



ORIGINAL RESEARCH ARTICLE

Bayesian Multivariate Logistic Regression Models for Comparing Preeclampsia Risk and Maternal Outcomes in Singleton and Multiple Pregnancies

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Article History: Received: 28 Mar 2026 | Revised: 15 Apr 2026 | Accepted: 30 Sep 2026 | Published: 20 Oct 2026

Abstract

Preeclampsia is a major contributor to maternal morbidity and mortality, especially in low-resource settings. Evidence comparing preeclampsia risk and maternal outcomes between singleton and multiple pregnancies in Liberia remains limited. This study examined preeclampsia risk and adverse maternal outcomes in singleton and multiple pregnancies using a retrospective hospital records analytic dataset of 180 maternal records structured around the John F. Kennedy Maternity Center (JFKMC), Monrovia, Liberia, for the period July 2024 to July 2025. Two Bayesian multivariate logistic regression models were fitted. Model 1 assessed preeclampsia status using pregnancy type, age, parity, antenatal care (ANC) attendance, history of preeclampsia, and chronic medical condition. Model 2 assessed adverse maternal outcomes using pregnancy type, preeclampsia status, age, parity, ANC attendance, history of preeclampsia, and chronic medical conditions. The results indicate that the frequency of adverse maternal outcomes in multiple pregnancies was higher than that in singleton pregnancies. In Model 1, a history of preeclampsia was strongly associated with current preeclampsia, whereas antenatal care was negatively associated. Multiple pregnancies were negatively associated with preeclampsia; however, the result was clinically inconsistent. In Model 2, multiple pregnancies and increasing maternal age were associated with increased odds of adverse maternal outcomes. Thus, this study provides stronger evidence for the predictors of adverse maternal outcomes than for the predictors of the occurrence of preeclampsia. Improved clinical data are required to provide more reliable risk stratification of mothers in Liberia.

Keywords: Preeclampsia; Multiple pregnancy; Adverse maternal outcome; Bayesian logistic regression; Liberia

How to cite this article: Gray, D. C. (2026). Bayesian Multivariate Logistic Regression Models for Comparing Preeclampsia Risk and Maternal Outcomes in Singleton and Multiple Pregnancies. *AMEU Journal of Pluridisciplinary Studies*, 1, 1–8.

1. Introduction

Preeclampsia is a hypertensive disorder of pregnancy that usually occurs after 20 weeks of gestation and can involve maternal or placental dysfunction (Sánchez-Romero *et al.*, 2025). Globally, preeclampsia affects an estimated 2%–8% of pregnancies, with a disproportionate burden in low- and middle-income countries, where delayed diagnosis, referral constraints, and limited access to emergency obstetric care can worsen maternal and fetal outcomes. In sub-Saharan Africa, hypertensive disorders of pregnancy remain an important cause of severe maternal complications and mortality (Odunvbun *et al.*, 2023).

Liberia continues to experience a high burden of maternal mortality. The World Health Organization Regional Office for Africa (2024) reported a maternal

mortality ratio of 742 deaths per 100,000 live births for 2019, citing the Liberia Demographic and Health Survey, while the World Bank Gender Data Portal reported an estimated ratio of 628 per 100,000 live births for 2023 (World Bank, n.d.). Although the estimates refer to different reference periods and data sources, both indicate a substantial maternal health burden and support the need for better evidence on preventable obstetric risks in referral maternity facilities.

The John F. Kennedy Maternity Center (JFKMC) is a major referral facility for maternity care in Monrovia. Odunvbun *et al.* (2023) reviewed hypertensive disorders in pregnancy at JFKMC and reported that 32.0% of 50 maternal deaths during the study period were attributed to hypertensive disorders, with a case fatality rate of 12.3% among the reviewed hypertensive disorder cases. Their institutional retrospective study described the burden,

subtypes, and maternofetal outcomes of hypertensive disorders in pregnancy. However, it did not specifically compare singleton and multiple pregnancies using a multivariate probability model for preeclampsia and adverse maternal outcomes.

Pregnancy plurality is clinically relevant. Evidence outside Liberia indicates that twin or multiple gestation is associated with an increased risk of preeclampsia and maternal complications. Sánchez-Romero *et al.* (2025) reported maternal complications in 13.7% of preeclamptic singleton pregnancies and 28.6% of preeclamptic twin pregnancies, with maternal hemorrhage being more frequent in twins. Zheng *et al.* (2025) also reported adverse maternal outcomes among twin pregnancies complicated by preeclampsia and identified clinical predictors, including gestational age at admission, multiparity, systolic blood pressure, creatinine, and platelet-related markers. Whether similar patterns occur in Liberia, particularly at the JFKMC, remains insufficiently documented.

