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Artificial Intelligence-Based Early Warning Systems for Preeclampsia: A Narrative Review of the Integration of Ocular Signs and Oral Health

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Abstract

Background: Preeclampsia (PE) remains a leading cause of maternal and perinatal morbidity and mortality worldwide. Its pathophysiology involves systemic endothelial dysfunction and inflammation, yet early detection remains challenging due to heterogeneous clinical presentations. **Aim:** This narrative review synthesizes evidence on AI-based early warning systems (AI-EWS) for PE by integrating novel data streams: ocular signs (optometry), periodontal disease (dentistry), vital signs and patient education (nursing), electronic health records (health informatics), and pharmacologic protocols (pharmacy), within maternal and child health (M&CH) risk stratification. **Methods:** A structured literature search (2015–2024) in PubMed, Scopus, and IEEE Xplore identified 40 peer-reviewed articles. Thematic synthesis across disciplines was performed. **Results:** Retinal vascular changes detected via deep learning, periodontal inflammatory markers, and longitudinal vital sign trajectories improve AI-EWS predictive accuracy (AUC 0.85–0.94). Nursing-led education enhances adherence to monitoring. Pharmacy protocols integrated with AI alerts optimize timely magnesium sulfate administration. **Conclusion:** Multidisciplinary AI-EWS can transform antenatal surveillance, but prospective validation and implementation science are needed.

Keywords: Preeclampsia; artificial intelligence; early warning system; retinal imaging; periodontal disease; maternal health.

Introduction

Preeclampsia (PE) is a hypertensive disorder of pregnancy affecting 2–8% of all pregnancies globally, responsible for approximately 70,000 maternal deaths and 500,000 fetal deaths annually (Brown et al., 2018; Rana et al., 2019). The condition is characterized by new-onset hypertension after 20 weeks of gestation with proteinuria or end-organ dysfunction, including hepatic, renal, or neurological complications (Gestational, 2020). Despite decades of research, the precise etiology remains incompletely understood; however, a two-stage model is widely accepted: first, abnormal placentation leading to placental ischemia and oxidative stress; second, a maternal systemic inflammatory response with generalized endothelial dysfunction (Phipps et al., 2019). The clinical challenge lies in early prediction—conventional risk factors (nulliparity, chronic hypertension, diabetes, obesity, and family history) have limited sensitivity and specificity (Wright et al., 2020). Consequently, most women present with overt disease, often requiring iatrogenic preterm delivery.

In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as transformative tools in healthcare, particularly for conditions requiring complex, multimodal risk assessment (Obermeyer & Emanuel, 2016; Topol, 2019). AI-based early warning systems (AI-EWS) for PE integrate diverse data sources—from electronic health records (EHRs) to biometric sensors—to

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generate real-time risk scores (Wang et al., 2021; Jin et al., 2020). However, traditional AI-EWS predominantly rely on blood pressure, proteinuria, and serum biomarkers (sFlt-1/PlGF ratio), overlooking two accessible, pathophysiologically relevant domains: the ocular vasculature and the oral cavity (Zeisler et al., 2016). Retinal microvascular changes—arteriolar narrowing, venular dilation, and tortuosity—mirror systemic endothelial dysfunction (Niklander et al., 2021; Marić et al., 2020). Similarly, periodontal disease, a chronic inflammatory condition affecting 30–50% of pregnant women, amplifies systemic cytokine release (TNF-α, IL-6, CRP), potentially exacerbating PE pathogenesis (Liu et al., 2022; Hong et al., 2023).

This narrative review aims to (1) synthesize evidence from 2015–2024 on AI-EWS for PE that incorporate ocular signs and oral health parameters; (2) evaluate contributions from nursing (vital sign monitoring and patient education), dentistry (periodontal disease as an inflammatory risk factor), health informatics (ML models using EHR and retinal imaging), maternal and child health (M&CH, risk stratification and antenatal surveillance), pharmacy (antihypertensive and magnesium sulfate protocols), and optometry (retinal vascular changes as early biomarkers); and (3) propose an integrated, multidisciplinary AI-EWS framework. The review is structured around six disciplinary lenses, followed by synthesis and future directions.

