United States, Spain, the Republic of Korea, Japan, and multi-country meta-analyses), and — for Level 2/3 — AI/ML methods and performance metrics that are not directly comparable across studies (AUC computed on different outcome definitions and prevalence levels cannot be meaningfully averaged). A structured narrative synthesis, organized by the three-level framework below, was therefore judged the only methodologically appropriate approach at this stage.

3.7 Three-Level Evidence Framework and Study Classification

Consistent with Section 2, evidence is organized into three levels, each corresponding to one of the three search streams in Section 3.2: Level 1 / Category A (environmental/climate exposure → maternal cardiovascular outcome), Level 2 / Category B (AI/ML → maternal cardiovascular prediction), and Level 3 / Category C (environmental exposure + AI/ML → maternal cardiovascular prediction). Level 3 / Category C is treated, from the outset, as the review's critical test case rather than assumed to contain a comparable volume of evidence to Levels 1 and 2, and an absence claim at this level is made only to the

extent the completed search supports it, and is revised if a broadened search identifies additional evidence (Section 3.2).

Within each level, sources are further classified by evidence type — primary observational study, prediction-model development study, systematic review, meta-analysis, or methodological/reporting reference — and this classification is preserved throughout Tables 1–5 and the narrative synthesis. Systematic reviews and meta-analyses are used to characterize the evidence landscape and to report pooled estimates where the reviewing authors calculated them, but are not counted as additional independent primary evidence alongside the primary studies they themselves summarize; where a primary study is discussed both directly and as part of an included review's synthesis, this is noted explicitly rather than treated as two separate pieces of evidence.

Within Group 3 (Section 3.2), environmental/climate exposures are further classified as: climate-sensitive (ambient temperature, extreme heat, heat waves, meteorological conditions, and wildfire smoke or ambient air pollution insofar as their occurrence is climate-influenced); conventional ambient exposures whose link to climate change specifically was not established by the source study (e.g., traffic-related air pollution studied without a climate framing); environmental chemical exposures/biomarkers (e.g., lead, cadmium, mercury, endocrine-disrupting chemicals); and lifestyle, dietary, occupational or indoor exposures, which fall outside this review's exposure definition even where a source describes them using the word "environmental" (Section 4.4 reports one such case in detail). A study is not classified as evaluating a climate-informed or climate-sensitive exposure merely because it uses the word "environmental," "climate," or "exposome" in its title or abstract; classification in this review follows the specific exposure variables the source study actually measured and analysed.

4. RESULTS AND DISCUSSION

4.1 Study Selection and Evidence Landscape

Study selection followed the eligibility criteria in Section 3.3, applied to the search strategy in Section 3.2. Sources meeting these criteria are summarized in Table 1 and organized throughout this section around the three-level evidence structure (Section 3.7). A PRISMA flow diagram with database-specific record and screening counts is not presented in this version of the manuscript, consistent with the search scope described in Section 3.2; it will be generated once the broader database search identified in Section 7 has been completed, and is not approximated here in order to avoid reporting figures that are not yet established.

The evidence base is geographically concentrated in a small number of countries — principally China, the United States, the Republic of Korea, Japan and Spain — together with several multi-country systematic reviews and meta-analyses that themselves draw predominantly on studies from high- and upper-middle-income settings (Table 1). Study designs include large retrospective and prospective cohorts, systematic reviews with meta-analysis, and one narrative mechanistic review. A quantitative geographic-distribution figure is not presented, as the underlying study-level extraction available for this draft does not yet support one; the qualitative pattern above is offered instead and is returned to, in relation to climate vulnerability, in Section 4.6.

4.2 Environmental Exposures and Maternal Cardiovascular Outcomes

4.2.1 Heat and Temperature

Three dedicated systematic reviews/meta-analyses and one large single-country cohort provide converging, though not perfectly consistent, evidence that heat exposure is associated with hypertensive disorders of pregnancy. Mao et al. (2023) pooled 15 studies (n = 4,481,888) and reported that heat exposure during the first half of pregnancy increased the odds of preeclampsia or eclampsia (OR 1.54, 95% CI 1.10–2.15), while cold exposure was associated with reduced odds (OR 0.90, 95% CI 0.84–0.97); fourteen of the fifteen included studies showed a significant association in some direction. A 2026 update of the same question by Zheng et al. (2026), pooling 28 studies and more than 23 million participants, reported a broadly consistent conclusion at substantially larger scale. In a single large Chinese cohort (n = 2,043,182), Xiong et al. (2020) found a dose–response relationship between ambient temperature and hypertensive disorders of pregnancy in the first and early second trimester (OR 1.16, 95% CI 1.10–1.22). The most comprehensive synthesis, Lakhoo et al. (2025) (198 studies across 66 countries, 23 outcomes), found hypertensive disorders of pregnancy associated with heat exposure in 21 of 28 relevant studies, alongside heat-associated increases in preterm birth (OR 1.04, 95% CI 1.03–1.06 per 1°C; OR 1.26, 95% CI 1.08–1.47 during heat waves), gestational diabetes (28% increase, 95% CI 1.05–1.74) and any obstetric complication during heat waves

(OR 1.25, 95% CI 1.09–1.42).

4.2.2 Air Pollution — Overview

Air pollution exposure and hypertensive disorders of pregnancy is the most extensively studied Level 1 exposure–outcome pairing identified in this review, spanning two 2014 meta-analyses that reached somewhat different conclusions, more recent updated meta-analyses, and individual large cohort studies from Spain and the United States.

4.2.3 Particulate Matter

Pedersen et al. (2014), the most frequently cited meta-analysis in this space, reported that a 5 μg/m³ increase in PM2.5 during pregnancy was associated with OR 1.57 (95% CI 1.26–1.96) for combined hypertensive disorders of pregnancy and OR 1.31 (95% CI 1.14–1.50) for preeclampsia specifically, with less heterogeneity among the ten studies reporting on preeclampsia alone; a 10 μg/m³ increase in NO2 was associated with OR 1.10 for preeclampsia. Published the same year, Hu et al. (2014) reported smaller and non-statistically-significant effects for the same 5 μg/m³ PM2.5 increment (first trimester OR 1.18, 95% CI 0.98–1.41; second trimester OR 1.17, 95% CI 0.79–1.75) — a discrepancy the field has generally attributed to differences in included studies and exposure-window definitions rather than to either meta-analysis being in error. Dadvand et al. (2013), a Barcelona cohort of 8,398 pregnancies (103 preeclampsia cases), found traffic-related NO2 and PM exposure associated with increased preeclampsia odds, with the first trimester as the most sensitive window. A 2025 update, Gao et al. (2025) (15 studies, n = 78,427), reported an entire-pregnancy PM2.5–preeclampsia association (OR 1.11, 95% CI 1.06–1.15), rising to OR 1.18 (95% CI 1.12–1.24) at the highest exposure quartile. The reported gradient was monotonic across exposure categories, although, as an observational association, the exposure-response form may depend on the exposure metric, exposure window and modelling approach used, and does not by itself establish a causal dose-response relationship.

4.2.4 Ozone and Nitrogen Dioxide

Evidence for gaseous pollutants other than NO2 is markedly weaker and more inconsistent than for particulate matter. The narrative review by Bearblock et al. (2021) concluded that associations with hypertensive disorders of pregnancy were positive and reasonably consistent for NO2 but weak or absent for ozone and carbon monoxide, a pattern also reflected in Hu et al.'s (2014) finding of increased risk for particulate pollutants but not consistently for gaseous co-pollutants.

4.2.5 Wildfire Smoke and Extreme Weather

Zhang et al. (2024), a cohort of 2,686,939 pregnancies across eight southwestern U.S. states (2001–2004), found that wildfire-sourced PM2.5 and its black-carbon and organic-carbon components were associated with larger increases in gestational hypertension and eclampsia risk than equivalent increases in urban-source PM2.5: for gestational hypertension, OR 1.125 (95% CI 1.109–1.141) for total wildfire PM2.5, OR 1.247 (95% CI 1.214–1.281) for black carbon, and OR 1.153 (95% CI 1.132–1.174) for organic carbon; for eclampsia, the corresponding figures were OR 1.217 (95% CI 1.145–1.293), OR 1.458 (95% CI 1.291–1.646) and OR 1.309 (95% CI 1.208–1.418). These findings indicate that the source and composition of particulate exposure may be relevant to the magnitude of the observed associations and warrant further investigation; as a single observational study, it does not by itself establish that composition determines cardiovascular risk more generally.

4.2.6 Multiple Environmental Exposures

A small number of studies modelled multiple environmental exposures jointly rather than one pollutant or exposure at a time. Sun et al. (2024), a Kaiser Permanente Southern California cohort (2008–2017), examined total PM2.5 mass alongside its constituent components and found component-specific adjusted hazard ratios for preeclampsia/eclampsia per interquartile-range increase (total PM2.5 mass: HR 1.07, 95% CI 1.04–1.10; black carbon: HR 1.12, 95% CI 1.08–[upper bound not specified in the source consulted]), with an estimated population-attributable fraction of 6.37% for preeclampsia/eclampsia at the US EPA annual PM2.5 standard (9 μg/m³); associations with gestational hypertension specifically were not consistently observed — underscoring that "air pollution" is not a single exposure and that aggregating across constituents can mask or dilute true associations. Hu et al. (2020), an earlier exposome-wide association study using Florida vital statistics (n = 819,399, 2010–2013), and its 2026 methodological successor (Hu et al., 2026) (Section 4.4; n = 686,412, 2013–2018) represent the most comprehensive multi-exposure approach identified in this review, jointly screening dozens of spatial and contextual exposure domains — including air toxicants, meteorological conditions, ultraviolet radiation, neighborhood socioeconomic and safety indicators, noise, and coastal proximity — rather than testing exposures one at a time. No study identified in this

review jointly modelled heat and air pollution specifically as combined or interacting exposures for a maternal cardiovascular outcome.