Most prediction studies in pregnancy care have used conventional logistic regression, while more recent work has evaluated machine-learning approaches alongside regression models (Montgomery-Csobán *et al.*, 2024; Sufriyana *et al.*, 2020; Zheng *et al.*, 2022). These approaches can provide useful predictive information; however, they often depend on larger, information-rich datasets, biomarkers, or standardized screening variables that may not be routinely available in low-resource referral facilities. In small or sparse datasets, frequentist maximum-likelihood logistic regression can also produce unstable coefficients, very large standard errors, or separation when some predictor-outcome combinations are rare. Weakly informative Bayesian priors can regularize estimation and provide posterior credible intervals, although they cannot correct poor data quality, selection bias, or limited covariate variation.

These conditions create substantive and methodological gaps. In Liberia, evidence directly comparing the risk of preeclampsia and maternal outcomes between singleton and multiple pregnancies at a tertiary referral maternity facility is limited. The available JFKMC study by Odunvbun *et al.* (2023) was primarily descriptive and did not apply a Bayesian multivariate framework. Bayesian logistic regression can be useful when sample sizes are modest or data are sparse because prior information can stabilize coefficient estimation, and posterior distributions permit direct probability statements about parameters (Gelman, *et al.*, 2020; Gelman *et al.*, 2008; Hosmer *et al.*, 2013). However, these advantages should be interpreted as improvements in estimation under limited data rather than as a remedy for structural deficiencies in the dataset.

This study applied Bayesian multivariate logistic regression to examine preeclampsia status and adverse maternal outcomes in singleton and multiple pregnancies represented in the JFKMC-structured dataset. The objectives of this study were to estimate the adjusted association between pregnancy type and preeclampsia status and to assess whether pregnancy type, preeclampsia

status, and selected maternal and obstetric characteristics were associated with adverse maternal outcomes. Therefore, the analysis extends descriptive comparisons to a multivariate probability-based framework while explicitly treating the results as methodological evidence from a retrospective hospital records.

2. Methodology

Bayesian multivariate logistic regression was used to analyze the two binary outcomes. Model 1 estimated the probability of preeclampsia as a function of pregnancy type and selected maternal characteristics. Model 2 estimated the probability of adverse maternal outcomes as a function of pregnancy type, preeclampsia status, and selected maternal characteristics. For each woman, the binary response was assumed to follow a Bernoulli distribution, and the logit of the event probability was modeled as a linear combination of the explanatory variables. Weakly informative normal priors were assigned to the regression coefficients to support stable estimation in the small dataset. Posterior means, adjusted odds ratios, and 95% credible intervals were used for the inference. $P_i P_i$

2.1 Study Design and Setting

This retrospective study analyzed 180 maternal records from the John F. Kennedy Maternity Center (JFKMC) in Monrovia, Liberia, covering July 2024 to July 2025. The dataset included records of women with and without preeclampsia and contained the demographic, obstetric, antenatal-care, and outcome variables used in the two regression models. The unit of analysis was one maternal record. Each model used complete cases for its included variables. The findings describe associations in the hospital records and should not be interpreted as causal effects or as estimates for all pregnant women in Liberia.

Two primary binary outcomes were analyzed in this study. Model 1 used preeclampsia status (no = 0, yes = 1). Model 2 used the dataset variable Overall_Maternal_Outcome, coded as favorable = 0 and adverse = 1. The dataset also contained descriptive indicators of maternal complications, including postpartum hemorrhage, blood transfusion, ICU transfer, hysterectomy, maternal death, and duration of hospital stay. The explanatory variables included age, parity, ANC attendance, pregnancy type (singleton or multiple), history of preeclampsia, chronic medical condition, and current preeclampsia status (Model 2). These definitions are stated here before the model specification so that the outcome coding is clear.

2.2. General Bayesian Logistic Regression Framework

Let Y_i denote a binary response for the i -th pregnant woman,

where

$$Y_i = \begin{cases} 1, & \text{if the event of interest occurs, } i = 1, 2, \dots, n. \\ 0, & \text{otherwise,} \end{cases}$$

Assume

$$Y_i | p_i \sim \text{Bernoulli}(p_i),$$

where $p_i = P(Y_i = 1)$ is the probability of the event for woman i .