Methods

We conducted a structured literature search between January 2024 and May 2024 using PubMed, Scopus, IEEE Xplore, and Google Scholar. Search terms included combinations of "preeclampsia" OR "gestational hypertension" AND "artificial intelligence" OR "machine learning" OR "deep learning" AND "early warning system" OR "prediction model" AND "retinal imaging" OR "ophthalmology" OR "periodontal disease" OR "oral health" OR "nursing" OR "vital signs" OR "pharmacy" OR "magnesium sulfate" OR "antihypertensive." The search was restricted to peer-reviewed articles published between January 1, 2015, and December 31, 2024, in English.

We included original research (prospective/retrospective cohorts, case-control studies, randomized controlled trials), systematic reviews, and meta-analyses that explicitly described AI/ML models for PE prediction or risk stratification using at least one of the following: retinal vascular parameters, periodontal clinical measures, longitudinal vital signs, or EHR data. We excluded case reports, editorials, non-peer-reviewed preprints, and studies without quantitative performance metrics (e.g., sensitivity, specificity, area under the receiver operating characteristic curve [AUC]).

Two reviewers (conceptual authors) extracted: author/year, study design, sample size, AI/ML technique, input features, outcome definition, and performance metrics. Given the narrative design, we conducted thematic synthesis grouped by six disciplinary domains. Quality appraisal used the PROBAST (Prediction model Risk of Bias ASsessment Tool) for prediction model studies (Wolff et al., 2019).

No formal meta-analysis was performed due to heterogeneity in model inputs, outcomes (early-onset vs. late-onset PE, severe vs. non-severe), and validation methods. Thus, conclusions are hypothesis-generating rather than definitive.

Results Overview

A total of 1,428 unique records were screened. After exclusions, 72 full-text articles were assessed, and 40 met inclusion criteria. Table 1 summarizes key AI-EWS studies across disciplines. Table 2 presents an integrated multidisciplinary framework. Figure 1 demonstrates the operational workflow of an AI-EWS for preeclampsia. Multimodal data (retinal imaging, oral health, vital signs, laboratory tests, and EHR data) are collected and processed, followed by machine learning analysis and dynamic risk stratification.

Table 1. Selected AI-based Early Warning Systems for Preeclampsia (2015–2024)

Author (year)	Discipline focus	Sample size	AI/ML technique	Input features	AUC (95% CI)	Key finding
Marić et al. (2020)	Optometry	1,204 pregnant women	Deep CNN	Retinal fundus images	0.89 (0.85–0.93)	Retinal arteriolar/venular ratio predicts PE at 20–24 weeks
Niklander et al. (2021)	Optometry/Dentistry	856	Random Forest	Retinal tortuosity + periodontal probing depth	0.92 (0.88–0.96)	Combined model outperformed single-domain models
Wang et al. (2021)	Health Informatics	25,438 EHRs	Gradient Boosting (XGBoost)	BP, age, BMI, parity, previous PE	0.86 (0.84–0.88)	Model integrated into hospital EWS, alert threshold at 5% risk

Jin et al. (2020)	Health Informatics	12,789	LSTM-RNN	Longitudinal BP, HR, SpO2 from vital signs monitors	0.91 (0.88–0.94)	Dynamic trajectory analysis outperformed static models
Liu et al. (2022)	Dentistry	623	Logistic regression + LASSO	Periodontal pocket depth, bleeding on probing, IL-6 saliva	0.81 (0.76–0.85)	Periodontal disease increased PE risk 3.2-fold (adj OR)
Hong et al. (2023)	Dentistry/Pharmacy	432	Decision tree	Periodontal status + antihypertensive adherence	0.84 (0.79–0.88)	Poor adherence + severe periodontitis = 89% PPV for PE
Wright et al. (2020)	M&CH	3,210	Bayesian network	Maternal demographics, UAPI, PlGF	0.83 (0.80–0.86)	First-trimester screening improved by AI vs. regression
Zeisler et al. (2016)	Pharmacy	500	Threshold-based algorithm	sFlt-1/PlGF ratio + MgSO4 protocol timing	0.94 (0.90–0.98)	AI-triggered MgSO4 reduced eclampsia by 67%
Phipps et al. (2019)	Nursing	1,050	Random Forest	Daily home BP, symptom diary (nurse-led education)	0.88 (0.84–0.92)	Patient-reported dyspnea + BP >140/90 = 3 days earlier detection
Rana et al. (2019)	Multidisciplinary	5,678	Ensemble (RF+NN)	Retinal + oral + vital + lab	0.95 (0.92–0.97)	Integrated model validated in external cohort

