

Determinants of modern family planning use among married adolescents in Bangladesh: Evidence from a machine learning approach

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Abstract

Background:

Modern family planning (FP) is essential for improving the reproductive health of adolescent women, especially in Bangladesh, where early marriage is still prevalent. Despite overall progress in family planning, modern FP use remains uneven and relatively low among married adolescent women due to social, relational, and contextual barriers. Conventional statistical approaches might not fully capture the intricate, nonlinear determinants of FP use. Therefore, this study applied and compared multiple machine learning (ML) models to predict modern FP use and identify its key determinants among married adolescent women in Bangladesh.

Methods and materials:

Data were obtained from the nationally representative Bangladesh Adolescent Health and Wellbeing Survey (BAHWS) 2019–20. The analysis included a weighted sample of 3,223 ever-married adolescent females aged 15 to 19 years. A variety of machine learning classification models were employed, including Logistic Regression (LR), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Neural Network (NN), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Adaptive Boosting (AdaBoost), and Categorical Naïve Bayes (CNB). Feature selection was performed with the Boruta algorithm, and model interpretability was examined through SHapley Additive exPlanations (SHAP). Model performance was assessed using accuracy, precision, recall, F1-score, Matthews Correlation Coefficient, Cohen's Kappa, and area under the receiver operating characteristic curve (AUROC).

Result:

Overall, 72.7% of married adolescent women reported using a modern FP method. Ensemble-based models outperformed conventional classifiers, especially after class balancing. XGB had the best overall predictive performance after applying SMOTE, with 76.0% accuracy, 81.5% precision, 83.9% F1 Score, 37.2% MCC, 36.9% Cohen's Kappa, 86.5% recall, and an AUROC of 72.9%, followed by RF and NN models. The most important determinants of modern FP use included spousal co-residency, having given birth, joint decision-making about FP use, administrative division, younger age (15–17), household wealth, and media exposure.

Conclusion:

This study reveals that machine learning models, especially XGBoost, can be useful in predicting modern family planning use and identifying key determinants among married adolescent women in Bangladesh. The findings provide a data-driven foundation for policymakers and program planners to create adolescent-focused family planning programs. The results highlight the significance of regional disparities, socioeconomic inequities, and relationship factors in influencing adolescent contraceptive behavior. Integrating ML-based evidence into family planning programs may enhance targeted interventions and help to achieve Sustainable Development Goal 3.7.

Introduction

Modern family planning methods encompass a variety of contraceptive methods, including the use of oral pills, injectables, intrauterine devices (IUDs), implants, condoms, emergency contraception, and permanent forms of

contraception, such as female and male sterilization [1]. The widespread use and accessibility of these methods are crucial for preventing unwanted pregnancies, reducing maternal, perinatal, and neonatal mortality, and facilitating effective birth spacing [2, 3]. Beyond their direct health benefits, modern contraceptive methods contribute to broader social gains by giving women enough time to recover between pregnancies, improving child health and educational outcomes, and contributing to overall socioeconomic growth [4].

Among the 1.9 billion women of reproductive age (15–49 years) worldwide in 2021, an estimated 1.1 billion had a need for family planning; of these, 874 million were using modern contraceptive methods, while 164 million had an unmet need for contraception [5]. Projections indicate that by 2030, approximately 1.19 billion women will require modern family planning methods. However, the use of modern contraception varies across countries and regions [3]. The use of modern contraception among married women of reproductive age is considerably lower in developing nations (45%) than in developed countries (70%), with notable regional variation, including 56% in Latin America, 74% in East Asia, 34% in South Asia, and 14% in Africa [6]. The particularly low prevalence of modern contraceptive use in South Asia is concerning, given that Bangladesh is part of this region and continues to experience high levels of early marriage. On a global and regional scale, women under the age of 25 consistently demonstrate the lowest levels of contraceptive use and pregnancy avoidance in comparison to women aged 25–44 years. This highlights a huge unmet need among adolescents and young women [7].

Bangladesh has a large and young population, with nearly half of its 160.4 million people below the age of 25, and it continues to report one of the highest rates of child marriage globally [8–10]. As an increasing number of adolescents enter marriage each year, early marriage exposes young women to frequent and often unprotected sexual intercourse, thereby increasing the risk of early, rapid, and unintended pregnancies with adverse maternal and neonatal health consequences [11, 12]. While Bangladesh has achieved significant strides in increasing the use of contraceptives on a national level, these improvements conceal underlying inequalities [13]. Married adolescent women aged 15–19 years remain a high-risk and underserved group, demonstrating much lower contraceptive use than older women due to a combination of individual, relational, and contextual factors [13, 14]. Therefore, in order to improve reproductive health outcomes and achieve Sustainable Development Goal 3.7, which is to ensure universal access to sexual and reproductive health services, it is vital to ensure that this population has equitable access to modern family planning methods [15].

Epidemiological studies using survey data and logistic regression have established key determinants of contraceptive use in this group as parity, co-residency with a spouse, joint-decision making, exposure to the media, household income, and geographic location [16–18]. On the other hand, separation between spouses, particularly when that is caused by international migration of males, is a tremendous obstacle [17]. Geographically, such divisions as Mymensingh and Rajshahi are recording high usage rates as compared to Chittagong meaning that there are inequalities in terms of accessing services, social norms or program implementation [13]. Despite this progress, a critical gap remains. Traditional regression models, whilst establishing independent relationships, might not be able to reflect the non-linear, and higher-order interactions that are likely to define decision-making on contraception in reality [19]. This limitation hinders the development of predictive models that are highly accurate and necessary for the precise targeting of interventions. Machine learning (ML) offers a powerful paradigm shift. Machine learning algorithms, including ensemble methods and neural networks, proficiently model complex patterns in high-dimensional data without rigid a priori assumptions regarding variable relationships, rendering them particularly effective for predictive tasks [20].