4.3 AI/ML for Maternal Cardiovascular Risk Prediction

Published systematic reviews of ML/AI approaches to preeclampsia prediction describe a methodologically diverse literature; no equivalent systematic review specific to gestational hypertension alone, peripartum cardiomyopathy, or other maternal cardiovascular outcomes was identified, suggesting preeclampsia is disproportionately the focus of this literature relative to other maternal cardiovascular complications. Ranjbar et al. (2024) reported AUCs (discrimination) between 0.86 and 0.97 across differing algorithms among their eligible primary studies. Malik et al. (2024) described wide diversity in algorithms used across their eligible studies and noted that external validation of the resulting models was uncommon. The most methodologically detailed synthesis, Liu et al. (2026) (26 studies, 31 ML models; literature searched across PubMed, Web of Science, IEEE Xplore and CNKI through February 2025; PROSPERO-registered; PROBAST-assessed), pooled a discrimination estimate of AUC 0.91 (95% CI 0.87–0.92) but reported extreme between-study heterogeneity ($I^2 > 99\%$) and a wide 95% prediction interval for sensitivity (0.32–0.96), meaning a newly applied model's real-world sensitivity could plausibly fall far below the pooled estimate. Critically, only 6 of the 31 models were externally validated; pooled sensitivity among those six dropped to 0.68 (95% prediction interval 0.25–0.94). Mohamed Dkeen et al. (2025), searching five databases (PubMed, Embase, Scopus, Web of Science, Cochrane Library) through April 2025 and applying PRISMA 2020 and PROBAST, synthesized 11 studies spanning 116,253 pregnancies with reported AUCs between 0.84 and 0.973, but concluded that most included studies were at high or unclear risk of bias by PROBAST criteria. Taken together, these reviews indicate that a high pooled AUC in this literature reflects internal, development-cohort discrimination rather than demonstrated external transferability; discrimination, calibration, diagnostic accuracy, and clinical usefulness are distinct properties, and only the first is well characterized across this literature as a whole.

4.4 Environmental Variables within AI-Based Prediction Models

Two studies identified in this review incorporate a genuine environmental exposure variable within an AI/ML-based analytic framework targeting a maternal cardiovascular outcome — more than the single example identified earlier in this review's search, though the two differ in evidence type from one another and from the discriminative prediction-model literature in Section 4.3. The first is Wang et al. (2026) (Scientific Reports, July 2026): an explainable XGBoost classifier trained on 4,260 pregnant women in the Korean Children's Environmental Health Study (Ko-CHENS) cohort, integrating 18 environmental chemical biomarkers — including blood lead, cadmium, mercury and endocrine-disrupting chemicals — alongside maternal clinical covariates, to predict hypertensive disorders of pregnancy. The model achieved a cross-validated ROC-AUC of 0.787 and an independent test AUC of 0.748 (95% CI 0.587–0.887), with a negative predictive value of 0.994. This NPV was reported under a severe class imbalance (HDP prevalence 1.7% in this cohort); predictive values depend strongly on outcome prevalence, and a high NPV is expected under low prevalence regardless of a model's discriminative ability, so this figure should not be read in isolation as evidence of exceptional clinical performance. SHAP analysis identified late-pregnancy blood lead concentration and pre-pregnancy BMI as the dominant predictors, each showing a non-linear risk gradient, with an interaction analysis ($\beta = 0.418$, 95% CI −0.278–1.115, $p = 0.239$) suggesting an additive rather than synergistic relationship between the two. The source article as consulted for this review did not report a comparison of model performance with versus without the environmental biomarkers; the incremental predictive value of the environmental variables specifically is therefore not reported, rather than demonstrated or refuted (Table 4).

The second, and the only identified study incorporating a climate-sensitive ambient exposure, is Hu et al. (2026) (Exposome, March 2026): a spatial and contextual exposome analysis of 686,412 singleton pregnancies conceived between 2013 and 2018, using linked electronic health records and vital statistics from Florida. The study distinguished hypertensive disorders of pregnancy subtypes (gestational hypertension, preeclampsia, eclampsia, and chronic hypertension with or without superimposed preeclampsia) using computable phenotyping and applied a two-phase double machine learning approach — a causal-inference method that uses machine learning models to flexibly adjust for a large set of confounders while estimating each exposure's association with the outcome. In Phase 1, 26 of a broader candidate set of exposome measures replicated an association with gestational hypertension and 34 with overall hypertensive disorders of pregnancy; in Phase 2, applying double machine learning to formally test these candidates, 12 measures remained associated with gestational hypertension and 11 with overall hypertensive disorders of pregnancy. These 11–12 measures spanned an aggregate meteorological measure and

ultraviolet radiation (climate-sensitive, per the classification in Section 3.7), air toxicants (ambient air pollution, not automatically climate-sensitive under the same classification), and neighborhood crime indicators, environmental noise, and coastal proximity (non-climate contextual factors). No exposure passed multiple-comparison thresholds for preeclampsia or eclampsia specifically. This study demonstrates that a climate-sensitive exposure (an aggregate meteorological measure, and separately ultraviolet radiation) can be, and in this instance has been, incorporated into a machine-learning-based analytic framework alongside a maternal cardiovascular outcome. It should not, however, be read as equivalent to the discriminative prediction-model studies in Section 4.3: double machine learning in this study was used to estimate confounder-adjusted exposure associations, not to build a classifier, and the study did not report AUC, sensitivity, specificity, or an incremental-value comparison against a clinical-only model; "incremental predictive value" in the sense used in Table 4 is therefore not applicable to this study rather than demonstrated.

A third source requires explicit exclusion rather than inclusion, as a direct illustration of why the classification distinction in Section 3.7 of this review's framework matters in practice. Mizuno et al. (2024), using approximately 23,000 pregnancies from the Tohoku Medical Megabank Birth and Three-Generation Cohort Study, developed logistic-regression, random-forest and XGBoost models described in the source article's own title and abstract as using "comprehensive environmental factors." On inspection of the full source, however, the dominant contributors to the best-performing models were self-reported eating habits, accounting for 82.7% and 58.1% of feature importance in the two highest-performing models respectively, and the authors' own conclusion characterizes the models as based on "comprehensive lifestyles." This is a lifestyle/dietary self-report exposure category, not an ambient climate exposure, an environmental chemical biomarker, or another exposure meeting this review's eligibility criteria (Section 3.3), and it is accordingly excluded from Table 4 and from this review's Category C evidence base, despite the terminology used in the source's own title.

4.5 The Integration Gap

Sections 4.2 and 4.3 each describe an active evidence base considered independently. Within Category C (Section 4.4), the two identified studies occupy different subcategories: Level 3A (environmental exposure + discriminative predictive AI/ML) is represented by Wang et al. (2026), using environmental chemical-biomarker exposure; Level 3B (environmental exposure + causal/associational ML) is represented by Hu et al. (2026), using climate-sensitive spatial/contextual exposure. No study identified in this review occupies Level 3C (climate-sensitive ambient exposure + discriminative AI/ML prediction with demonstrated incremental predictive value): no source reports a discriminative prediction model — of the kind characterized in Section 4.3, with AUC, sensitivity, specificity and an internal/external validation split — that takes ambient temperature or ambient air-pollutant concentration as an input feature, targets a maternal cardiovascular outcome, and formally evaluates the incremental predictive value of the environmental input against a clinical-only comparator model.

Three factors are identifiable from the sources reviewed as plausibly relevant to this pattern. First, the cohorts underlying the Level 2 discriminative prediction-model literature (Section 4.3) are largely existing clinical or biobank cohorts assembled for other purposes, in which ambient environmental exposure was not necessarily collected or linked at the time of data collection, whereas Hu et al.'s (2026) Level 3B analysis was purpose-built around linked geospatial and administrative data. Second, the Level 3A and Level 3B studies identified in this review use different exposure types (chemical biomarker; climate-sensitive spatial/contextual) and different analytic aims (discriminative prediction; causal-inference association estimation), consistent with limited apparent cross-citation between these methodological approaches in the sources reviewed. Third, no source identified in this review reports a formal quantification of the incremental discriminative value contributed by an ambient environmental variable once added to a clinical-only prediction model.

4.6 Model Validation, Explainability, and Geographic Representation

Across the AI/ML sources identified in this review, internal validation (cross-validation or a held-out internal test split) was standard practice, but external validation — testing a model on a genuinely independent cohort, ideally from a different country or health system — was consistently described as uncommon. Mohamed Dkeen et al. (2025) linked this to elevated PROBAST-assessed risk of bias across most of their included preeclampsia-prediction studies. Wang et al.'s (2026) reported test-set AUC of 0.748, lower than its cross-validated AUC of 0.787, with a wide confidence interval (0.587–0.887) reflecting the outcome's low prevalence (1.7%) in that cohort; this illustrates a pattern noted across this literature more broadly, in which performance estimated under internal cross-validation can be materially more uncertain once evaluated on a held-out

split, before external, cross-cohort validation is even attempted.

