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Method Article

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A Biopsychosocial Machine Learning Framework for Predicting Mode of Delivery and Exploring Secondary Infertility Risk

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Abstract

Background

Caesarean section (CS) rates continue to exceed the WHO-recommended threshold of 10-15%, with a global weighted mean of 21.1%. Existing prediction models rarely integrate clinical and psychosocial determinants within a unified, interpretable architecture. The relationship between childbirth experiences and subsequent secondary infertility (SI) remains insufficiently explored.

Methods

A proof-of-concept explainable machine learning (ML) framework was developed on a synthetic, literature-parameterized dataset (131 studies, 2002-2026). A dual-stage CS model separating antepartum (n = 1,164; 27 features) and intrapartum (n = 1,836; **40 features**) decision points was constructed using Gradient Boosted Decision Trees, calibrated to target rates of 21.1% and 29.0%. An exploratory SI model (n = 4,000; LightGBM; target prevalence 12.0%) was additionally developed. Model interpretability was assessed using Shapley additive explanations (SHAP).

Results

Within the simulation environment, the antepartum and intrapartum CS models achieved area under the receiver operating characteristic curve (AUC-ROC) values of 0.638 and 0.731 in the reference simulation run. To assess the stability of this comparison, the complete pipeline was repeated across 30 independent simulation replicates with fixed model hyperparameters; the intrapartum model outperformed the antepartum model in 29/30 replicates (mean Δ AUC = +0.093, 95% CI (0.016, 0.204)). At Youden-optimal thresholds of 43.7% and 41.1%, negative predictive values (NPVs) were 86.8% and 85.8% (indicating reliable rule-out capacity) while unnecessary alert rates were 66.2% and 54.6%, reflecting the precision limits of probabilistic screening. The exploratory SI model achieved an AUC-ROC of 0.777; at a threshold of 12.1%, NPV was 95.6% and positive predictive value (PPV) was 0.250, consistent with low-prevalence outcome prediction. SHAP analyses confirmed that fear of childbirth (FOC), birth trauma, depressive symptoms, and supportive care contributed measurable predictive weight alongside clinical variables.

Conclusions

This framework demonstrates that temporally stratified integration of biopsychosocial predictors within an interpretable, multi-outcome architecture is methodologically feasible. All findings reflect properties of the simulation and require prospective validation in real-world populations before any clinical application can be considered.

Keyword: Caesarean section; vaginal birth; secondary infertility; synthetic data; machine learning; explainable artificial intelligence; biopsychosocial model; fear of childbirth; birth trauma; doula support; Asherman syndrome; VBAC; proof-of-concept

1 Introduction

The mode of delivery represents a critical clinical decision with immediate and long-term implications for both maternal and neonatal outcomes. The selection between vaginal delivery and cesarean section (CS) extends beyond a purely physiological event into a complex, multidimensional decision-making process [1]. CS is performed by surgical incision of the abdomen and uterus [2], when the health or life of the mother or baby is at risk [3]; however, its global prevalence has risen far beyond medically justified levels. The WHO recommends that CS should account for 10-15% of all deliveries [4], yet this threshold is consistently exceeded across numerous settings with rates reaching 32% in above-average income countries [5], and exceeding 50% in parts of the developing world [6]. This growing discrepancy between evidence-based recommendations and real-world clinical practice represents a substantive public health concern [7], and underscores the need for more effective, evidence-informed counseling frameworks at the point of antenatal decision-making.

Delivery mode decisions are shaped by a heterogeneous combination of clinical, psychological, and contextual factors that are rarely considered together in existing models. On the clinical side, established predictors of CS include parity, maternal age, body mass index (BMI), prior CS history, fetal presentation, gestational age, induction of labor (IOL), and cervical status [8]. On the psychosocial side, fear of childbirth (FOC), anxiety, perceived pain, prior birth trauma, and availability of continuous supportive care have emerged as equally important (yet frequently overlooked) determinants of delivery mode and maternal experience [9-18]. Public information-seeking behavior reflects this complexity: common queries focus on labor pain, safety, duration, and comparisons between delivery methods [19], highlighting the uncertainty and anxiety that many women experience in the antenatal period. Despite the breadth of evidence on both domains, clinical and psychosocial determinants of delivery mode

are typically studied in isolation, limiting their combined applicability in real-world counseling [20]. Accordingly, there remains a need for frameworks capable of integrating these diverse determinants within a unified decision-support approach.

ML has emerged as a potentially useful approach for integrating heterogeneous clinical and psychosocial predictors and exploring complex interactions among obstetric risk factors. Owusu FO et al. (2025)[21] demonstrated that ML models can effectively identify pregnant women at increased risk of CS, supporting early intervention and informing maternal healthcare policy. Zimmerman RM et al. (2025)[22] further showed that an explainable probabilistic graphical model can uncover previously unrecognized high-risk clinical profiles by modeling the interaction of multiple clinical variables in fetal growth restriction. These developments suggest that interpretable, multi-predictor ML architectures may have potential utility for supporting evidence-informed decision-making in maternity care.

To address the gap between the available evidence and its integration into delivery counseling practice, the present study proposes an evidence-synthesized, explainable ML framework combining biopsychosocial and supportive factors within a proof-of-concept simulation environment. The primary model focuses on delivery mode classification (vaginal delivery versus CS), while an exploratory secondary framework investigates whether the proposed modeling architecture can be extended to SI risk as a related reproductive-health outcome that has received limited attention within delivery-mode decision-support research. The framework is intended as a proof-of-concept exploration of the potential integration of multidimensional biopsychosocial variables within an interpretable multi-outcome decision-support architecture.

90 2 Methods

91 2.1 Study design and conceptual framework

92 This study presents a proof-of-concept explainable ML framework developed entirely on
93 synthetic patient-level data parameterized from published literature. The primary objective was
94 not to establish clinical associations, infer causal mechanisms, or validate predictive
95 performance in real populations, but rather to demonstrate a transparent and reproducible
96 modelling architecture capable of integrating biological, psychological, and social predictors
97 across reproductive health outcomes.

98 The framework consists of two independent yet methodologically aligned components. The
99 first component is a dual-stage CS prediction framework designed to operate at two clinically
100 distinct decision points: (i) the antepartum period during antenatal counselling and (ii) the
101 intrapartum period during active labor. The second component is a SI risk prediction
102 framework designed to explore a hypothetical long-term reproductive outcome within a
103 separate synthetic postpartum cohort.

104 The SI framework is presented as an exploratory simulation only and should not be
105 interpreted as evidence of a validated causal relationship between childbirth experiences and
106 subsequent infertility. Because all datasets were generated using predefined literature-derived
107 assumptions, the resulting model performance metrics, threshold analyses, SHAP rankings,
108 calibration statistics, and explainability outputs represent properties of the simulation
109 architecture itself rather than empirical findings regarding real patients.

110 The study was reported in accordance with the TRIPOD+AI framework for prediction
111 model development and transparent reporting of artificial intelligence (AI) systems. A
112 schematic overview of the complete workflow is presented in Figure 1

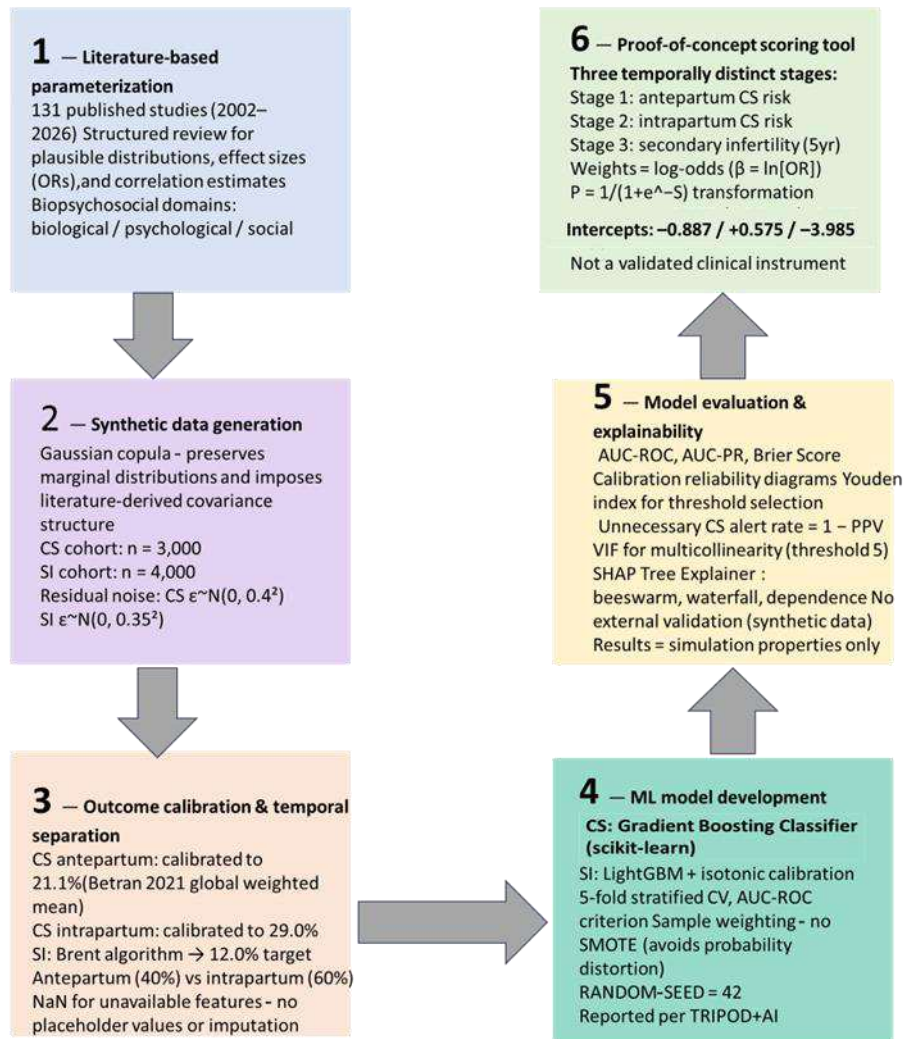


Figure 1: Overall study workflow. Literature review and parameter extraction, synthetic data generation, outcome calibration, model development, validation, calibration assessment, threshold analysis, and SHAP-based explainability.

2.2 Literature-based parameterization

All synthetic datasets were parameterized using evidence extracted from 131 published studies identified through a structured literature review conducted between 2002 and 2026. The review was intended to obtain plausible distributions, effect sizes, and correlation estimates for simulation purposes and should not be interpreted as a formal PRISMA-compliant systematic review. Variables were organized according to a biopsychosocial framework encompassing

biological/clinical, psychological, and social domains. Predictor definitions, temporal availability, and domain classifications are summarized in Table 1.

Table 1: Biopsychosocial feature organization and temporal availability. Features included in the synthetic datasets together with domain classification and stage-specific availability.

Domain	Antepartum Features (n = 27)	Intrapartum-Added Features (n = 13)
Biological / Clinical	Maternal age, BMI, height, parity, gravidity, previous CS, previous vaginal birth, previous VBAC, gestational age, estimated fetal weight, ART conception, hypertensive disorder, gestational diabetes, pregnancy complication, planned induction of labor (IOL), fetal sex	Bishop Score, cervical length, cervical dilation, fetal station, occiput-posterior position, oxytocin augmentation, max oxytocin dose, amniotic fluid status, Robson group, epidural analgesia (active labor duration was generated only to inform the correlated oxytocin-dose distribution and was excluded from the model feature set and outcome equation to avoid temporal leakage)
Psychological	FOC (W-DEQ), State Anxiety (STAI), Depressive Symptoms (CES-D), Depression Severity (SDS), Childbirth Self-Efficacy (CBSEI)	-
Social / Behavioral	Prenatal education, doula support, hypnobirthing/relaxation, antenatal perineal massage, ethnicity	VR/non-pharmacological pain relief, intrapartum perineal massage, waterbirth

For each predictor, marginal distributions were specified using literature-derived parameters. Depending on the variable type, normal, Bernoulli, categorical, ordinal, or exponential distributions were employed. The complete generative specification, including all distributional parameters, is provided in the accompanying source code and supplementary material.

2.3 Synthetic data generation

2.3.1 Correlation structure

To generate clinically plausible covariance patterns while preserving predefined marginal distributions, a Gaussian copula framework was employed. Let

$$Z \sim N(0, \Sigma) \quad 1$$

where Σ denotes the target correlation matrix. Observed variables were then obtained through inverse marginal transformations:

$$X_i = F_i^{-1}(\Phi(Z_i)) \quad 2$$

where F_i^{-1} denotes the inverse cumulative distribution function of the target marginal distribution and Φ denotes the standard normal cumulative distribution function.

For the CS framework, clinically grounded correlations were imposed between bishop score, cervical length, cervical dilation, state anxiety, FOC, BMI, active labor duration, and oxytocin dose. Active labor duration was retained within this correlation structure solely to generate a clinically plausible oxytocin-dose distribution; it was excluded from the outcome-generating equation and from the intrapartum feature set supplied to the classifier, since its value is not established until labor is substantially advanced and its association with delivery mode plausibly reflects the process leading to CS rather than an independent antecedent risk factor. For the SI framework, psychosocial variables and selected reproductive-health variables were similarly generated using literature-derived copula structures. The complete correlation matrices are reported Figure 2-b

2.3.2 Outcome label generation

152 Binary outcomes were generated using logistic models parameterized from published odds
 153 ratios (ORs) and adjusted odds ratios (AORs). Predictor coefficients were transformed to the
 154 log-odds scale according to:

$$\beta_i = \ln(OR_i) \quad 3$$

155 Outcome probabilities were calculated using:

$$\text{logit}(P(Y = 1)) = \beta_0 + \sum_{i=1}^p \beta_i X_i + \epsilon \quad 4$$

156 and therefore

$$P(Y = 1) = \frac{1}{1 + \exp[-(\beta_0 + \sum_{i=1}^p \beta_i X_i + \epsilon)]} \quad 5$$

157 where Y represents the binary outcome, β_0 is the intercept, β_i are literature-derived coefficients,
 158 and ϵ represents residual unexplained variability. For the CS framework:

$$\epsilon \sim N(0, 0.4^2) \quad 6$$

159 For the SI framework:

$$\epsilon \sim N(0, 0.35^2) \quad 7$$

160 Complete coefficient tables are provided in Table 2a (antepartum CS framework), Table
 161 2b (intrapartum-added CS predictors), and Table 3 (SI framework)

162 **Table 2:** (a) Literature-derived logistic coefficients used for synthetic CS outcome
 163 generation during the antepartum stage. (b): Literature-derived logistic coefficients used for
 164 synthetic CS outcome generation during the intrapartum stage (COEF-IP).