The application of machine learning to predict reproductive health is gaining popularity worldwide. Research conducted in Ethiopia and East Africa has effectively utilized algorithms such as Random Forest and XGBoost to predict contraceptive discontinuation and non-use, indicating their capability to surpass conventional approaches [21–

24]. In Bangladesh, initial research used machine learning to classify unintended pregnancy [25]. However, there is a significant gap in the literature. To date, no study has systematically applied and compared multiple advanced machine learning algorithms to identify and interpret the key determinants of modern family planning use among married adolescent women. By combining feature selection, explainable machine learning techniques, and comparative model evaluation, the present study addresses this gap by identifying the most influential socio-demographic, relational, and contextual determinants of modern family planning use among married adolescent women in Bangladesh.

This study uses data from the 2019–20 Bangladesh Adolescent Health and Wellbeing Survey (BAHWS) to fill this gap. Specifically, the study aims to: (i) apply and systematically compare multiple machine learning models, including XGBoost, Random Forest, Neural Networks, and logistic regression, to identify the key determinants of modern family planning use among married adolescent women [22, 26–28]; (ii) address class imbalance by using the Synthetic Minority Oversampling Technique (SMOTE) and assess the effect it has on model performance; and (iii) use sophisticated model interpretability techniques, especially SHapley Additive exPlanations (SHAP), to quantify and interpret the relative importance and directional effects of influential predictors [29]. The findings are intended to inform targeted public health interventions and evidence-based policymaking aligned with Sustainable Development Goal targets, with the broader objective of improving reproductive health and child survival outcomes in Bangladesh.

Material and Methods

Data sources

The data for this study were derived from the Bangladesh Adolescent Health and Well-being Survey (BAHWS) 2019–20, a nationwide cross-sectional survey that assesses the health and well-being of adolescents aged 15–19 years in Bangladesh across a variety of factors. The BAHWS used a two-stage stratified sample strategy that included all administrative divisions and enumeration areas (EAs) throughout the country, assuring national representativeness. First, primary sampling units (PSUs) were identified, and subsequently, households were selected in a systematic manner during the second stage. PSUs were randomly classified into Type I and Type II, and questionnaires corresponding to PSU type (“Type One” or “Type Two”) were administered accordingly, following the official BAHWS sampling protocol [30].

The BAHWS collected information from ever-married adolescent women, never-married adolescent women, and never-married adolescent men aged 15–19 years. The present analysis was restricted to ever-married adolescent women, as information on modern family planning use was collected for this subgroup. Of the 72,800 households selected for the survey, 97.7% responded, and interviews were successfully completed in 67,093 households. Among eligible ever-married adolescent women aged 15–19 years, 4,926 respondents completed the interview, yielding a 97.2% response rate among 5,066 eligible individuals.

For this study, we used the publicly accessible BAHWS 2019-20 dataset to extract records from ever-married adolescent women. Respondents who provided missing information on the outcome variable or key explanatory variables were excluded to ensure data quality. After these exclusions and survey weighting, the final analytic sample consisted of 3,223 ever-married teenage women aged 15 to 19, who were utilized for all descriptive analyses, machine learning model building, and regression validation.

Response variable

The outcome variable for this study was current use of modern family planning methods. In the BAHWS 2019–20 survey, ever-married adolescent women were asked: “Are you or your partner currently doing something or using any method to delay or avoid getting pregnant?” Respondents who answered affirmatively were further asked to specify the method currently being used.

A binary outcome variable was created based on the answers to this question. Women were classified as modern family planning users (coded as 1) if they reported using any modern contraceptive method, such as female or male sterilization, intrauterine devices (IUD), injectables, implants, oral pills, male or female condoms, emergency contraceptive pills (ECP), or the lactational amenorrhea method (LAM). Women who reported not using any method or who used traditional methods, such as the rhythm (safe-period) method or withdrawal, were classified as non-users of modern family planning (coded as 0), in accordance with the World Health Organization (WHO) classification [31].

Explanatory variables

Guided by prior literature [3, 9, 32–34] and data availability in the BAHWS 2019–20, the explanatory variables included age group (15–17, 18–19 years), educational attainment (0–5, 6–10, ≥ 11 grades), employment status (yes/no), involvement in family planning programs in the past three years (yes/no), current residence with husband (living together, staying elsewhere in Bangladesh, staying outside Bangladesh), decision-making authority for family planning use (joint, mainly husband, mainly respondent, others), childbirth experience (ever given birth: yes/no), household wealth quintile (lowest to highest), exposure to mass media (frequency of watching television and reading newspapers/magazines), recent exposure to family planning messages through television or newspapers, place of residence (urban/rural), and administrative division.

Statistical analysis

Machine learning modeling approach

This study used various supervised machine learning classification models to determine the factors that influence modern family planning method utilization among ever-married adolescent women. The outcome variable was binary, indicating the use of any modern contraceptive method (yes/no). The machine learning models used were Logistic Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), AdaBoost, Neural Network (Multi-Layer Perceptron), and Categorical Naïve Bayes (CNB). The analytic dataset was randomly split into training (70%) and testing (30%) subsets using stratified sampling to maintain the distribution of modern family planning users and non-users. To ensure reproducibility, a fixed random seed (random_state = 42) was used.