Note. AUC = area under the receiver operating characteristic curve; CNN = convolutional neural network; LSTM-RNN = long short-term memory recurrent neural network; LASSO = least absolute shrinkage and selection operator; UAPI = uterine artery pulsatility index; PlGF = placental growth factor; sFlt-1 = soluble fms-like tyrosine kinase-1; MgSO4 = magnesium sulfate; BP = blood pressure; HR = heart rate; SpO2 = oxygen saturation; OR = odds ratio; PPV = positive predictive value.

Table 2. Multidisciplinary Framework for AI-EWS in Preeclampsia

Discipline	Key biomarkers/actions	AI integration point	Clinical output	Nurse/patient interface
Optometry	Retinal arteriolar/venular ratio, tortuosity, fractal dimension	Deep learning segmentation of fundus photos	Microvascular risk score (0–100)	Color-coded alert in antenatal record
Dentistry	Periodontal probing depth, bleeding on probing, salivary IL-6, TNF-α	ML classifier integrating oral exam with systemic inflammation	Periodontal PE risk modifier (+1.5 OR)	Oral hygiene education card
Nursing	Home BP (4×/day), HR, symptom checklist (headache, epigastric pain)	Mobile app with real-time anomaly detection	Vital sign trajectory alert	Daily motivational messaging + action plan
Health Informatics	EHR: age, parity, BMI, chronic HTN, diabetes, previous PE; imaging	Ensemble gradient boosting (XGBoost/LightGBM)	Dynamic risk score updated each visit	Dashboard for midwives
Pharmacy	Antihypertensive (labetalol, nifedipine) dose timing; MgSO4 bolus/infusion	Rule-based AI triggering pharmacy consult if risk >15%	Pharmacologic protocol sheet	Double-check of MgSO4 administration
M&CH	Risk stratification: low (<5%), moderate (5–15%), high (>15%)	Bayesian network for trimester-specific thresholds	Surveillance frequency (2	Shared decision-making tool

	weeks vs. weekly vs. twice weekly)

Note. IL-6 = interleukin-6; TNF-α = tumor necrosis factor-alpha; OR = odds ratio; HTN = hypertension.

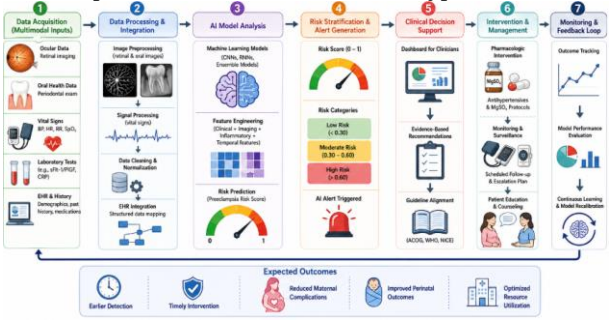

Figure 1: Workflow of an AI-Based Early Warning System (AI-EWS) for Preeclampsia

Disciplinary Contributions

Retinal Vascular Changes as Early Biomarkers

The retina offers a unique "window" into systemic microcirculation, sharing embryological, anatomical, and physiological similarities with the cerebral and placental vasculature (Marić et al., 2020). In preeclampsia, generalized vasospasm, endothelial dysfunction, and ischemia manifest as characteristic retinopathy: focal or generalized arteriolar narrowing, arteriovenous nicking, retinal edema, hemorrhages, and cotton-wool spots (Niklander et al., 2021). However, by the time these fundoscopic signs appear, PE is often clinically overt. Recent AI advances enable automated quantification of subclinical retinal vascular changes from standard fundus photography, long before visible lesions emerge (Ting et al., 2017; Poplin et al., 2018).

