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Machine Learning Identification of High-Risk Profiles for Unintended Pregnancy in the Benin Republic: Evidence from DHS Data

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Abstract: Unintended pregnancy affects 26.0% of women of reproductive age in Benin and remains a critical obstacle to improving maternal and reproductive health outcomes. This study applied a comparative machine learning framework to data from the 2017–2018 Benin Demographic and Health Survey (n = 8,993 women aged 15–49 with a recent live birth) to predict unintended pregnancy and identify high-risk profiles. Eight supervised algorithms were evaluated under three validation schemes (70/30, 80/20, and 10-fold cross-validation), with class imbalance corrected within each training fold to prevent data leakage. XGBoost emerged as the best-performing model (Accuracy = 0.63, AUROC = 0.62, false positive rate = 0.16), with stable performance across all validation schemes. SHAP analysis identified marital status (14.7%), number of living children (13.4%), region of residence (11.1%), age (9.8%), and ideal number of children (7.9%) as the dominant predictors, collectively explaining 56.9% of the model's predictive contribution. All ten highest-risk profiles corresponded to young married or cohabiting women aged 15–24 with one or two children, spanning multiple regions and all wealth quintiles, demonstrating that vulnerability to unintended pregnancy is not confined to economic disadvantage. Geographically targeted interventions prioritizing young women in early unions with low parity and explicitly addressing contraceptive spacing are recommended.

Keywords: unintended pregnancy, machine learning, predictive modeling, SHAP, Benin Republic, DHS

1. Introduction

Reproductive health is a fundamental component of overall well-being and a key determinant of social and economic development globally [1]. Central to reproductive health is the prevention of unintended pregnancy, which continues to affect millions of women worldwide, particularly in low- and middle-income countries (LMICs) [2,3]. Unintended pregnancies are associated with adverse outcomes for women, children, and communities, underscoring the urgent need for effective prevention strategies [4]. At the individual level, they are linked to increased risks of maternal mortality and morbidity, unsafe abortion, and poor mental health outcomes [1,3]. At the societal level, they perpetuate cycles of poverty and inequality, limit women's educational and economic opportunities, and strain household resources [2]. From a public health perspective, unintended pregnancies generate considerable healthcare costs and impose substantial burdens on already strained health systems, particularly in LMICs [4].

Despite sustained global efforts, the Republic of Benin continues to face acute reproductive health challenges characterized by a high maternal mortality ratio (518 per 100,000 live births) [5]. The modern contraceptive prevalence rate remains low at 12% as of 2019, while unmet need for contraception stands at 36% [6]. The total fertility rate is estimated at 5.7 births per woman, and the adolescent birth rate is 108 births per 1,000 girls aged 15–19—among the highest in West Africa [6]. Between 2015 and 2019, the Republic of Benin recorded approximately 589,000 pregnancies annually, of which 227,000 (39%) were unintended; notably, 37% of these unintended pregnancies ended in abortion [7]. These figures reflect persistent gaps in access to family planning services, particularly long-acting and emergency contraceptive methods, which are often unavailable in primary health facilities [6]. Prior studies across sub-Saharan Africa have most consistently identified younger age, single or non-cohabiting marital status, low parity, lower educational attainment, and subregional disparities as robust determinants of unintended pregnancy [8–18], with household wealth, media exposure, and distance to health facilities emerging as secondary correlates.

While broad-based awareness campaigns and efforts to expand access to reproductive health and family planning services have been implemented [2], existing interventions often lack the precision required to effectively target high-risk women, limiting progress toward national reproductive health goals.

In recent years, machine learning algorithms have gained considerable traction in reproductive and global health research, offering improved capacity to detect non-linear relationships, high-dimensional interactions, and heterogeneous subgroup effects that conventional regression methods may overlook [9,11]. Several studies have applied machine learning to predict unintended pregnancy using DHS and MICS data across sub-Saharan Africa and South Asia, including Random Forest [9], XGBoost [8], and explainable AI approaches [11]. However, these studies either focus on other country contexts, restrict their samples to married or in-union women, rely on a single algorithm without comparative benchmarking, or apply resampling techniques in ways that risk data leakage, limiting the validity of their performance estimates. Moreover, most have used information gain or Gini-based importance measures for variable ranking, which are known to favor high-cardinality variables and do not provide directional interpretability. Few studies have applied a rigorous, multi-algorithm machine learning framework with SHAP-based interpretation to characterize population-level risk profiles of unintended pregnancy specifically in the Republic of Benin.

The present study addresses this gap. Machine learning is particularly suited to this problem because: (i) it can capture non-linear and interaction effects among sociodemographic, geographic, and fertility-related variables that are likely to co-determine unintended pregnancy risk; (ii) it enables the construction of multidimensional risk profiles that go beyond pairwise associations; and (iii) SHAP values provide theoretically grounded, model-agnostic importance scores that improve on conventional feature importance metrics and permit directional interpretation. By applying a comparative benchmarking framework across eight algorithms—combined with SHAP profiling on the best-performing model—this work generates geographically and socially nuanced risk profiles to serve as an evidence base for designing more targeted interventions, optimizing resource allocation, and ultimately contributing to greater equity in reproductive health outcomes in the Republic of Benin.

2. Materials and Methods

2.1. Data and target population

This study analyzes data from the 2017–2018 Benin Demographic and Health Survey (BDHS), focusing on women aged 15–49 whose most recent completed pregnancy resulted in a live birth. We used the Individual Recode (IR) dataset,

publicly available via the DHS Program repository. Of the 15,928 surveyed women, 8,993 met the inclusion criterion and constituted the analytic sample. The BDHS employs a two-stage stratified cluster sampling design, which generates complex survey weights to account for unequal probabilities of selection, clustering, and stratification. Individual-level sampling weights were applied to all descriptive statistics and logistic regression analyses to produce nationally representative estimates. For the machine learning models, which operate on individual-level predictions rather than population-level inference, standard unweighted observations were used; this limitation is explicitly acknowledged in the limitations section.

2.2. Variables and measurement

2.2.1. Outcome variable

The outcome of interest was unintended pregnancy, assessed through retrospective self-reporting of the wantedness of the most recent live birth. A pregnancy was classified as unintended if the woman reported it as either mistimed (wanted later) or unwanted (not wanted at all) at the time of conception. This binary indicator (1 = unintended; 0 = intended) reflects a discordance between fertility preferences and actual reproductive outcomes.

2.2.2. Independent variables

The selection of independent variables was informed by prior research on the determinants of unintended pregnancy across sub-Saharan Africa. The seventeen variables retained were: age at survey, age at first sexual intercourse, number of ever-born children, number of living children, ideal number of children, highest educational level attained, employment status, household wealth index, sex of the household head, exposure to mass media (newspapers/magazines, radio, television, internet), perceived distance to the nearest health facility, marital status, religious affiliation, place of residence (urban/rural), and region of residence. These variables have consistently emerged as significant predictors of unintended pregnancy in the regional literature [8–18].

2.3. Data processing and modelling

2.3.1. Data pre-processing and class imbalance considerations

Data were cleaned, recoded, and prepared for analysis. Of the 8,993 weighted observations, 2,340 (26.0%) reported an unintended pregnancy and 6,653 (74.0%) reported an intended pregnancy. This class imbalance, although moderate, can bias machine learning models toward the majority class. To address this without introducing data leakage, resampling strategies were applied *exclusively within each training fold* of the cross-validation procedure, never on the full dataset before splitting. For distance-based and probabilistic algorithms (Logistic Regression, *k*-Nearest Neighbors, Support Vector Machine, Artificial Neural Networks, J48 Decision Tree), we applied the Synthetic Minority Oversampling Technique (SMOTE) [19] within the training subset only. For tree-based models (Random Forest, XGBoost), we relied on the algorithms' native class-weighting parameters (`sampsize` for Random Forest and `scale_pos_weight` for XGBoost), which preserve probability calibration on the original class distribution. Naïve Bayes was trained on the original imbalanced data, since it estimates class priors directly from the empirical distribution.