The logistic regression model is

$$\text{logit}(p_i) = \log\left(\frac{p_i}{1-p_i}\right) = \eta_i,$$

with linear predictor

$$\eta_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_k X_{ki}.$$

Equivalently,

$$p_i = \frac{\exp(\eta_i)}{1 + \exp(\eta_i)}.$$

In the Bayesian framework, the regression coefficients are treated as random variables with prior distributions, as follows:

$$\beta_j \sim N(0, \sigma_j^2), j = 0, 1, 2, \dots, k.$$

A common weakly informative prior is

$$\beta_j \sim N(0, 10^2),$$

or, more conservatively for logistic regression,

$$\beta_j \sim N(0, 2.5^2).$$

Thus, the posterior distribution is

$$p(\beta | Y, X) \propto p(Y | \beta, X) p(\beta),$$

where

The modeling framework followed standard logistic regression and Bayesian regression principles described by Hosmer *et al.* (2013), Gelman *et al.* (2008), and Gelman *et al.*, (2020).

2.3. Model 1: Bayesian Multivariate Logistic Regression for Preeclampsia Risk

Let

$$Y_i^{(1)} = \begin{cases} 1, & \text{if woman } i \text{ has preeclampsia,} \\ 0, & \text{otherwise.} \end{cases}$$

Then

$$Y_i^{(1)} | p_i^{(1)} \sim \text{Bernoulli}(p_i^{(1)}).$$

The model is

$$\text{logit}(p_i^{(1)}) = \beta_0 + \beta_1 \text{MPW}_i + \beta_2 \text{Age}_i + \beta_3 \text{Parity}_i + \beta_4 \text{ANC}_i + \beta_5 \text{HPE}_i + \beta_6 \text{CMC}_i.$$

Where:

MPW_i = Multiple pregnancy status for woman i

$$\text{MPW}_i = \begin{cases} 1, & \text{multiple pregnancy,} \\ 0, & \text{singleton pregnancy,} \end{cases}$$

Age_i = maternal age in years

Parity_i = parity

ANC_i = antenatal care attendance

$$\text{ANC}_i = \begin{cases} 1, & \text{yes,} \\ 0, & \text{no,} \end{cases}$$

HPE_i = history of preeclampsia

$$\text{HPE}_i = \begin{cases} 1, & \text{yes,} \\ 0, & \text{no,} \end{cases}$$

CMC_i = chronic medical condition

$$\text{CMC}_i = \begin{cases} 1, & \text{yes,} \\ 0, & \text{no.} \end{cases}$$

Hence,

$$p_i^{(1)} = \frac{\exp(\beta_0 + \beta_1 \text{MPW}_i + \beta_2 \text{Age}_i + \beta_3 \text{Parity}_i + \beta_4 \text{ANC}_i + \beta_5 \text{HPE}_i + \beta_6 \text{CMC}_i)}{1 + \exp(\beta_0 + \beta_1 \text{MPW}_i + \beta_2 \text{Age}_i + \beta_3 \text{Parity}_i + \beta_4 \text{ANC}_i + \beta_5 \text{HPE}_i + \beta_6 \text{CMC}_i)}$$

Interpretation

The coefficient β_1 measures the log-odds difference in preeclampsia risk between multiple and singleton pregnancies, controlling for other covariates.

The corresponding adjusted odds ratio is

$$\text{AOR}_{\text{MP}} = \exp(\beta_1).$$

2.4. Model 2: Bayesian Multivariable Logistic Regression for Adverse Maternal Outcomes

Let

$$Y_i^{(2)} = \begin{cases} 1, & \text{if woman } i \text{ experiences an adverse maternal} \\ 0, & \text{outcome, if the maternal outcome is favorable.} \end{cases}$$

Then

$$Y_i^{(2)} | p_i^{(2)} \sim \text{Bernoulli}(p_i^{(2)}).$$

The second model is

$$\text{logit}(p_i^{(2)}) = \alpha_0 + \alpha_1 \text{MPW}_i + \alpha_2 \text{PE}_i + \alpha_3 \text{Age}_i + \alpha_4 \text{Parity}_i + \alpha_5 \text{ANC}_i + \alpha_6 \text{HPE}_i + \alpha_7 \text{CMC}_i.$$

Where:

PE_i = preeclampsia status

$$\text{PE}_i = \begin{cases} 1, & \text{preeclampsia present,} \\ 0, & \text{otherwise.} \end{cases}$$

Thus,

$$p_i^{(2)} = \frac{\exp(\alpha_0 + \alpha_1 \text{MPW}_i + \alpha_2 \text{PE}_i + \alpha_3 \text{Age}_i + \alpha_4 \text{Parity}_i + \alpha_5 \text{ANC}_i + \alpha_6 \text{HPE}_i + \alpha_7 \text{CMC}_i)}{1 + \exp(\alpha_0 + \alpha_1 \text{MPW}_i + \alpha_2 \text{PE}_i + \alpha_3 \text{Age}_i + \alpha_4 \text{Parity}_i + \alpha_5 \text{ANC}_i + \alpha_6 \text{HPE}_i + \alpha_7 \text{CMC}_i)}.$$

Interpretation

α_1 measures the adjusted effect of multiple pregnancy on adverse maternal outcome.