Explainable AI, and SHAP specifically, appears in the most recent discriminative prediction-model study identified in this review (Wang et al. (2026)), consistent with a broader shift in the clinical ML literature toward feature-attribution methods alongside performance reporting. SHAP-based attribution characterized the functional form of the dominant predictors (non-linear risk gradients for blood lead and pre-pregnancy BMI) and distinguished an additive from a synergistic relationship between them — a more detailed use of explainability than a simple variable-importance ranking, though still evaluated within a single cohort without external confirmation. Hu et al.'s (2026) double-machine-learning analysis reports confounder-adjusted association estimates for each exposure rather than SHAP-style feature attribution; the two studies are not directly comparable on this dimension.

The AI/ML evidence identified in this review is concentrated in China, the United States and the Republic of Korea. Within the sources identified by the present search, no eligible AI/ML study of maternal cardiovascular risk prediction incorporating an environmental exposure variable was located from Sub-Saharan Africa, South Asia, or Latin America. This is reported here as an observed feature of the evidence base located by this review's search, not as a direct measurement of comparative regional risk; published climate projections indicate substantial increases in extreme-heat exposure in parts of these regions, but this review did not identify AI/ML maternal cardiovascular prediction studies evaluating that projected risk directly. This distinction, and its implications, is discussed further in Section 4.16. The gaps synthesized across Sections 4.2–4.6 are summarized formally in Table 5 and translated into a proposed research agenda in Table 6.

Table 1. Characteristics of included studies

Study (author, year)	Design	Setting / population	Exposure or AI focus	Outcome	Principal finding (brief)
Mao et al., 2023	Systematic review & meta-analysis (15 studies)	Multi-country, n = 4,481,888	Ambient/extreme temperature	Preeclampsia, eclampsia, GH	Heat OR 1.54 (1.10–2.15) first-half pregnancy; cold OR 0.90 (0.84–0.97)
Zheng et al., 2026	Systematic review & meta-analysis (28 studies)	Multi-country, n > 23,268,235	Extreme temperature	Hypertensive disorders of pregnancy	Updated, larger-scale confirmation of temperature–HDP association
Xiong et al., 2020	Retrospective cohort	China, n = 2,043,182	Ambient temperature	Hypertensive disorders of pregnancy	Dose–response OR 1.16 (1.10–1.22), 1st/early 2nd trimester
Lakhoo et al., 2025	Systematic review & meta-analysis (198 studies, 66 countries)	Multi-country	Heat exposure / heat waves	HDP + preterm birth, GDM, obstetric complications	HDP linked to heat in 21/28 relevant studies; preterm birth OR 1.04–1.26
Pedersen et al., 2014	Systematic review & meta-analysis	Multi-country (5 cohorts)	PM2.5, PM10, NO2	HDP, preeclampsia	PM2.5 OR 1.57 (1.26–1.96) HDP; OR 1.31 (1.14–1.50) PE, per 5 μg/m³

Study (author, year)	Design	Setting / population	Exposure or AI focus	Outcome	Principal finding (brief)
Hu et al., 2014	Systematic review & meta-analysis	Multi-country	PM, NO2, O3, SO2, CO	Hypertensive disorders of pregnancy	Smaller, non-significant PM2.5 effects vs. Pedersen et al. (2014); inconsistent for gases
Dadvand et al., 2013	Prospective cohort	Barcelona, Spain; n = 8,398 (103 PE)	Traffic-related NO2, PM	Preeclampsia	Increased PE odds; first trimester most sensitive window
Bearblock et al., 2021	Narrative review	Multi-country	PM2.5, PM10, NO2, O3	Preeclampsia (mechanisms)	NO2 consistently associated; O3/CO weak or absent
Gao et al., 2025	Systematic review & meta-analysis (15 studies)	Multi-country, n = 78,427	Prenatal PM2.5	Preeclampsia, GH, HDP	Entire-pregnancy PE OR 1.11 (1.06–1.15); Q4 OR 1.18 (1.12–1.24)
Zhang et al., 2024	Retrospective cohort	SW USA (8 states), n = 2,686,939	Wildfire PM2.5, black carbon, organic carbon	Gestational hypertension, eclampsia	Wildfire-source effects exceed urban-source PM2.5 (eclampsia OR up to 1.458)
Sun et al., 2024	Retrospective cohort	S. California, USA (2008–2017)	PM2.5 total mass + constituents	HDP (GH, PE-E)	Component-specific associations; no association with GH alone
Ranjbar et al., 2024	Systematic review (4 primary ML studies)	Multi-country	ML (elastic net, random forest, other)	Preeclampsia prediction	AUC 0.86–0.97 across included models
Malik et al., 2024	Systematic review (35 of 183 screened)	Multi-country	ML/DL, diverse algorithms	Preeclampsia prediction	Wide algorithm diversity; external validation uncommon
Mohamed Dkeen et al., 2025	Systematic review (11 studies, PRISMA + PROBAST)	Multi-country, n = 116,253 pregnancies	ML/DL	Preeclampsia prediction	AUC 0.84–0.973; most studies high/unclear PROBAST risk of bias
Wang et al., 2026	Prospective cohort, explainable ML (discriminative prediction)	Republic of Korea (Ko-CHENS), n = 4,260	18 environmental chemical biomarkers (Pb, Cd, Hg, EDCs) + clinical data; XGBoost/SHAP	Hypertensive disorder of pregnancy	Cross-val AUC 0.787; test AUC 0.748; blood lead + BMI dominant SHAP predictors

Study (author, year)	Design	Setting / population	Exposure or AI focus	Outcome	Principal finding (brief)
Liu et al., 2026	Systematic review & meta-analysis (26 studies, 31 ML models)	Multi-country (PubMed, Web of Science, IEEE Xplore, CNKI to Feb 2025)	ML/DL algorithms, PROSPERO-registered, PROBAST-assessed	Preeclampsia prediction	Pooled AUC 0.91 (0.87–0.92); I^2>99%; only 6/31 models externally validated (pooled sensitivity 0.68)
Hu et al., 2026	Retrospective cohort, double machine learning (causal/associational, not discriminative prediction)	Florida, USA, n = 686,412 (2013–2018)	Spatial/contextual exposome: meteorological measure + UV radiation (climate-sensitive); air toxicants (ambient air pollution); neighborhood/noise/coastal factors (non-climate)	HDP subtypes (GH, PE, eclampsia, chronic HTN)	12 measures associated with GH, 11 with overall HDP after ML-based confounder adjustment; none for PE/eclampsia specifically
Hu et al., 2020	Exposome-wide association study (retrospective cohort)	Florida, USA, n = 819,399 (2010–2013)	Broad external exposome (multiple domains)	Hypertensive disorders of pregnancy	Precursor/companion study to Hu et al. (2026); establishes candidate exposome measures later tested with double ML
Mizuno et al., 2024	Prospective cohort, interpretable ML	Japan (Tohoku Medical Megabank), n ≈ 23,000	Self-reported lifestyle/dietary factors (termed "environmental factors" by the source; eating habits dominant, 58–83% of feature importance) + clinical data; LR/RF/XGBoost	Early HDP prediction	AUC 0.93; excluded from this review's Category C (Table 4) — exposure is lifestyle/dietary, not ambient or chemical environmental exposure (Section 4.4)

Table 2. Environmental Exposures and Maternal Cardiovascular Outcomes — Reported Effect Estimates

Exposure	Reference	Population (n)	Outcome	Reported effect measure (95% CI)	Notes / exposure window
Heat exposure (first half of pregnancy)	(Mao et al., 2023)	4,481,888 (15 studies)	Preeclampsia / eclampsia	OR 1.54 (1.10–2.15)	Cold exposure inversely associated: OR 0.90 (0.84–0.97)

Natural Resources for Human Health
eISSN: 2583-1194

Exposure	Reference	Population (n)	Outcome	Reported effect measure (95% CI)	Notes / exposure window
Ambient temperature (dose–response)	(Xiong et al., 2020)	2,043,182	Hypertensive disorders of pregnancy	OR 1.16 (1.10–1.22)	1st and early 2nd trimester
PM2.5, per 5 μg/m³	(Pedersen et al., 2014)	Pooled, 5 cohorts	Combined HDP	OR 1.57 (1.26–1.96)	Preeclampsia alone: OR 1.31 (1.14–1.50)
NO2, per 10 μg/m³	(Pedersen et al., 2014)	Pooled, 5 cohorts	Preeclampsia	OR 1.10	Individual studies ranged 4–23% increase
PM2.5, per 5 μg/m³ (1st trimester)	(Hu et al., 2014)	Multi-country pooled	Hypertensive disorders of pregnancy	OR 1.18 (0.98–1.41)	Not statistically significant
PM2.5, entire pregnancy	(Gao et al., 2025)	78,427 (15 studies)	Preeclampsia	OR 1.11 (1.06–1.15)	Highest exposure quartile (Q4): OR 1.18 (1.12–1.24)
Wildfire PM2.5	(Zhang et al., 2024)	2,686,939	Gestational hypertension	OR 1.125 (1.109–1.141)	Black carbon: OR 1.247 (1.214–1.281); organic carbon: OR 1.153 (1.132–1.174)
Wildfire PM2.5	(Zhang et al., 2024)	2,686,939	Eclampsia	OR 1.217 (1.145–1.293)	Black carbon: OR 1.458 (1.291–1.646); organic carbon: OR 1.309 (1.208–1.418)
Traffic-related NO2/PM (spatiotemporal)	(Dadvand et al., 2013)	8,398 (103 PE cases)	Preeclampsia	Positive association (exact pooled OR: NR in sources consulted)	First trimester identified as most sensitive window
PM2.5 total mass, per IQR	(Sun et al., 2024)	Kaiser Permanente S. California cohort	Preeclampsia/eclampsia	HR 1.07 (1.04–1.10)	Population-attributable fraction 6.37% at US EPA annual standard (9 μg/m³); no association with GH alone
Black carbon, per IQR	(Sun et al., 2024)	Kaiser Permanente S. California cohort	Preeclampsia/eclampsia	HR 1.12 (lower bound 1.08; upper bound NR in source consulted)	Component-specific; not uniform across PM2.5 constituents

NR = not reported in the sources consulted for this draft. All effect estimates above are reproduced from the cited original publications; none were calculated by the present authors.