2.3.2. Model Building

To characterize marginal and adjusted associations between covariates and the outcome, bivariate and multivariable logistic regression models were estimated as analytic baselines. Eight supervised machine learning algorithms were

then compared: Logistic Regression [20], J48 Decision Tree [21], Random Forest [22], *k*-Nearest Neighbors [23], Support Vector Machine [24], Artificial Neural Networks [25], Naïve Bayes [26], and XGBoost [27]. These eight algorithms were deliberately selected to represent a diverse range of learning paradigms —linear (Logistic Regression), rule-based (J48), distance-based (*k*-NN), probabilistic (Naïve Bayes), margin-based (SVM), ensemble (Random Forest, XGBoost), and connectionist (ANN)—enabling a comprehensive evaluation of whether the predictor–outcome relationships are better captured by linear, non-linear, or ensemble approaches. Their inclusion also facilitates comparison with prior machine learning studies on unintended pregnancy in sub-Saharan Africa, which have used subsets of these same algorithms [9,11]. Each algorithm was evaluated under three validation schemes: a 70/30 train–test split, an 80/20 train–test split, and 10-fold cross-validation repeated five times. Hyperparameters for each algorithm were tuned via grid search within the training data (e.g., tree depth and regularization strength for the ensemble and margin-based models, and neighborhood size for k-Nearest Neighbors). All numerical predictors were centered and scaled before training distance- and margin-based models.

2.3.3. *Performance evaluation, variable ranking, and risk profiling*

Model performance was evaluated using metrics derived from the confusion matrix: true positive rate (sensitivity), false positive rate, precision, F1-score, accuracy, Matthews Correlation Coefficient (MCC), and the Area Under the Receiver Operating Characteristic Curve (AUROC). Reporting these metrics across the three validation schemes allowed assessment of both absolute performance and consistency across data partitions. The best-performing classifier was selected on the basis of overall AUROC and accuracy, with secondary attention to the false positive rate —a critical consideration for public health targeting, where misclassifying women not at risk wastes scarce intervention resources. To identify the most influential predictors, we computed SHAP (SHapley Additive exPlanations) values [28] using the predcontrib functionality of XGBoost, which provides exact and computationally efficient SHAP estimates. Each variable's mean absolute SHAP value across all observations was used to rank its global predictive importance, while the sign of the average SHAP value indicated the directionality of its contribution. We emphasize that these importance scores reflect *predictive* contribution and should not be interpreted as causal effects. Multidimensional high-risk profiles were then constructed by stratifying the dataset across the six top-ranked SHAP variables and computing the mean predicted probability of unintended pregnancy within each stratum. Profiles containing fewer than ten women were excluded to ensure statistical stability.

2.4. *Statistical analysis tools*

All analyses were conducted in R[29] using specialized packages: haven[30], dplyr[31], summarytools[32], ROSE[33], caret[34], randomForest[35], e1071[36], nnet[37], rpart[38], pROC[39], and visualizations with ggplot2[40]. Tables were exported using flex table[41] and officer[42].

2.5. *Ethical Considerations*

The DHS [43] were conducted with formal ethical approval and informed consent from all participants. Permission to use the BDHS dataset was granted by the DHS Program following standard application procedures. As this study used de-identified secondary data, no additional ethical approval was required.

3. Results

3.1. Characteristics of study population

Table 1 summarizes the sociodemographic profile of the 8,993 women included in the analysis. Most women were young (mean age 29.3 years), had no formal education (64.3%), were married or cohabiting (92.4%), and lived in rural areas (61.0%); fertility levels were high, with a mean ideal family size of 4.85 children. These characteristics—age, education, marital status, residence, and parity—correspond to the leading predictors identified in the SHAP analysis reported in Section 3.4. The overall prevalence of unintended pregnancy was 26.0%.

Table 1: Characteristics of study participants

Variable	Weighted Frequency (n=8,993)	Per cent (%)
Unintended pregnancy (last child)		
No	6,653	74.0
Yes	2,340	26.0
Age at the survey - (Mean: 29.28 years)		
15-19 years	504	5.6
20-24 years	1,923	21.4
25-29 years	2,531	28.1
30-34 years	1,855	20.6
35-39 years	1,323	14.7
40-44 years	602	6.7
45-49 years	256	2.8
Age at first sex - (Mean: 16.67 years)		
15-19 years	6,367	70.8
20 years+	1,220	13.6
Before 15 years	1,406	15.6
Highest level of education		
None	5,783	64.3
Primary	1,644	18.3
Secondary or higher	1,566	17.4
Number of ever born children		
4 - 6 children	2,975	33.1
7 - 8 children	837	9.3
9 children or more	313	3.5
Less than 4 children	4,868	54.1
Number of living children		
Five children	925	10.3
Four children	1,361	15.1
No child	77	0.9
One child	1,919	21.3
Seven children or more	668	7.4
Six children	652	7.3

Variable	Weighted Frequency (n=8,993)	Per cent (%)
Three children	1,597	17.8
Two children	1,794	19.9
Ideal number of children - (Mean: 4.85 Enfants)		
3 or less	1,068	11.9
4-5 children	3,671	40.8
6-7 children	4,254	47.3
Employment		
No	1,524	16.9
Yes	7,469	83.1
Sex of the head of household		
Female	1,513	16.8
Male	7,480	83.2
Household wealth index		
Middle	1,830	20.3
Poor	1,819	20.2
Poorest	1,819	20.2
Richer	1,849	20.6
The richest	1,676	18.6
Religious membership		
Christian	4,525	50.3
Muslim	3,002	33.4
Other	613	6.8
Traditional	852	9.5
Reading newspapers and magazines		
No	8,462	94.1
Yes	531	5.9
Listen to radio		
No	3,987	44.3
Yes	5,006	55.7
Watch TV		
No	5,875	65.3
Yes	3,118	34.7
Perception of the distance to get to health Center		
Big problem	5,981	66.5
Not a big problem	3,012	33.5
Use internet		
No, never	8,555	95.1
Yes	438	4.9
Marital status		

Variable	Weighted Frequency (n=8,993)	Per cent (%)
Married/Cohabiting	8,314	92.4
Single/not cohabiting	679	7.6
Place of residence		
Rural	5,485	61.0
Urban	3,508	39.0
Region/Department of residence		
Alibori	1,221	13.6
Atacora	797	8.9
Atlantique	1,038	11.5
Borgou	1,159	12.9
Collines	602	6.7
Couffo	580	6.5
Donga	597	6.6
Littoral	406	4.5
Mono	391	4.3
Ouémé	795	8.8
Plateau	548	6.1
Zou	859	9.6
Total	8,993	100.0

3.2. Prevalence of unintended pregnancy in Benin Republic

The pie chart below (Figure 1) illustrates the distribution of unintended pregnancy among reproductive age women in the Benin Republic. Unintended pregnancy accounts for 26.0% of all reported pregnancies in the study population.

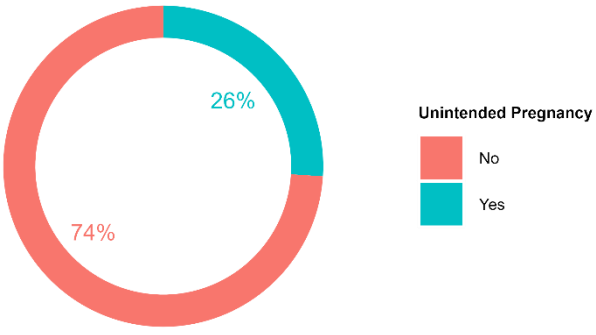


Figure 1: Unintended pregnancy rate in the Benin Republic. Just over one in four pregnancies (26.0%) in the study population was unintended.