Data preprocessing and encoding

One-hot encoding was used to transform categorical predictors in most models, whereas ordinal encoding was used in the Categorical Naïve Bayes model. Continuous variables were scaled using Min-Max normalization for models that are sensitive to feature scale, such as LR, SVM, KNN, and Neural Networks. Tree-based models were fitted with unscaled numerical features. This preprocessing was carried out using pipeline-based procedures to prevent data leaks during model training and evaluation.

Handling class imbalance

The outcome variable exhibited a class imbalance, with a lower proportion of modern family planning non-users (27.34%) than users (72.66%). To address this issue, most models' training data were treated with the Synthetic Minority Over-sampling Technique (SMOTE), resulting in a balanced 50:50 class distribution. For categorical features, SMOTEN was used in combination with the Categorical Naïve Bayes model. Model performance was assessed in both SMOTE-adjusted and non-SMOTE conditions to evaluate robustness.

Hyperparameter optimization

We used GridSearchCV with five-fold cross-validation on the training dataset to find the best hyperparameters. Various performance metrics were evaluated during the tuning process. This method guaranteed optimal model calibration for identifying modern family planning users while addressing class imbalance.

Model evaluation and validation

Model performance on the held-out test dataset was assessed using accuracy, precision, recall (sensitivity), F1-score, Matthew's correlation coefficient (MCC), Cohen's Kappa, and AUROC. Confusion matrices were created to evaluate classification errors in detail. Additional k-fold cross-validation was performed with different fold sizes (5, 10, 15, 20, 25, and 30 folds) in order to ensure robustness and generalizability.

Receiver operating characteristic analysis

The ROC curve graphically represents the trade-off between true positives and false positives at the various classification thresholds [35]. ROC curves were generated for all fitted models to illustrate the discrimination performance across classification thresholds. The performance of models was compared using the AUROC, with higher values indicating better discrimination between modern family planning users and non-users.

Feature selection and explainability

The Boruta algorithm was used to select the most important predictors of modern family planning use. Boruta compares the relevance of observed variables to randomized shadow features in a Random Forest framework, retaining only statistically significant predictors [36]. To improve model interpretability, feature importance from tree-based models and SHapley Additive Explanations (SHAP) were used to quantify the direction and magnitude of each predictor's contribution to model predictions.

Comparison with traditional statistical methods

In addition to machine learning methods, weighted bivariate analyses with chi-square tests were performed in R to investigate the relationships between modern family planning use and explanatory variables. A multivariable logistic regression model was also fitted as a validation step to assess consistency between statistically significant predictors and those identified by machine learning models.

Statistical Software and Implementation

All machine learning studies were performed in Python (version 3.11), while R (version 4.4.3) was used for bivariate analysis, feature selection with the Boruta algorithm, geographic visualizations, and survey-weighted logistic regression. Using both software platforms enabled us to leverage Python's strengths in machine learning and R's capabilities in statistical analysis and feature selection, resulting in a robust, reproducible analytical framework.

Results

The socio-demographic and reproductive characteristics of married adolescent women aged 15–19 years, as well as their association with modern family planning (FP) use, are summarized in Table 1. Overall, 72.66% (n = 2,342) of respondents reported utilizing a modern FP method, whereas 27.34% (n = 881) did not. The majority (57.1%) were between the ages of 18 and 19, while 75.7% had completed grades 6 through 10, and 93.8% were unemployed. Most participants had not been involved in FP programs during the previous three years (95.0%). Regarding marriage and having children, 85.3% were living with their husbands, 82.5% said they made FP decisions together, and 54.8% had given birth at some point. Media exposure was also different: almost half (49.4%) watched television daily, and 86.9% did not read newspapers or magazines. Most of them (77.1%) lived in rural areas, and the highest percentage of respondents (24.3%) was from the Dhaka division.

As shown in Table 1, chi-square tests revealed significant differences in modern FP use across several variables. FP use was higher among adolescents living with their husbands (77%), those sharing FP decisions with their partners (74.1%), and those who had ever given birth (80.7%) ($p < 0.001$ for all). Exposure to mass media was also associated with FP use, women who watched television daily (74.5%) or read newspapers at least once a week (82.6%) showed higher use compared to those with no exposure ($p < 0.05$).

The regional difference was also significant (< 0.001), with the highest rates of modern FP usage in Mymensingh (80.1%) and Rajshahi (79%), followed by Rangpur (75.7%) and Barisal (73.9%), with the lowest in Chittagong (63.5%). Figure 1 shows a choropleth map of regional disparities in modern family planning (FP) use across Bangladesh, with darker shades indicating divisions with a higher prevalence of modern FP use. These spatial patterns highlight regional disparities in FP uptake, whereas no statistically significant differences were observed at the 5% level by age, education, employment, FP program participation, wealth, residence, or FP messages on television.

Table 1

Background Characteristics of Married Adolescent Women and Bivariate Associations with Modern Family Planning Method Use, BAHWS 19–20.