Table 3. AI/ML Studies in Maternal Cardiovascular Risk Prediction (Level 2)

Reference	Studies / population reviewed	AI/ML methods represented	Outcome	Reported AUC (discrimination)	Sensitivity / specificity / calibration	External validation & key limitation
Ranjbar et al., 2024	4 primary studies	Elastic net, random forest, other ML	Preeclampsia prediction	0.86–0.97	NR in sources consulted	NR in sources consulted; small number of eligible primary studies
Malik et al., 2024	35 of 183 screened studies	Diverse ML/DL algorithms	Preeclampsia prediction	NR (range not specified in sources consulted)	NR in sources consulted	Described as uncommon across included studies
Mohamed Dkeen et al., 2025	11 studies, 116,253 pregnancies (5 databases: PubMed, Embase, Scopus, Web of Science, Cochrane, to Apr 2025)	ML/DL, PRISMA 2020 + PROBAST applied	Preeclampsia prediction	0.84–0.973	NR in sources consulted	Most studies at high/unclear PROBAST risk of bias
Liu et al., 2026	26 studies, 31 ML models (PubMed, Web of Science, IEEE Xplore, CNKI, to Feb 2025, PROSPERO CRD420251005830)	ML/DL, meta-analysed with 95% prediction intervals; PROBAST-assessed	Preeclampsia prediction	Pooled 0.91 (95% CI 0.87–0.92); I^2>99%	Sensitivity 95% PI 0.32–0.96 overall; externally validated subset (6 models): pooled sensitivity 0.68 (PI 0.25–0.94)	Only 6 of 31 models externally validated; authors conclude high internal AUC reflects development-cohort performance, not demonstrated clinical effectiveness

Predictor variables used by the individual primary studies underlying these three reviews were not extracted at the level of detail needed for a per-study predictor list in this draft; each review reports that clinical, demographic and/or biochemical variables were the dominant predictor categories used.

Table 4. Environmental Exposure + AI/ML Integration Studies (Category C)

Reference	Level	Population / outcome	Environmental variable(s)	AI/ML method & purpose	Comparator model	Performance	Incremental predictive value	Key limitation
Wang et al., 2026	3A	Ko-CHENS cohort, Republic of Korea, n = 4,260; hypertensive disorder of pregnancy	18 chemical biomarkers (blood lead, cadmium, mercury, endocrine-disrupting chemicals) — not climate-sensitive	XGBoost — discriminative prediction model	Not reported in the source consulted	Cross-val AUC 0.787; test AUC 0.748 (0.587–0.887); NPV 0.994 (prevalence-dependent; HDP prevalence 1.7%)	Not reported	Single cohort; no external validation; severe class imbalance

Reference	Level	Population / outcome	Environmental variable(s)	AI/ML method & purpose	Comparator model	Performance	Incremental predictive value	Key limitation
Hu et al., 2026	3B	Florida, USA, n = 686,412; HDP subtypes (GH, PE, eclampsia, chronic HTN)	Meteorological measure and UV radiation (climate-sensitive); air toxicants (ambient air pollution, not automatically climate-sensitive, Section 3.7); neighborhood/noise/coastal factors (non-climate)	Double machine learning — causal/associational, not discriminative prediction	Not applicable — no clinical-only comparator; not a classifier	Confounder-adjusted associations for 11–12 exposures (Section 4.4), not AUC/sensitivity/specificity	Not applicable	Single US state; no external validation; no SHAP-style attribution

No study identified in this review occupies Level 3C (climate-sensitive ambient exposure combined with a discriminative AI/ML prediction model with a demonstrated incremental predictive value). Mizuno et al. (2024) is excluded from this table: on inspection, its "environmental factors" are self-reported lifestyle/dietary measures (Section 4.4), not an ambient, climate-sensitive, or chemical-biomarker exposure meeting this review's eligibility criteria.

4.7 Summary of Principal Findings

This review's findings can be summarized as a chain of four connected observations. First, published epidemiological evidence links ambient heat and particulate air pollution with hypertensive disorders of pregnancy, with associations that are broadly, though not universally, concordant across independent cohorts and meta-analyses (Section 4.2). Second, a separate and methodologically diverse literature has applied AI/ML methods to predict maternal cardiovascular complications, principally preeclampsia, reporting discriminative performance (AUC) that is often strong under internal validation (Section 4.3). Third, on the evidence located by this review, existing AI/ML prediction models rarely incorporate the climate-sensitive ambient exposures identified in the first observation as model inputs; where an environmental variable has been incorporated, it has generally been a chemical-biomarker exposure rather than ambient temperature or air quality (Section 4.4). Fourth, this pattern reflects specific, identifiable methodological and data-infrastructure factors — rather than an arbitrary absence of interest — that are set out in Section 4.5 and that motivate the research agenda proposed in Section 5. This chain of findings, rather than any single number in Sections 4.2–4.6, is this review's central contribution.

4.8 Environmental Exposure and Maternal Cardiovascular Risk

The evidence is comparatively consistent for heat and particulate air pollution in relation to hypertensive disorders of pregnancy, drawn from varied settings (China, the United States, Spain, and 66-country pooled analyses), although heterogeneity remains in exposure definitions, exposure windows and outcome ascertainment, and the observational designs involved support an association rather than a demonstrated causal effect. Evidence for gaseous pollutants other than NO2, for peripartum cardiomyopathy, and for heart failure or arrhythmia in pregnancy in relation to any environmental exposure is comparatively thin or, in the case of peripartum cardiomyopathy, was not identified at all in this review (Section 7).

4.9 Current State of AI-Based Maternal Cardiovascular Prediction

The AI/ML literature for preeclampsia prediction is active and methodologically diverse, but the systematic reviews synthesizing it are consistent on one point: risk of bias is common and external validation is rare. Reported AUCs in the high 0.8s and low 0.9s should be read against that backdrop rather than as evidence of near-clinical-grade performance.

4.10 Interpreting the Integration Gap

A distinction central to this review is that *evidence that an environmental exposure is associated with a maternal cardiovascular outcome is not, by itself, evidence that the exposure has been incorporated into an AI/ML prediction model.* Sections 4.2 and 4.3 each describe a reasonably active literature considered on its own terms. Within Category C (Section 4.4–4.5), Level 3A (chemical-biomarker exposure with a discriminative prediction model (Wang et al., 2026)) and Level 3B (climate-sensitive exposure with a causal

machine-learning method (Hu et al., 2026)) are each represented by one study; Level 3C (climate-sensitive ambient exposure with a discriminative prediction model and a demonstrated incremental predictive value) is not represented by any study identified in this review. This is the specific evidence gap this review identifies, distinct from the broader question of whether environmental exposure and AI/ML methods have ever been used together in a maternal cardiovascular analysis, which the Level 3A and 3B evidence answers in the affirmative.

4.11 From Static Prediction to Dynamic, Climate-Informed Risk Prediction

Every Level 2 and Level 3 model identified in this review is, in the sense used in the original brief for this manuscript, a static prediction: a model trained once on a fixed dataset and evaluated at a point in time, rather than one that updates a woman's predicted risk as her real-time or recent environmental exposure changes across pregnancy. Dynamic, temporally updating climate-informed risk prediction was not represented in the evidence identified here and should be treated as a research aspiration rather than a described current capability.

4.12 Explainable AI

SHAP-based explainability, used in the identified discriminative integration study (Wang et al., 2026), is a methodological strength worth preserving as this field develops: it allowed the authors to characterize non-linear risk gradients and to test additivity versus interaction between an environmental and a clinical predictor, rather than reporting only an aggregate performance metric. Any future climate-informed discriminative model should be expected to meet at least this standard of interpretability.

4.13 Spatial and Temporal Environmental Data

Geospatial exposure modelling (e.g., satellite-derived PM2.5 surfaces, spatiotemporal temperature interpolation) is established in Level 1 epidemiology (e.g., Dadvand et al. (2013)) and appears within the causal machine-learning framework of Hu et al. (2026), which drew on spatially resolved contextual and ambient exposure measures. This review identified limited evidence of integration of geospatial exposure-modelling approaches into discriminative AI/ML prediction models specifically (Section 4.3): the one identified example combining geospatial/contextual exposure with a machine-learning method (Hu et al., 2026) used a causal-inference rather than a discriminative-prediction framing. Whether geospatial exposure modelling can be incorporated into a discriminative prediction model of the kind characterized in Section 4.3, and whether doing so improves prediction, remains to be directly tested.

4.14 Data Quality and Interoperability

Linking individual-level clinical/obstetric records with individual- or address-level environmental exposure data raises practical data-governance and interoperability challenges — geocoding of maternal residence, exposure-window alignment with gestational age, and consistent data-sharing agreements between health systems and environmental-monitoring agencies — that are not solved by AI/ML methodology alone and were not the primary focus of any source identified in this review.