At the bivariate level (Table 2), most variables were significantly associated with unintended pregnancy, except for employment status. The strongest associations emerged for marital status (single or non-cohabiting women: 43.2%),

region/department of residence (Atlantique: 47.3%; Littoral: 37.5%; Mono: 37.6%), and age (adolescents 15–19: 32.0%), consistent with the SHAP-based predictor ranking reported later. Lower prevalence was observed among women with no formal education (22.0%) and those desiring six or more children (20.3%), suggesting that high fertility aspirations are associated with more intentional pregnancies.

Table 2: Bivariate analysis of factors associated with unintended pregnancy in Benin Republic

Variable	Unintended pregnancy (last child)		Chi-square	Pvalue
	Yes	No		
Age at the survey - (Mean: 29.28 years)				
15-19 years	161 (32.0)	343 (68.0)	35.5	0.000
20-24 years	569 (29.6)	1354 (70.4)		
25-29 years	610 (24.1)	1921 (75.9)		
30-34 years	451 (24.3)	1404 (75.7)		
35-39 years	321 (24.3)	1002 (75.7)		
40-44 years	152 (25.3)	450 (74.7)		
45-49 years	74 (29.1)	182 (70.9)		
Age at first sex - (Mean: 16.67 years)				
Before 15 years	1700 (26.7)	4667 (73.3)	7.1	0.028
15-19 years	325 (26.6)	895 (73.4)		
20 years+	312 (22.2)	1094 (77.8)		
Highest level of education				
None	1272 (22.0)	4511 (78.0)	145.3	0.000
Primary	544 (33.1)	1100 (66.9)		
Secondary or higher	523 (33.4)	1043 (66.6)		
Number of ever-born children				
Less than 4 children	744 (25.0)	2231 (75.0)	27.7	0.000
4 - 6 children	212 (25.3)	625 (74.7)		
7 - 8 children	101 (32.4)	212 (67.6)		
9 children or more	1553 (31.9)	3315 (68.1)		
Number of living children				
No child	284 (30.7)	641 (69.3)	50.6	0.000
One child	352 (25.9)	1009 (74.1)		
Two children	18 (23.7)	59 (76.3)		
Three children	439 (22.9)	1480 (77.1)		
Four children	172 (25.8)	496 (74.2)		
Five children	181 (27.7)	471 (72.3)		
Six children	457 (28.6)	1140 (71.4)		
Seven children or more	631 (35.2)	1163 (64.8)		
Ideal number of children - (Mean: 4.85 Enfants)				
3 or less	279 (26.1)	789 (73.9)	144.2	0.000
4-5 children	1197 (32.6)	2474 (67.4)		

Variable	Unintended pregnancy (last child)		Chi-square	Pvalue
	Yes	No		
6-7 children	864 (20.3)	3390 (79.7)		
Employment				
Yes	398 (26.1)	1126 (73.9)	0.7	0.389
No	1897 (25.4)	5572 (74.6)		
Sex of the head of household				
Male	377 (24.9)	1136 (75.1)	34.8	0.000
Female	2379 (31.8)	5101 (68.2)		
Household wealth index				
The richest	578 (31.6)	1252 (68.4)	97.4	0.000
Poorest	347 (19.1)	1472 (80.9)		
Poor	437 (24.0)	1382 (76.0)		
Middle	483 (26.1)	1366 (73.9)		
Richer	499 (29.8)	1177 (70.2)		
Religious membership				
Traditional	1308 (28.9)	3217 (71.1)	365.9	0.000
Muslim	420 (14.0)	2582 (86.0)		
Christian	208 (33.9)	405 (66.1)		
Other	196 (23.0)	656 (77.0)		
Reading newspapers and magazines				
No	2192 (25.9)	6270 (74.1)	4.0	0.045
Yes	150 (28.3)	381 (71.7)		
Listen to radio				
Yes	1088 (27.3)	2899 (72.7)	10.2	0.001
No	1226 (24.5)	3780 (75.5)		
Watch TV				
No	1480 (25.2)	4394 (74.8)	10.4	0.001
Yes	861 (27.6)	2257 (72.4)		
Perception of the distance to get to the health Center				
Big problem	1615 (27.0)	4366 (73.0)	9.9	0.002
Not a big problem	729 (24.2)	2283 (75.8)		
Use internet				
Yes	2532 (29.6)	6023 (70.4)	7.7	0.006
No, never	113 (25.8)	325 (74.2)		
Marital status				
Married/Cohabiting	2045 (24.6)	6269 (75.4)	92.2	0.000
Single/not cohabiting	293 (43.2)	386 (56.8)		
Place of residence				
Rural	1349 (24.6)	4136 (75.4)	17.5	0.000
Urban	993 (28.3)	2515 (71.7)		

Variable	Unintended pregnancy (last child)		Chi-square	Pvalue
	Yes	No		
Region/Department of residence				
Littoral	458 (37.5)	763 (62.5)	696.8	0.000
Alibori	46 (5.8)	751 (94.2)		
Atacora	193 (18.6)	845 (81.4)		
Atlantique	548 (47.3)	611 (52.7)		
Borgou	104 (17.2)	498 (82.8)		
Collines	205 (35.3)	375 (64.7)		
Couffo	166 (27.8)	431 (72.2)		
Donga	66 (16.3)	340 (83.7)		
Mono	147 (37.6)	244 (62.4)		
Ouémé	262 (32.9)	533 (67.1)		
Plateau	133 (24.3)	415 (75.7)		
Zou	265 (30.8)	594 (69.2)		
Total	2338 (26.0)	6655 (74.0)		

3.3. Multivariate analysis of factors associated with unintended pregnancy in Benin Republic

The table 3 summarizes the results of the multivariable logistic regression of unintended pregnancy among women of reproductive age in the Benin Republic, with adjusted odds ratios (AOR) and 95% confidence intervals (CI). Consistent with the SHAP-based ranking reported in Section 3.4, marital status, age, and region of residence emerged as the strongest predictors: single or non-cohabiting women had twice the adjusted odds of unintended pregnancy (AOR = 2.06; 95% CI: 1.70–2.49), younger age groups showed progressively higher odds relative to adolescents (AOR = 0.30–0.60 for older groups), and substantial regional disparities were observed, with Alibori (AOR = 0.09), Borgou (AOR = 0.28), and Donga (AOR = 0.30) showing markedly lower odds than Littoral. Educational attainment, parity, and religious affiliation were also significant, but of secondary magnitude. The model achieved good discrimination (C-statistic = 0.737), comparable to the machine learning classifiers reported below.