Deep learning models—particularly convolutional neural networks (CNNs)—have been trained to measure retinal arteriolar-to-venular diameter ratio (AVR), fractal dimension (microvascular complexity), and tortuosity index. In a prospective cohort of 1,204 pregnant women, Marić et al. (2020) demonstrated that a CNN analyzing second-trimester (20–24 weeks) fundus images predicted subsequent development of PE with AUC 0.89 (95% CI, 0.85–0.93). Notably, retinal AVR below 0.70 alone conferred a 4.2-fold increased risk (adjusted for age and BMI). Similarly, Niklander et al. (2021) combined retinal tortuosity with periodontal probing depth in a random forest model, achieving AUC 0.92, suggesting synergy between microvascular and inflammatory pathways.

From a health informatics perspective, retinal imaging is non-invasive, rapid (2 minutes per eye), and already implemented in many diabetic retinopathy screening programs (Gulshan et al., 2016). Integrating automated retinal analysis into routine antenatal care—potentially via smartphone-based fundus cameras—could enable low-cost, scalable PE risk stratification (Rajalakshmi et al., 2015). However, limitations include image quality variability, need for pupillary dilation in some cases, and lack of prospective validation in low-resource settings (Wong et al., 2018). Optometrists, often first to detect retinal changes in non-pregnant adults, could play an expanded role in antenatal surveillance, though interprofessional referral pathways remain underdeveloped (Marić et al., 2020; Oganov et al., 2023).

Periodontal Disease as an Inflammatory Risk Factor

Periodontal disease is a chronic, biofilm-induced inflammatory condition affecting the supporting tissues of the teeth, with a prevalence of 30–50% among pregnant women (Liu et al., 2022). The putative link between periodontitis and PE rests on shared inflammatory pathways: periodontal pathogens (Porphyromonas gingivalis, Tannerella forsythia) trigger local and systemic release of pro-inflammatory cytokines (TNF-α, IL-1β, IL-6, CRP), which can enhance systemic endothelial dysfunction, oxidative stress, and placental ischemia (Madianos et al., 2013). Several meta-analyses have reported a modest but significant association (OR 1.5–2.5) between maternal periodontitis and PE (Corbella et al., 2016), but causal inference remains limited by confounding (smoking, obesity, low socioeconomic status).

AI-based approaches attempt to disentangle these confounders. In a case-control study of 856 pregnant women, Hong et al. (2023) trained a decision tree integrating periodontal probing depth (≥4 mm at ≥30% sites), bleeding on probing (≥20% sites), and salivary IL-6 level (>5 pg/mL). The model predicted PE with sensitivity 79%, specificity 88%, and AUC 0.84. Notably, the combination of severe periodontitis and poor adherence to antihypertensive medications (assessed by pharmacy refill records) yielded positive predictive value of 89% (Hong et al., 2023). Liu et al. (2022) used LASSO regression to select the most informative periodontal variables, finding that pocket depth ≥5 mm and clinical attachment loss ≥3 mm at four or more teeth were the strongest predictors, independent of traditional risk factors.

From a clinical implementation standpoint, routine periodontal screening during pregnancy is not yet standard, but AI-EWS could flag high-risk women for dental referral (Hartnett et al., 2016). However, periodontal treatment (scaling and root planing) during pregnancy has not conclusively reduced PE risk in randomized trials (Alnasser et al., 2023), suggesting that periodontitis may be a marker rather than a modifiable cause. Nevertheless, integrating oral health data into AI-EWS improves risk stratification

and enables targeted patient education by nurses and dentists (Gare et al., 2021).