Predictor	β (log-odds)	OR	Direction	Source
Previous CS	+1.386	4.00	+	Hunt 2025
Hypertensive Disorder / Pre-eclampsia (HDP)	+0.916	2.50	+	Tun 2022
ART / IVF / ICSI Conception	+0.693	2.00	+	Liu 2026
Planned IOL	+0.693	2.00	+	Wu 2019
Gestational Diabetes Mellitus (GDM)	+0.588	1.80	+	Tun 2022
Doula Support (continuous)	-0.511	0.60	-	Chaudhary 2025
Previous Vaginal Birth	-0.511	0.60	-	Tun 2022
Elevated Depressive Symptoms (CES-D ≥ 16)	+0.336	1.40	+	Tun 2022

a

Hypnobirthing				Huang
/Relaxation	-0.357	0.70	-	2026
Programmed				
Prenatal				
Education /				
Preparation	-0.431	0.65	-	Liu 2026
Classes				
Parity				Tun
(Multiparous)	-0.405	0.67	-	2022
BMI (kg/m ² ,				Tun
per unit above	+0.046	1.05	+	2022 / Al-
reference)				Omari 2026
FOC - W-				Zhu
DEQ (per point)	+0.022	1.02	+	2025
Estimated				
Fetal Weight (per	+0.0003	1.0003	+	Wu 2019
gram)				
Gestational				Hunt
Age (weeks, per				2025 /
week above	-0.182	0.83	-	Crabtree
reference)				2026

Predictor	β (log-odds)	OR	Direction	Source	b
Bishop Score (per point)	-0.154	0.86	-	Hunt 2025	
Cervical Dilation (cm, per cm)	-0.223	0.80	-	Hunt 2025	
Cervical Length (mm, per mm)	+0.039	1.04	+	Sinha 2024	

Fetal Station	-0.126	0.88	-	Hunt 2025
Occiput-Posterior Position	+0.916	2.50	+	Verhoeven 2012
Oxytocin Use	+0.642	1.90	+	Nicoli 2026
Maximum Oxytocin Dose (mU/min)	+0.095	1.10	+	Nicoli 2026
Amniotic Fluid Status (abnormal)	+0.441	1.55	+	Whittington 2023
Active Labor Duration (hours)	+0.088	1.09	+	Oruc 2025
Epidural Analgesia	+0.405	1.50	+	Tun 2022
VR / non-pharmacological pain relief	-0.223	0.80	-	Internal assumption
Intrapartum Perineal Massage	-0.105	0.90	-	Internal assumption
Waterbirth	-0.357	0.70	-	Internal assumption
Robson Group	+0.182	1.20	+	Robson 2001

Table 3: Literature-derived log-odds coefficients ($\beta = \ln [\text{OR}]$) used for synthetic secondary infertility outcome generation. All values represent parameters of the synthetic data-generating process and should not be interpreted as empirical clinical findings.

Predictor	Beta	OR	Source
Asherman / IUA	+1.792	6.00	Guo 2019; Hooker 2014
Prior Subfertility History	+1.504	4.50	te Velde 2002
Endometriosis	+1.386	4.00	Bulletti 2010
Recurrent Miscarriage	+1.253	3.50	Rai & Regan 2006 (Lancet)
Birth Trauma / PTSD	+1.099	3.00	Storksens 2013
Irregular Menstrual Cycle	+1.030	2.80	Clinical consensus
Thyroid Disorder	+0.742	2.10	Mintziori 2016
Male Factor Infertility	+0.588	1.80	Thoma 2013
Intracavitary Fluid (ICF)	+0.494	1.64	Ma 2025
Severe PPH (≥ 1000 mL)	+0.406	1.50	Clinical (Asherman risk)
Caesarean Scar Disorder	+0.431	1.54	Ma 2025
Elevated Depression (CES-D)	+0.337	1.40	Tun 2022
Prior D&C History	+0.288	1.33	Hooker 2014
Previous CS	+0.151	1.163	Ma 2025
Maternal Age (per year)	+0.077	1.080	te Velde 2002
EPDS Score (per point)	+0.072	1.074	Kinouchi 2026
W-DEQ Score (per point)	+0.015	1.015	Laursen 2009
STAI (per point)	+0.010	1.010	Sydsjö 2012
Doula Support (protective)	-0.223	0.800	Chaudhary 2025

2.4 Outcome calibration

To ensure that simulated outcome frequencies aligned with published prevalence estimates, model intercepts were calibrated prior to the development of ML models. In the CS framework, distinct intercepts were estimated for antepartum and intrapartum populations to match target caesarean rates of 21.1% and 29.0%, respectively. The antepartum target of 21.1% was derived from Betrán et al. (2021)[23], WHO reported a global weighted mean CS rate of 21.1% based on nationally representative data from 154 countries, covering approximately 94.5% of global live births (95% uncertainty interval: 19.7%-22.5%) [23]. The intrapartum target of 29.0% was selected to reflect the consistently higher CS rates observed in hospital-based intrapartum cohorts compared with population-level estimates. Hunt et al. (2025)[24] reported intrapartum CS rates of approximately 28-31% in contemporary obstetric unit data, and Betran et al. (2021)[23] projected a global mean approaching 28.5% by 2030, both supporting a value of 29.0% as a conservative but plausible intrapartum calibration target. This value should be regarded as a modelling assumption rather than an empirical prevalence estimate. This higher value was selected as a modelling assumption to reflect the known enrichment of obstetric risk factors in actively laboring populations relative to the general antenatal population, and should not be interpreted as an empirically derived prevalence estimate.

For the SI framework, the intercept parameter β_0 was calibrated numerically using Brent's root-finding algorithm. The calibration objective was defined as:

$$f(\beta_0) = E[P(Y = 1)] - p_{target} \quad 8$$

where $p_{target} = 0.12$ represents the desired prevalence of SI. According to the World Health Organization (2023) infertility report, which synthesized evidence from 133 studies spanning 1990–2021, the global pooled period prevalence of infertility is 12.6%. Within this, SI has a pooled period prevalence of 4.9%, while lifetime prevalence is estimated at 6.5%. The selected target of 12.0% reflects a deliberately conservative, enriched-risk estimate for a postpartum

cohort with combined clinical, psychosocial, and uterine risk factors, consistent with clinical literature reporting a broader 10-15% range for SI [25].

The optimal intercept was obtained by solving: $f(\beta_0) = 0$

ensuring that the expected prevalence generated by the logistic model matched the predefined target prevalence. Calibration was performed using 500,000 Monte Carlo samples and incorporated both residual noise and conditional dependencies embedded within the synthetic data-generating process

2.5 Temporal separation strategy

A primary methodological requirement was strict temporal separation of predictors to avoid information leakage and address concerns regarding temporality and confounding.

The caesarean dataset was therefore divided into two independent subsets:

- **Antepartum cohort ($\approx 40\%$)** consisting exclusively of variables available during antenatal counselling.
- **Intrapartum cohort ($\approx 60\%$)** including all antepartum variables plus labor-specific predictors observable only after labor onset.

Intrapartum variables were stored as missing values (NaN) within the antepartum subset and were never imputed or encoded using placeholder values. Separate machine-learning models were subsequently trained and evaluated on their respective temporal datasets.

This design was implemented specifically to prevent future information from influencing earlier clinical decision points and to ensure that intrapartum variables such as epidural analgesia, oxytocin augmentation, labor duration, and fetal position were evaluated only within the temporal context in which they become clinically observable.

214 **2.6 ML model development**

215 2.6.1 CS framework

216 The antepartum and intrapartum models were developed using Gradient Boosted Decision
217 Trees implemented through the gradient boosting classifier algorithm (scikit-learn v1.8.0).

218 Hyperparameters were optimized using five-fold stratified cross-validation (CV) with
219 AUC-ROC as the optimization criterion. The search space included:

- 220 • N-estimators = (200, 400)
- 221 • max-depth = (3, 5)
- 222 • learning-rate = (0.05, 0.10)
- 223 • subsample = 0.8
- 224 • min-samples-leaf = 20

225 Class imbalance was addressed through observation-level sample weighting rather than
226 synthetic oversampling techniques.

227 2.6.2 SI framework

228 The SI framework employed a LightGBM classifier followed by isotonic probability
229 calibration. Hyperparameter optimization was performed using five-fold stratified Grid Search
230 CV with AUC-ROC as the objective function.

231 The final model incorporated sample weighting without SMOTE augmentation, thereby
232 avoiding probability distortions associated with synthetic oversampling.

233 2.6.3 Proof-of-concept interactive scoring tool

234 To provide an illustrative representation of the proposed modelling architecture, a three-
235 stage, paper-based scoring tool was developed using the literature-parameterized logistic

coefficients that informed the generation of the synthetic dataset. The tool is organized into three temporally distinct stages: (i) antenatal counselling (Stage 1), (ii) active labor (Stage 2), and (iii) postpartum projection of SI risk (Stage 3).

For each stage, predictor weights are presented as log-odds units corresponding to the literature-derived regression coefficients reported in Table 2a, Table 2b and Table 3. Users may identify the response option most consistent with a given clinical profile, record the associated log-odds value, and calculate a total score by summing the selected values together with the stage-specific calibrated intercept (Stage 1: -0.887; Stage 2: +0.311; Stage 3: -3.985). These intercepts were derived numerically to align simulated outcome prevalences with their respective calibration targets: Stage 1 intercept was computed as $\text{logit}(0.211) - \sum(\beta_i \times \bar{E}[X_i])$ to achieve a mean CS probability of 21.1%; Stage 2 intercept was similarly calibrated to 29.0%; and Stage 3 intercept was solved using Brent's root-finding algorithm (`scipy.optimize.brentq`) applied to 500,000 Monte Carlo samples to achieve a mean SI probability of 12.0% (see Section 2.4 and Supplementary Material S3 for complete derivation).

The resulting score (S) can then be transformed into an estimated probability using the standard logistic function, $P = \frac{1}{1+e^{-S}}$. Probability ranges and corresponding risk categories for each stage are provided in the interpretation guides accompanying the scoring tables (Supplementary Material S1, Tables S1-1 to S1-3).

This scoring tool should be regarded as an exploratory proof-of-concept instrument derived from a synthetic, literature-parameterized dataset. As it has not undergone validation in real-world patient populations, its outputs should not be interpreted as clinically validated risk estimates or used to guide clinical decision-making. Rather, the tool is intended to offer a

transparent illustration of the biopsychosocial factor structure underlying the modelling framework and to facilitate interpretation of the relative contribution of individual predictors.

2.7 Model evaluation

2.7.1 Internal validation

Datasets were partitioned using stratified 80/20 train-test splits.

Internal validation was performed using repeated stratified CV within each synthetic dataset. During model development, hyperparameter optimization was conducted using five-fold stratified CV, ensuring that outcome proportions were preserved across folds. Final model performance was subsequently assessed on an independent hold-out test set comprising 20% of the data. Internal validation therefore evaluated the ability of the modelling framework to generalize within the distribution defined by the synthetic data-generating process.

Discrimination performance was evaluated using:

- AUC-ROC
- Area under the precision-recall curve (AUC-PR)
- Calibration performance was evaluated using:
- Calibration reliability diagrams
- Brier score

Decision thresholds were selected using the Youden index:

$$J = \text{Sensitivity} + \text{Specificity} - 1 \quad 9$$

The optimal threshold was defined as:

$$\text{Threshold}^* = \arg \max(J) \quad 10$$

At the selected threshold, the following metrics were reported:

- Sensitivity
- Specificity
- PPV
- NPV

To address concerns regarding unnecessary intervention alerts, the unnecessary caesarean alert rate was additionally calculated as:

$$\text{Unnecessary alert rate} = 1 - \text{PPV}$$

11

Threshold sensitivity analyses were performed across the full probability range to characterize the trade-off between detection performance and false-positive alerts.

2.7.2 External validation

No independent external dataset was available for validation.

Because the study was conducted entirely on synthetic data, true external validation could not be performed. Consequently, all reported performance metrics represent internal validation only and should not be interpreted as evidence of model generalizability to real-world clinical populations.

2.8 Multicollinearity assessment

To evaluate potential redundancy among predictors, variance inflation factors (VIFs) were calculated for all complete-case predictors.

VIF was defined as:

$$VIF_i = \frac{1}{1 - R_i^2}$$

where R_i^2 represents the coefficient of determination obtained by regressing predictor i against all remaining predictors.

Predictors with $VIF > 5$ were considered moderately collinear, whereas $VIF > 10$ was considered indicative of substantial multicollinearity. No variables were removed based solely on VIF values; results were reported for transparency.

2.9 Explainability analysis

Model interpretability was assessed using SHAP Tree Explainer.

Four complementary explainability outputs were generated:

1. Mean absolute SHAP importance rankings.
2. SHAP beeswarm summary plots.
3. SHAP dependence plots.
4. SHAP waterfall explanations for representative high-risk patients.

Because the underlying datasets were generated using predefined coefficients, SHAP analyses were interpreted exclusively as demonstrations of the framework's ability to recover and transparently display embedded relationships rather than as evidence of causal importance or clinical relevance. Accordingly, all explainability outputs were interpreted as verification of the synthetic data-generation assumptions rather than as discovery of novel biological, psychological, or clinical relationships.

314 **3 Results**

315 **3.1 CS decision support framework**

316 3.1.1 Cohort characteristics, outcome calibration, and data structure

317 The synthetic cohort consisted of 3,000 simulated pregnancies, including 1,164 antepartum
318 cases (38.8%) and 1,836 intrapartum cases (61.2%). The observed CS rates were 21.0% in the
319 antepartum subset and 26.1% in the intrapartum subset. These values were generally consistent
320 with the literature-informed target rates used during dataset generation (21.1% and 29.0%,
321 respectively), suggesting that the calibrated intercepts produced outcome frequencies
322 reasonably aligned with the intended simulation design. The larger deviation observed in the
323 intrapartum subset (26.1% versus target 29.0%) is attributable to stochastic variability inherent
324 in finite-sample synthetic data generation and is within the range expected for a dataset of this
325 size.

326 As shown in Figure 2-a, the observed CS rates closely approximated the predefined target
327 rates derived from the literature-based parameterization process. Because outcome labels were
328 generated using predefined coefficients and calibrated intercepts, these findings should be
329 interpreted as verification of the synthetic data generation procedure rather than evidence
330 regarding real-world CS prevalence.