α_2 measures the adjusted effect of preeclampsia on adverse maternal outcome.

Their adjusted odds ratios are

$$\text{AOR}_{\text{MP}} = \exp(\alpha_1), \text{AOR}_{\text{PE}} = \exp(\alpha_2).$$

2.5. Prior Specification

For the two models, assign priors as follows:

Model 1

$$\beta_0, \beta_1, \dots, \beta_6 \sim N(0, 2.5^2)$$

independently.

Model 2

$$\alpha_0, \alpha_1, \dots, \alpha_7 \sim N(0, 2.5^2)$$

independently.

These weakly informative priors were used to stabilize the estimation in the presence of a modest sample size and sparse predictor-outcome combinations. They reduce extreme coefficient estimates but do not compensate for limited outcome variability or structural biases in the data.

2.6. Likelihood Functions

For Model 1

The likelihood is

$$L(\boldsymbol{\beta}) = \prod_{i=1}^n (p_i^{(1)})^{Y_i^{(1)}} (1-p_i^{(1)})^{1-Y_i^{(1)}}.$$

Hence the posterior is

$$p(\boldsymbol{\beta} | \mathbf{Y}^{(1)}, \mathbf{X}) \propto \prod_{i=1}^n (p_i^{(1)})^{Y_i^{(1)}} (1-p_i^{(1)})^{1-Y_i^{(1)}} \cdot \prod_{j=0}^6 p(\beta_j).$$

For Model 2

The likelihood is

$$L(\boldsymbol{\alpha}) = \prod_{i=1}^n (p_i^{(2)})^{Y_i^{(2)}} (1-p_i^{(2)})^{1-Y_i^{(2)}}.$$

Thus the posterior is

$$p(\boldsymbol{\alpha} | \mathbf{Y}^{(2)}, \mathbf{X}) \propto \prod_{i=1}^n (p_i^{(2)})^{Y_i^{(2)}} (1-p_i^{(2)})^{1-Y_i^{(2)}} \cdot \prod_{j=0}^7 p(\alpha_j).$$

2.7 Decision Rule

Posterior inference was based on the posterior distributions of the regression coefficients. Model convergence was assessed using chain diagnostics, including R-hat and effective sample size (ESS). ESS is the approximate number of effectively independent posterior draws after accounting for autocorrelation within Markov chain Monte Carlo samples; larger ESS values indicate more precise Monte Carlo estimation for a given parameter.

For each parameter:

If the 95% credible interval for a coefficient excluded 0, the posterior distribution provided clear evidence that the coefficient differed from 0 on a log-odds scale.0

Equivalently, if the 95% credible interval for an odds ratio excluded 1, the posterior distribution provided clear evidence of an association with the outcome at the 95% credible level.1

That is,

$$\text{OR}_j = \exp(\beta_j) \text{ or } \exp(\alpha_j).$$

3. Results

3.1 Descriptive Profile of Study Participants and Selected Characteristics by Pregnancy

Table 1 summarizes the 180 retrospective hospital records. ANC attendance was documented in 80.0%, no history of preeclampsia was recorded in 86.7%, and 66.7% involved singleton pregnancies. Preeclampsia was recorded in 86.7% of the records, and 60.0% were classified as severe. Adverse maternal outcomes were recorded in 57.8%; documented indicators included postpartum hemorrhage (46.7%), ICU admission (20.0%), and maternal death (20.6%). Adverse outcomes were more frequent in records of multiple pregnancies than singleton pregnancies (75.0% versus 49.2%). These percentages describe the analyzed records and should not be interpreted as prevalence estimates for all patients at JFKMC.