Table 3: Multivariable analysis of factors associated with unintended pregnancy

Variable	Unintended pregnancy (last child)		unadjusted OR ~ 95 CI%	adjusted OR ~ 95% CI
	Yes	No		
Age at the survey - (Mean: 29.28 years)				
15-19 years	161 (32.0)	343 (68.0)	1.00	1.00
20-24 years	569 (29.6)	1354 (70.4)	0.83 [0.67-1.02] *	0.60 [0.47-0.77] ***
25-29 years	610 (24.1)	1921 (75.9)	0.63 [0.51-0.78] ***	0.30 [0.23-0.39] ***
30-34 years	451 (24.3)	1404 (75.7)	0.64 [0.52-0.80] ***	0.20 [0.15-0.27] ***
35-39 years	321 (24.3)	1002 (75.7)	0.64 [0.51-0.80] ***	0.14 [0.10-0.19] ***
40-44 years	152 (25.3)	450 (74.7)	0.73 [0.57-0.95] **	0.13 [0.09-0.18] ***
45-49 years	74 (29.1)	182 (70.9)	0.81 [0.59-1.12]	0.11 [0.07-0.18] ***

Variable	Unintended pregnancy (last child)		unadjusted OR ~ 95 CI%	adjusted OR ~ 95% CI
	Yes	No		
Age at first sex - (Mean: 16.67 years)				
Before 15 years	1700 (26.7)	4667 (73.3)	1.00	1.00
15-19 years	325 (26.6)	895 (73.4)	1.00 [0.88-1.14]	1.09 [0.94-1.26]
20 years+	312 (22.2)	1094 (77.8)	0.82 [0.69-0.98] **	1.07 [0.86-1.32]
Highest level of education				
None	1272 (22.0)	4511 (78.0)	1.00	1.00
Primary	544 (33.1)	1100 (66.9)	1.79 [1.59-2.02] ***	1.30 [1.13-1.50] ***
Secondary or higher	523 (33.4)	1043 (66.6)	1.81 [1.60-2.04] ***	1.48 [1.25-1.75] ***
Number of ever-born children				
Less than 4 children	744 (25.0)	2231 (75.0)	1.00	1.00
4 - 6 children	212 (25.3)	625 (74.7)	1.00 [0.90-1.11]	0.97 [0.73-1.26]
7 - 8 children	101 (32.4)	212 (67.6)	1.38 [1.17-1.61] ***	1.19 [0.81-1.74]
9 children or more	1553 (31.9)	3315 (68.1)	1.55 [1.22-1.96] ***	1.71 [1.06-2.72] **
Number of living children				
No child	284 (30.7)	641 (69.3)	1.00	1.00
One child	352 (25.9)	1009 (74.1)	0.71 [0.44-1.18]	0.65 [0.38-1.15]
Two children	18 (23.7)	59 (76.3)	0.65 [0.40-1.08] *	1.03 [0.60-1.82]
Three children	439 (22.9)	1480 (77.1)	0.62 [0.38-1.03] *	1.40 [0.80-2.48]
Four children	172 (25.8)	496 (74.2)	0.69 [0.43-1.15]	2.27 [1.23-4.28] **
Five children	181 (27.7)	471 (72.3)	0.83 [0.51-1.39]	3.59 [1.93-6.84] ***
Six children	457 (28.6)	1140 (71.4)	0.81 [0.49-1.36]	4.16 [2.19-8.06] ***
Seven children or more	631 (35.2)	1163 (64.8)	1.15 [0.70-1.92]	6.28 [3.17-12.67] ***
Ideal number of children - (Mean: 4.85 Enfants)				
3 or less	279 (26.1)	789 (73.9)	1.00	1.00
4-5 children	1197 (32.6)	2474 (67.4)	1.24 [1.07-1.45] ***	1.02 [0.86-1.21]
6-7 children	864 (20.3)	3390 (79.7)	0.67 [0.58-0.78] ***	0.73 [0.61-0.88] ***
Employment				
Yes	398 (26.1)	1126 (73.9)	1.00	1.00
No	1897 (25.4)	5572 (74.6)	0.94 [0.83-1.07]	1.14 [0.99-1.33] *
Sex of the head of household				
Male	377 (24.9)	1136 (75.1)	1.00	1.00
Female	2379 (31.8)	5101 (68.2)	1.44 [1.27-1.62] ***	0.97 [0.85-1.12]
Household wealth index				
The richest	578 (31.6)	1252 (68.4)	1.00	1.00
Poorest	347 (19.1)	1472 (80.9)	0.49 [0.42-0.57] ***	0.87 [0.69-1.10]
Poor	437 (24.0)	1382 (76.0)	0.67 [0.58-0.77] ***	0.96 [0.77-1.19]
Middle	483 (26.1)	1366 (73.9)	0.74 [0.64-0.86] ***	0.98 [0.80-1.20]

Variable	Unintended pregnancy (last child)		unadjusted OR ~ 95 CI%	adjusted OR ~ 95% CI
	Yes	No		
Richer	499 (29.8)	1177 (70.2)	0.88 [0.76-1.01] *	1.04 [0.87-1.24]
Religious membership				
Traditional	1308 (28.9)	3217 (71.1)	1.00	1.00
Muslim	420 (14.0)	2582 (86.0)	0.41 [0.34-0.49] ***	0.76 [0.61-0.96] **
Christian	208 (33.9)	405 (66.1)	1.27 [1.08-1.49] ***	1.11 [0.93-1.33]
Other	196 (23.0)	656 (77.0)	0.73 [0.57-0.92] ***	0.89 [0.68-1.15]
Reading newspapers and magazines				
No	2192 (25.9)	6270 (74.1)	1.00	1.00
Yes	150 (28.3)	381 (71.7)	1.22 [1.01-1.48] **	0.92 [0.73-1.15]
Listen to radio				
Yes	1088 (27.3)	2899 (72.7)	1.00	1.00
No	1226 (24.5)	3780 (75.5)	0.86 [0.78-0.94] ***	1.14 [1.01-1.28] **
Watch TV				
No	1480 (25.2)	4394 (74.8)	1.00	1.00
Yes	861 (27.6)	2257 (72.4)	1.18 [1.07-1.30] ***	0.91 [0.80-1.05]
Perception of the distance to get to the health Center				
Big problem	1615 (27.0)	4366 (73.0)	1.00	1.00
Not a big problem	729 (24.2)	2283 (75.8)	0.85 [0.77-0.94] ***	1.10 [0.97-1.23]
Use internet				
Yes	2532 (29.6)	6023 (70.4)	1.00	1.00
No, never	113 (25.8)	325 (74.2)	0.75 [0.61-0.92] ***	1.05 [0.82-1.35]
Marital status				
Married/Cohabiting	2045 (24.6)	6269 (75.4)	1.00	1.00
Single/not cohabiting	293 (43.2)	386 (56.8)	2.19 [1.86-2.57] ***	2.06 [1.70-2.49] ***
Place of residence				
Rural	1349 (24.6)	4136 (75.4)	1.00	1.00
Urban	993 (28.3)	2515 (71.7)	1.23 [1.12-1.35] ***	1.04 [0.92-1.17]
Region/Department of residence				
Littoral	458 (37.5)	763 (62.5)	1.00	1.00
Alibori	46 (5.8)	751 (94.2)	0.09 [0.07-0.12] ***	0.09 [0.07-0.13] ***
Atacora	193 (18.6)	845 (81.4)	0.32 [0.26-0.41] ***	0.26 [0.19-0.35] ***
Atlantique	548 (47.3)	611 (52.7)	1.34 [1.08-1.65] ***	1.09 [0.86-1.39]
Borgou	104 (17.2)	498 (82.8)	0.29 [0.23-0.36] ***	0.28 [0.21-0.37] ***
Collines	205 (35.3)	375 (64.7)	0.81 [0.65-1.02] *	0.64 [0.49-0.83] ***
Couffo	166 (27.8)	431 (72.2)	0.58 [0.45-0.74] ***	0.55 [0.41-0.74] ***
Donga	66 (16.3)	340 (83.7)	0.29 [0.22-0.37] ***	0.30 [0.22-0.41] ***
Mono	147 (37.6)	244 (62.4)	0.85 [0.66-1.09]	0.71 [0.53-0.95] **
Ouémé	262 (32.9)	533 (67.1)	0.71 [0.57-0.90] ***	0.62 [0.48-0.79] ***

Variable	Unintended pregnancy (last child)		unadjusted OR ~ 95 CI%	adjusted OR ~ 95% CI
	Yes	No		
Plateau	133 (24.3)	415 (75.7)	0.52 [0.40-0.67] ***	0.50 [0.37-0.66] ***
Zou	265 (30.8)	594 (69.2)	0.67 [0.54-0.84] ***	0.54 [0.42-0.70] ***

Number in dataframe = 8993, Number in model = 8993, Missing = 0, AIC = 9135.1, C-statistic = 0.737, H&L = Chi-sq (8) 15.56 (p=0.049)

3.4. Development and evaluation of models

Table 4 presents the comparative performance of the eight machine learning classifiers across the three validation schemes. Performance metrics were notably stable across 70/30, 80/20, and 10-fold cross-validation, indicating robustness against overfitting and the absence of validation-scheme dependence. XGBoost achieved the best overall performance, with an average accuracy of 0.63, AUROC of 0.62, and a notably low false positive rate of 0.16. Random Forest and Logistic Regression followed closely, both reaching an average AUROC of 0.62. The comparable performance of logistic regression to more flexible ensemble methods is itself a meaningful finding: it suggests that the relationships between predictors and the outcome are largely linear and additive, offering limited marginal gain from non-linear models. *k*-Nearest Neighbors yielded the weakest discrimination (AUROC = 0.56), while Naïve Bayes exhibited the highest sensitivity (TP rate = 0.81) but at the cost of a high false positive rate (0.68), limiting its practical utility for targeted public health interventions.