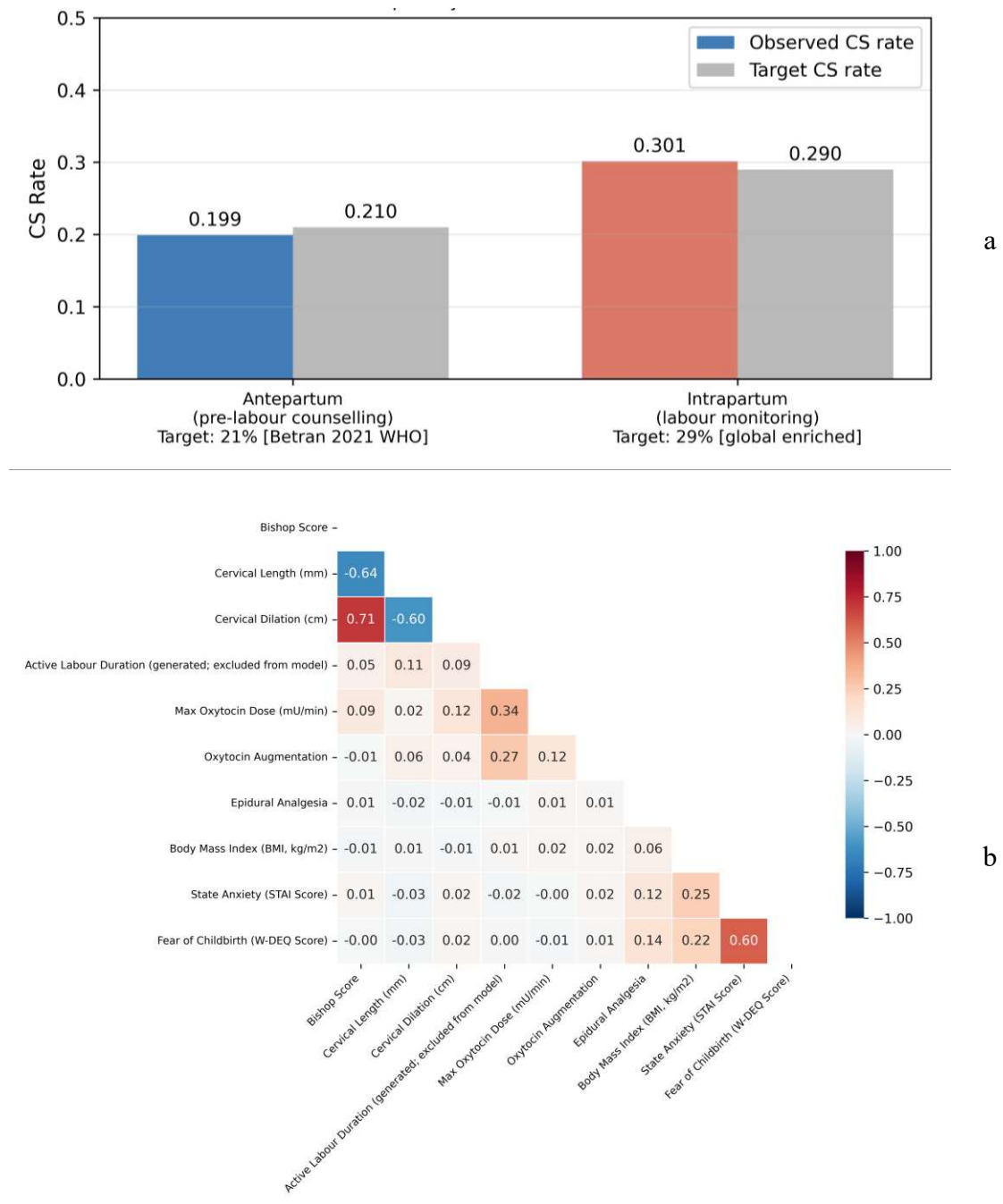


Figure 2: Synthetic cohort validation and feature structure. (a) Observed versus target CS rates in the antepartum and intrapartum cohorts. (b) Pearson correlation matrix of selected clinical and psychosocial predictors generated through the Gaussian copula framework. Correlations reflect predefined relationships incorporated during synthetic data generation and should not be interpreted as empirical observations.

To assess the realism of the simulated feature space, multicollinearity and correlation structures were examined. VIF analysis indicated that all predictors remained below the

conventional threshold of 5, with the highest values observed for Bishop Score (VIF = 2.46), Cervical Dilation (VIF = 2.22), and Cervical Length (VIF = 2.17). These relationships were expected because the synthetic data generation process explicitly incorporated clinically plausible dependencies among cervical readiness indicators. Full VIF results for all predictors are presented in Table 4.

Table 4: VIF analysis of the synthetic predictor set. All VIF values remained below the conventional threshold of 5, indicating acceptable multicollinearity. Higher VIF values for Bishop Score, Cervical Dilation, and Cervical Length reflect the clinically plausible dependencies intentionally incorporated during synthetic data generation.

Feature (Readable Name)	VIF	Flag	Domain
Bishop Score	2.46	OK (<5)	Biological-IP
Cervical Dilation (cm)	2.22	OK (<5)	Biological-IP
Cervical Length (mm)	2.17	OK (<5)	Biological-IP
State Anxiety (STAI)	1.84	OK (<5)	Psychological
FOC (W-DEQ)	1.76	OK (<5)	Psychological
SDS	1.68	OK (<5)	Psychological
Body Mass Index (BMI)	1.22	OK (<5)	Biological-AP
Doula / Continuous Support	1.22	OK (<5)	Social
All remaining features	< 1.22	OK (<5)	Various

The correlation matrix further demonstrated that the strongest relationships occurred between Bishop Score and Cervical Dilation ($r = 0.72$) and between Bishop Score and Cervical Length ($r = -0.65$), while psychosocial measures such as FOC and State Anxiety exhibited moderate positive correlation ($r = 0.58$). As illustrated in Figure 2-b, these patterns were consistent with the imposed Gaussian copula structure and served primarily as validation of the synthetic dataset architecture.

3.1.2 Predictive performance of the dual-stage models

Model discrimination and calibration metrics are summarized in Table 5.

Table 5: Performance metrics of the Stage 1 (Antepartum) and Stage 2 (Intrapartum) CS prediction models. Metrics were calculated using the Youden-optimal threshold. All results represent properties of the synthetic simulation framework and should not be interpreted as clinical validation.

Metric	Stage 1 Antepartum	Stage 2 Intrapartum	Δ (IP - AP)	AP n test	IP n test	Notes
AUC-ROC	0.638	0.731	+0.094	239	361	Youden threshold
AUC-PR	0.326	0.527	+0.201	239	361	CS positive class
Brier Score	0.188	0.203	+0.014	239	361	Lower = better
Threshold (Youden J)	0.437	0.411	-	239	361	Optimal cut-off
Sensitivity	0.562	0.771	+0.209	239	361	True CS detection
Specificity	0.723	0.599	-0.124	239	361	True vaginal ID
PPV	0.338	0.454	+0.116	239	361	Precision for CS
NPV	0.868	0.858	-0.010	239	361	Rule-out accuracy
Unnecessary CS Rate	66.2%	54.6%	-11.6%	239	361	1 - PPV (FP/all predicted CS)

Within the simulation environment, the Stage 1 Antepartum Model achieved an AUC-ROC of 0.638 and a Brier Score of 0.188, whereas the Stage 2 Intrapartum Model achieved an AUC-ROC of 0.731 and a Brier Score of 0.203. The higher Brier Score observed for the intrapartum model indicates comparatively weaker probability calibration despite better discrimination. This pattern may reflect the greater outcome prevalence in the intrapartum cohort (30.2% versus 20.1%), the larger and more heterogeneous intrapartum feature set, or the influence of sample weighting on predicted probability distributions. Within a synthetic framework, this divergence between discrimination and calibration does not necessarily indicate model failure;

rather, it underscores that AUC and Brier Score capture distinct and sometimes dissociable aspects of model behavior, and that interpreting either metric in isolation may provide an incomplete picture of model behavior within the simulation.

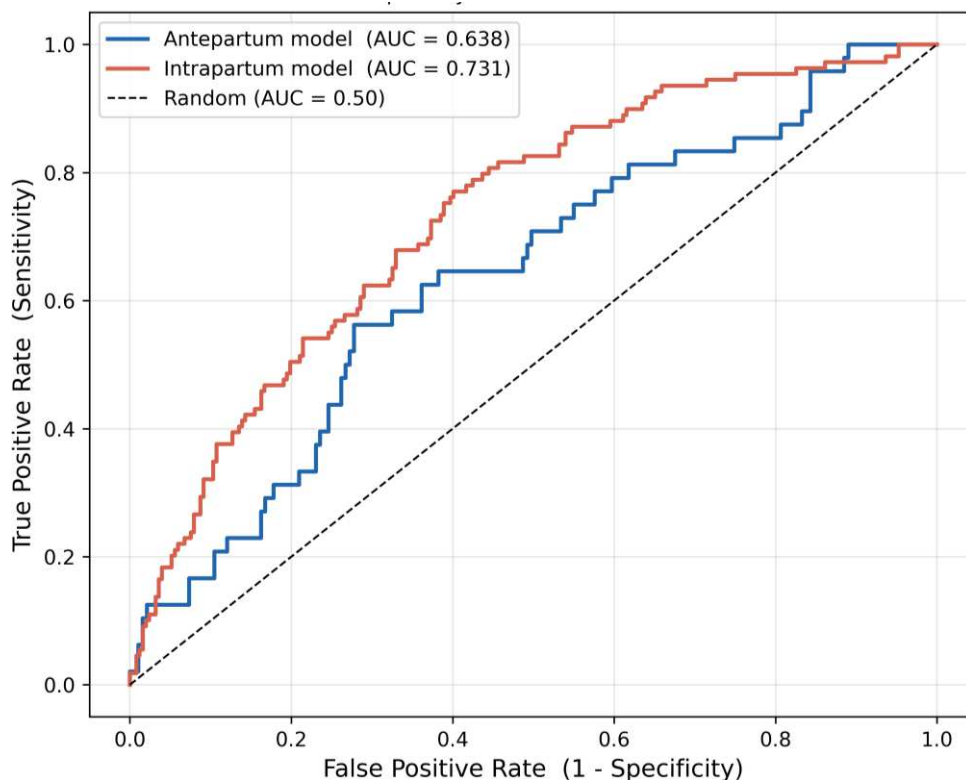
The increase in discrimination observed for the intrapartum model ($\Delta\text{AUC} = +0.094$) is consistent with the larger feature set available at Stage 2, which incorporated 13 additional labor-specific variables with non-zero embedded coefficients. This pattern reflects the arithmetic consequence of including more signal-carrying features in the generative model rather than evidence of incremental predictive validity in clinical populations. However, because the outcome labels were generated using predefined coefficients, these performance differences should not be interpreted as evidence of predictive superiority in clinical populations.

3.1.3 Robustness across simulation replicates

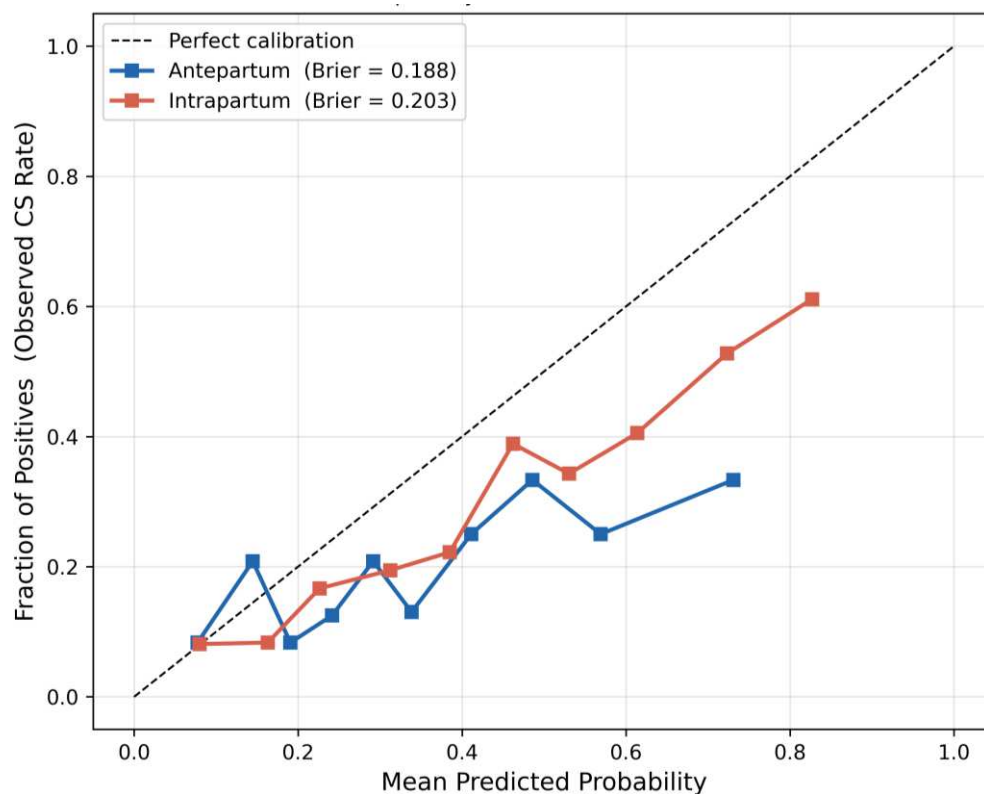
Because a single random seed provides only one draw from the underlying stochastic simulation, the full data-generation-training-evaluation cycle was repeated across 30 independent simulation replicates (fresh synthetic cohorts, fixed model hyperparameters). Across replicates, the antepartum model showed a mean AUC-ROC of 0.663 (95% empirical CI (0.549, 0.752)) and the intrapartum model a mean AUC-ROC of 0.755 (95% CI (0.704, 0.787)); the intrapartum model outperformed the antepartum model in 29 of 30 replicates (mean $\Delta\text{AUC} = +0.093$, 95% CI (0.016, 0.204)). The antepartum model's performance was itself more variable across replicates than the intrapartum model's (95% CI width of 0.203 versus 0.083), plausibly reflecting its smaller cohort share (40% of the simulated population) and narrower feature set. These results indicate that the direction of the intrapartum performance advantage is stable across replicates, although its magnitude varies and should not be over-interpreted from any single simulation run.

As shown in Figure 3-a, both models demonstrated discrimination substantially above random classification. The ROC curves primarily illustrate the ability of the proposed dual-stage architecture to recover relationships embedded during data generation.

Calibration analysis is presented in Figure 3-b. The antepartum model appeared to demonstrate somewhat closer agreement between predicted probabilities and observed event frequencies than the intrapartum model. Although calibration was generally reasonable within the simulation setting, deviations from the ideal calibration line were observed, particularly in intermediate probability ranges. These findings emphasize the importance of calibration assessment in threshold-based decision-support systems.



a



b

Figure 3: Performance of the dual-stage CS prediction framework. (a) Receiver operating characteristic (ROC) curves for the antepartum and intrapartum models. (b) Calibration reliability diagrams showing agreement between predicted probabilities and observed event frequencies. Results represent properties of the simulation and do not constitute clinical validation.

3.1.4 Threshold behavior and potential unnecessary caesarean alerts

To explore how classification performance varies across different decision boundaries, threshold sensitivity analyses were conducted across the full probability range for both models. The Youden index was used to identify the operating point that best balances the detection of true CS cases against the avoidance of false alarms within the synthetic dataset.

For the antepartum model, the Youden-optimal threshold was 43.7%. At this operating point, the model identified 56.2% of simulated CS cases (sensitivity) and correctly classified 72.3% of simulated vaginal births as low-risk (specificity). The PPV was 0.338, meaning that of every 100 women the model flagged as high-risk, approximately 34 had a CS outcome in

the simulation and 66 did not, corresponding to an unnecessary alert rate of 66.2%. The NPV was 0.868, indicating that 86.8% of women classified as low-risk did not have a CS outcome in the simulation.