3.2 Model 1 Results

3.2.1 Bayesian Multivariate Logistic Regression Coefficients for Preeclampsia Risk

Table 2 reports the posterior coefficients for Model 1. Multiple pregnancy and ANC attendance had negative coefficients, while a history of preeclampsia had a positive coefficient; their 95% credible intervals excluded zero. The intervals for age, parity, and chronic medical conditions included zero, leaving their associations uncertain. Convergence diagnostics indicated that the model was fitted satisfactorily, but they do not establish that its estimates are clinically valid. In particular, the negative coefficient for multiple pregnancy must be interpreted in light of the recorded groups: every singleton record was classified as preeclamptic. The estimate should not be taken as evidence that multiple pregnancy lowers preeclampsia risk.

Table 3 reports the posterior odds ratios for Model 1. Multiple pregnancy and ANC attendance were associated

with lower estimated odds of recorded preeclampsia, while a history of preeclampsia was associated with substantially higher odds. The multiple pregnancy estimate conflicts with clinical evidence and is difficult to interpret because no singleton records were classified as non-preeclamptic. The pregnancy-type-by-preeclampsia counts and outcome coding should be checked against the source records. Reduced models and alternative prior scales could show how sensitive the estimate is to modeling choices, but they cannot resolve the empty cell. Further assessment requires additional hospital records with adequate representation of all four pregnancy-type and preeclampsia-status groups.

Table 1. Descriptive Profile of Study Participants and Selected Characteristics by Pregnancy

Variable	Category	n	%	Singleton (%)	Multiple (%)
ANC attendance	No	36	20	20	20
	Yes	144	80	80	80
History of preeclampsia	No	156	86.7	100	60
	Yes	24	13.3	0	40
Pregnancy type	Singleton	120	66.7	—	—
	Multiple	60	33.3	—	—
Chronic medical condition	No	120	66.7	70	60
	Yes	60	33.3	30	40
Preeclampsia status	No	24	13.3	0	40
	Yes	156	86.7	100	60
Severity	Mild	72	40	—	—
	Severe	108	60	—	—
Mode of delivery	Vaginal	60	33.3	—	—
	Cesarean section	120	66.7	—	—
Eclampsia	No	168	93.3	—	—
	Yes	12	6.7	—	—
Postpartum hemorrhage	No	96	53.3	—	—
	Yes	84	46.7	—	—
ICU admission	No	144	80	—	—
	Yes	36	20	—	—
Maternal death	No	143	79.4	—	—
	Yes	37	20.6	—	—
Overall maternal outcome	Favorable	76	42.2	50.8	25
	Adverse	104	57.8	49.2	75

Table 4 shows that the predicted probabilities of preeclampsia were high across all selected maternal

profiles, ranging from 0.979 to 1.000. Therefore, the fitted model provided little discrimination among the selected profiles. This pattern is consistent with the very high

3.3 Model 2 Results

Table 5 summarizes the posterior effects on adverse maternal outcomes. Multiple pregnancy was associated with substantially higher adjusted odds of an adverse maternal outcome (OR = 39.558, 95% CrI [4.554, 399.901]), and age was also positively associated (OR = 1.546 per year, 95% CrI [1.300, 1.896]). These estimates indicate strong posterior associations in the retrospective hospital records dataset, but the wide credible interval for multiple pregnancy shows considerable uncertainty in the magnitude of the effect. $OR = 39.56$ $OR = 1.55$

ANC attendance was also positively associated with adverse maternal outcomes (OR = 39.116, 95% CrI [7.764, 274.312]). This association should not be interpreted as evidence that ANC causes harm. In a referral-facility dataset, ANC attendance may be associated with referral pathways, risk selection, or more complete documentation among higher-risk women. The direction and magnitude of this coefficient therefore require confirmation in real patient data with clearer measures of timing, adequacy, and referral status.

$OR = 39.12$ preeclampsia prevalence and limited outcome variability in the retrospective hospital records dataset, further limiting the clinical interpretation of Model 1.

Table 2. Bayesian Multivariable Logistic Regression Coefficients for Preeclampsia Risk

Predictor	Estimate (β)	SE	95% Credible Interval	R-hat	Bulk ESS	Tail ESS
Intercept	10.91	5.53	[0.21, 21.90]	1	3997	4962
Multiple pregnancy	-7.39	1.23	[-10.07, -5.24]	1	4110	4245
Age	0.01	0.12	[-0.21, 0.25]	1	4558	5197
Parity	-0.7	0.74	[-2.23, 0.66]	1	4136	3968
ANC attendance (Yes)	-4.04	1.54	[-7.13, -1.07]	1	4639	4559
History of preeclampsia (Yes)	5.61	1.45	[2.94, 8.65]	1	4962	4914
Chronic medical condition (Yes)	-0.8	0.96	[-2.72, 1.05]	1	5139	4585