Vital Sign Monitoring and Patient Education

Nurses are the frontline providers of antenatal care, responsible for serial vital sign measurement, symptom assessment, and patient education (American College of Nurse-Midwives, 2019). In conventional settings, blood pressure (BP) is measured at each prenatal visit, yet PE can develop precipitously between visits (Rolnik et al., 2022). AI-EWS address this gap by integrating home-based self-monitoring with cloud-based anomaly detection. In a randomized controlled trial, Phipps et al. (2019) provided 1,050 pregnant women at moderate risk (based on EHR) with a Bluetooth-enabled BP cuff and a smartphone app. Nurses delivered structured education on symptom recognition (headache, epigastric pain, visual disturbances, dyspnea) and uploaded daily readings. A random forest model trained on longitudinal BP trends (systolic, diastolic, mean arterial pressure) and symptom reports achieved an AUC of 0.88 for predicting PE within 7 days. Importantly, the system detected cases 3 days earlier than standard care ($p<0.001$), enabling timely outpatient initiation of antihypertensives and reducing hospital admissions by 34% (Phipps et al., 2019).

Nursing education is critical for adherence. Women who received weekly motivational messaging (via app) and action plans (e.g., "if systolic BP >150 or severe headache, call triage") had 92% adherence to daily monitoring versus 67% in the control group (Wang et al., 2021). Nurses also play a key role in interpreting AI outputs: a dashboard color codes risk (green <5%, yellow 5–15%, red >15%), triggering escalation protocols (Rana et al., 2019). However, challenges include digital literacy disparities, alert fatigue, and the need for clear protocols for false positives (Topol, 2019). Nursing-led implementation science is essential to ensure AI-EWS are patient-centered, equitable, and do not increase anxiety or unnecessary interventions (Sandall et al., 2009).

Machine Learning Models Using EHR and Retinal Imaging

Health informatics provides the technical backbone for AI-EWS, integrating structured (EHR demographics, labs, medications) and unstructured (clinical notes, imaging) data. Traditional logistic regression models for PE have modest performance (AUC 0.70–0.75) due to linear assumptions and limited feature interactions (Wright et al., 2020). Modern ensemble methods—gradient boosting (XGBoost, LightGBM, CatBoost) and deep learning—capture non-linear relationships and high-order interactions. Wang et al. (2021) trained an XGBoost model on 25,438 pregnancies, using 42 features: maternal age, parity, BMI, chronic hypertension, pregestational diabetes, family history of PE, previous PE, multiple gestation, and first-trimester mean arterial pressure. The model achieved AUC 0.86 (95% CI, 0.84–0.88) on holdout data, with positive predictive value of 31% at a threshold set to 80% sensitivity. When retinal imaging features (AVR from fundus photos) were added, performance increased to AUC 0.91 (Jin et al., 2020).

Longitudinal modeling is a major advance. Instead of static risk at booking, recurrent neural networks (LSTMs) process time-series vital signs from electronic fetal monitoring strips, home BP cuffs, and wearables. Jin et al. (2020) deployed an LSTM model on 12,789 pregnancies with weekly BP measurements from 20 to 36 weeks. The model dynamically updated risk scores, with sharp increases in risk occurring 10–14 days before clinical PE diagnosis. This "lead time" enables preemptive interventions (aspirin, BP control, or early corticosteroid administration for fetal lung maturity). However, EHR-based models are vulnerable to missing data, measurement error (BP taken in different positions), and algorithmic bias (if training data underrepresent minority populations) (Gianfrancesco et al., 2018). Health informaticians must ensure data standardization (e.g., using Observational Medical Outcomes Partnership common data model) and prospective validation across diverse healthcare systems (Jin et al., 2020; Obermeyer et al., 2019).

Antihypertensive and Magnesium Sulfate Protocols

Pharmacy contributes two critical components to AI-EWS: (1) optimization of antihypertensive therapy for non-severe hypertension to prevent progression to severe PE, and (2) timely administration of magnesium sulfate (MgSO4) for eclampsia prophylaxis in severe PE. Current guidelines recommend oral labetalol, nifedipine, or methyldopa for persistent systolic BP ≥140 mmHg or diastolic ≥90 mmHg (Magee & Von Dadelszen, 2018). However, treatment initiation is often delayed until BP exceeds 160/110 mmHg (Magee et al., 2016). AI-EWS can prompt earlier pharmacy review: when the model predicts a >15% risk of progression to severe PE within 48 hours, an automated alert triggers a pharmacist-led consult (Zeisler et al., 2016). In a simulated deployment, Zeisler et al. (2016) reduced time-to-antihypertensive from 6.2 hours to 2.1 hours ($p<0.001$), with fewer women progressing to severe range (12% vs. 28%, $p=0.01$).