For the intrapartum model, the Youden-optimal threshold was 41.1%. This difference may reflect the availability of 13 additional labor-specific variables in Stage 2 (including cervical dilation, Bishop score, and fetal position), which are not observable before labor onset. At this threshold, sensitivity was 77.1%, specificity was 59.9%, PPV was 0.454 (45 true CS per 100 alerts; unnecessary alert rate 54.6%), and NPV was 0.858.

The divergence between the two thresholds (43.7% versus 41.1%) illustrates that the same outcome may warrant different operating points depending on what clinical information is available at the time of assessment. This observation is consistent with the rationale for temporal separation as a design principle, though it should be interpreted cautiously as a property of the simulation rather than a generalizable clinical finding.

Across both models, unnecessary alert rates of 54-66% indicate that roughly half to two-thirds of all positive alerts within the simulation did not correspond to true CS outcomes. This reflects the inherent precision limitations of probabilistic classification at moderate outcome prevalence and underscores that the selected thresholds are simulation-derived operating points only. They should not be interpreted as clinically actionable recommendations or applied outside the synthetic framework without external validation and recalibration.

As shown in Figure 4-a, Figure 4-b, the threshold analyses revealed a substantial trade-off between sensitivity and false-positive alerts. Increasing the decision threshold reduced unnecessary alerts but simultaneously decreased sensitivity. Consequently, the threshold

selected within this proof-of-concept framework should be viewed only as a simulation-derived operating point rather than a clinically actionable recommendation.

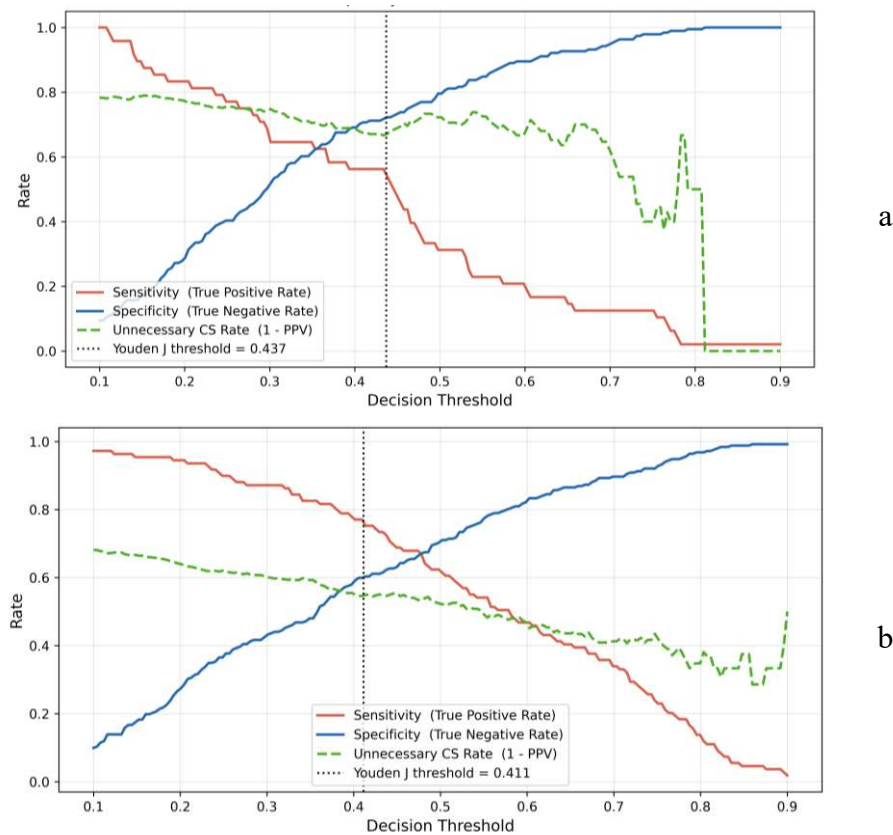


Figure 4: Threshold sensitivity analyses. (a) Antepartum model. (b) Intrapartum model. Curves illustrate the trade-offs between sensitivity, specificity, and unnecessary caesarean alerts across decision thresholds. Vertical dashed lines indicate Youden-optimal thresholds.

3.1.5 Explainability analysis

Global model explainability was investigated using SHAP. Because the synthetic dataset was generated using predefined literature-informed coefficients, SHAP rankings are expected to reflect the imposed relationships and should not be interpreted as independent clinical discoveries.

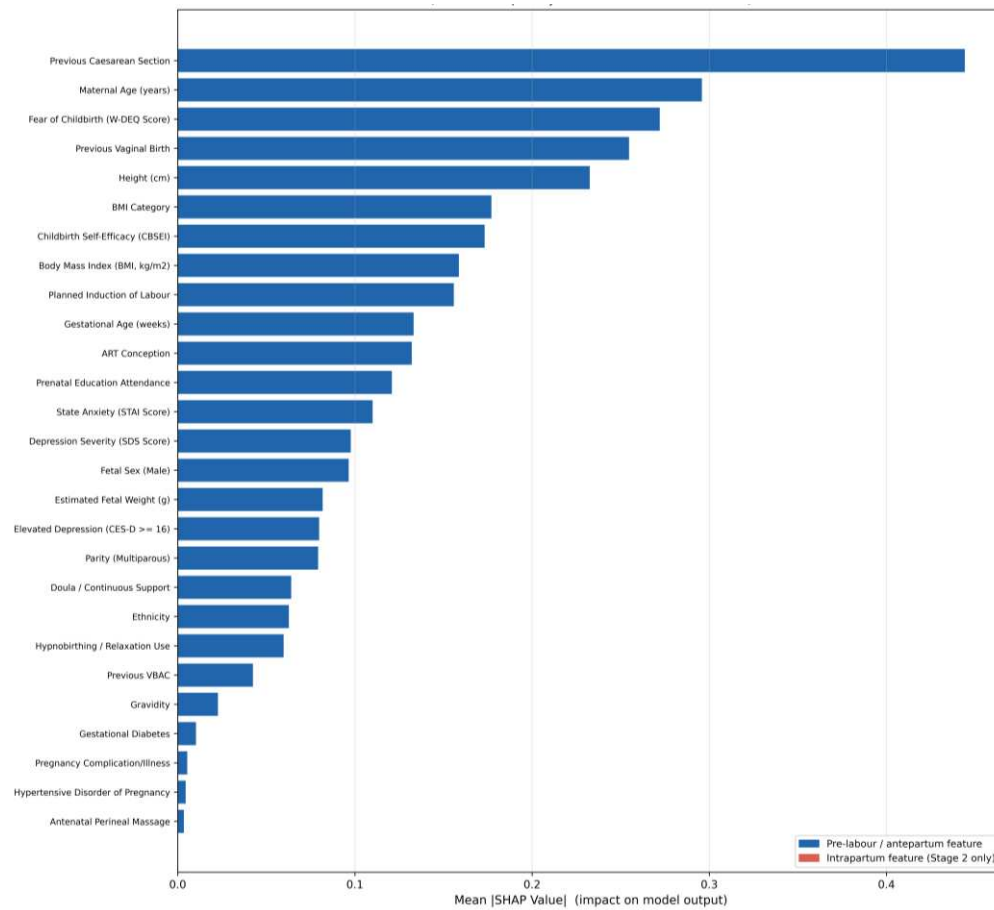
As shown in Figure 5, Previous CS, Maternal Age, BMI, FOC, State Anxiety, Planned Induction of Labor (IOL), and Pregnancy Risk Status appeared among the most influential predictors within the synthetic framework. As shown in Figure 6, Bishop Score, Cervical

Dilation, Fetal Head Position, Epidural Analgesia, Oxytocin Augmentation, Previous CS, and Maternal Age demonstrated comparatively larger SHAP contributions. In both models, the highest-ranked features generally corresponded to variables assigned stronger effects during the literature-informed parameterization process.

The SHAP beeswarm plots further illustrated the direction and distribution of feature contributions across individual simulated patients. These visualizations primarily demonstrate the transparency and interpretability of the proposed architecture rather than providing evidence regarding causal mechanisms or clinical importance. Exploratory subgroup analyses were additionally performed to examine model behavior across clinically and psychosocially defined populations. The corresponding results are summarized in Table 6.

Table 6: Subgroup-specific AUC-ROC values and CS rates for the antepartum and intrapartum frameworks. Results are exploratory and reflect performance within the synthetic dataset only. Small subgroup sizes may contribute to uncertainty in several estimates.

Subgroup	AP n	AP AUC	AP CS rate	IP n	IP AUC	IP CS rate
Nulliparous	123	0.614	24.4%	186	0.719	31.7%
Multiparous + Previous CS	26	0.673	34.6%	46	0.585	58.7%
Obesity (BMI ≥ 30)	50	0.615	26.0%	83	0.767	31.3%
Planned IOL	59	0.493	30.5%	79	0.698	35.4%
High FOC (W-DEQ ≥ 60)	49	0.708	28.6%	98	0.742	38.8%
High STAI (≥ 60)	45	0.635	15.6%	91	0.708	42.9%
Elevated Depression (CES-D +)	77	0.600	22.1%	114	0.783	37.7%

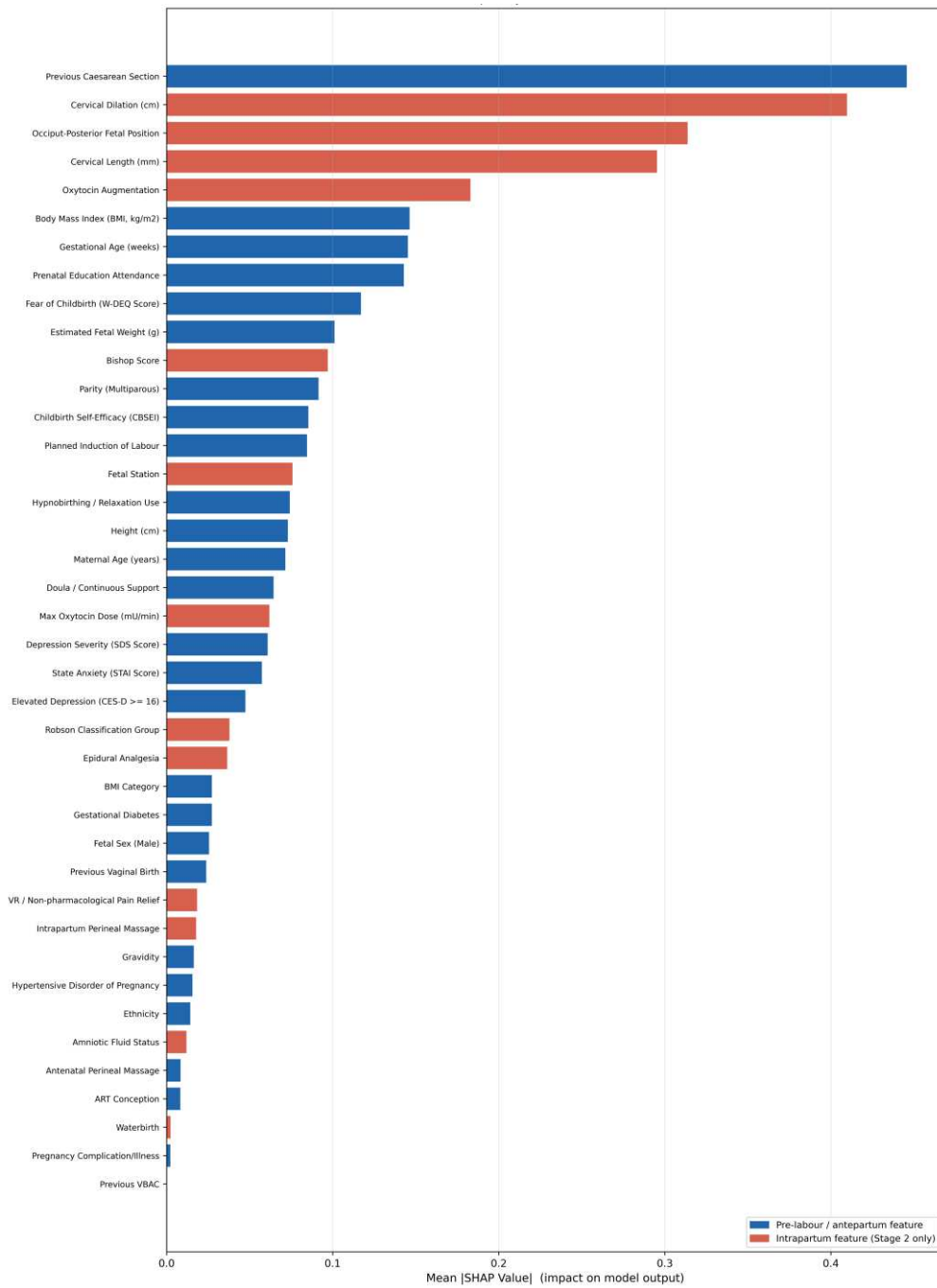


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b

Figure 5: SHAP explainability results for the Antepartum Model. (a) Mean absolute SHAP importance ranking. (b) SHAP beeswarm summary plot showing the distribution and direction of feature contributions.



a



b

Figure 6: SHAP explainability results for the Intrapartum Model. (a) Mean absolute SHAP importance ranking. (b) SHAP beeswarm summary plot showing the distribution and direction of feature contributions.

468 The dependence and waterfall plots are presented in Figure 7. These patient-level and
469 feature-level visualizations illustrate how the model combines multiple predictors to generate
470 individual risk estimates. Because the observed patterns originate from the predefined synthetic
471 framework, they should be interpreted as demonstrations of explainability functionality rather
472 than empirical evidence regarding delivery-mode determinants.