4.15 External Validation and Generalizability

The near-absence of external validation noted in Section 4.6 is a limitation for the whole Level 2/3 literature, not only for a climate-informed extension of it. A model validated only within the cohort in which it was developed — as is true of Wang et al. (2026) and, on the evidence available, most Level 2 studies — cannot be assumed to generalize to a different population, environmental exposure profile, or health system.

4.16 Health Equity and Climate Vulnerability

The geographic concentration described in Section 4.6 — AI/ML evidence clustered in China, the United States and the Republic of Korea, with none identified from Sub-Saharan Africa, South Asia or Latin America — warrants a careful distinction between observed evidence, projected risk, and theoretical vulnerability. Published climate projections indicate substantial increases in extreme-heat exposure in parts of these under-represented regions; this is projected environmental risk, established independently of this review. Whether that translates into disproportionately higher climate-driven maternal cardiovascular risk in those specific populations is a plausible hypothesis consistent with the Level 1 mechanisms reviewed in Section 4.2, but it was not directly evaluated by any source identified in this review and should be treated as a research question rather than an established finding. What this review can state directly is the mismatch between where projected

environmental risk is highest and where the AI/ML predictive-modelling literature is currently concentrated.

4.17 Ethical and Privacy Considerations

Combining fine-grained geospatial or biomarker exposure data with individual clinical records raises privacy and potential-for-misuse considerations (e.g., residential geolocation as a re-identification risk) that were not directly addressed as a methodological topic in any source identified in this review, but that any future climate-informed clinical model would need to address before deployment.

4.18 Clinical Translation

No source identified in this review described a climate-informed AI/ML model for maternal cardiovascular risk that has been deployed, or piloted, in a real clinical workflow. The proposed framework in Section 6 is offered explicitly as a research target, not a description of existing practice.

5. RESEARCH AGENDA

The priorities below are derived directly from the evidence gaps identified in Section 4 (Table 5) rather than proposed independently of them; priorities not traceable to a specific gap identified in this review were not retained. They are organized into four stages, from data integration through to clinical translation, reflecting the sequence in which each priority would need to be addressed.

Table 5. Evidence Gaps

Evidence domain	What is currently known	Major limitation	Research gap	Recommended future research
Environment → maternal CV outcome	Heat and PM2.5 are consistently associated with hypertensive disorders of pregnancy across multiple meta-analyses	Evidence for gaseous pollutants (O3, CO), peripartum cardiomyopathy and heart failure is thin or absent	No systematic review identified evaluating environmental/climate exposures specifically for peripartum cardiomyopathy	Dedicated epidemiological studies of climate exposure and peripartum cardiomyopathy / heart failure in pregnancy
AI/ML → CV prediction	Multiple ML/DL models predict preeclampsia with reported AUC 0.76–0.97	External validation rare; most studies at high/unclear PROBAST risk of bias	Near-total absence of externally validated, low-risk-of-bias prediction models	Multi-centre, multi-country model development with mandatory external validation and PROBAST reporting
Environment + AI/ML integration	Environmental chemical-biomarker exposure has been integrated into a discriminative ML prediction model (Level 3A (Wang et al., 2026)); climate-sensitive exposure (an aggregate meteorological measure, UV radiation) has been jointly analysed with a machine-learning-based causal method (Level 3B (Hu et al., 2026))	No identified study occupies Level 3C: a discriminative AI/ML prediction model (with AUC/sensitivity/specificity and validation, as in Table 3) that takes ambient temperature or ambient air-quality data as an input for a maternal cardiovascular outcome, with a demonstrated incremental predictive value (Table 4)	Level 3C, as defined in Section 3.7, is not represented in the evidence identified in this review (Section 4.5)	Development and evaluation of Level 3C discriminative AI/ML prediction models incorporating ambient temperature and PM2.5/NO2 as first-class predictors, with formal incremental-value analysis against clinical-only models

Evidence domain	What is currently known	Major limitation	Research gap	Recommended future research
Spatial/temporal exposure modelling	Geospatial exposure modelling is established in Level 1 epidemiology (Dadvand et al., 2013) and used within a causal ML framework (Hu et al., 2026)	Not yet used within a discriminative AI/ML prediction model (Section 4.3)	Geospatial and temporal exposure techniques have not yet migrated into discriminative predictive modelling specifically	Incorporate satellite-derived and spatiotemporal exposure surfaces into discriminative AI/ML pipelines
Validation & generalizability	Internal cross-validation is standard practice	External, cross-cohort, cross-country validation is rare	Unknown generalizability of existing models beyond their development cohort	Prospective external validation studies, ideally across health systems and countries
Geographic / population representation	Evidence concentrated in China, USA, Republic of Korea	Within the sources identified by the present search, no eligible study was located from Sub-Saharan Africa, South Asia or Latin America	Highest projected climate-exposure-increase regions are least represented in this literature	Increase representation of high-heat and lower-resource settings in climate-informed maternal AI research

Table 6. Proposed Research Agenda

Stage	Priority area	Current limitation	Proposed methodological direction	Potential data sources	Expected contribution	Implementation challenge
1. Data integration	Integration of clinical and environmental datasets	Clinical and environmental data are held in separate systems	Standardized data-linkage protocols between health systems and environmental agencies	Electronic health records; national/regional air-quality and meteorological databases	Reusable infrastructure for future climate-health prediction research	Data governance, consent, and interoperability across agencies
1. Data integration	Spatially resolved exposure assessment	Geospatial modelling used in Level 1 epidemiology but not yet in AI/ML prediction studies (Section 4.5)	Incorporate satellite-derived PM2.5/temperature surfaces as model features	Satellite and ground-monitor exposure products; geocoded residential history	More precise, individual-level exposure estimates for prediction models	Fine-resolution exposure data not available in all settings

Stage	Priority area	Current limitation	Proposed methodological direction	Potential data sources	Expected contribution	Implementation challenge
1. Data integration	Standardization of environmental exposure variables	Exposure metrics vary widely (categorical heat waves vs. continuous temperature; total vs. component PM2.5)	Adopt common exposure-metric definitions across studies	Existing meta-analyses' methods sections as a starting reference	Enables future comparison and pooling of AI/ML integration studies	Field-wide coordination without a governing body
2. Climate-informed model development	Climate-informed prediction models	No identified model incorporates ambient temperature/ air quality as an input (Table 4)	Add climate-sensitive ambient exposure variables to existing preeclampsia/HDP prediction pipelines	National birth cohorts linked to meteorological/ air-quality monitoring networks	A direct empirical test of whether ambient climate exposure adds predictive value beyond clinical variables	Linking individual residential exposure to clinical records at scale
2. Climate-informed model development	Dynamic / temporal risk prediction	Identified models are evaluated at a single point in time rather than updated across gestation	Recurrent or landmark models updating risk as exposure accrues across pregnancy	Longitudinal cohorts with repeated exposure and clinical measurement	Risk estimates that reflect accumulating or recent exposure rather than a single baseline	Requires frequent, low-burden data collection across pregnancy
2. Climate-informed model development	Explainable AI	SHAP-based explainability identified in one discriminative integration study (Wang et al., 2026); not yet paired with a climate-sensitive-exposure prediction model	Report explainability analyses (e.g., SHAP) alongside performance for any climate-informed discriminative model	N/A — methodological standard, not a data source	Clinically interpretable, trust-supporting model outputs	Explainability methods for spatiotemporal/longitudinal features are less mature

Stage	Priority area	Current limitation	Proposed methodological direction	Potential data sources	Expected contribution	Implementation challenge
3. External and multicentre validation	External validation	Described as uncommon across the identified AI/ML literature (Section 4.6)	External, ideally cross-country, validation as a standard step before publication of new models	Independent cohorts from a different health system/country	Credible evidence of generalizability	Access to comparable independent cohorts and harmonized outcome definitions
3. External and multicentre validation	Multi-centre / multi-country validation	Evidence concentrated in a small number of countries (Section 4.6)	Consortium-based model development and validation	Multi-country birth cohort consortia	Evidence applicable beyond a single health system	Coordinating harmonized data collection across countries
3. External and multicentre validation	Inclusion of climate-vulnerable populations	No identified study from Sub-Saharan Africa, South Asia, or Latin America (Section 4.6)	Increase representation of high-heat and lower-resource settings in climate-informed maternal AI research	Regional birth cohorts and maternal health surveillance systems	Evidence from settings with plausibly high but currently uncharacterized climate-driven risk	Under-resourced research and health-data infrastructure in many such settings
4. Clinical translation	Prospective clinical validation	No climate-informed model has been prospectively tested in a clinical workflow	Prospective evaluation of a climate-informed decision-support tool, calibration and clinical utility included	Prospective obstetric clinical trial infrastructure	Evidence of real-world clinical utility, not only retrospective discrimination	Ethical and logistical complexity of prospective clinical AI trials
4. Clinical translation	Responsible AI and privacy	Not directly addressed in any identified source	Formal privacy-impact and re-identification-risk assessment for geospatial/biomarker exposure data	N/A — governance framework, not a data source	Safer handling of sensitive location and biomarker data	Balancing exposure precision against re-identification risk
4. Clinical translation	Integration into maternal healthcare systems	No deployed or piloted climate-informed model identified	Implementation-science studies conducted alongside model development	Health-system quality-improvement partnerships	A pathway from a validated model to actual clinical use	Workflow integration, clinician trust, and liability considerations

6. PROPOSED CLIMATE-INFORMED CARDIO-OBSTETRIC AI FRAMEWORK

Figure 4 sets out a proposed framework combining maternal demographic, obstetric, clinical, cardiovascular, environmental, meteorological, geographic and temporal-exposure data within an AI/ML analytics engine to generate an explainable risk prediction, feeding into proposed clinical monitoring or decision support. This framework is explicitly proposed and is not a validated clinical model: as Sections 4.4, 4.5 and 4.10 establish, no study identified in this review has built or tested a model combining ambient climate exposure data with the full range of inputs shown here. The framework is offered as a target architecture against which the research agenda in Table 6 can be organized, not as a description of an existing system.