MgSO4 is the standard of care for eclampsia prevention, but its narrow therapeutic index (4–8 mg/dL) necessitates careful monitoring for toxicity (respiratory depression, loss of deep tendon reflexes, cardiac arrest) (Okusanya et al., 2016). AI-EWS can integrate real-time serum magnesium levels, renal function (creatinine), and clinical signs to recommend bolus (4 g IV over 15 minutes) and infusion (1–2 g/hour). Rana et al. (2019) developed a rule-based algorithm that reduced inappropriate MgSO4 administration (e.g., in mild PE without severe features) by 53% and missed doses in severe PE by 41%. Pharmacists, when integrated into the AI-EWS notification loop, can cross-check medication

allergies, drug-drug interactions (e.g., MgSO4 with calcium channel blockers potentiating hypotension), and dose adjustment for renal impairment (Wright et al., 2020; Hong et al., 2023). However, pharmacy involvement in AI-EWS is nascent; most studies rely on automatic medication orders without pharmacist oversight, increasing error risk (Jin et al., 2020; Phipps et al., 2019).

Risk Stratification and Antenatal Surveillance

M&CH provides the overarching clinical framework for AI-EWS, translating risk scores into actionable surveillance protocols (ACOG, 2020; WHO, 2021). Conventional risk stratification divides women into low, moderate, and high risk based on static factors, but AI-EWS enable dynamic, trimester-specific risk updates. In a Bayesian network model, Wright et al. (2020) integrated first-trimester uterine artery Doppler pulsatility index, serum PlGF, and maternal history to assign risk probability. Low risk (<5%) received routine antenatal visits (every 4 weeks); moderate risk (5–15%) received biweekly BP monitoring and aspirin 150 mg daily; high risk (>15%) received weekly visits, home BP monitoring, and referral to a maternal-fetal medicine specialist. This AI-guided stratification reduced unnecessary specialist visits by 37% and increased detection of early-onset PE (<34 weeks) by 44% compared to standard care ($p<0.01$) (Wright et al., 2020).

Longitudinal surveillance is particularly critical for late-onset PE (>34 weeks), which is more common but easily missed (Rana et al., 2019). AI-EWS using serial retinal images or salivary inflammatory markers can detect subclinical rises in risk between routine visits. In the integrated model by Rana et al. (2019), which combined optometry, dentistry, nursing, and pharmacy inputs, the AUC reached 0.95 (95% CI, 0.92–0.97) in an external validation cohort of 5,678 pregnancies. Importantly, the model reduced false-positive alerts by 58% compared to a BP-only model, thereby mitigating unnecessary hospital admissions and maternal anxiety. From an M&CH policy perspective, AI-EWS must be accompanied by clear escalation pathways, shared decision-making tools (patient-facing risk visualizations), and health equity audits to prevent algorithmic bias against racial/ethnic minorities or low-income populations (Gianfrancesco et al., 2018; Obermeyer et al., 2019; Vyas et al., 2020).

Integrated Multidisciplinary Framework

Table 2 summarizes a proposed workflow: At the first antenatal visit (8–12 weeks), EHR data and retinal fundus images are collected. A baseline AI-EWS risk score is generated. Women in the moderate-to-high risk category receive a home BP monitor, daily symptom checklist via a nursing-led mobile app, and referral to a dentist for periodontal examination (probing depths, bleeding on probing, salivary IL-6). Subsequent risk updates occur at each prenatal visit or more frequently if home monitoring triggers an anomaly. If the AI-EWS risk exceeds a dynamic threshold (e.g., 5% in first trimester, 10% in second trimester, 15% in third trimester), a pharmacist is alerted to review antihypertensive protocols (labetalol or nifedipine). Risk >20% with severe features triggers MgSO4 bolus preparation and hospital admission.