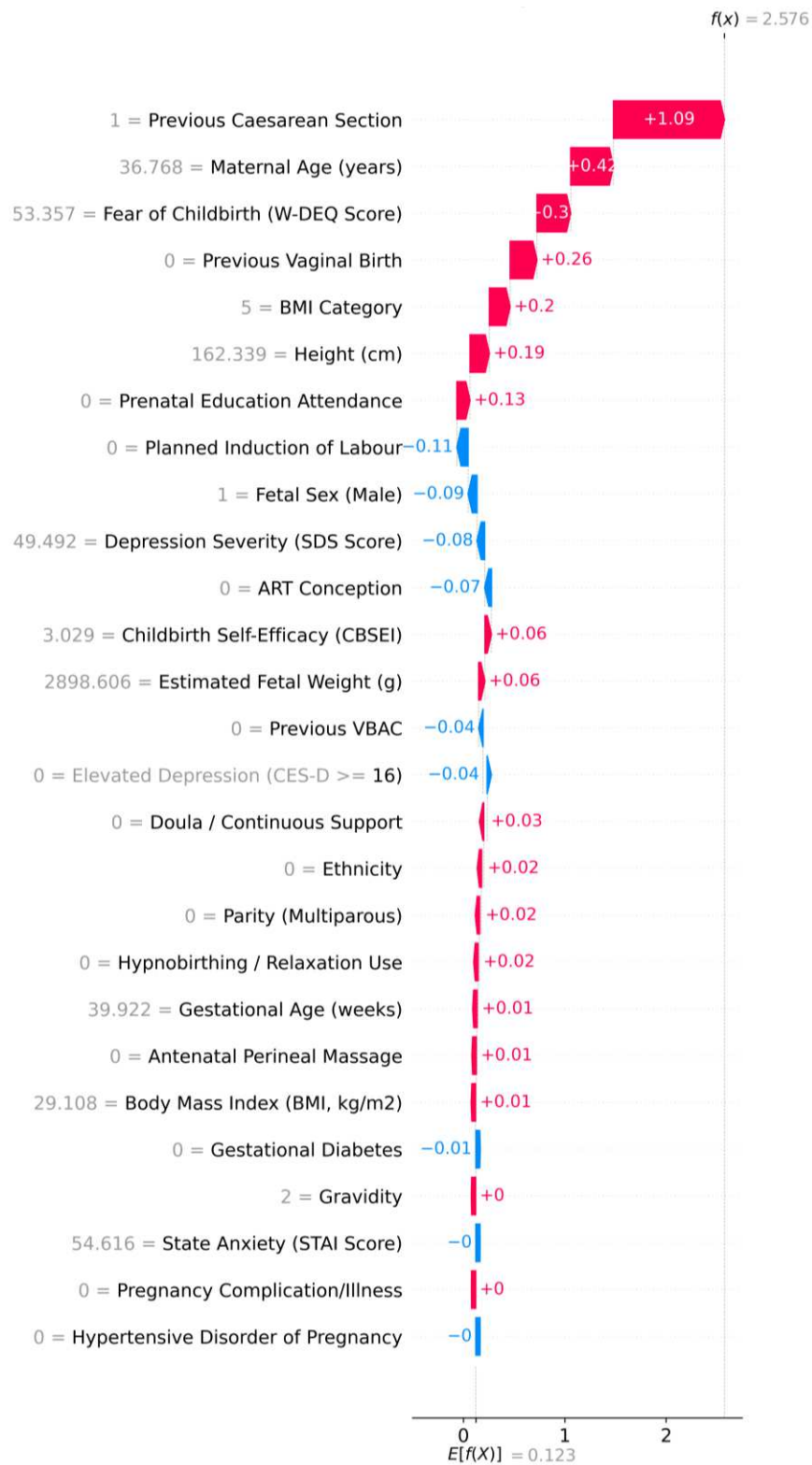


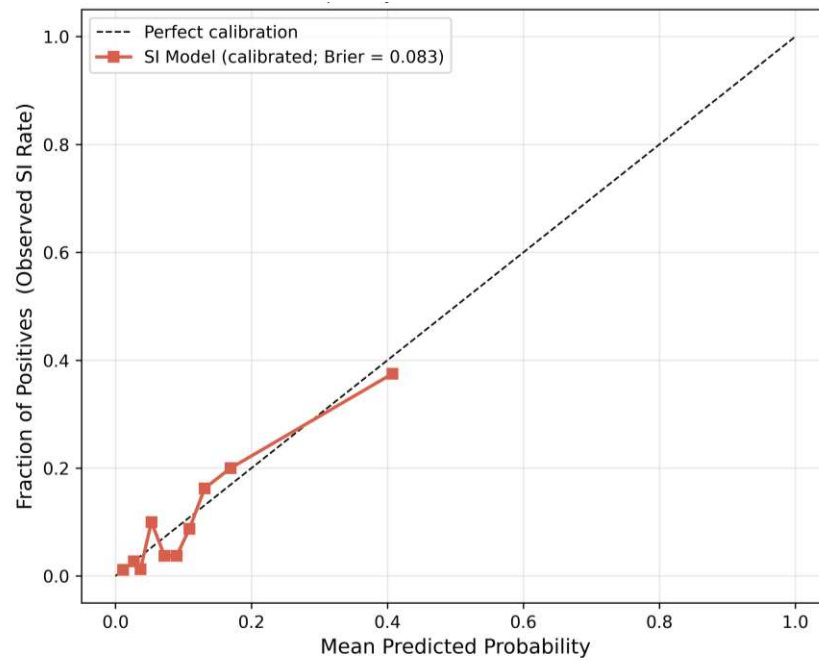
Figure 7: Advanced explainability analyses for the dual-stage caesarean prediction framework. Dependence plots and representative waterfall plots demonstrating feature-level and patient-level model interpretation.

3.2 SI risk prediction framework transition between frameworks

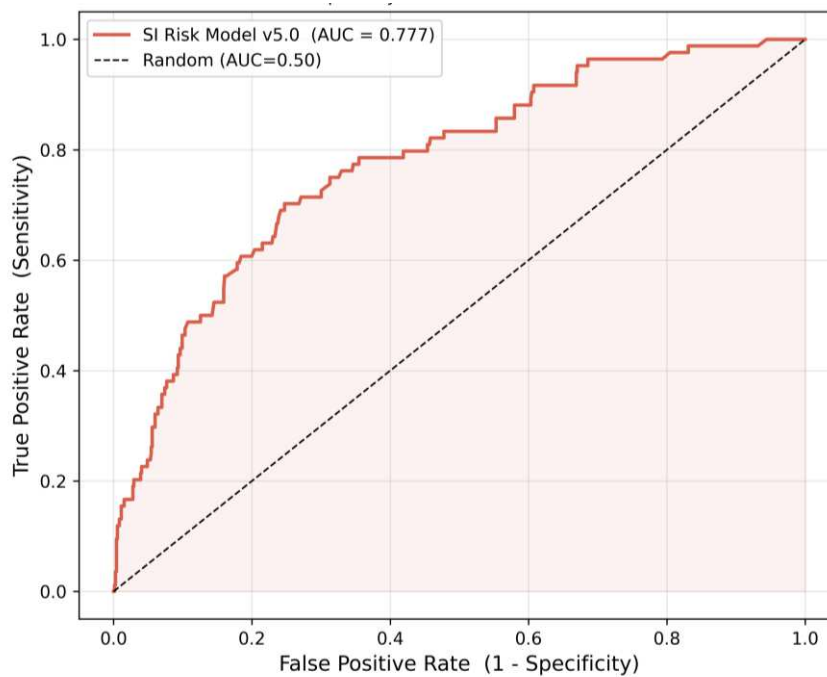
The first framework focused on delivery-mode prediction during pregnancy and labor, whereas the second framework explored a distinct long-term outcome: SI following childbirth. Mode of delivery does not occur in isolation but forms part of a broader reproductive trajectory that may influence subsequent fertility and reproductive health. Because several determinants of caesarean delivery (including maternal characteristics, obstetric history, psychological factors, and social determinants) have also been implicated in secondary infertility, this study hypothesized that the biopsychosocial feature space developed for delivery-mode prediction might contain information relevant to later reproductive outcomes. Consequently, secondary infertility was examined as an exploratory downstream endpoint within the same analytic.

3.2.1 Cohort characteristics and outcome calibration

The SI cohort consisted of 4,000 simulated postpartum women. The observed SI rate was 10.5%, compared with a predefined target rate of 12.0% used during model parameterization. This prevalence reflects the parameterization of the synthetic data generator rather than an epidemiological estimate of SI in real-world populations. In practical terms, approximately 10–12% of simulated women were assigned a SI outcome label according to the predefined probability structure embedded within the data-generating process. These outcome frequencies were determined by literature-informed coefficients and calibrated intercepts and were intended to provide a realistic testing environment for machine-learning model development rather than to reproduce true population prevalence. As shown in Figure 8, the observed prevalence remained reasonably close to the target value and was considered consistent with expected stochastic variation during synthetic data generation.



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b

Figure 8: SI cohort validation and discrimination performance. (a) Observed versus target SI prevalence. (b) ROC curve for the SI model.

3.2.2 Model performance and calibration

Within the simulation environment, the model achieved an AUC-ROC of 0.777, AUC-PR of 0.332, and Brier Score of 0.083. Additional discrimination, calibration, and classification metrics obtained at the Youden-optimal threshold are summarized in Table 7.

Table 7: Predictive performance metrics for the SI risk prediction framework. Metrics are reported at the Youden-optimal threshold and describe model behavior within the synthetic simulation environment.

Metric	Value	Interpretation
AUC-ROC	0.7772	Moderate-good discrimination
AUC-PR	0.3322	Positive class (SI) precision-recall
Brier Score	0.0831	Good calibration (lower = better)
CV AUC-ROC (5-fold)	0.7355	Cross-validated; confirms no overfitting
Threshold (Youden J)	0.121	Optimal decision cut-point
Sensitivity	0.702	70.2% of SI cases identified
Specificity	0.753	75.3% of non-SI correctly excluded
PPV	0.250	1 in 4 positive alerts is a true SI
NPV	0.956	95.6% of negative alerts correctly rule out SI
n (test)	800	20% held-out stratified test set

CV yielded an average AUC-ROC of 0.736, suggesting that model performance remained relatively stable within the synthetic data distribution.

As illustrated in Figure 9, calibration analysis indicated generally reasonable agreement between predicted probabilities and observed frequencies, although deviations were apparent at higher probability ranges. The confusion matrix further demonstrated the challenges associated with predicting relatively infrequent outcomes, where sensitivity and PPV may diverge substantially. Within the simulation, the model identified 70 out of every 100 women

who had a SI outcome (sensitivity 70.2%), and correctly classified 75 out of every 100 women without SI as low-risk (specificity 75.3%). However, of every 100 women the model flagged as high-risk, only 25 genuinely had a SI outcome in the simulation meaning 75 alerts were false positives (PPV 0.250). Conversely, of every 100 women classified as low-risk, 95.6 genuinely did not have a SI outcome (NPV 0.956). This pattern (strong rule-out performance alongside modest rule-in precision) is an expected mathematical consequence of predicting a relatively infrequent outcome, and should not be interpreted as evidence of clinical utility.

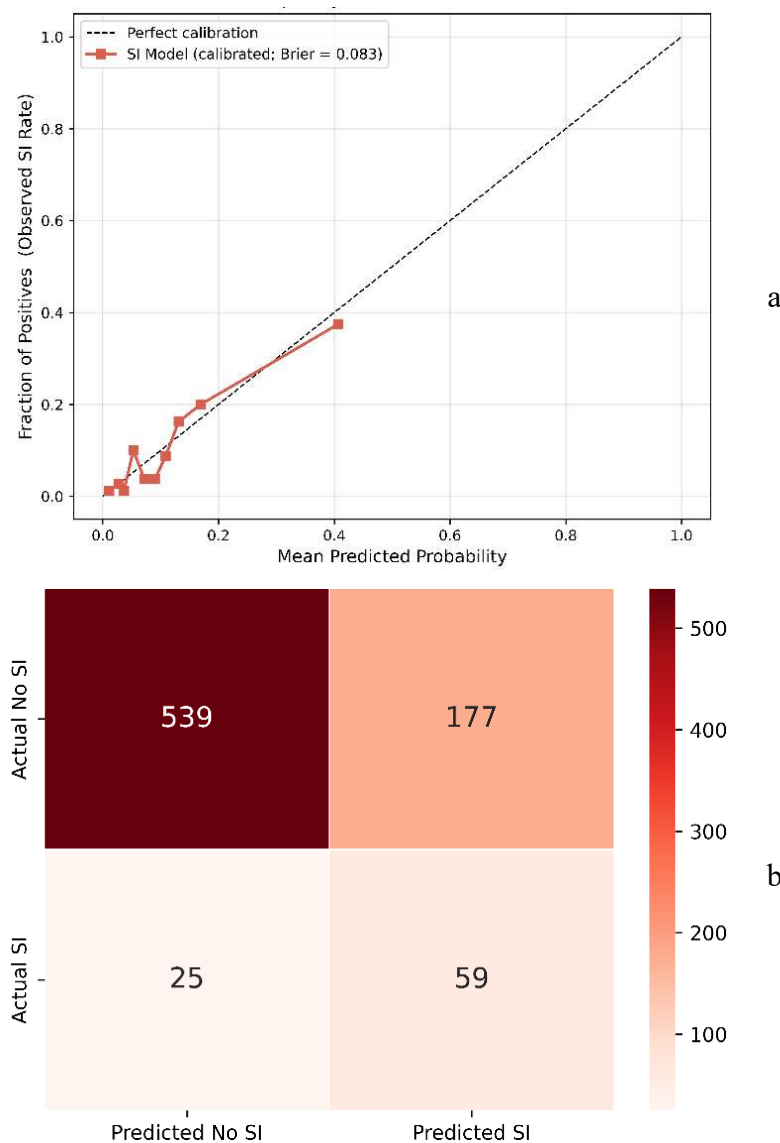
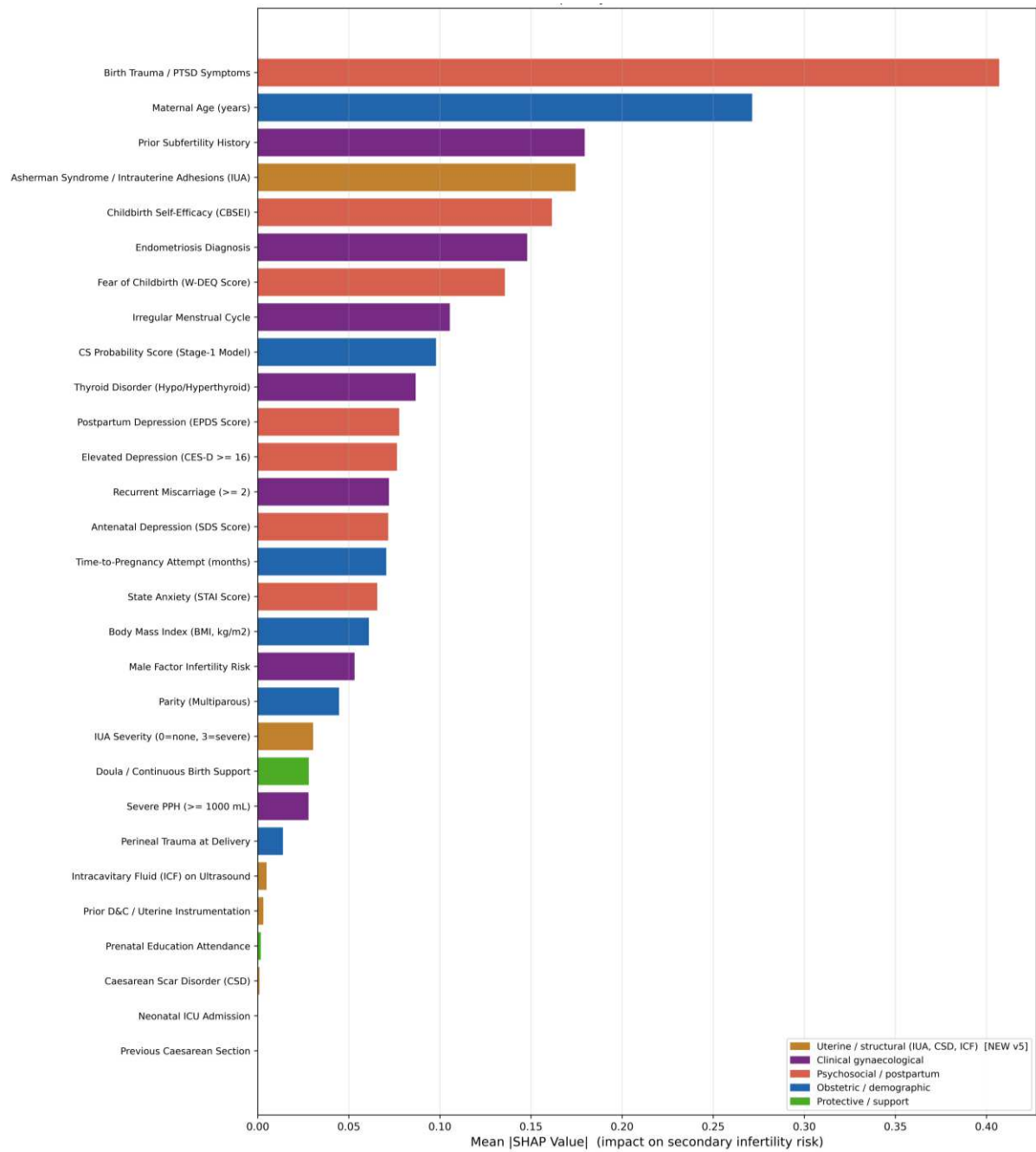