Table 4: Comparison of machine learning algorithms' performance

Training-Test Ratio	Measure	ANN	k.NN	LR	SVM	J48	NB	XGBoost	RF
70/30	TP Rate	0.49	0.50	0.64	0.35	0.45	0.82	0.26	0.50
	FP Rate	0.36	0.40	0.49	0.28	0.33	0.68	0.20	0.37
	Precision	0.44	0.42	0.43	0.42	0.45	0.41	0.44	0.44
	F1 Score	0.47	0.46	0.52	0.38	0.45	0.55	0.33	0.47
	Accuracy	0.59	0.56	0.56	0.58	0.59	0.50	0.61	0.59
	AUROC	0.60	0.56	0.61	0.56	0.58	0.61	0.60	0.61
80/20	TP Rate	0.48	0.49	0.64	0.40	0.42	0.80	0.25	0.50
	FP Rate	0.33	0.39	0.49	0.28	0.31	0.68	0.15	0.35
	Precision	0.46	0.44	0.45	0.44	0.43	0.41	0.48	0.44
	F1 Score	0.47	0.46	0.53	0.42	0.42	0.54	0.33	0.47
	Accuracy	0.60	0.56	0.56	0.60	0.60	0.50	0.63	0.60

Training-Test Ratio	Measure	ANN	k.NN	LR	SVM	J48	NB	XGBoost	RF
	AUROC	0.61	0.56	0.63	0.60	0.58	0.59	0.61	0.62
10-fold	TP Rate	0.49	0.49	0.65	0.41	0.42	0.81	0.23	0.52
	FP Rate	0.35	0.39	0.49	0.28	0.31	0.67	0.12	0.35
	Precision	0.45	0.42	0.44	0.46	0.45	0.41	0.53	0.47
	F1 Score	0.47	0.45	0.52	0.43	0.43	0.55	0.32	0.49
	Accuracy	0.59	0.56	0.56	0.60	0.59	0.51	0.64	0.60
	AUROC	0.61	0.57	0.62	0.59	0.58	0.60	0.64	0.63
Mean	TP Rate	0.49	0.49	0.64	0.39	0.43	0.81	0.25	0.51
	FP Rate	0.35	0.39	0.49	0.28	0.32	0.68	0.16	0.36
	Precision	0.45	0.43	0.44	0.44	0.44	0.41	0.48	0.45
	F1 Score	0.47	0.46	0.52	0.41	0.43	0.55	0.33	0.48
	Accuracy	0.59	0.56	0.56	0.59	0.59	0.50	0.63	0.60
	AUROC	0.61	0.56	0.62	0.58	0.58	0.60	0.62	0.62

Figure 2 displays the same information graphically through a radar chart, further illustrating the consistency of XGBoost across accuracy, F1-score, and AUROC.

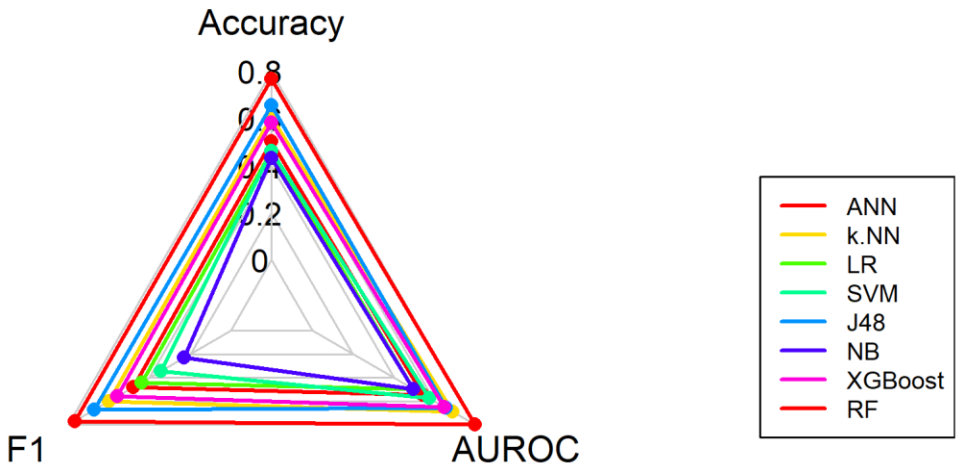


Figure 2: Comparative radar chart of classification model performance. XGBoost consistently outperforms the other seven classifiers across accuracy, F1-score, and AUROC.

3.5. Variable importance in predicting unintended pregnancy

To gain insight into the contribution of individual predictors to the XGBoost model's output, we computed SHAP values for the full analytic sample (Figure 3). The top five predictors—marital status, number of living children, region of residence, age, and ideal number of children—accounted for 56.9% of the model's total predictive contribution. Marital status alone contributed 14.7%, with married or cohabiting women associated with a lower predicted probability of unintended pregnancy (negative mean SHAP value). Number of living children contributed 13.4%, with higher parity associated with lower predicted risk—plausibly reflecting greater contraceptive uptake among women who have completed their desired family size. Regional differences (11.1%) and age (9.8%) confirmed the patterns observed in the multivariable regression, with younger women and those in Littoral showing higher predicted risk. Ideal number of children was the strongest *positive* contributor (7.9%), indicating that women whose stated ideal family size exceeded their current parity were more likely to experience unintended pregnancy—suggesting an unmet desire for contraceptive spacing rather than family-size limitation. Lower-ranked predictors included religious affiliation (6.7%), perceived distance to health facilities (5.8%), radio exposure (5.1%), and place of residence (4.6%). These SHAP values measure each variable's predictive contribution to the model's output and should not be interpreted as causal effects.