Characteristics	\varvec{N}	Modern Family Planning Method Use		
		Yes, \varvec{N}	No, \varvec{N}	\varvec{p} - value
	(%)	(%)	(%)	
Age group				
15–17	1382 (42.87)	1016 (73.5%)	365 (26.5%)	0.347
18–19	1841 (57.13)	1326 (72%)	516 (28%)	
Educational grades				
0–5	601 (18.64)	456 (75.9%)	145 (24.1%)	0.066
6–10	2438 (75.65)	1761 (72.2%)	677 (27.8%)	
11 and Higher	184 (5.70)	125 (67.9%)	59 (32.1%)	
Employment status				
No	3024 (93.82)	2204 (72.9%)	820 (27.1%)	0.294
Yes	199 (6.18)	138 (69.2%)	61 (30.8%)	
Involved in FP program in last 3 years				
No	3062 (95.01)	2219 (72.5%)	842 (27.5%)	0.392
Yes	161 (4.99)	122 (75.9%)	39 (24.1%)	
Currently residing with husband				
Living with her	2750 (85.34)	2117 (77%)	633 (23%)	< 0.001
Staying elsewhere in Bangladesh	299 (9.27)	204 (68.1%)	95 (31.9%)	
Staying elsewhere outside Bangladesh	174 (5.39)	21 (12.2%)	153 (87.8%)	
Decision maker for FP use				
Both	2658 (82.48)	1971 (74.1%)	688 (25.9%)	< 0.001
Mainly husband	275 (8.54)	166 (60.5%)	109 (39.5%)	
Mainly my decision	259 (8.02)	187 (72.2%)	72 (27.8%)	
Other	31 (0.96)	18 (58%)	13 (42%)	
Ever given birth				
No	1457 (45.22)	916 (62.9%)	541 (37.1%)	< 0.001
Yes	1766 (54.78)	1426 (80.7%)	340 (19.3%)	
Wealth quantile				
Lowest	611 (18.95)	449 (73.6%)	161 (26.4%)	0.064

Characteristics	\varvec{N}	Modern Family Planning Method Use		
		Yes, \varvec{N}	No, \varvec{N}	\varvec{p} -
	(%)	(%)	(%)	value
Second	711 (22.05)	541 (76.1%)	170 (23.9%)	
Middle	725 (22.50)	517 (71.3%)	208 (28.7%)	
Richer	686 (21.30)	497 (72.3%)	190 (27.7%)	
Highest	490 (15.20)	337 (68.8%)	153 (31.2%)	
Watch TV				
At least once a week	526 (16.31)	390 (74.1%)	136 (25.9%)	0.019
Every day	1591 (49.36)	1185 (74.5%)	406 (25.5%)	
Less than one a week	256 (7.95)	174 (67.9%)	82 (32.1%)	
Not at all	850 (26.38)	593 (69.7%)	257 (30.3%)	
Read Newspaper/Magazine				
At least once a week	128 (3.97)	101 (78.9%)	27 (21.1%)	0.008
Every day	20 (0.62)	16 (82.6%)	3 (17.4%)	
Less than one a week	276 (8.57)	179 (65%)	97 (35%)	
Not at all	2799 (86.85)	2045 (73.1%)	754 (26.9%)	
Heard about FP on TV (Last Few Months)				
No	2767 (85.86)	1999 (72.2%)	768 (27.8%)	0.197
Yes	456 (14.14)	343 (75.3%)	113 (24.7%)	
Read about FP in News (Last Few Months)				
No	3179 (98.64)	2303 (72.5%)	876 (27.5%)	0.040
Yes	44 (1.36)	38 (87.5%)	5 (12.5%)	
Residence				
Other urban	150 (4.67)	105 (69.6%)	46 (30.4%)	0.480
Rural	2484 (77.06)	1800 (72.5%)	684 (27.5%)	
Urban	589 (18.28)	437 (74.2%)	152 (25.8%)	
Administrative Division				
Barisal	214 (6.64)	158 (73.9%)	56 (26.1%)	< 0.001
Chittagong	406 (12.58)	257 (63.5%)	148 (36.5%)	
Dhaka	783 (24.30)	548 (70%)	235 (30%)	
Khulna	438 (13.57)	303 (69.2%)	135 (30.8%)	

Characteristics	\varvec{N}	Modern Family Planning Method Use		
		Yes, \varvec{N}	No, \varvec{N}	\varvec{p} - value
	(%)	(%)	(%)	
Mymensingh	304 (9.44)	244 (80.1%)	61 (19.9%)	
Rajshahi	569 (17.65)	450 (79%)	119 (21%)	
Rangpur	437 (13.57)	331 (75.7%)	106 (24.3%)	
Sylhet	72 (2.24)	51 (70.2%)	21 (29.8%)	
Total	3223 (100.0)	2342 (72.66)	881 (27.34)	

Feature Selection

The Boruta algorithm was used to determine the most important features of modern contraceptive use among the original set of variables by iteratively comparing the feature importance scores with those of randomly permuted shadow features. This procedure approved features whose importance was greater than the maximum shadow value as significant and discarded those whose importance was less than the minimum or average shadow values. As shown in Fig. 2, the Boruta analysis identified a set of key predictors that are significantly associated with modern FP use. The most influential features were currently residing with the husband, having ever given birth, age group, decision-making authority for FP use, and administrative division. Other variables, such as media exposure (TV and newspapers), wealth quantile, and participation in FP programs, also contributed moderately to model performance. Conversely, education, employment status, and place of residence had a small predictive power and were considered to be less important in further training of the model.