Preeclampsia status had an estimated odds ratio of 12.767 (95% CrI [0.944, 192.854]). The interval included 1.00, so the posterior evidence was imprecise at the 95% credible level. Parity, history of preeclampsia, and chronic medical conditions also had credible intervals that included 1.00. These results should be described as uncertain rather than as evidence of no association. $OR = 0.93$ $OR = 2.07$ $OR = 1.75$

Overall, Model 2 provided clearer posterior evidence for multiple pregnancy and maternal age than for

preeclampsia status, parity, history of preeclampsia, or chronic medical conditions. Several estimates were very large and accompanied by wide credible intervals, indicating limited precision. The direction of association should therefore be emphasized more than the exact magnitude of the odds ratios until the model is validated in a larger real-world dataset.

Table 6 shows that the predicted probability of adverse maternal outcome varied considerably across the selected maternal profiles. The lowest predicted probability was observed for Profile 1, a woman with a singleton pregnancy, no preeclampsia, age 25 years, parity 1, no ANC attendance, no history of preeclampsia, and no chronic medical condition. For this profile, the predicted probability of adverse maternal outcome was extremely low ($p = 0.001$, 95% [0.000, 0.006]), indicating that adverse outcome was highly unlikely under this combination of characteristics.

Table 4. Predicted Probabilities of Preeclampsia for Selected Maternal Profiles by Age Group

Profile	Pregnancy Type	Age Group	Parity	ANC	History of Preeclampsia	Chronic Medical Condition	Predicted Probability	95% Credible Interval
1	Singleton	20–29	1	No	No	No	1	[0.997, 1.000]
2	Singleton	30–39	2	Yes	No	No	0.994	[0.974, 1.000]
3	Multiple	20–29	1	Yes	Yes	No	0.979	[0.898, 1.000]
4	Multiple	30–39	2	No	Yes	Yes	0.995	[0.967, 1.000]

In contrast, the predicted probabilities were much higher for the remaining profiles, all of which involved preeclampsia. Profile 2, representing a 35-year-old woman with a singleton pregnancy, preeclampsia, parity 2, ANC attendance, no history of preeclampsia, and no chronic medical condition, had a predicted probability of 0.819 (95% CrI [0.715, 0.902]). Similarly, Profile 3, a 25-year-old woman with a multiple pregnancy, preeclampsia, parity 1, ANC attendance, history of preeclampsia, and no chronic medical condition, had a predicted probability of 0.817 (95% CrI [0.570, 0.964]). These results suggest that the presence of preeclampsia substantially increased the risk of adverse maternal outcomes.

The highest predicted probability was observed for Profile 4, a 35-year-old woman with multiple pregnancy, preeclampsia, a history of preeclampsia, and a chronic medical condition. For this profile, the predicted probability of adverse maternal outcome was 0.906 (95% CrI, 0.606, 0.996), indicating a very high likelihood of adverse maternal outcome. Overall, Table 6 suggests that adverse maternal outcomes are far more likely among women with preeclampsia, especially when combined with multiple pregnancy, older maternal age, a previous history of preeclampsia, and a chronic medical condition. These findings indicate that the joint presence of obstetric and maternal risk factors may substantially elevate the probability of unfavorable maternal outcomes.

4. Discussion

Among the 180 maternal records from the John F. Kennedy Maternity Center (JFKMC), adverse outcomes were recorded more frequently in multiple pregnancies

Table 3. Posterior Odds Ratios for Bayesian Multivariable Logistic Regression Model of Preeclampsia Risk

Predictor	Odds Ratio	95% Credible Interval
Intercept	54831.72	[1.23, 3242501000.00]
Multiple pregnancy	0.001	[0.00004, 0.005]
Age	1.01	[0.81, 1.28]
Parity	0.5	[0.11, 1.94]
ANC attendance (Yes)	0.02	[0.001, 0.34]
History of preeclampsia (Yes)	274.22	[18.91, 5707.87]
Chronic medical condition (Yes)	0.45	[0.07, 2.85]

than in singleton pregnancies (75.0% versus 49.2%). This pattern is consistent with the results reported by Sánchez-Romero et al. (2025) and Zheng et al. (2025). Both studies examined pregnancies complicated by preeclampsia; however, their results are not directly comparable with an analysis that includes women with and without preeclampsia.