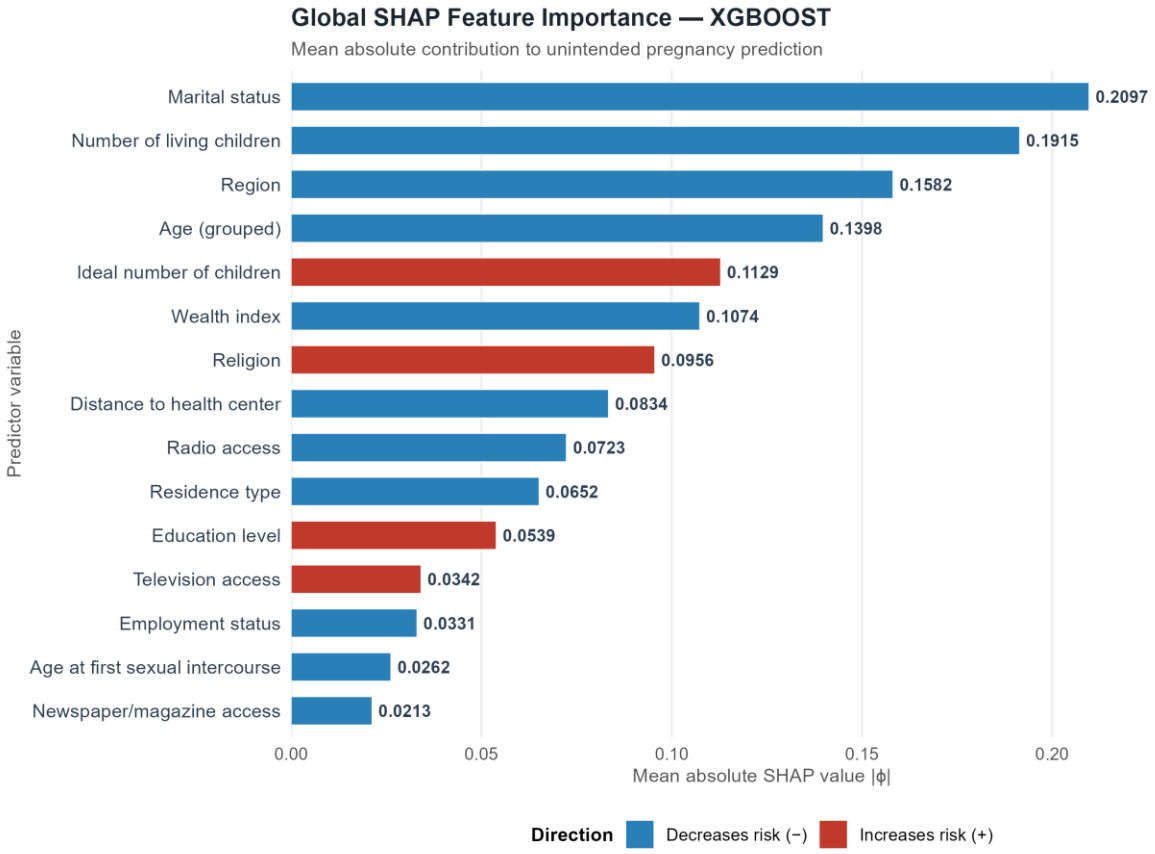


Figure 3: Ranking of predictive variables for unintended pregnancy in the Benin Republic. Marital status, parity, region, age, and ideal family size jointly account for 56.9% of the model's predictive contribution.

Table 5 presents the global SHAP values for all seventeen predictor variables ranked by their mean absolute contribution to the XGBoost model's output. While Figure 2 illustrates the top predictors, the full table shows the complete contribution structure across the entire set of variables. Beyond the top five (marital status, number of living children, region, age, and ideal number of children), wealth index (7.5%), perceived distance to health facilities (5.8%), and radio access (5.1%) constitute a second tier of moderate predictors with negative SHAP directions. A third tier of lower-ranking variables—including television access, employment status, newspaper access, internet use, and age at first sexual intercourse—each contributed less than 2.5% of total importance, consistent with their non-significant or marginal associations in the multivariable regression. Across all seventeen predictors, nine exhibited negative SHAP directions (associated with lower predicted risk), and eight exhibited positive directions (associated with higher predicted risk), underscoring that the determinants of unintended pregnancy in the Benin Republic operate in both protective and risk-increasing directions simultaneously.

Table 5: Global SHAP values and predictive importance of variables in the XGBoost model for unintended pregnancy

Rank	Label	Mean SHAP |ϕ|	Direction	% Importance
1	**Marital status**	**0.21**	**-**	**14.7**
2	**Number of living children**	**0.19**	**-**	**13.4**
3	**Region**	**0.16**	**-**	**11.1**
4	**Age (grouped)**	**0.14**	**-**	**9.8**
5	**Ideal number of children**	**0.11**	**+**	**7.9**
6	Wealth index	0.11	-	7.5
7	Religion	0.10	+	6.7
8	Distance to health center	0.08	-	5.8
9	Radio access	0.07	-	5.1
10	Residence type	0.07	-	4.6
11	Education level	0.05	+	3.8
12	Television access	0.03	+	2.4
13	Employment status	0.03	-	2.3
14	Age at first sexual intercourse	0.03	-	1.8
15	Newspaper/magazine access	0.02	-	1.5
16	Sex of household head	0.01	+	1.0

Rank	Label	Mean SHAP |ϕ|	Direction	% Importance
17	Internet use	0.01	-	0.6

3.6. High-risk profiles for unintended pregnancy in Benin Republic

Multidimensional risk profiles were constructed by stratifying the analytic sample across the six top-ranked SHAP variables: marital status, number of living children, region of residence, age, ideal number of children, and household wealth index. The mean predicted probability of unintended pregnancy was computed within each stratum, retaining only profiles with at least ten women to ensure statistical stability. Figure 4 displays the ten profiles associated with the highest predicted probabilities of unintended pregnancy.

A striking and counterintuitive finding is that all ten high-risk profiles correspond to married or cohabiting women, not to single or non-cohabiting women. This result does not contradict the SHAP analysis—which correctly identifies marital status as the strongest predictor, with being single associated with higher predicted risk at the individual level. Rather, it reflects a sampling constraint: single or non-cohabiting women represent only 7.6% of the analytic sample (n = 679), and when their already small subgroup is further stratified across five additional variables, the resulting strata almost universally contain fewer than ten women and are therefore excluded from the profiling stage. The top ten profiles thus identify the highest-risk configurations within the numerically dominant married or cohabiting group. This methodologically important distinction underscores the need for cautious interpretation of profile-based results alongside individual-level SHAP contributions.

Within this group, predicted probabilities range from 59% to 65% across the top ten profiles—a range that is both meaningful and consistent with the model's overall AUROC of 0.62, confirming that the profiles are discriminating real heterogeneity in risk rather than artefacts of the algorithm. Two universal features cut across all ten profiles: young age (15–19 or 20–24 years) and low parity (one or two living children). Together, these dimensions define a specific life-course juncture—early union, early childbearing, unfulfilled fertility trajectory—that consistently generates elevated predicted risk regardless of region, wealth, or fertility preferences.

The two highest-risk profiles, both carrying a predicted probability of 65%, reveal an important contrast that speaks to the multidimensional nature of vulnerability. The first and highest-risk profile comprises married women aged 15–19 with one living child, residing in Alibori (the northernmost department), whose ideal family size is three children or fewer, from poor households. This profile captures a form of vulnerability rooted in early marriage, geographic remoteness, limited wealth, and a relatively modest fertility aspiration—suggesting that, for these women, a pregnancy occurring early in a union may be experienced as mistimed against a backdrop of limited family planning access and economic constraint. The second profile, with an identical predicted probability of 65%, presents a starkly different socioeconomic configuration: married women aged 20–24 with two children in Littoral (the country's economic hub, home to Cotonou), whose ideal family size is 4–5 children, from the wealthiest households. That two such contrasting profiles—one poor and northern, the other affluent and urban—share the same predicted probability of unintended pregnancy strongly illustrates that risk in the Benin Republic is not confined to any single axis of disadvantage.

The northern departments generate two additional high-risk profiles through Atacora. The third profile mirrors the Alibori configuration in its age group (15–19 years) and wealth (poor households), but features an ideal of 4–5 children and a predicted probability of 62%—slightly lower, yet still among the highest observed. The sixth profile shifts to an

older age bracket (20–24 years) within the same department, with middle-wealth households and an ideal of 4–5 children, reaching 61%. Together, these two Atacora profiles suggest that north-western Benin concentrates a specific cluster of risk among young primiparous women in early unions, irrespective of their stated fertility preferences, likely reflecting the documented shortfalls in family planning service coverage in this region [6].