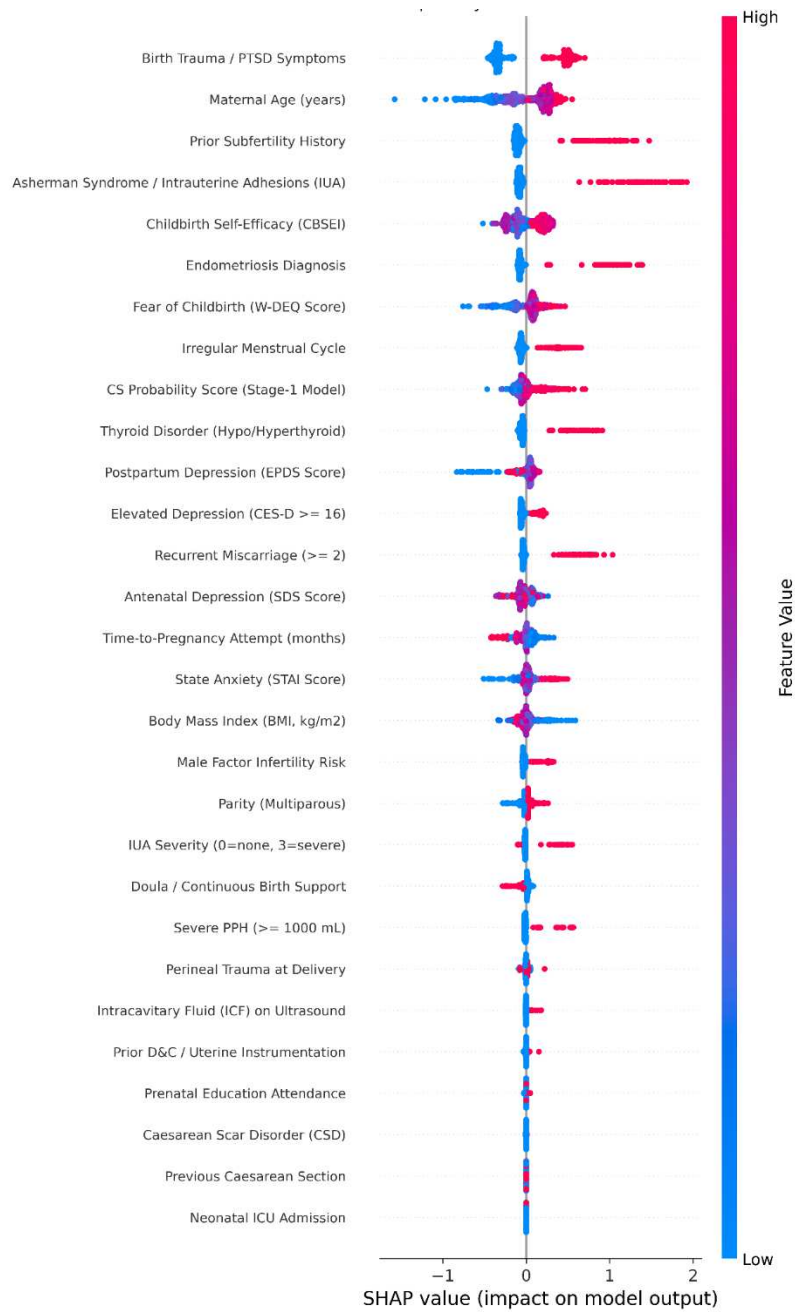
Figure 9: Calibration and classification performance of the SI model. (a) Calibration reliability diagram. (b) Confusion matrix at the Youden-optimal threshold.

3.2.3 Explainability and threshold analysis

SHAP analyses demonstrated that the highest-ranked predictors generally corresponded to variables assigned stronger effects during the synthetic data generation process. As illustrated in Figure 10, uterine pathology, postpartum complications, maternal age, psychological distress indicators, social support measures, and childbirth-related experience variables appeared among the most influential contributors to model output. The dependence plots presented in Figure 11 further demonstrated how variations in these factors affected model predictions across the simulated cohort. These findings should not be interpreted as evidence that such variables are causally associated with SI. Rather, they illustrate that the proposed explainable architecture is capable of recovering and transparently displaying the relationships embedded within the synthetic dataset.



a



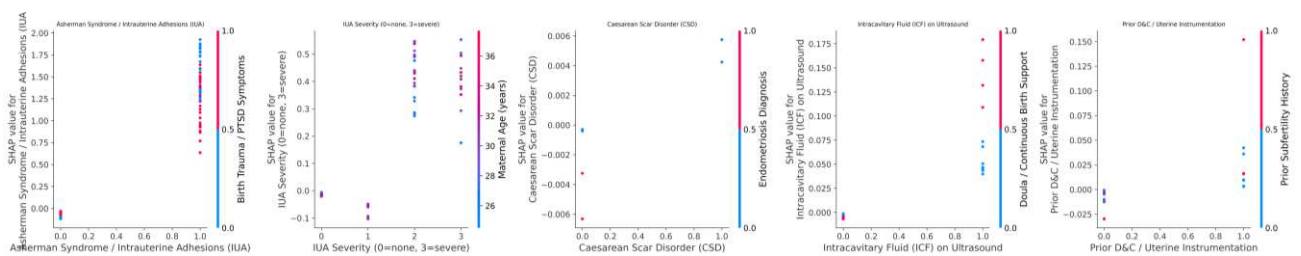
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Figure 10: Global explainability results for the SI model. (a) Mean absolute SHAP

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importance ranking. (b) SHAP beeswarm summary plot.



a

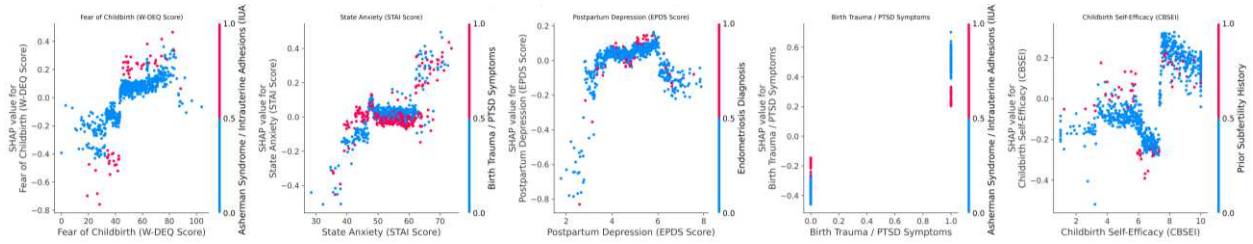
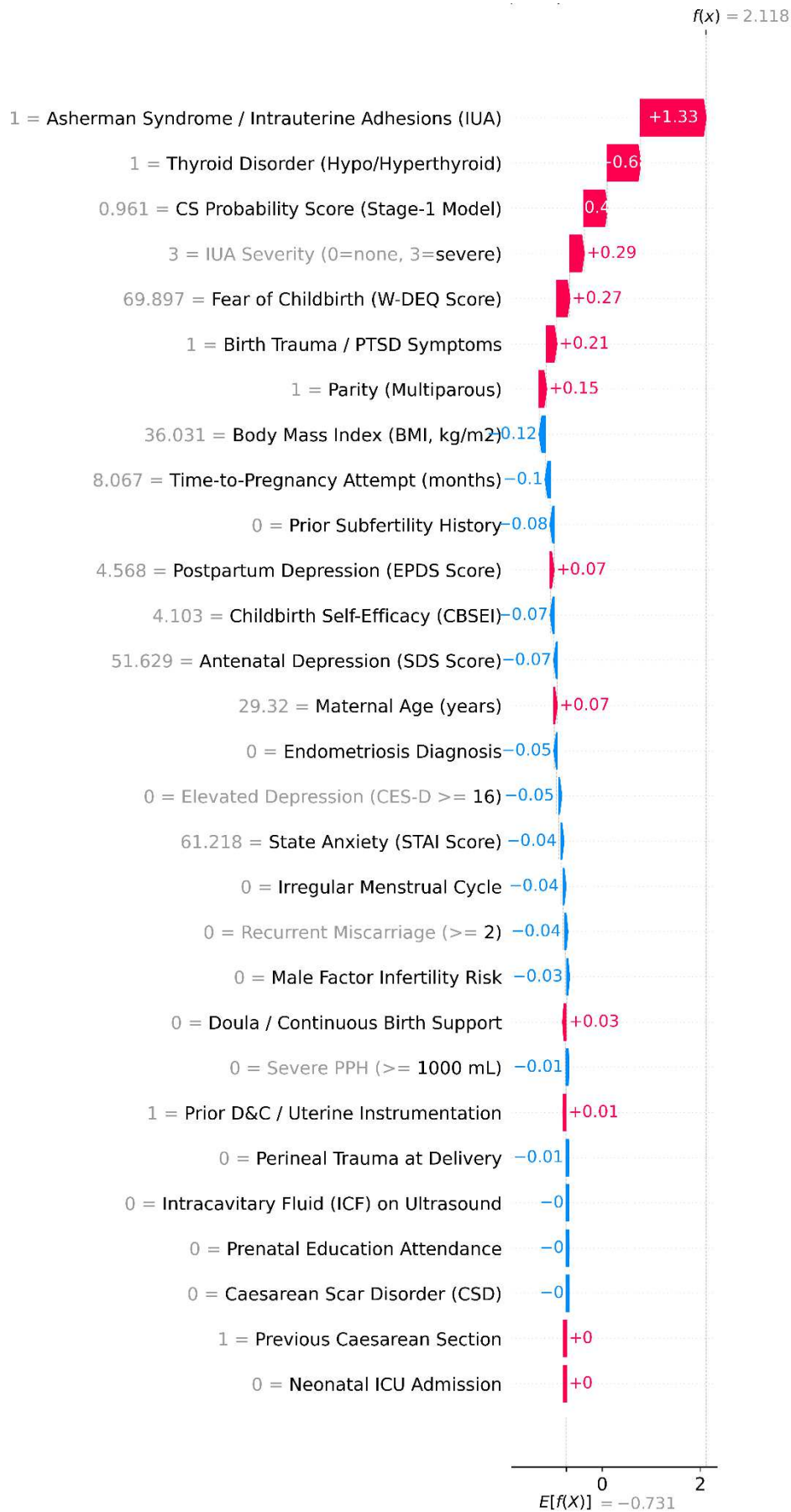


Figure 11: Feature-level explainability analyses. (a) Dependence plots for uterine and structural variables. (b) Dependence plots for psychosocial predictors.

A representative patient-level waterfall explanation and threshold sensitivity analysis are presented in Figure 12. The threshold analysis again demonstrated a trade-off between sensitivity and precision, highlighting the importance of threshold selection when evaluating decision-support systems.



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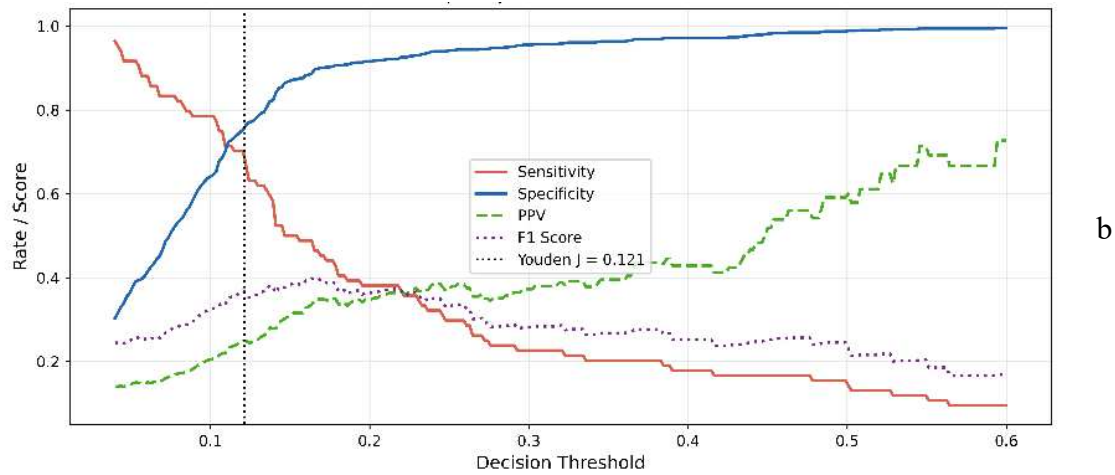


Figure 12: Patient-level explainability and threshold sensitivity analysis. (a) SHAP waterfall plot for a representative high-risk simulated patient. (b) Threshold sensitivity analysis across the full operating range.

3.2.4 Subgroup analysis

Subgroup analyses were conducted to explore model behavior across clinically and psychosocially defined populations. The resulting subgroup-specific AUC values, SI rates, and sample sizes are summarized in Table 8.

Table 8: Exploratory subgroup analyses for the SI framework across clinically, psychosocially, uterine, and demographic subgroups. Results should be interpreted cautiously because they originate from a synthetic dataset and several subgroup sample sizes are limited.