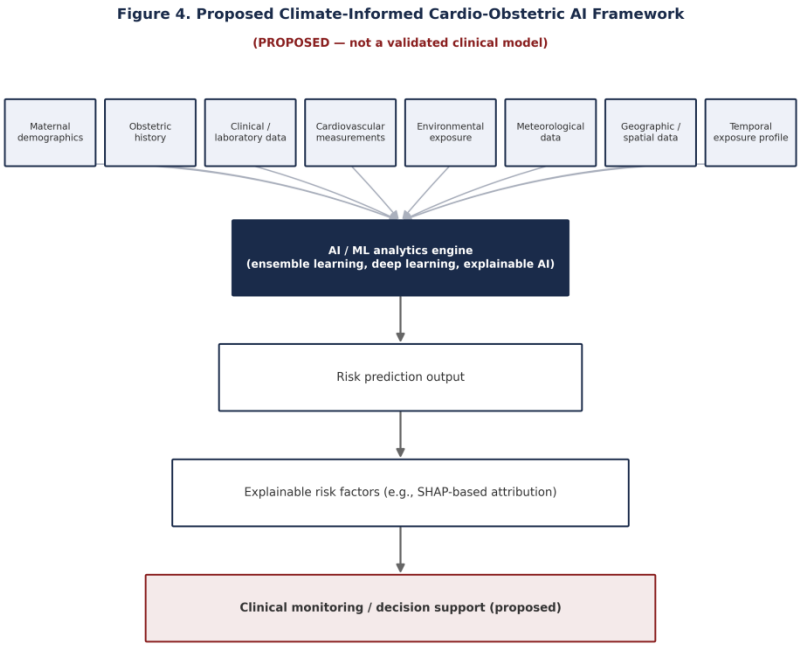

Figure 4. Proposed climate-informed cardio-obstetric AI framework. Proposed — not a validated clinical model.

7. LIMITATIONS

As with any evidence synthesis, the scope of the search and the methods used to appraise the included literature bound the conclusions that can be drawn. Article retrieval for this review (Section 3.2) was concentrated on PubMed/MEDLINE and publisher-hosted sources cross-checked against PubMed and Crossref records; extending retrieval to Embase, Scopus, Web of Science and the Cochrane Library, together with forward- and backward-citation searching, would provide fuller assurance that all eligible studies — particularly further Level 3 integration studies — have been located, and is recommended before this review is submitted externally. Searches were restricted to English-language publications, and study identification, eligibility screening and data extraction were carried out by the author team without a second, independent reviewer; PRISMA 2020 recommends dual independent screening with a documented conflict-resolution procedure, and adopting that process is a further recommended step prior to submission.

A PRISMA flow diagram with database-specific record and screening counts is not presented in this version of the manuscript (Section 4.1) and will be produced once the broader database search described in Section 3.2 has been executed; reporting estimated or partial counts in its place was judged less useful than deferring the figure until accurate counts are available. Risk-of-bias assessment (Section 3.5, Supplementary Table S2) combines ratings reported by the authors of included systematic reviews with reasoned, design-level judgements by the present authors for primary studies not covered by those reviews; a full independent domain-by-domain Newcastle–Ottawa Scale or PROBAST scoring against complete published protocols and supplementary materials has not yet been performed. Quantitative pooling (meta-analysis) was not attempted

by the present authors, for the heterogeneity reasons set out in Section 3.6; this narrative-synthesis approach is a considered methodological choice rather than a fallback, but it means this review does not offer its own pooled effect estimate for any exposure–outcome pair beyond the pooled estimates already reported by the meta-analyses cited. For one reference (Malik et al., 2024), the complete author list could not be independently confirmed from the sources consulted; this is recorded against that entry in the Reference Verification Table (Section 11) and should be resolved before submission.

Finally, this review's account of the Level 3 integration evidence (Sections 4.4–4.5) reflects the studies located by the search actually performed; the broader search recommended above could identify additional integration studies not captured here. Any such addition would refine, rather than overturn, the qualitative pattern reported in this review, since it would need to be weighed against the correspondingly larger Level 1 and Level 2 evidence bases described in Sections 4.2 and 4.3.

Reference Verification Table

Bibliographic details were cross-checked against available publication records; elements that could not be independently confirmed are identified in the verification table below rather than assumed. "Yes" indicates the element was independently confirmed from the sources consulted for this manuscript; "Not confirmed" indicates it could not be.

First author	Year	Article title (short)	Journal	Citation verified?	DOI verified?
Bearblock E	2021	Air pollution and pre-eclampsia; associations and potential mechanisms	Placenta	Yes	Yes
Dadvand P	2013	Ambient air pollution and preeclampsia: a spatiotemporal analysis	Environmental Health Perspectives	Yes	Yes
Gao S	2025	Prenatal PM2.5 exposure and hypertensive disorders of pregnancy	Frontiers in Public Health	Yes	Yes
Hu H	2014	Ambient air pollution and hypertensive disorders of pregnancy	Atmospheric Environment	Yes	Yes
Hu H	2020	An external exposome-wide association study of hypertensive disorders of pregnancy	Environment International	Yes	Yes
Hu H	2026	The spatial and contextual exposome and subtypes of hypertensive disorders of pregnancy: a double machine learning-based analysis	Exposome	Yes	Yes
Lakhoo DP	2025	A systematic review and meta-analysis of heat exposure impacts on maternal, fetal and neonatal health	Nature Medicine	Yes	Yes
Liu L	2026	Machine learning prediction models for preeclampsia: systematic review and meta-analysis	Journal of Medical Internet Research	Yes	Yes
Malik V	2024	Prediction of preeclampsia using machine learning: a systematic review	Cureus	Not confirmed (full author list)	Yes

First author	Year	Article title (short)	Journal	Citation verified?	DOI verified?
Mao Y	2023	Associations between extreme temperature exposure and hypertensive disorders in pregnancy	Hypertension in Pregnancy	Yes	Yes
Mizuno S	2024	Early prediction of hypertensive disorders of pregnancy toward preventive early intervention	AJOG Global Reports	Yes	Yes
Mohamed Dkeen NO	2025	Artificial intelligence applications in obstetric risk prediction...	Cureus	Yes	Yes
Page MJ	2021	The PRISMA 2020 statement: an updated guideline for reporting systematic reviews	BMJ	Yes	Yes
Pedersen M	2014	Ambient air pollution and pregnancy-induced hypertensive disorders	Hypertension	Yes	Yes
Ranjbar A	2024	Machine learning models for predicting preeclampsia: a systematic review	BMC Pregnancy and Childbirth	Yes	Yes
Sun Y	2024	Association between particulate air pollution and hypertensive disorders in pregnancy	PLOS Medicine	Yes	Yes
Wang C	2026	Explainable machine learning integrating environmental chemical biomarkers...	Scientific Reports	Yes	Yes
Wolff RF	2019	PROBAST: a tool to assess the risk of bias and applicability of prediction model studies	Annals of Internal Medicine	Yes	Yes
Xiong T	2020	Association between ambient temperature and hypertensive disorders in pregnancy in China	Nature Communications	Yes	Yes
Zhang T	2024	Gestational exposure to wildfire PM2.5 and its specific components...	Science of The Total Environment	Yes	Yes
Zheng Y	2026	Associations between extreme temperature exposure and hypertensive disorders of pregnancy	Ecotoxicology and Environmental Safety	Yes	Yes

Supplementary Table S1: Search Strings

This table records representative search queries actually executed for this review, organized by search stream (Section 3.2). Searches were run as a structured, iterative web-based bibliographic search (returning PubMed/MEDLINE-indexed and publisher-hosted records, cross-checked against PubMed and Crossref) rather than as native syntax queries submitted directly to a database's own search interface; no query-specific retrieved-record counts were logged during the search process and none are reported below, consistent with Section 8. This is not a substitute for the platform-native, reproducible search strings (e.g., PubMed MeSH/title-abstract syntax) that a subsequent execution of this review across Embase, Scopus, Web of

Science and the Cochrane Library should use and document.

Stream	Representative query text	Date	Platform / sources returned
A	ambient heat exposure preeclampsia systematic review	Sep 2026	Web-based search; PubMed/MEDLINE-indexed and publisher records
A	PM2.5 air pollution preeclampsia meta-analysis systematic review	Sep 2026	As above
A	wildfire smoke exposure pregnancy cardiovascular hypertension	Sep 2026	As above
A	nitrogen dioxide ozone gestational hypertension meta-analysis	Sep 2026	As above
A	peripartum cardiomyopathy environmental risk factors climate	Sep 2026	As above (no eligible source located)
B	machine learning prediction preeclampsia systematic review	Sep 2026	As above
B	ambient temperature machine learning preeclampsia prediction model	Sep 2026	As above
B	random forest neural network ambient temperature air pollution preeclampsia risk score prediction	Sep 2026	As above (confirmatory search; no additional Category C source located)
C	machine learning model incorporating air pollution temperature predict preeclampsia hypertensive pregnancy	Sep 2026	As above
C	explainable AI environmental exposure pregnancy outcome prediction	Sep 2026	As above (located (Wang et al., 2026))
C	geospatial machine learning heat exposure adverse pregnancy outcome prediction model	Sep 2026	As above
C	geospatial exposure model machine learning maternal hypertension prediction pregnancy	Sep 2026	As above (located (Hu et al., 2026))
C	air pollution machine learning hypertensive disorders pregnancy prediction model	Sep 2026	As above (located source clarifying (Mizuno et al., 2024)'s exposure definition)
C	wildfire smoke artificial intelligence machine learning pregnancy hypertension prediction model	Sep 2026	As above (no eligible source located)

Reference lists and citing-article lists of Ranjbar et al. (2024), Malik et al. (2024), Mohamed Dkeen et al. (2025), Wang et al. (2026) and Liu et al. (2026) were also examined for additional eligible studies (forward/backward citation searching); this did not identify additional Category C sources beyond (Wang et al., 2026) and (Hu et al., 2026).