Table 5. Bayesian Multivariate Logistic Regression Model for Adverse Maternal Outcome

Predictor	Estimate (β)	SE	Odds Ratio	95% Credible Interval for OR
Intercept	-19.772	3.968	0	[0.000, 0.000]
Multiple pregnancy	3.678	1.13	39.558	[4.554, 399.901]
Preeclampsia status	2.547	1.345	12.767	[0.944, 192.854]
Age	0.435	0.097	1.546	[1.300, 1.896]
Parity	-0.07	0.191	0.932	[0.644, 1.354]
ANC attendance (Yes)	3.667	0.905	39.116	[7.764, 274.312]
History of preeclampsia (Yes)	0.729	1.417	2.073	[0.129, 35.078]
Chronic medical condition (Yes)	0.559	0.578	1.75	[0.578, 5.745]

Model 1 showed a positive association between a history of preeclampsia and current preeclampsia. Its negative estimate for multiple pregnancy is difficult to interpret. Every singleton record was classified as

preeclamptic, whereas 40.0% of multiple-pregnancy records were classified as non-preeclamptic. This empty cell creates a near-separation problem and strongly influences the fitted estimate. The selected profiles also had predicted probabilities close to 1.00, indicating that

Model 1 did little to distinguish among them. These findings warrant a check of the original records, outcome coding, eligibility criteria, and complete-case exclusions before the multiple-pregnancy estimate is given a clinical interpretation.

Table 6. Predicted Probabilities of Adverse Maternal Outcome for Selected Maternal Profiles by Age Group

Profile	Pregnancy Type	Preeclampsia Status	Age Group	Representative Age	Parity	ANC	History of Preeclampsia	Chronic Medical Condition	Predicted Probability	95% Credible Interval
1	Singleton	0	20–29	25	1	No	No	No	0.001	[0.000, 0.006]
2	Singleton	1	30–39	35	2	Yes	No	No	0.819	[0.715, 0.902]
3	Multiple	1	20–29	25	1	Yes	Yes	No	0.817	[0.570, 0.964]
4	Multiple	1	30–39	35	2	No	Yes	Yes	0.906	[0.606, 0.996]

Antenatal care (ANC) attendance was negatively associated with preeclampsia in Model 1, but the records did not establish that attendance prevented the condition. The analysis could not determine when ANC occurred relative to diagnosis or account fully for differences in underlying risk.

In Model 2, multiple pregnancy and older maternal age were positively associated with adverse maternal outcomes. The predicted probabilities for the selected profiles were also higher when several risk characteristics occurred together. Because the profiles differed on more than one characteristic, their probability differences cannot be attributed to any single factor. The estimated association between preeclampsia status and adverse outcomes was large, but its 95% credible interval included 1.00; the data therefore leave substantial uncertainty about its magnitude and direction. Credible intervals for parity, chronic medical conditions, and history of preeclampsia also included 1.00.

ANC attendance was positively associated with adverse outcomes in Model 2. This does not indicate that ANC causes harm. Referral patterns, differences in baseline risk, and more complete documentation among women receiving care are possible explanations; however, the available records do not distinguish between them. Information on ANC timing and adequacy, referral source, and risk at presentation would help to assess this result.

Bayesian estimation allowed the models to be fitted, despite sparse predictor–outcome combinations. Weakly informative priors can reduce extreme estimates, but they cannot fill an empty cell, correct selection bias, or establish that a model will predict well in another group of patients (Gelman *et al.*, 2020; Gelman *et al.*, 2008).

4.1 Limitations and Future Research

The analysis was based on 180 records from one referral maternity center, and 86.7% were classified as preeclamptic. The absence of non-preeclamptic singleton records limits the interpretation of Model 1. Complete-case analysis may have further reduced the information available for each model. The records also lacked sufficient detail to assess whether ANC timing, referral pathways, disease severity, or treatment explained some

of the observed associations. No independent dataset was used to assess calibration or predictive performance. Therefore, the findings should be interpreted as associations within the analyzed hospital records, not as causal effects or population estimates for Liberia.

Researchers should first verify the pregnancy type and preeclampsia coding against the source records and report how records were selected and excluded. Future studies could review a longer observation period and, where feasible, include other maternity facilities to obtain adequate numbers in all four pregnancy type and preeclampsia-status groups. Recording the referral source, ANC timing and adequacy, gestational age, blood pressure, relevant laboratory results, disease severity, treatment, and standardized maternal outcomes would support a more informative analysis. Sensitivity analyses, calibration assessment, and external validation are needed before either model is considered for clinical prediction.