The Atlantique department generates three distinct profiles, ranked seventh to ninth with predicted probabilities of 60%, 59%, and 59%, respectively. All three share the same age group (20–24 years) and one living child, but differ in ideal family size (4–5 children vs. three or fewer) and wealth quintile (richest vs. richer). The clustering of three separate profiles within Atlantique alone—the department surrounding the coastal economic corridor—underscores the particular vulnerability of young women in this fast-urbanising context, where rapid socioeconomic change may outpace the expansion of reproductive health services and generate new forms of spacing failure. A fifth profile in the southern belt, the fourth overall with a predicted probability of 61%, captures married women aged 20–24 with one child in Couffo, with an ideal of 6–7 children from middle-wealth households—one of only two profiles in the top ten with a large stated ideal family size, suggesting that for these women elevated risk may stem more from contraceptive discontinuation during a period of high fertility desire than from opposition to childbearing per se.

The tenth and final profile—married women aged 20–24 with two children in Borgou, with an ideal of 4–5 children from richer households, predicted probability 59%—extends the geographic reach of high-risk profiles into north-central Benin Republic and demonstrates that elevated risk is not geographically confined to either the southern coast or the far north. Across the full set of ten profiles, household wealth spans the entire distribution: poor and poorest households appear alongside middle, richer, and richest quintiles, with the wealthiest category appearing in four of the ten profiles. This heterogeneity constitutes perhaps the most policy-relevant finding of the profiling exercise: vulnerability to unintended pregnancy in the Republic of Benin cannot be equated with poverty. Programs that restrict their targeting to low-wealth populations will systematically miss a substantial share of high-risk women embedded in middle- and upper-wealth households, particularly in urban and peri-urban departments.

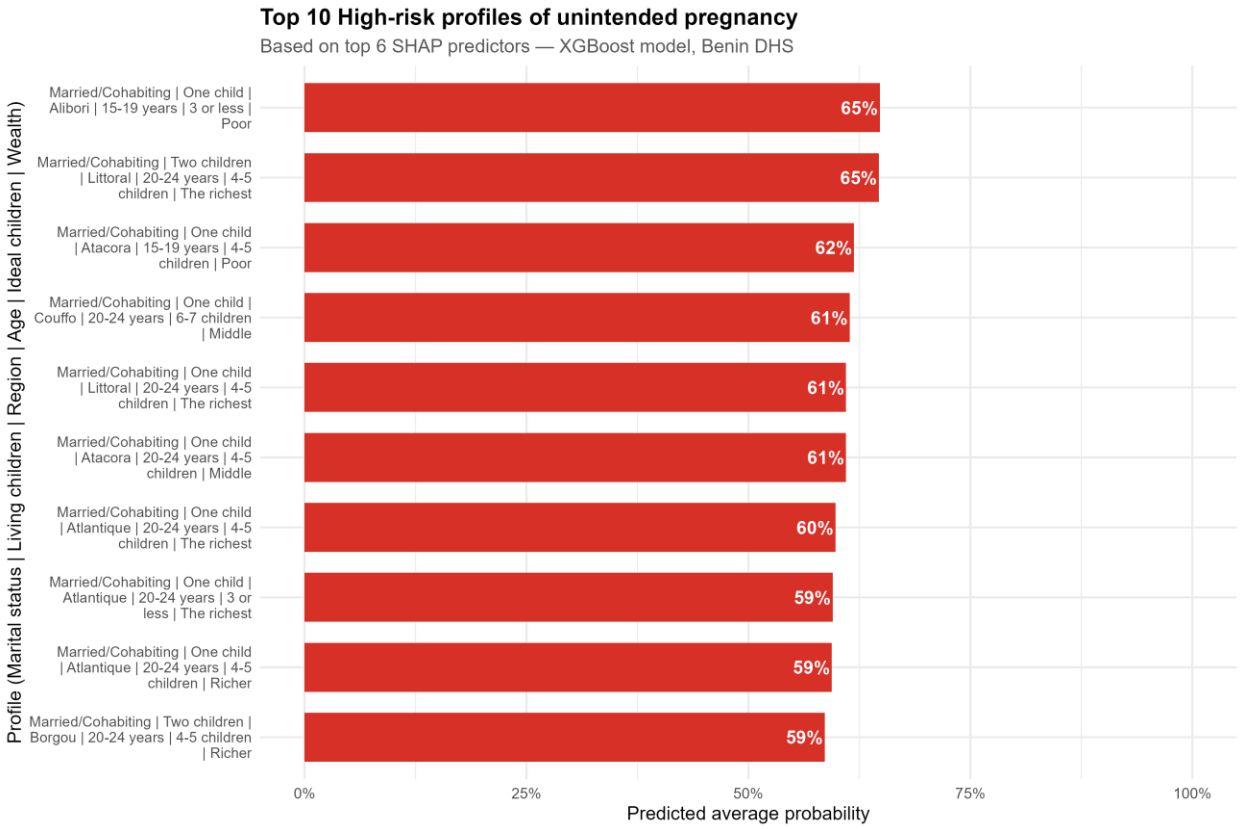


Figure 4: Top 10 profiles with elevated risk of unintended pregnancy in the Republic. All ten highest-risk profiles are young, low-parity, married or cohabiting women, spanning every wealth quintile and both northern and southern departments.

4. Discussion

This study leveraged a comparative machine learning framework, complemented by SHAP-based interpretation, to identify and profile women at elevated risk of unintended pregnancy in the Republic. Three findings stand out for their interpretive and policy implications: the moderate but consistent predictive performance achieved across all eight algorithms, the dominance of marital status, parity, region, age, and fertility preferences as SHAP-ranked predictors, and the concentration of the ten highest-risk profiles among young married women with low parity, distributed across both southern and northern departments and spanning the entire wealth spectrum—directly challenging the common assumption that unintended pregnancy is primarily a poverty-driven phenomenon.

The stability of model performance across all three validation schemes provides reassuring evidence of robustness and confirms the absence of optimistic bias that would otherwise undermine inferential confidence. The moderate AUROC of approximately 0.62 is consistent with the predictive ceiling typically observed in DHS-based studies of reproductive health outcomes [11], and reflects the inherent unpredictability of pregnancy intention from sociodemographic data alone—important psychosocial and contextual drivers such as partner attitudes, relationship dynamics, and contraceptive availability at the precise moment of conception are not captured in the DHS instrument. From a methodological standpoint, the comparable performance of logistic regression and XGBoost (both reaching AUROC = 0.62) is noteworthy in its own right: it suggests that predictor–outcome relationships in this dataset are largely linear and additive,

offering little marginal gain from non-linear ensemble methods. This finding has important practical implications for national health systems with limited analytic capacity—transparent, interpretable models can deliver most of the predictive value of complex algorithms while remaining considerably easier to communicate, audit, and integrate into routine decision-making processes.