Natural Resources for Human Health
eISSN: 2583-1194

Supplementary Table S2: Risk-of-Bias and Quality Assessment

Where an included systematic review reported its own risk-of-bias appraisal, that appraisal is reproduced with attribution (not re-derived). For primary studies not covered by an included review, this table reports a reasoned judgement based on the study design and methodological details available in the abstract and methods sections consulted for this review; it is not a full independent domain-by-domain Newcastle–Ottawa Scale or PROBAST scoring against the complete published protocol and supplementary materials, which would require full-text access beyond what was used to build this table and is identified in Section 7 as outstanding work.

Reference	Study type / design	Applicable tool	Reasoned judgement based on available design information	Source of judgement
Mao et al., 2023; Zheng et al., 2026	Meta-analyses of observational studies (temperature)	Newcastle–Ottawa Scale (for primary studies)	Not independently assessed — would require the full published appraisal of each meta-analysis's included primary studies	Internal to each meta-analysis; not reproduced in the abstract-level sources consulted
Xiong et al., 2020	Retrospective population-based cohort, n = 2,043,182	Newcastle–Ottawa Scale	Likely low risk for selection (near-complete administrative birth cohort) and outcome ascertainment; moderate risk for exposure misclassification (residence-linked ambient monitoring does not capture individual time-activity patterns)	Reasoned judgement by the present authors from design details in the abstract; not an independent full NOS scoring
Lakhoo et al., 2025	Systematic review & meta-analysis (198 studies)	Study-design-specific tools (varies by included study)	Not independently assessed — a 198-study review's internal quality appraisal was not reproduced in the sources consulted	Internal to the review; not reproduced here
Pedersen et al., 2014; Hu et al., 2014	Meta-analyses of observational studies (air pollution)	Newcastle–Ottawa Scale (for primary studies)	Not independently assessed	Internal to each meta-analysis
Dadvand et al., 2013	Prospective cohort, n = 8,398	Newcastle–Ottawa Scale	Likely low-moderate risk: relatively small but well-characterized cohort with a spatiotemporal exposure model (more precise exposure assessment than residence-only assignment), single-city setting limits generalizability	Reasoned judgement by the present authors
Bearblock et al., 2021	Narrative review	Not applicable	Not applicable (non-systematic narrative synthesis, not a primary study)	Not applicable

Reference	Study type / design	Applicable tool	Reasoned judgement based on available design information	Source of judgement
Gao et al., 2025	Systematic review & meta-analysis (15 studies)	Newcastle–Ottawa Scale (for primary studies)	Not independently assessed	Internal to the review
Zhang et al., 2024	Retrospective cohort, n = 2,686,939	Newcastle–Ottawa Scale	Likely low risk for selection and outcome ascertainment (administrative data); moderate risk for exposure misclassification (source-apportioned PM2.5 modelled, not individually measured)	Reasoned judgement by the present authors
Sun et al., 2024	Retrospective cohort, n ≈ not specified in abstract consulted	Newcastle–Ottawa Scale	Likely low-moderate risk: large integrated health-system cohort (Kaiser Permanente Southern California) with individual-level PM2.5 component exposure modelling; single health system limits geographic generalizability	Reasoned judgement by the present authors
Ranjbar et al., 2024	Systematic review of prediction-model studies	PROBAST	Not reported in the source consulted	Not stated in the review as consulted
Malik et al., 2024	Systematic review of prediction-model studies	PROBAST	Not reported in the source consulted	Not stated in the review as consulted
Mohamed Dkeen et al., 2025	Systematic review of prediction-model studies (5 databases)	PROBAST	Most included studies rated high/unclear risk of bias	Reported by the review's own authors (Mohamed Dkeen et al., 2025); reproduced here, not independently re-derived
Liu et al., 2026	Systematic review & meta-analysis of prediction-model studies	PROBAST	High between-study heterogeneity (I^2>99%) and a wide sensitivity prediction interval reported by the authors as evidence that internal AUC over-represents likely real-world performance	Reported by the review's own authors (Liu et al., 2026); reproduced here

Natural Resources for Human Health
eISSN: 2583-1194

Reference	Study type / design	Applicable tool	Reasoned judgement based on available design information	Source of judgement
Wang et al., 2026	Single-cohort prediction-model development study, n = 4,260	PROBAST	Likely high risk in the Analysis domain: an HDP prevalence of 1.7% implies approximately 72 events among 4,260 participants, a small absolute event count relative to an 18+ predictor XGBoost model (a recognized PROBAST over-fitting concern regardless of reported AUC); no external validation	Reasoned judgement by the present authors, based on prevalence and sample size stated in the source
Hu et al., 2026	Retrospective cohort, double machine learning, n = 686,412	Not a PROBAST-type prediction-model study; causal/associational design	Large sample and machine-learning-based confounder adjustment reduce (but do not eliminate) residual confounding risk; single US state; exposure measured at residential/contextual level, not individual biomonitoring	Reasoned judgement by the present authors
Hu et al., 2020	Exposome-wide association study, n = 819,399	Not a PROBAST-type prediction-model study; hypothesis-generating association design	Hypothesis-generating by design (multiple-testing across a broad exposome); the authors' own follow-up study (Hu et al., 2026) retested candidates with a more conservative method, consistent with appropriate caution about false-positive associations from the earlier study	Reasoned judgement by the present authors

Supplementary Figures

Figures 2 and 3, referenced in Section 4, are presented here.

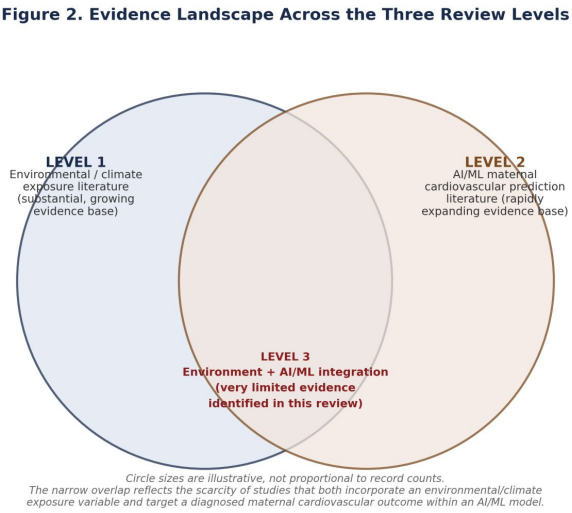

Figure 2. Evidence landscape across the three review levels. Circle sizes are illustrative, not proportional to record counts; the narrow overlap reflects the scarcity of Level 3 integration studies identified.

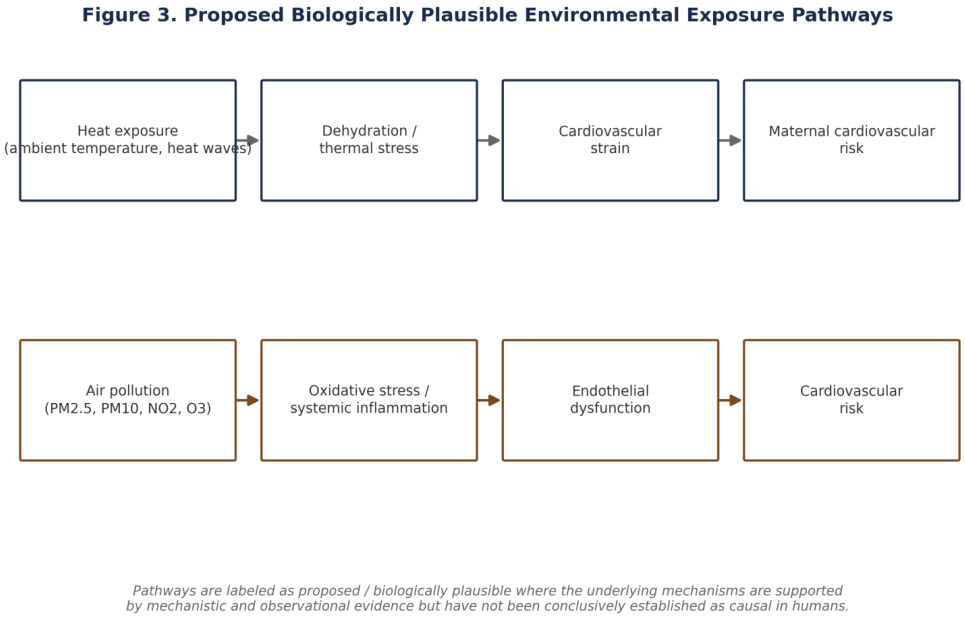

Figure 3. Proposed biologically plausible environmental exposure pathways for heat and air pollution. Labeled as proposed/plausible because these mechanisms are not conclusively established as causal in humans on the evidence reviewed.