Subgroup	n	AUC	SI rate	Domain
Asherman Syndrome / IUA	56	0.667	32.1%	Uterine [NEW]
Caesarean Scar Disorder	30	0.951	10.0%	Uterine [NEW]
Prior D&C History	162	0.746	16.0%	Uterine [NEW]
Birth Trauma / PTSD	355	0.744	16.1%	Psychosocial
Endometriosis Diagnosis	63	0.719	17.5%	Clinical
Recurrent Miscarriage (≥ 2)	50	0.759	22.0%	Clinical
Thyroid Disorder	49	0.735	16.3%	Clinical
Prior Subfertility History	72	0.802	26.4%	Clinical

Previous CS	422	0.767	12.3%	Obstetric
High FOC (W-DEQ $\geq$ 60)	215	0.749	13.5%	Psychosocial
High STAI $\geq$ 60)	149	0.783	13.4%	Psychosocial
Elevated Depression (CES-D +)	197	0.776	9.1%	Psychosocial
Maternal Age $\geq$ 35	118	0.735	12.7%	Demographic
Severe PPH ($\geq$ 1000 mL)	37	0.848	10.8%	Clinical
No Doula Support	602	0.792	10.8%	Social

As shown in Figure 13 and Table 8, performance estimates varied across subgroups. However, several subgroups contained relatively small sample sizes, resulting in wide uncertainty and potentially unstable estimates. Consequently, these subgroup findings should be regarded as exploratory outputs of the simulation rather than evidence of differential performance in real-world populations.

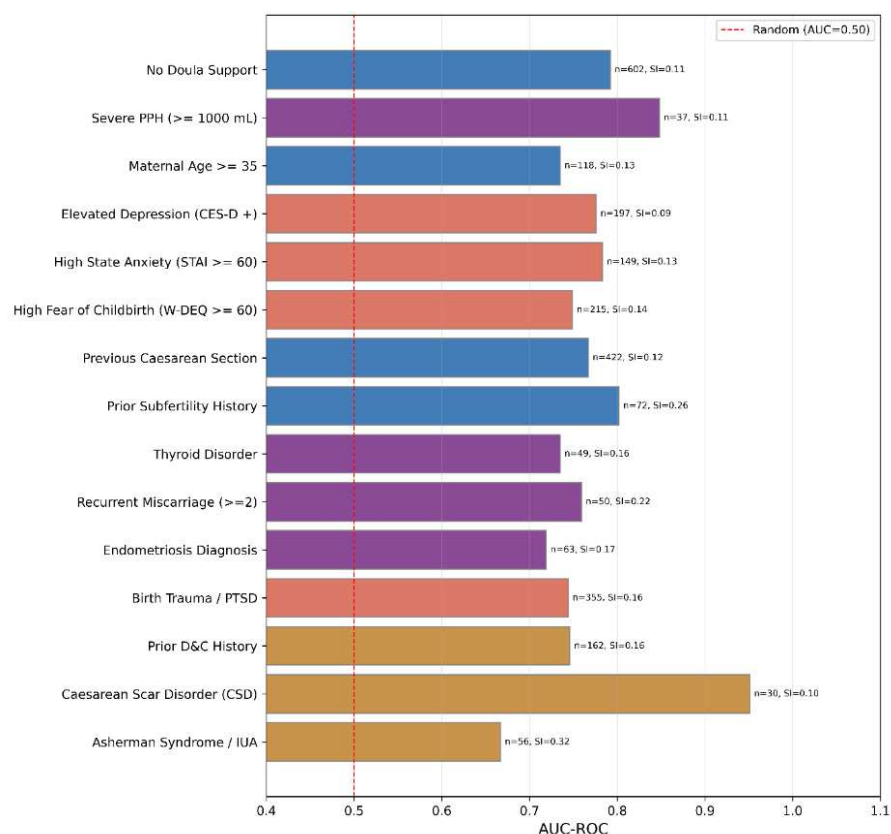


Figure 13: Exploratory subgroup analysis of the SI framework. Area-under-the-curve estimates across clinically and psychosocially defined subgroups. Results are simulation-derived and intended only to demonstrate framework functionality.

A three-stage proof-of-concept scoring tool derived from the literature-parameterized logistic coefficients is provided in Supplementary Material S1 (Tables S1-1 through S1-3). The tool is intended solely to illustrate the factor structure of the modelling architecture and does not constitute a validated clinical instrument.

4 Discussion

The following discussion focuses on the methodological contributions of the proposed architecture addresses the critical issues of variable temporality. Because the dataset was generated synthetically from literature-derived effect sizes and associations, the modeling results reflect the internal consistency of the simulation environment rather than empirical clinical findings.

4.1 Contextualizing the model within a biopsychosocial framework

As outlined in the Introduction, delivery mode is determined by the interaction of established clinical predictors and psychosocial factors that are rarely modeled together. The present framework was designed to capture this multidimensionality, integrating clinical, psychological, and supportive variables within a unified modeling structure. Critically, however, the framework does not replace conventional clinical risk assessment; rather, it complements it by incorporating the psychosocial dimensions that conventional models systematically exclude. CS carries well-documented clinical trade-offs relative to vaginal birth including higher short-term maternal morbidity [26], scar adhesions, placenta accreta spectrum risk in subsequent pregnancies [27], increased neonatal respiratory morbidity (RR = 1.95; 95% CI: 1.40–2.73) [26], and longer-term immune-related conditions in offspring including asthma [28, 29], type 1 diabetes [30], and obesity [31-36], while vaginal birth is associated with faster maternal recovery, lower rates of postpartum depression [37], and microbiota-mediated neonatal immune benefits [38]. These well-established profiles formed part of the evidence

base used to parameterize the synthetic dataset and are directly relevant to interpreting why both CS risk reduction and supportive intervention features carry meaningful predictive weight in the model.

On the patient side, delivery mode preferences are further shaped by factors including educational level, prior birth experience, and access to supportive care [8]. On the provider side, defensive medicine practices, time constraints, and workforce limitations contribute to non-medically indicated CS [5, 39]. Acknowledging both patient- and provider-level drivers is essential for interpreting the model's feature structure and for designing the integrated counseling approaches that this framework is ultimately intended to support.

4.2 Classical predictors and temporality of variables

A recent explainable ML model trained on over 100,000 Australian births demonstrated that LightGBM achieves strong discriminative performance for CS following IOL when these clinical variables are included [40]. The present framework incorporates a temporally stratified design: the antepartum model (trained on 27 pre-labor features) excludes all intrapartum variables, while the intrapartum model (trained on 40 features, i.e. the 27 antepartum plus 13 labor-specific variables) uses only data from patients already in active labor. Gestational age and estimated fetal weight are both assigned to the antepartum feature set, since both are routinely available from antenatal dating and growth ultrasound prior to labor onset and do not require intrapartum observation.

Antepartum-only features (collected before labor onset) include: maternal age, height, BMI, BMI category, parity, gravidity, previous CS, previous vaginal birth, previous vaginal birth after caesarean (VBAC), gestational age, estimated fetal weight, assisted reproductive technology (ART) conception, hypertensive disorder of pregnancy, gestational diabetes, other pregnancy illness, planned IOL, fetal sex, ethnicity, elevated depression (CES-D), FOC (W-

DEQ score), childbirth self-efficacy (CBSEI), state anxiety (STAI score), depression severity (SDS score), prenatal education attendance, doula support, hypnobirthing/relaxation use, and antenatal perineal massage.

Intrapartum-specific features (added in the second stage) are: Bishop score, cervical length, cervical dilation, fetal station, occiput-posterior fetal position, oxytocin use, maximum oxytocin dose, amniotic fluid status, Robson group, epidural use, Virtual reality (VR) non-pharmacological pain relief, intrapartum perineal massage, and waterbirth.

Despite this clear temporal separation, several clinically relevant predictors are not represented. Fetal malpresentation (breech, transverse, or oblique lie)- a well-established absolute indication for CS - was not included. Moreover, other potentially important variables such as detailed cervical assessment prior to labor (other than Bishop score, which is marked as intrapartum) and precise parity-specific Robson sub-classification may not fully capture real-world clinical nuance.

Therefore, any direct comparison of this framework with conventional clinical risk models remains preliminary. Future validation using real-world data should consider adding fetal presentation as a mandatory covariate and carefully re-evaluate the temporal assignment of each predictor to avoid conflation between antenatal, intrapartum, and postpartum periods. The current synthetic proof-of-concept should not be interpreted as a clinically ready decision support tool without external validation. It should also be noted that, within the CS outcome-generating equations, maternal age was retained as a descriptive antepartum covariate but was not assigned an independent literature-derived coefficient in the present version of the framework (unlike its treatment in the secondary infertility model, where an explicit age effect is specified); any age-related signal recovered by the antepartum model therefore arises

indirectly, through its correlation with other parameterized predictors, and should not be interpreted as a direct, independently estimated age effect on CS probability.

4.3 Psychological predictors: fear, anxiety, pain, and birth trauma

The SHAP-based explainability analysis identified FOC score, anxiety, and pain intensity as the primary drivers of the modeled delivery mode outcome, among the highest-ranked features in the antepartum SHAP importance analysis, consistent with their relatively larger embedded coefficients during data generation. FOC is one of the most consistently documented non-clinical predictors of elective CS [9, 11, 18], encompassing both prospective fears related to anticipated labor and retrospective fears linked to prior negative birth experiences [10]. It adversely affects labor duration, analgesic use, and overall birth outcomes [12-15], and is associated with heightened neuroendocrine stress responses that amplify pain perception and reinforce the fear-tension-pain cycle [41, 42]. Psychological birth trauma (PBT), reported in 20-68.6% of women across settings [43], further compounds these associations by contributing to postpartum anxiety, depression, early breastfeeding cessation, impaired partner relationships [44-48], and in severe cases post-traumatic stress disorder (PTSD) [45]. Women with a history of traumatic birth or high baseline FOC represent a clinically identifiable subgroup for whom targeted psychological intervention before a subsequent labor onset may meaningfully alter both delivery trajectory and longer-term reproductive outcomes.

Pain intensity during labor (shaped by physiological, psychological, and contextual factors) emerged as a high-weight predictor in both model stages. Labor pain arises from uterine contractions and cervical dilation (transmitted via T10-L1 spinal segments) and perineal stretching (via the pudendal nerve, S2-S4) [49]. Anxiety, fear, and stress hormones including cortisol and catecholamines further lower the pain threshold [50], creating a bidirectional amplification dynamic. The prominence of pain-related and FOC variables in the model's

feature ranking reflects these documented interdependencies and is consistent with the design assumption that psychological screening instruments carry embedded predictive weight within this simulation framework (FOC measures, anxiety scales, and subjective pain ratings) as core antenatal inputs in a future real-world decision support tool. These findings do not constitute independent empirical discoveries, as the associations were embedded in the generative model from the outset; rather, they demonstrate that the gradient-boosted architecture was able to recover the biopsychosocial signal structure embedded during data generation, as expected given the circular relationship between the generative coefficients and the training labels.

4.4 Non-pharmacological and supportive interventions as modifiable protective factors

Among the protective features in the model, doula support, partner presence, mindfulness-based childbirth and parenting (MBCP) practice, and hypnosis were consistently associated with reduced modeled CS probability. Continuous doula-supported care is associated with significantly reduced odds of CS (AOR = 0.59; 95% CI: 0.51-0.68), with particularly strong reductions for non-indicated CS (AOR = 0.17) [51, 52], alongside lower epidural use, higher spontaneous vaginal birth rates, and improved breastfeeding initiation [53-55]. MBCP programs have demonstrated reductions in perceived stress, FOC, and non-urgent obstetric interventions in RCTs [56-58]. A non-randomized controlled trial of hypnosis reported reduced fear of losing control (OR = 0.511; 95% CI: 0.266-0.980), lower pain intensity (OR = 0.425; 95% CI: 0.189-0.955), and reduced epidural use (OR = 0.415; 95% CI: 0.210-0.818) [59], with effect heterogeneity by baseline FOC level, a pattern multi-outcome frameworks are well positioned to capture.

A broader range of non-pharmacological strategies (birthing balls, positional changes, music therapy, dance, noise reduction, massage, TENS, and breathing techniques) have demonstrated measurable effects on labor pain, anxiety, and maternal satisfaction [60-74].

Dance during labor has been shown to alleviate pain, shorten labor duration, and improve maternal satisfaction without adverse neonatal effects [71]; noise-canceling headphones reduced anxiety and first-stage labor pain in a single-center study [75]. Childbirth-related perineal trauma (CRPT), affecting up to 85% of women following vaginal birth [76, 77], intersects with delivery preferences through psychological sequelae including anxiety about future pregnancies and reduced sexual function [78-83]. Preventive strategies such as antenatal perineal massage, associated with reduced episiotomy rates (16.3% vs. 21.2%) and shorter second-stage labor [84], VR with moderate perineal protection [85], and respectful maternity care practices with structured birth plans [86-90], further reinforce the importance of the experiential and psychosocial dimensions captured by the included features.

Consistent with these literature findings, the present synthetic framework recovered the protective direction of these features. In the antepartum SHAP analysis (Figure 5), doula support, hypnobirthing/relaxation use, and antenatal perineal massage each exhibited negative mean absolute SHAP values, indicating that their presence reduced the predicted probability of CS within the simulation environment. Similarly, in the intrapartum model (Figure 6), waterbirth and VR-based pain relief appeared among the protective features, though their absolute contributions were smaller than those of clinical labor variables.

4.5 Pharmacological pain management and the decision framework

Among the most effective methods of intrapartum pain relief, epidural analgesia is associated with maternal side effects including fever, motor block, urinary retention, and intrapartum hyperthermia [91-95], however, evidence suggests that its impact on neonatal outcomes (including Apgar scores and NICU admission rates) remains modest [96]. The pharmacological landscape further includes combined spinal-epidural (CSE) techniques, intrathecal opioids such as fentanyl and sufentanyl [97-99], and adjuvants including

dexmedetomidine [100-104]. Inhaled nitrous oxide offers a self-administered, rapidly reversible option that reduces anxiety through GABA receptor modulation and NMDA receptor inhibition without the same degree of pain relief as regional techniques [105-108]. The relevance of these modalities to the proposed framework lies in their role in modulating the fear-pain-intervention cycle: effective pharmacological pain management may attenuate the escalating anxiety-pain dynamic and reduce the cumulative modeled risk score. These variables should be treated as intrapartum covariates.

Within the intrapartum model, epidural analgesia was included as a binary predictor and, as shown in the SHAP importance ranking (Figure 6), contributed positively to modelled CS probability. This positive association is consistent with the literature-derived coefficient ($\beta = +0.405$, OR ≈ 1.5) used during data generation (see Table 2b for the complete intrapartum coefficient set). The synthetic data generation process embedded a conditional relationship whereby the probability of epidural use increased with higher FOC (W-DEQ) scores, reflecting the clinically plausible pathway from pain and anxiety to epidural request. However, epidural analgesia itself may prolong labor, increase the need for oxytocin augmentation, and contribute to urinary retention or maternal fever factors that can independently raise the likelihood of CS. Therefore, the positive epidural-CS association recovered by the model is consistent with the literature-derived coefficient ($\beta = +0.405$) embedded during data generation, which itself reflects the documented association between complex labor trajectories and both epidural request and CS outcome. This finding should not be interpreted as an independent empirical discovery; rather, it confirms that the simulation architecture encoded a clinically plausible relationship between these variables.