Turning to the substantive interpretation of the predictors, the dominant role of marital status in the SHAP ranking—with its negative direction indicating that being married or cohabiting is associated with lower predicted risk at the individual level—aligns with the multivariable regression (AOR = 2.06 for single women) and with prior research documenting that single or non-cohabiting women face structural barriers to consistent contraceptive use, including social stigma, limited partner involvement in reproductive decisions, and unstable sexual relationships [8,10]. The profile-level finding that all ten highest-risk profiles nevertheless correspond to married or cohabiting women does not contradict this individual-level pattern: it reflects the sampling reality that single or non-cohabiting women represent only 7.6% of the analytic sample, generating strata too small for stable profiling once five additional variables are applied. Within the married/cohabiting group, the consistently low parity across all ten profiles (one or two living children) is directly coherent with the second SHAP finding: the protective association between higher parity and lower predicted risk reflects increased motivation and greater exposure to family planning services once desired family size approaches completion [12], while young women with few children—precisely those captured in the profiles—have not yet reached that threshold. Conversely, the strong positive SHAP contribution of ideal number of children illustrates that women whose fertility preferences exceed their current parity tend to use contraception less consistently for spacing, leading to mistimed pregnancies even without opposition to childbearing [16]. This spacing–limiting distinction is directly evidenced by the profile data: the highest-risk profile (65%) in Alibori features women with an ideal of three or fewer children and one living child—a configuration suggestive of contraceptive discontinuation or non-use during the interpregnancy interval—while other profiles feature ideal sizes of 4–7 children, where spacing failures are the more plausible pathway. The substantial geographic contribution of region of residence (11.1%) confirms the subnational disparities documented in the regression, reflecting well-documented inequalities in contraceptive service access and prevailing fertility norms across Benin Republic's departments [6,7]. The positive direction of educational attainment was initially counterintuitive yet is consistent with several DHS-based studies in West Africa [10,16]; a plausible explanation is that more educated women tend to delay first births and express higher reproductive ambitions—factors that increase the visibility of mistimed pregnancies. This should be interpreted as a predictive signature in DHS data, not as evidence that education causally increases unintended pregnancy.

Placed in broader perspective, our findings corroborate several determinants consistently reported across sub-Saharan Africa. The strong association between low parity and elevated predicted risk aligns with prior regional work [8,9], while marital status as a leading predictor is consistent with multi-country DHS analyses by Yilak et al. [10] and Bekele and Fekadu [12]. The geographic disparities we observe echo patterns documented for the Benin Republic specifically by Mintogbe et al. [14] and across sub-Saharan Africa more broadly [18]. These cross-national similarities likely reflect structural features common to the region—early marriage norms, high unmet need for family planning, and uneven rural health infrastructure—while the sharper regional gradient observed here plausibly reflects Benin Republic's markedly low modern contraceptive prevalence (12%) and high unmet need (36%) relative to several comparator countries, conditions that would be expected to amplify subnational disparities in family planning access and, consequently, in unintended pregnancy risk. Our contribution lies in moving beyond single-variable association estimates toward multidimensional risk profiles that combine the top SHAP-ranked variables to generate actionable population segments.

While Kebede et al. [11] applied explainable machine learning to married or in-union women across multiple countries using MICS data, the present work is, to our knowledge, the first to combine within-fold resampling, comparative algorithm benchmarking, and exact SHAP-based profiling to produce intervention-ready risk segments specifically for the Beninese context. Regarding employment status, unlike prior studies in which working status was broadly protective [15,16], our model did not identify employment as a meaningful predictor—a finding that likely reflects the predominantly informal nature of female employment in the Benin Republic, where occupational status may not independently influence contraceptive uptake.

Translating these findings into actionable priorities, several strategic directions emerge. The universal concentration of highest-risk profiles among young women aged 15–24 with one or two living children—regardless of region, wealth, or fertility preferences—calls for systematic integration of spacing-focused family planning counseling into routine postnatal and antenatal care, reaching newly married and recently cohabiting women from the very first health contact following delivery. Concurrently, the individual-level SHAP evidence that single or non-cohabiting women bear the highest predicted risk underscores the continued need for youth-friendly reproductive health services that address confidentiality concerns and social stigma for unmarried women, even though this subgroup generated no stable profiles due to small cell sizes. Geographically, the even distribution of profiles across both northern departments (Alibori, Atacora, Borgou) and southern departments (Atlantique, Littoral, Couffo) calls for a fully decentralized national strategy rather than regionally concentrated programs; the highest predicted probability (65%) was observed in Alibori—a northern department with documented gaps in service coverage [6]—underscoring that the risk landscape is not confined to the more urbanized south. The persistence of high-risk profiles from the poorest to the wealthiest quintile confirms that poverty-targeted programs alone will systematically miss a large share of vulnerable women; culturally sensitive provider training, structured community engagement, and active male partner involvement are equally necessary components of a comprehensive strategy. Finally, the profile in Couffo featuring an ideal of 6–7 children illustrates that even women with high fertility aspirations can experience spacing failures, reinforcing the need for counseling that normalizes inter-pregnancy contraceptive use across all fertility preference profiles.

5. Strengths and Limitations

This study has several notable strengths. First, it draws on a large, nationally representative dataset enabling generalizability to reproductive women in the Republic. Second, it adopts a machine learning pipeline in which class-imbalance correction is performed within each cross-validation fold, eliminating a common and consequential source of optimistic bias reported in the machine learning and health literature. Third, the use of SHAP values provides a model-agnostic, theoretically grounded basis for variable importance estimation and directional interpretation that goes beyond conventional feature importance heuristics. Fourth, the systematic comparison of eight algorithms under three independent validation schemes constitutes a transparent benchmarking exercise and contextualizes the predictive ceiling achievable for this outcome within the DHS data structure.

Several limitations warrant acknowledgement. First, the analytical sample is restricted to women whose most recent pregnancy resulted in a live birth, excluding women whose pregnancies ended in miscarriage, stillbirth, or abortion. Because abortion is substantially more common following unintended pregnancy [7], this restriction may introduce selection bias and lead to underestimation of the true prevalence of unintended pregnancy, as well as attenuation of some predictor–outcome associations. Second, pregnancy intention is measured retrospectively, which is subject to

recall bias and post-rationalization, particularly for older births and for births resulting in surviving children. Third, the DHS instrument does not capture several theoretically important predictors—including contraceptive availability at the time of conception, partner attitudes and involvement, spousal communication about family planning, and exposure to specific reproductive health campaigns—which likely contribute to the modest predictive ceiling observed (AUROC ≈ 0.62). Fourth, the analyses do not formally incorporate the complex DHS sampling design (clustering, stratification, and individual-level weights) within the machine learning models; while sampling weights were applied to descriptive and regression estimates, fully design-adjusted machine learning remains an active methodological frontier that was beyond the scope of this work. Fifth, the SHAP values and model predictions reflect predictive associations and must not be interpreted causally: they quantify each variable's contribution to the model's output, not its causal effect on pregnancy intention. Sixth, the cross-sectional nature of the BDHS precludes analysis of temporal dynamics in risk-factor configurations. Future research should pursue longitudinal designs, integrate qualitative insights into partner- and community-level determinants, and explore design-based machine learning methods to formally accommodate the complex survey structure.

6. Conclusion and recommendations

This study profiled women at elevated risk of unintended pregnancy in the Benin Republic using a validated machine learning pipeline complemented by SHAP-based interpretation. The findings demonstrate that unintended pregnancy in the Benin Republic is shaped by a complex and intersecting configuration of demographic, relational, geographic, and socioeconomic factors, with marital status, parity, region of residence, age, and ideal family size emerging as the dominant predictors. Risk extends across wealth quintiles, confirming that economic empowerment alone is insufficient to address the issue. We recommend: (i) the development of geographically tailored reproductive health programs prioritizing the departments where high-risk profiles were concentrated—Atlantique, Littoral, and Couffo in the south, and Atacora, Alibori, and Borgou in the north—reflecting the fully decentralized geographic spread of predicted risk; (ii) the expansion of youth-friendly, unmarried-women-centered family planning services that address confidentiality concerns and reduce access-related stigma; (iii) the systematic integration of spacing counseling for women whose fertility preferences exceed their current parity, reaching them proactively before they approach their desired family size; (iv) the combination of educational and economic empowerment initiatives—including scholarships, vocational training, and microfinance programs—with culturally sensitive provider training and structured male partner engagement; and (v) sustained investment in subnational data systems capable of tracking profile-specific reproductive health outcomes over time to support adaptive, evidence-driven programming. These recommendations, grounded in the predictive profiles generated in this study, can support more precise and equitable use of public health resources to advance reproductive autonomy in the Republic.

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