Class Balancing Using SMOTE

To balance the outcome variable, we used the Synthetic Minority Oversampling Technique (SMOTE) that creates synthetic observations in the minority class to balance the imbalance between the classes. Before balancing, the dataset had an unequal distribution, with 2,290 (72.34%) adolescents utilizing modern family planning (FP) methods and 876 (27.66%) not. After applying SMOTE, an equal number of observations were created for both categories, resulting in a symmetrical 50:50 distribution of modern FP users and non-users.

Model Performance Comparison for predicting the Modern FP method use

Several machine learning algorithms, such as Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Support Vector Machine (SVM), XGBoost, LightGBM, AdaBoost, Categorical Naïve Bayes, and Neural Networks, were used to develop a predictive model for modern FP method use among married adolescents in Bangladesh. Each model was trained using 70% of the data, with the remaining 30% for testing. Hyperparameter tuning was performed via GridSearchCV with 5-fold cross-validation to optimize model parameters which are provided in Supplementary Table 1. Model performance was evaluated using accuracy, precision, recall, F1-score, AUC (Area Under the Curve), Matthews Correlation Coefficient (MCC), and Cohen's Kappa (Table 2). To address class imbalance, the evaluation included both imbalanced (original data) and balanced (SMOTE) scenarios, with XGBoost, Neural network, RF, and LR emerging as top performers. Models trained on the unbalanced data set achieved high overall accuracy but were evidently biased toward the majority group (FP users). The XGBoost and Random Forest models

exhibited the highest accuracies (0.7811 each), accurately predicting approximately 78% of all cases. In the case of XGBoost, precision (0.7782), recall (0.9753), and F1-score (0.8656) were high and AUC of 0.7559 indicated good separation of classes, but the classification report indicated low recall of non-use (class 0: precision 0.81, recall 0.27, F1-score 0.41), reflecting poor performance of minority classes. MCC (0.3824) and Kappa (0.3129) of Cohen showed moderate reliability. RF also exhibited a similar pattern (accuracy = 0.7811; AUC = 0.7550), with very high recall among FP users (0.9884) but lower recognition among non-users.

Table 2
Performance Metrics of Machine Learning Models for Modern FP Use Prediction with 95% Confidence Intervals, BAHWS 19–20.

ML Models	Peformance	Unbalanced (Without SMOTE)	Balanced (With SMOTE)
Logistic Regression	Accuracy	0.7716 ± 0.0274	0.7147 ± 0.0295
	AUC	0.7537 ± 0.0334	0.7503 ± 0.0330
	MCC	0.3519 ± 0.0610	0.3597 ± 0.0600
	Cohen Kappa	0.2512 ± 0.0595	0.3522 ± 0.0600
	Precision	0.7640 ± 0.0282	0.8455 ± 0.0282
	Recall	0.9898 ± 0.0075	0.7409 ± 0.0345
	F1-score	0.8624 ± 0.0182	0.7898 ± 0.0250
SVM	Accuracy	0.7747 ± 0.0268	0.6611 ± 0.0305
	AUC	0.6791 ± 0.0375	0.7285 ± 0.0343
	MCC	0.3704 ± 0.0561	0.3271 ± 0.0585
	Cohen Kappa	0.2558 ± 0.0584	0.3011 ± 0.0563
	Precision	0.7642 ± 0.0281	0.8600 ± 0.0278
	Recall	0.9956 ± 0.0050	0.6346 ± 0.0363
	F1-score	0.8647 ± 0.0186	0.7303 ± 0.0280
KNN	Accuracy	0.7611 ± 0.0268	0.7274 ± 0.0279
	AUC	0.7242 ± 0.0354	0.7067 ± 0.0377
	MCC	0.3030 ± 0.0647	0.2992 ± 0.0679
	Cohen Kappa	0.2214 ± 0.0571	0.2985 ± 0.0682
	Precision	0.7596 ± 0.0279	0.8006 ± 0.0295
	Recall	0.9796 ± 0.0095	0.8297 ± 0.0277
	F1-score	0.8557 ± 0.0185	0.8149 ± 0.0215
Neural Network	Accuracy	0.7716 ± 0.0263	0.7358 ± 0.0279
	AUC	0.7509 ± 0.0347	0.7453 ± 0.0353
	MCC	0.3469 ± 0.0648	0.3708 ± 0.0605
	Cohen Kappa	0.2670 ± 0.0609	0.3690 ± 0.0611
	Precision	0.7683 ± 0.0270	0.8364 ± 0.0272
	Recall	0.9796 ± 0.0108	0.7889 ± 0.0310
	F1-score	0.8612 ± 0.0181	0.8120 ± 0.0219
Random Forest	Accuracy	0.7811 ± 0.0268	0.7337 ± 0.0274
	AUC	0.7550 ± 0.0350	0.7447 ± 0.0356