Within this synthetic framework, cervical dilation, Bishop score, and fetal head position exhibited larger mean absolute SHAP values than epidural analgesia, indicating that labor

progress variables dominated the prediction. This pattern should not be overinterpreted, as it directly reflects the coefficient magnitudes and correlation structures imposed during simulation.

4.6 Previous cesarean section and subsequent delivery decision-making

Prior CS history is a critical clinical factor influencing future delivery mode decisions. VBAC is achievable in appropriately selected cases (with reported success rates of approximately 74% in the absence of additional contraindications) and is associated with lower maternal mortality, shorter hospital stays, and higher breastfeeding rates compared with elective repeat cesarean delivery (ERCD) [109-111]. However, VBAC carries increased uterine rupture risk, and failed trial of labor after caesarean (TOLAC) necessitates emergency repeat CS with associated adverse neonatal outcomes [112, 113]. Prediction of VBAC success requires integration of multiple clinical variables including maternal BMI, prior vaginal delivery history, interpregnancy interval, and cervical status [113], several of which overlap with features in the present model. The framework proposed here complements rather than replaces these clinical predictors.

In the present framework, previous CS was one of the strongest predictors in both the antepartum (Figure 5) and intrapartum (Figure 6) SHAP rankings, with a positive direction of effect (increased CS probability). This is consistent with the literature-derived coefficient of +0.151 (OR $\approx$ 1.16) used in the generative model. The framework does not replace VBAC prediction tools but demonstrates how prior CS can be integrated alongside psychosocial variables.

4.7 SI Framework as an exploratory architectural extension

The SI framework was incorporated as an exploratory extension of the primary delivery-mode prediction architecture. A growing body of literature has examined whether childbirth-

related factors may influence subsequent fecundability and reproductive outcomes [114-116]. Among these, previous CS has received particular attention. A systematic review and meta-analysis by O'Neill et al. (2013)[117], reported a modest association between prior CS and prolonged time-to-next-pregnancy, with a pooled OR of 0.90 (95% CI: 0.86–0.93). However, the authors highlighted substantial methodological limitations across the included studies, including heterogeneous outcome definitions, incomplete adjustment for confounding variables, and limited consideration of voluntary childbearing delay [117].

More recent prospective studies have produced mixed findings. In a large population-based cohort, Sima et al. (2024)[118], observed an adjusted relative risk (RR) of infertility (time-to-pregnancy ≥ 12 months) of 1.21 (95% CI: 1.10-1.33) among women with a previous CS, together with a reduced fecundability ratio of 0.90 (95% CI: 0.88-0.93). Importantly, the same study identified a reciprocal association, whereby women who required longer to conceive were themselves more likely to undergo CS in a subsequent pregnancy [118]. This bidirectional relationship suggests that shared underlying biological, obstetric, or psychosocial factors may contribute to both reduced fecundability and increased likelihood of CS, complicating causal interpretation. Similarly, Radin et al. (2016)[119], demonstrated that associations varied according to indication for CS, with planned CS and breech-related CS showing stronger reductions in fecundability than emergency CS performed for cephalic presentations. Other studies have reported attenuated or null associations after adjustment for maternal characteristics, reproductive history, and fertility-treatment utilization [120, 121].

Beyond delivery mode itself, several childbirth-related conditions incorporated within the present framework have recognized biological plausibility for influencing subsequent fertility. Importantly, these factors were incorporated because biologically plausible mechanisms have been proposed in the literature, not because definitive causal effects have been established.

Intrauterine adhesions (IUA) (Asherman syndrome), uterine instrumentation following miscarriage or postpartum complications, caesarean scar defects (isthmocele), severe postpartum hemorrhage (PPH) requiring surgical intervention, and other forms of uterine injury have all been associated with impaired implantation, menstrual abnormalities, or reduced reproductive potential in selected populations [122, 123]. However, the magnitude and generalizability of these associations remain uncertain, and high-quality prospective evidence is limited. For psychosocial exposures (including FOC, anxiety, depression, and psychological birth trauma) the evidence linking these factors directly to clinically confirmed SI is even less developed, with most studies suggesting indirect pathways mediated through reproductive decision-making, health behaviors, stress-related biological mechanisms, or delayed childbearing intentions [124-126].

Finally, the current literature does not support a simple or universally applicable causal pathway linking childbirth experiences to SI. Rather, the available evidence suggests a complex interplay of obstetric indications, pre-existing reproductive characteristics, uterine pathology, psychosocial factors, and potential confounding mechanisms [127-129]. Many reported associations vary substantially across populations, study designs, and outcome definitions, and relatively few studies have employed prospective longitudinal designs capable of distinguishing voluntary postponement of pregnancy from involuntary infertility [119, 130].

Within this context, the present SI framework should be interpreted as a hypothesis-generating methodological exercise rather than a clinically validated infertility prediction model. The synthetic dataset was parameterized using assumptions derived from an incomplete and heterogeneous evidence base, and therefore the resulting model outputs, feature rankings, calibration characteristics, and threshold analyses reflect properties of the simulation environment rather than verified biological relationships. The principal contribution of this

component is methodological: it demonstrates that the proposed explainable machine-learning architecture can accommodate multiple reproductive-health outcomes while preserving transparency, interpretability, and analytical consistency across modelling stages.

Consequently, the findings derived from the SI framework should not be interpreted as evidence that childbirth-related exposures cause, predict, or protect against SI in real-world populations. Future research will require large prospective preconception and longitudinal reproductive cohorts with detailed documentation of pregnancy intentions, infertility diagnoses, obstetric indications, uterine pathology, psychosocial exposures, and fertility-treatment outcomes. Such studies will be necessary before any robust conclusions regarding the relationship between childbirth experiences and SI can be established.

4.8 Limitations

Several limitations should be considered when interpreting the findings of this study. First, and most importantly, all analyses were conducted using synthetic datasets generated from literature-derived assumptions rather than real patient observations. Consequently, the machine-learning models primarily reflect relationships embedded within the generative process by design. Specifically, because outcome labels were generated using predefined coefficients (COEF-AP and COEF-IP), the models recover these relationships by construction - a circularity inherent to synthetic-data studies. Model discrimination, calibration, threshold analyses, and SHAP-derived feature importance rankings should therefore be interpreted as properties of the simulation framework rather than evidence of predictive performance or clinical validity in real-world populations.

Second, although extensive efforts were made to parameterize the synthetic cohorts using published evidence, the quality of the generated data remains dependent on the quality, completeness, and heterogeneity of the underlying literature sources. Any uncertainty, bias, or

826 inconsistency in the source studies may propagate into the simulated datasets and influence
827 model behavior.

828 Third, the imposed correlation structures and outcome-generating mechanisms necessarily
829 represent simplified approximations of highly complex biological, psychological, and social
830 processes. Real-world reproductive outcomes are shaped by dynamic interactions, healthcare
831 system factors, behavioral adaptations, and unmeasured confounding variables that cannot be
832 fully captured within a predefined synthetic framework.

833 Fourth, the secondary infertility (SI) component should be regarded as an exploratory
834 proof-of-concept extension of the modelling architecture. Although parameterized using
835 published evidence and calibrated to a plausible prevalence target, robust prospective evidence
836 linking childbirth-related factors to subsequent SI remains limited. Accordingly, this
837 component should not be interpreted as establishing causal relationships or providing clinically
838 actionable risk estimates.

839 Fifth, internal validation was limited to train-test splitting and cross-validation within the
840 synthetic data distributions used during model development. No external validation using
841 independent clinical cohorts was performed. Consequently, the generalizability,
842 transportability, and clinical utility of the proposed framework remain unknown.

843 Sixth, despite the use of observation-level sample weighting to address class imbalance,
844 the relatively low outcome prevalence in both the CS antepartum cohort (21.1%) and the SI
845 cohort (12.0%) resulted in modest positive predictive values at the selected operating
846 thresholds, reflecting the inherent challenge of achieving high PPV in low-prevalence risk
847 prediction settings.

Seventh, single-run performance estimates from a stochastic simulation of this size carry non-trivial sampling uncertainty. When the full pipeline was repeated across 30 independent simulation replicates, the antepartum model's AUC-ROC ranged widely (95% empirical CI (0.549, 0.752)) compared with the intrapartum model's narrower range (95% CI (0.704, 0.787)). While the direction of the intrapartum performance advantage was consistent across replicates (29/30; mean Δ AUC = +0.093, 95% CI (0.016, 0.204)), its magnitude should not be inferred from any single simulation run, including the reference run reported in Table 5.

Future work should focus on prospective data collection, external validation in diverse clinical populations, formal assessment of model transportability, and comparison of synthetic-data-derived findings with empirically observed outcomes.

5 Conclusion

The present study demonstrates that a temporally stratified, biopsychosocial ML architecture can be successfully constructed and evaluated within a reproducible synthetic simulation environment, offering a structured proof-of-concept for integrating clinical, psychological, and social predictors within a unified obstetric decision-support framework. While the reported performance metrics (including AUC-ROC values of 0.638 and 0.731 for the antepartum and intrapartum CS models, stable in direction though variable in magnitude across 30 simulation replicates (mean Δ AUC = +0.093, 95% CI (0.016, 0.204)), and 0.777 for the exploratory SI framework) reflect the inherent properties of the simulation rather than real-world predictive validity, they confirm that the proposed architecture can coherently recover and rank complex biopsychosocial signals in an interpretable and auditable manner.

A key methodological contribution of this work is the demonstration that strict temporal separation of antepartum and intrapartum predictors is both feasible and necessary in synthetic

decision-support modelling, directly addressing confounding concerns that have limited prior composite frameworks. The divergence between the antepartum operating threshold (43.7%) and the intrapartum threshold (41.1%) illustrates how the same clinical outcome warrants meaningfully different decision boundaries depending on the temporal moment of assessment. Similarly, the exploratory SI framework, calibrated to an enriched-risk postpartum cohort (12.0% target prevalence), suggests that the proposed architecture may be extensible to long-term reproductive outcomes. However, this component remains strictly hypothesis-generating and must be interpreted with caution given the limited individual-level empirical evidence base.

Perhaps most importantly, this work highlights that FOC, psychological birth trauma, depressive symptoms, and access to continuous supportive care are not peripheral considerations in obstetric risk modelling; they carry measurable, recoverable predictive weight alongside established clinical variables. Whether this structural finding translates into real-world clinical utility remains an open empirical question that only prospective validation can answer. Omission of certain classical predictors, such as fetal malpresentation, represents a acknowledged limitation to be addressed in future real-data validations.

Ultimately, the framework proposed here serves as a methodological template: it identifies the multi-domain variables worth measuring, the analytical separations worth preserving, and the validation questions worth prioritizing. Prospective clinical validation across diverse, real-world populations (with formal assessment of calibration, transportability, and clinical impact) remains the indispensable next step before this holistic pipeline can safely inform obstetric practice.

6 Declarations

6.1 Abbreviation

Abbreviation	Full Form
ART	Assisted reproductive technology
BMI	Body mass index
CBSEI	Childbirth self-efficacy inventory
CES-D	Center for epidemiologic studies depression scale
CS	Caesarean section
CRPT	Childbirth-related perineal trauma
CSE	Combined spinal-epidural
ERCD	Elective repeat caesarean delivery
FOC	Fear of childbirth
GDM	Gestational diabetes mellitus
HDP	Hypertensive disorder of pregnancy
ICSI	Intracytoplasmic sperm injection
ICF	Intracavitary fluid
IOL	Induction of labour
IUA	Intrauterine adhesions
IVF	In vitro fertilisation
NICU	Neonatal intensive care unit
PPH	Postpartum haemorrhage
SI	Secondary infertility
TENS	Transcutaneous electrical nerve stimulation
TOLAC	Trial of labour after caesarean
VBAC	Vaginal birth after caesarean
VR	Virtual reality

EPDS	Edinburgh postnatal depression scale
MBCP	Mindfulness-based childbirth and parenting
PTSD	Post-traumatic stress disorder
SDS	Zung Self-Rating Depression Scale
STAI	State-Trait Anxiety Inventory
W-DEQ	Wijma Delivery Expectancy/Experience Questionnaire
AOR	Adjusted odds ratio
AI	Artificial intelligence
AUC-PR	Area under the precision-recall curve
AUC-ROC	Area under the receiver operating characteristic curve
CI	Confidence interval
CV	Cross-validation
ML	Machine learning
NPV	Negative predictive value
OR	Odds ratio
PPV	Positive predictive value
RR	Relative risk
SHAP	SHapley Additive exPlanations
SMOTE	Synthetic Minority Over-sampling Technique
VIF	Variance inflation factor
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
TRIPOD+AI	Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis - Artificial Intelligence
WHO	World Health Organization

6.2 Ethics approval

Not applicable. This study was conducted as a computational, mechanistic integrative simulation based exclusively on previously published experimental, clinical, and molecular data. No new human participants, identifiable personal data, or animal subjects were involved in the conduct of this research. All data sources were obtained from publicly accessible, peer-reviewed literature, and were used in accordance with applicable guidelines and standards for secondary data analysis. As such, formal ethical approval and informed consent to participate were not required. The study was carried out with careful consideration of research integrity principles, ensuring appropriate citation, responsible data handling, and respect for the original sources of all incorporated findings.

6.3 Consent for Publication

Not applicable. This manuscript does not contain any individual person's data in any form, including identifiable images, videos, or personal information. All information presented in this study is derived from previously published, anonymized, and publicly available sources. Therefore, consent for publication is not applicable.

6.4 Data availability

No primary or secondary patient dataset was used in this study. All data analyzed in this work were synthetically generated using a literature-parameterized simulation framework, as fully described in the Methods section (Section 2). No external or third-party database was accessed. The complete Python source code used for synthetic data generation, model development, calibration, explainability analyses, and scoring tool implementation is provided in the Supplementary Codes. The synthetic datasets can be fully regenerated using the supplied code and fixed random seed (RANDOM-SEED = 42), ensuring complete reproducibility of the reported analyses.

918 **6.5 Competing interests**

919 The author declares that there are no competing interests, financial or non-financial, that
920 could have influenced the work reported in this manuscript.

921 **6.6 Code availability**

922 The complete Python source code used for synthetic data generation, model development,
923 calibration, explainability analyses, and scoring tool implementation is provided in
924 Supplementary Codes.

925 **6.7 Authors' contributions**

926 The author solely conceived and designed the study, conducted the literature review and
927 data curation, developed the computational framework and performed the analysis, interpreted
928 the results, and wrote and revised the manuscript. The author has read and approved the final
929 version of the manuscript.

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6.10 Clinical trial registration

This study does not involve a clinical trial. Clinical trial number: not applicable

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