8. CONCLUSIONS

Environmental and climate-related exposures — particularly ambient heat and fine particulate air pollution — are associated with hypertensive disorders of pregnancy across a substantial and geographically varied evidence base, though exposure

definitions, exposure windows and outcome ascertainment vary across studies. Artificial intelligence and machine learning methods are increasingly applied to predict these same outcomes, with reported discriminative performance that is often strong under internal validation but rarely externally validated, and with extreme between-study heterogeneity where meta-analysed. These evidence streams have been brought together in at least two identified analyses: a discriminative prediction model incorporating environmental chemical biomarkers (Level 3A), and a causal machine-learning analysis linking an aggregate meteorological measure and ultraviolet radiation — alongside ambient air toxicants and non-climate contextual factors — to hypertensive disorders of pregnancy (Level 3B). What remains specifically and demonstrably limited, on the evidence identified in this review, is Level 3C: a climate-sensitive ambient exposure combined with a discriminative AI/ML prediction model reporting standard performance metrics and a formal incremental-value analysis against clinical predictors alone. This specific gap, explained in Section 4.5 by identifiable methodological and data-infrastructure factors, is this review's central finding, and the four-stage research agenda in Table 6 is offered as a concrete, evidence-derived starting point for closing it.

9. DECLARATIONS

Funding

No specific funding was received for this work. [To be confirmed/completed by the author team prior to submission.]

Acknowledgement

None. [To be completed by the author team if applicable.]

Author Contributions

[To be completed by the author team per CRediT taxonomy — e.g., conceptualization, methodology, investigation, data curation, writing – original draft, writing – review & editing, supervision. All listed authors must meet ICMJE authorship criteria: substantial contribution to the work, drafting or critically revising it, final approval of the version to be published, and agreement to be accountable for all aspects of the work.]

Conflict of Interest

The authors declare no conflict of interest. [To be confirmed by all authors prior to submission; a completed ICMJE Disclosure of Interest form should be submitted for each author as required by the journal.]

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the author(s) used Claude (Anthropic; models spanning the Claude Sonnet/Opus 4.x and 5 series, 2025–2026) for literature search and identification, evidence extraction and synthesis, drafting of manuscript text, and construction of tables and figures. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the accuracy, integrity and scientific validity of the content of this publication. [Author team: please confirm the extent of your own independent verification and revision of the AI-assisted content before submission, and adjust this statement to accurately describe what was done, per the journal's Generative AI policy.]

Data Availability

This is a literature review; no new primary data were generated. All sources synthesized are cited in the reference list and are publicly available through their respective publishers or PubMed.

Ethics Statement

Not applicable — this work synthesizes previously published, publicly available literature and did not involve new human participant data collection.

REFERENCES

[1] Bearblock, E., Aiken, C.E., Burton, G.J., 2021. Air pollution and pre-eclampsia; associations and potential mechanisms. Placenta 104, 188-194. doi:10.1016/j.placenta.2020.12.009

[2] Dadvand, P., Figueras, F., Basagaña, X., Beelen, R., Martinez, D., Cirach, M., Schembari, A., Hoek, G., Brunekreef, B.,

Nieuwenhuijsen, M.J., 2013. Ambient air pollution and preeclampsia: a spatiotemporal analysis. Environmental Health Perspectives 121, 1365-1371. doi:10.1289/ehp.1206430

[3] Gao, S., Zhang, H., Kang, X., Cui, X., 2025. Prenatal PM2.5 exposure and hypertensive disorders of pregnancy: a systematic review and meta-analysis. Frontiers in Public Health 13, 1650913. doi:10.3389/fpubh.2025.1650913

[4] Hu, H., Ha, S., Roth, J., Kearney, G., Talbott, E.O., Xu, X., 2014. Ambient air pollution and hypertensive disorders of pregnancy: a systematic review and meta-analysis. Atmospheric Environment 97, 336-345. doi:10.1016/j.atmosenv.2014.08.027

[5] Hu, H., Zhao, J., Savitz, D.A., Prosperi, M., Zheng, Y., Pearson, T.A., 2020. An external exposome-wide association study of hypertensive disorders of pregnancy. Environment International 141, 105797. doi:10.1016/j.envint.2020.105797

[6] Hu, H., Leiser, C.L., He, X., Hart, J.E., Laden, F., Tao, C., Bian, J., 2026. The spatial and contextual exposome and subtypes of hypertensive disorders of pregnancy: a double machine learning-based analysis. Exposome 6, osag009. doi:10.1093/exposome/osag009

[7] Lakhoo, D.P., Brink, N., Radebe, L., Craig, M.H., Pham, M.D., Haghighi, M.M., Wise, A., Solarin, I., Luchters, S., Maimela, G., Chersich, M.F., 2025. A systematic review and meta-analysis of heat exposure impacts on maternal, fetal and neonatal health. Nature Medicine 31, 684-694. doi:10.1038/s41591-024-03395-8

[8] Liu, L., Zhu, Q., Zong, Y., Chen, X., Zhang, W., Wang, J., 2026. Machine learning prediction models for preeclampsia: systematic review and meta-analysis. Journal of Medical Internet Research 28, e78714. doi:10.2196/78714

[9] Malik, V., Agrawal, N., Madan, N., et al., 2024. Prediction of preeclampsia using machine learning: a systematic review. Cureus 16, e76095. doi:10.7759/cureus.76095 [full author list not independently confirmed]

[10] Mao, Y., Gao, Q., Zhang, Y., Yue, Y., Ruan, T., Yang, Y., Xiong, T., 2023. Associations between extreme temperature exposure and hypertensive disorders in pregnancy: a systematic review and meta-analysis. Hypertension in Pregnancy 42, 2288586. doi:10.1080/10641955.2023.2288586

[11] Mizuno, S., Nagaie, S., Sugawara, J., Tamiya, G., Obara, T., Ishikuro, M., Kuriyama, S., Yaegashi, N., Tanaka, H., Yamamoto, M., Ogishima, S., 2024. Early prediction of hypertensive disorders of pregnancy toward preventive early intervention. AJOG Global Reports 4, 100383. doi:10.1016/j.xagr.2024.100383

[12] Mohamed Dkeen, N.O., Dawelbait Radwan, M.E., Alnaw Zumam, I.A., Abd Elfrag Mohamed, N.A., Abbashar Abdelmahmoud, E.M., Magboul Elfadel Magboul, N., 2025. Artificial intelligence applications in obstetric risk prediction: a systematic review of machine learning models for preeclampsia. Cureus 17, e83961. doi:10.7759/cureus.83961

[13] Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., et al., 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 372, n71. doi:10.1136/bmj.n71

[14] Pedersen, M., Stayner, L., Slama, R., Sørensen, M., Figueras, F., Nieuwenhuijsen, M.J., Raaschou-Nielsen, O., Dadvand, P., 2014. Ambient air pollution and pregnancy-induced hypertensive disorders: a systematic review and meta-analysis. Hypertension 64, 494-500. doi:10.1161/HYPERTENSIONAHA.114.03545

[15] Ranjbar, A., Montazeri, F., Rezaei Ghamsari, S., Mehrnoush, V., Roozbeh, N., Darsareh, F., 2024. Machine learning models for predicting preeclampsia: a systematic review. BMC Pregnancy and Childbirth 24, 6. doi:10.1186/s12884-023-06220-1

[16] Sun, Y., Bhuyan, R., Jiao, A., Avila, C.C., Chiu, V.Y., Slezak, J.M., Sacks, D.A., Molitor, J., Benmarhnia, T., Chen, J.C., Getahun, D., Wu, J., 2024. Association between particulate air pollution and hypertensive disorders in pregnancy: a retrospective cohort study. PLoS Medicine 21, e1004395. doi:10.1371/journal.pmed.1004395

[17] Wang, C., Lee, J.D., Kim, J.H., 2026. Explainable machine learning integrating environmental chemical biomarkers and maternal clinical factors for prediction of hypertensive disorder of pregnancy. Scientific Reports (in press).

doi:10.1038/s41598-026-61841-8

[18] Wolff, R.F., Moons, K.G.M., Riley, R.D., Whiting, P.F., Westwood, M., Collins, G.S., Reitsma, J.B., Kleijnen, J., Mallett, S., 2019. PROBAST: a tool to assess the risk of bias and applicability of prediction model studies. Annals of Internal Medicine 170, 51-58. doi:10.7326/M18-1376

[19] Xiong, T., Chen, P., Mu, Y., Li, X., Di, B., Li, J., Qu, Y., Tang, J., Liang, J., Mu, D., 2020. Association between ambient temperature and hypertensive disorders in pregnancy in China. Nature Communications 11, 1-11. doi:10.1038/s41467-020-16775-8

[20] Zhang, T., Ren, A.X., Tong, M., Li, Y., Mendola, P., Chen, X., Wang, M., 2024. Gestational exposure to wildfire PM2.5 and its specific components and the risk of gestational hypertension and eclampsia in the southwestern United States. Science of The Total Environment 951, 175781. doi:10.1016/j.scitotenv.2024.175781

[21] Zheng, Y., Wang, Y., Zhu, Y., Ruan, F., Liu, Y., Xiong, Y., Zhao, H., Li, X., Zhou, Q., 2026. Associations between extreme temperature exposure and hypertensive disorders of pregnancy: a systematic review and meta-analysis. Ecotoxicology and Environmental Safety 323, 120694. doi:10.1016/j.ecoenv.2026.120694