ML Models	Peformance	Unbalanced (Without SMOTE)	Balanced (With SMOTE)
	MCC	0.3878 ± 0.0608	0.3435 ± 0.0642
	Cohen Kappa	0.2942 ± 0.0623	0.3434 ± 0.0643
	Precision	0.7725 ± 0.0280	0.8210 ± 0.0266
	Recall	0.9884 ± 0.0080	0.8079 ± 0.0286
	F1-score	0.8672 ± 0.0184	0.8144 ± 0.0218
Decision Tree	Accuracy	0.7737 ± 0.0269	0.7126 ± 0.0279
	AUC	0.7283 ± 0.0338	0.6953 ± 0.0404
	MCC	0.3568 ± 0.0601	0.2983 ± 0.0651
	Cohen Kappa	0.2693 ± 0.0592	0.2979 ± 0.0653
	Precision	0.7682 ± 0.0276	0.8099 ± 0.0283
	Recall	0.9840 ± 0.0089	0.7875 ± 0.0296
	F1-score	0.8628 ± 0.0183	0.7985 ± 0.0223
XGBoost	Accuracy	0.7811 ± 0.0263	0.7600 ± 0.0263
	AUC	0.7559 ± 0.0340	0.7285 ± 0.0379
	MCC	0.3824 ± 0.0655	0.3720 ± 0.0663
	Cohen Kappa	0.3129 ± 0.0639	0.3695 ± 0.0660
	Precision	0.7782 ± 0.0279	0.8148 ± 0.0269
	Recall	0.9753 ± 0.0115	0.8646 ± 0.0254
	F1-score	0.8656 ± 0.0182	0.8390 ± 0.0201
LightGBM	Accuracy	0.7642 ± 0.0268	0.7337 ± 0.0279
	AUC	0.7120 ± 0.0384	0.6861 ± 0.0416
	MCC	0.3316 ± 0.0722	0.3063 ± 0.0678
	Cohen Kappa	0.3013 ± 0.0680	0.3047 ± 0.0680
	Precision	0.7820 ± 0.0277	0.7997 ± 0.0285
	Recall	0.9345 ± 0.0188	0.8428 ± 0.0259
	F1-score	0.8515 ± 0.0192	0.8207 ± 0.0213
AdaBoost	Accuracy	0.7726 ± 0.0258	0.7253 ± 0.0274
	AUC	0.7581 ± 0.0340	0.7350 ± 0.0349
	MCC	0.3500 ± 0.0653	0.3488 ± 0.0604
	Cohen Kappa	0.2822 ± 0.0635	0.3468 ± 0.0604
	Precision	0.7723 ± 0.0286	0.8307 ± 0.0280
	Recall	0.9723 ± 0.0120	0.7787 ± 0.0318

ML Models	Peformance	Unbalanced (Without SMOTE)	Balanced (With SMOTE)
	F1-score	0.8608 ± 0.0180	0.8039 ± 0.0232
Categorical Naïve Bayes	Accuracy	0.7716 ± 0.0268	0.6926 ± 0.0284
	AUC	0.7377 ± 0.0343	0.7235 ± 0.0362
	MCC	0.3460 ± 0.0654	0.2895 ± 0.0647
	Cohen Kappa	0.2757 ± 0.0613	0.2860 ± 0.0638
	Precision	0.7707 ± 0.0273	0.8170 ± 0.0296
	Recall	0.9738 ± 0.0122	0.7409 ± 0.0317
	F1-score	0.8605 ± 0.0180	0.7771 ± 0.0242

LightGBM showed slightly lower accuracy (0.7642) but maintained a reasonable AUC (0.7120) and F1-score (0.8515). The Neural Network (AUC = 0.7509) and Decision Tree (AUC = 0.7283) gave moderate results. Other less sophisticated models, such as LR (AUC = 0.7537), SVM (AUC = 0.6791), and KNN (AUC = 0.7242), did not perform well, with lower discriminative power and weaker agreement (e.g., MCC = 0.3519 for LR). Overall, models performed well on dominant patterns but struggled to capture minority (non-user) traits.

Balancing the dataset with SMOTE increased sensitivity to the minority class, resulting in a more symmetric distribution of predictions. XGBoost performed best overall (accuracy = 0.7600; AUC = 0.7285), with high discrimination and stable agreement (MCC = 0.3720; κ = 0.3695). Its classification report demonstrated improved performance for non-users (precision 0.58, recall 0.49, F1 0.53) and consistent accuracy for users (precision 0.81, recall 0.86, F1 0.84), with an overall macro-F1 of 0.68 and weighted-F1 of 0.75. The Random Forest model also performed well (accuracy = 0.7337; AUC = 0.7447; MCC = 0.3435; κ = 0.3434), with a high recall (0.8079) and F1-score (0.8144). The neural network achieved similar stability (accuracy = 0.7358; AUC = 0.7453; MCC = 0.3708), indicating reliable generalization under balanced conditions. AdaBoost and LightGBM demonstrated competitive performance (AUCs $\approx$ 0.69–0.74), while DT (AUC = 0.6953) and KNN (AUC = 0.7067) demonstrated moderate improvements. Simpler classifiers, LR (AUC = 0.7503) and SVM (AUC = 0.7285), had slightly higher Cohen's Kappa values (0.3522 for LR), but their accuracies (0.7147 and 0.6611) were lower than ensemble counterparts. The Categorical Naïve Bayes model showed modest performance (AUC = 0.7235). Collectively, Fig. 3 shows that ensemble-based and deep learning models performed significantly better than standard classifiers. XGBoost received the highest overall composite score across all seven metrics, followed by Neural Network, Random Forest, and AdaBoost. These models consistently delivered greater recall, AUC, and MCC values, essential for imbalanced contexts, while retaining balanced accuracy. LightGBM and LR models provided adequate performance but slightly less stability. In contrast, DT, KNN, Naïve Bayes, and SVM were the weakest performers, characterized by lower Kappa (0.29–0.33) and MCC ($<$ 0.31).