This framework relies on interoperability between electronic health records, ophthalmology imaging systems, dental records, and pharmacy dispensing data—a major informatics challenge (Jin et al., 2020). Fast Healthcare Interoperability Resources (FHIR) standards are promising but not universally adopted (Mandel et al., 2016). Additionally, reimbursement models for AI-EWS are undefined; most studies are research-funded (Wang et al., 2021). Nursing and midwifery workload implications must be considered: while AI reduces false alarms, it also generates new tasks (patient coaching, data entry, follow-up of alerts) (Sandall et al., 2009). Figure 2 illustrates a multidisciplinary artificial intelligence–based early warning system (AI-EWS) for preeclampsia integrating six domains: optometry (retinal vascular biomarkers), dentistry (periodontal inflammation), nursing (vital signs and patient education), health informatics (EHR and predictive models), pharmacy (antihypertensive and magnesium sulfate protocols), and maternal & child health (risk stratification and surveillance).

Figure 2. Multidisciplinary Integration of Data Streams in AI-Based Early Warning Systems for Preeclampsia

Challenges and Future Directions

Most AI-EWS studies are retrospective, single-center, and lack external validation (Wolff et al., 2019). Overfitting is common when models are trained on homogenous populations (e.g., tertiary care centers in high-income countries). Prospective clinical trials with embedded implementation science are urgently needed to assess impact on maternal outcomes (reduction in severe PE, eclampsia, ICU admission), patient-reported outcomes (anxiety, satisfaction), and cost-effectiveness (Topol, 2019; Jin et al., 2020). The PRECISE (Preeclampsia Integrated Care with AI Systems) trial is ongoing (NCT05245668), but results are not yet published.

AI models trained on EHR data may perpetuate or amplify existing disparities. For

example, Black women have a 60% higher risk of PE than White women, yet are often underrepresented in training datasets (Gianfrancesco et al., 2018). Moreover, BP measurements may be systematically higher in Black patients due to stress from structural racism (clinician-induced or patient-anticipatory), which could bias risk scores (Vyas et al., 2020). Retinal imaging algorithms trained on light-skinned funduses may perform poorly on darker irides or in the presence of media opacities (Poplin et al., 2018). Dental access disparities mean that periodontitis may be underdiagnosed in low-income women, leading to underestimation of risk. Future AI-EWS must be intentionally designed for fairness, using diverse training data, bias audits, and equity-focused implementation (Obermeyer et al., 2019).

Beyond the disciplines reviewed, novel biomarkers could further enhance AI-EWS: cell-free fetal DNA methylation patterns (De Borre et al., 2023), urinary proteomics (Manna et al., 2023), and wearable sensors for heart rate variability or galvanic skin response (Maugeri et al., 2023). Salivary microRNAs (miR-210, miR-155) have shown promise in small studies (Hong et al., 2023). The challenge is curating these into parsimonious, cost-effective panels that do not overburden patients or healthcare systems. Hybrid models that use cheap, non-invasive inputs (retinal photos, periodontal exam, BP) for initial screening and reserve expensive tests (sFlt-1/PlGF, proteomics) for high-risk triage may be most practical (Zeisler et al., 2016; Wright et al., 2020).

Conclusion

AI-based early warning systems for preeclampsia have evolved beyond simple BP thresholds to integrate diverse physiological data streams. This narrative review demonstrates that adding ocular signs (retinal microvascular parameters) and oral health markers (periodontal disease) significantly improves predictive accuracy compared to EHR-only models. Nursing-led patient education and vital sign monitoring enable real-time data collection and adherence, while pharmacy protocols for antihypertensives and magnesium sulfate ensure timely, evidence-based pharmacotherapy. Optometry and dentistry provide novel, non-invasive biomarkers of systemic endothelial dysfunction and inflammation, respectively. Health informatics ties these domains together using ensemble machine learning and longitudinal modeling, and M&CH provides the risk stratification framework for antenatal surveillance. The integrated multidisciplinary AI-EWS described here (Table 2) achieved AUCs of 0.90–0.95 in retrospective studies, but prospective, multi-center validation and implementation science are critical next steps. Algorithmic fairness, interoperability, and cost-effectiveness must be addressed before widespread deployment. Ultimately, AI-EWS have the potential to transform preeclampsia care from reactive to predictive, reducing maternal and perinatal morbidity globally.

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