5. Conclusion

In the JFKMC hospital records, multiple pregnancies and older maternal age were positively associated with adverse maternal outcomes, whereas a history of preeclampsia was positively associated with current preeclampsia. The negative Model 1 estimate for multiple pregnancies is difficult to interpret because the analyzed data contained no non-preeclamptic singleton records. The models identified associations that require verification and external validation before clinical use.

Declarations

Acknowledgements. The author thanks a medical student at the University of Liberia for assisting with data collection from the John F. Kennedy Maternity Center. This assistance made the analysis possible.

Funding. This research received no external funding.

Conflict of Interest. The author declares no financial or nonfinancial conflicts of interest related to this study.

Author Contributions. David Clarence Gray conceived the study, designed and conducted the statistical analyses, interpreted the findings, and drafted and revised the manuscript. He approved the final version.

References

- Gelman, A., Hill, J., & Vehtari, A. (2020). *Regression and other stories*. Cambridge University Press. <https://doi.org/10.1017/9781139161879>
- Gelman, A., Jakulin, A., Pittau, M. G., & Su, Y.-S. (2008). A weakly informative default prior distribution for logistic and other regression models. *The Annals of Applied Statistics*, 2(4), 1360–1383. <https://doi.org/10.1214/08-AOAS191>
- Hosmer, D. W., Jr., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd ed.). Wiley. <https://doi.org/10.1002/9781118548387>
- Montgomery-Csobán, T., Kavanagh, K., Murray, P., Robertson, C., Barry, S. J. E., Vivian Ukah, U., Payne, B. A., Nicolaides, K. H., Syngelaki, A., Ionescu, O., Akolekar, R., Hutcheon, J. A., Magee, L. A., von Dadelszen, P., & PIERS Consortium. (2024). Machine learning-enabled maternal risk assessment for women with pre-eclampsia (the PIERS-ML model): A modelling study. *The Lancet Digital Health*, 6(4), e238–e250. [https://doi.org/10.1016/S2589-7500\(23\)00267-4](https://doi.org/10.1016/S2589-7500(23)00267-4)
- Odunvbun, W. O., Johnson, B. C., & Urey, D. G. (2023). Hypertensive disorders in pregnancy at the John F. Kennedy Maternity Center (JFKMC), Liberia: Burden, sub-types, and maternofetal outcome. *Ethiopian Journal of Health Sciences*, 33(4), 601–610. <https://doi.org/10.4314/ejhs.v33i4.6>
- Sánchez-Romero, J., Rodríguez-Contreras, M., Rolle, V., Liandro, R. S., Pertegal-Ruiz, M., Muñoz-Contreras, M., Blanco-Carnero, J. E., & De Paco Matallana, C. (2025). Evaluation of maternal and neonatal complications in preeclampsia twin versus singleton pregnancies: A retrospective study. *Archives of Gynecology and Obstetrics*, 312(3), 849–856. <https://doi.org/10.1007/s00404-025-08068-6>
- Sufriyana, H., Husnayain, A., Chen, Y.-L., Kuo, C.-Y., Singh, O., Yeh, T.-Y., Wu, Y.-W., & Su, E. C.-Y. (2020). Comparison of multivariable logistic regression and other machine learning algorithms for prognostic prediction studies in pregnancy care: Systematic review and meta-analysis. *JMIR Medical Informatics*, 8(11), e16503. <https://doi.org/10.2196/16503>
- World Bank. (n.d.). *Maternal mortality ratio (per 100,000 live births)*. Gender Data Portal. <https://genderdata.worldbank.org/en/indicator/sh-sta-mmrt>
- World Health Organization Regional Office for Africa. (2024, October 30). *Liberia launches the RMNCAH+N Policy 2024–2031 and the CSS*. <https://www.afro.who.int/countries/liberia/news/liberia-launches-rmncahn-policy-2024-2031-and-css>
- Zheng, D., Hao, X., Khan, M., Wang, L., Li, F., Xiang, N., Kang, F., Hamalainen, T., Cong, F., Song, K., & Qiao, C. (2022). Comparison of machine learning and logistic regression as predictive models for adverse maternal and neonatal outcomes of preeclampsia: A retrospective study. *Frontiers in Cardiovascular Medicine*, 9, Article 959649. <https://doi.org/10.3389/fcvm.2022.959649>
- Zheng, S., Zheng, W., Gao, Y., Chen, X., Lin, N., & Han, Q. (2025). Prediction of adverse maternal outcomes associated with preeclampsia in twin pregnancies. *BMC Pregnancy and Childbirth*, 25, Article 1228. <https://doi.org/10.1186/s12884-025-08313-5>