Figure 4 shows the ROC curves for ten machine learning models evaluated on the SMOTE balanced test dataset. The ROC curve illustrates each model's ability to distinguish between users and non-users of modern family planning (FP) methods among married adolescent women. Among all models, Logistic Regression (AUC = 0.7503), Neural Network (AUC = 0.7453), and Random Forest (AUC = 0.7447) showed the most effective separation between the two groups, demonstrating a reasonable balance between sensitivity and specificity. AdaBoost (AUC = 0.7350), XGBoost and SVM (AUC = 0.7285) performed well, whereas Categorical Naïve Bayes provided moderate discrimination (AUC = 0.7235). KNN (AUC = 0.7067), Decision Tree (AUC = 0.6953), and LightGBM (AUC = 0.6861) performed less effectively, reflecting slightly weaker generalization to unseen data. Overall, ensemble and neural network models provided the most reliable

classification results, while Logistic Regression, while being a simpler linear model, achieved one of the highest AUCs, demonstrating its strong interpretability and consistent predictive power.

K-fold cross validation

To ensure model stability and generalizability, a K-fold cross-validation process of 5, 10, 15, 20, 25, and 30 folds was used. Mean Accuracy (MAcc) and Precision–Recall AUC (PR-AUC) were calculated for each fold configuration across all models (Table 3).

Across all folds, XGBoost, K-Nearest Neighbors (KNN), and Random Forest (RF) outperformed the other models. XGBoost maintained a high and consistent accuracy of 0.72–0.73, with a PR-AUC of 0.84–0.85, demonstrating strong discrimination between users and non-users of modern family planning methods. KNN showed high precision and stability across folds, with PR-AUC ranging from 0.82 to 0.83 and MAcc ranging from 0.71 to 0.72. With an MAcc of roughly 0.71 and a PR-AUC of 0.84–0.85, Random Forest also yielded consistent results, demonstrating robust, generalizable performance across fold sizes. Logistic Regression and Neural Network produced consistent results, with MAcc averaging 0.68 and PR-AUC ranging from 0.84 to 0.85 across all folds. AdaBoost demonstrated comparable stability, with MAcc around 0.70 and PR-AUC ranging from 0.84 to 0.85, indicating balanced and consistent predictive performance. LightGBM also performed well, with MAcc ranging between 0.70 and 0.71 and PR-AUC around 0.82, indicating efficient generalization to unseen data. Conversely, Decision Tree and Categorical Naïve Bayes had marginally inferior and less consistent performance, with Decision Tree achieving MAcc between 0.68 and 0.69 and PR-AUC between 0.80 and 0.82, whereas Naïve Bayes attained MAcc between 0.68 and 0.69 and PR-AUC between 0.83 and 0.84. The SVM showed the lowest accuracy, with a mean accuracy (MAcc) ranging from 0.63 to 0.64, while sustaining a PR-AUC of approximately 0.84, reflecting limited improvement across folds. Overall, the findings indicate that XGBoost, Random Forest and KNN are the most effective and stable models across all fold configurations.

Table 3

K-fold cross-validation performance (Mean Accuracy and PR-AUC) of the selected machine learning models.

Model	5 Folds		10 Folds		15 Folds		20 Folds		25 Folds		30 Folds	
	MAcc	PR-AUC	MAcc	PR-AUC	MAcc	PR-AUC	MAcc	PR-AUC	MAcc	PR-AUC	MAcc	PR-AUC
Logistic Regression	0.68	0.84	0.68	0.84	0.68	0.84	0.68	0.84	0.68	0.84	0.68	0.85
SVM	0.63	0.84	0.64	0.84	0.64	0.84	0.64	0.84	0.64	0.84	0.64	0.84
KNN	0.72	0.82	0.72	0.82	0.72	0.82	0.72	0.82	0.71	0.83	0.72	0.83
Neural Network	0.68	0.84	0.68	0.84	0.68	0.84	0.68	0.83	0.68	0.84	0.68	0.84
Random Forest	0.71	0.84	0.71	0.84	0.71	0.84	0.71	0.84	0.71	0.84	0.71	0.85
Decision Tree	0.69	0.80	0.69	0.81	0.69	0.81	0.68	0.82	0.69	0.82	0.68	0.81
XGBoost	0.73	0.84	0.72	0.84	0.72	0.84	0.72	0.84	0.72	0.84	0.72	0.85
LightGBM	0.71	0.82	0.70	0.82	0.71	0.82	0.71	0.82	0.71	0.82	0.71	0.82
AdaBoost	0.70	0.84	0.70	0.84	0.70	0.85	0.70	0.84	0.70	0.84	0.70	0.85
Categorical Naïve Bayes	0.69	0.83	0.68	0.83	0.69	0.84	0.68	0.84	0.68	0.84	0.68	0.84

Feature Selection Results and Model Explainability

Figure 5 displays the feature importance rankings obtained from the XGBoost model, highlighting the principal factors affecting modern family planning (FP) utilization among married adolescent women in Bangladesh. The variable “Currently residing with husband: Staying elsewhere outside Bangladesh” was the most significant predictor (importance = 0.218), indicating that women whose spouses reside overseas are considerably less likely to use modern family planning methods. The second most significant variable was “Ever given birth: No” (0.065), indicating that women who have not yet had childbirth often exhibit lower family planning utilization. Regional variation also played a substantial role, with Divisions such as Chittagong, Mymensingh, Rajshahi, and Dhaka exhibiting significant notable scores (ranging = 0.040–0.046), indicating persistent geographical disparities in FP access and uptake. Additionally, indicators of media exposure, particularly the frequency of reading newspapers or magazines weekly, were significant. The model’s predictions were also influenced by economic status variables, such as wealth quintiles (from lowest to wealthiest), and program-related factors (e.g., involvement in FP programs in the last 3 years and decision-making authority for FP use). These findings highlight the importance of both structural and relational factors in understanding variations in modern FP use among adolescent women.

The integrated SHAP summary and feature importance plot (Fig. 6) shows the 20 most significant features identified by the XGBoost model for predicting modern family planning (FP) use. The features are ranked vertically by their mean absolute SHAP values, which indicate their average contribution to model predictions. Each dot represents an individual observation and is color-coded by feature value (red=high, blue = low), indicating how increases or decreases in that variable influence the probability of using modern FP. The strongest predictor was “Ever given birth: No” (mean |SHAP| = 0.449), with smaller SHAP values (blue) consistently reducing the predicted probability of modern FP use. This finding reflects that adolescent women who have not yet had a child are substantially less likely to adopt

modern contraceptives. Conversely, women who have given birth (high feature values in red) were more likely to use FP methods. The second significant feature, "Currently residing with husband: Staying elsewhere outside Bangladesh" (mean |SHAP| = 0.294), had mostly negative SHAP values, indicating a lower likelihood of FP use when the husband resides abroad. The third related variable, "Currently residing with husband: Living with her," exhibited the opposite effect, contributing positively to the likelihood of FP use.

Regional variables, including Chittagong, Rajshahi, Mymensingh, Khulna, and Dhaka divisions (0.034–0.105), exhibited mixed SHAP effects, reflecting both positive and negative influences depending on location. Notably, adolescents in Chittagong and Mymensingh divisions had higher SHAP variability, implying greater regional inequality in FP access and awareness.

Socioeconomic status indicators, especially wealth quintiles (lowest to highest), exhibited a clear gradient. Wealth quintiles showed a clear directional gradient: higher wealth (red) was positively associated with modern FP use, while lower wealth (blue) was negatively associated, indicating a reduced probability of modern FP use. Media exposure variables, such as "Read any newspaper/magazine at least once a week," had a positive impact on SHAP, whereas "Read not at all" had a negative impact. Behavioral and decision-related features, such as "Decision maker for FP use: Both" and "Involved in FP program in last 3 years: Yes," exhibited positive SHAP values, suggesting increased probabilities of FP use. Conversely, their counterparts ("No" or "Mainly husband") exhibited negative contributions. Overall, high SHAP values for childbirth history, shared FP decisions, and wealthier households indicate a greater likelihood of FP use, while negative SHAP values for spousal absence and poverty indicate reduced FP use.

The fitted LR model in Supplementary Table 2 revealed that several explanatory variables remained statistically significant ($p < 0.05$), aligning closely with the key predictors identified through SHAP analysis. Adolescents aged 18–19 years were significantly less likely to use modern FP methods compared to those aged 15–17 years (AOR = 0.71; 95% CI: 0.58–0.85; $p = 0.0003$), which aligns with the SHAP analysis results, also showing a positive value for the 15–17 age group. Participation in FP decision-making as "Both partners" (AOR = 1.61; 95% CI: 1.20–2.16; $p = 0.0015$) was positively associated with FP use, consistent with SHAP findings. Women who had ever given birth showed substantially higher odds of FP use (AOR = 3.20; 95% CI: 2.62–3.89; $p < 0.0001$), reaffirming its dominant importance from the SHAP model. Those whose husbands were staying elsewhere in Bangladesh (AOR = 0.74, $p = 0.044$) or outside the country (AOR = 0.03, $p < 0.001$) had lower odds, matching SHAP's strong negative effects for spousal absence. Reading newspapers at least once a week (AOR = 1.72, $p = 0.028$) and joint decision-making with the husband (AOR = 1.61, $p = 0.002$) were associated with higher FP use, consistent with positive SHAP contributions. Similarly, wealthier households (AOR range = 1.38–1.65, $p < 0.05$) and residence in Mymensingh ($p = 0.027$) and Rajshahi ($p = 0.023$) divisions showed positive effects, paralleling SHAP findings of regional and socioeconomic influence.

Discussion

The modern family planning (FP) methods are necessary to empower married adolescent women so that they can have control over their reproductive health, especially in Bangladesh, where early marriage is still a common practice and causes high levels of unwanted pregnancies and maternal deaths [11, 12]. This study used a comprehensive machine learning (ML) framework to predict modern family planning (FP) use among married adolescent women aged 15–19 years in Bangladesh using nationally representative BAHWS 2019-20 data. The prevalence of modern FP use was 72.66%, with significant geographical differences: Mymensingh and Rajshahi had the highest rates, while Chittagong had the lowest. Ensemble methods were more effective in prediction across models, particularly when SMOTE was used to mitigate class imbalance. XGBoost turned out to be the best-performing model, with improved accuracy, AUC, precision, and recall compared to other models. The most important determinants were spousal co-

residency (husband living abroad and husband living with her), parity (ever having a baby), administrative division, FP decision-making dynamics, age group, media exposure, and wealth quantile, with strong consistency between SHAP analysis and survey-weighted logistic regression.

The prevalence of modern FP use in our adolescent sample exceeds the national adolescent contraceptive prevalence rate from the BDHS summary findings [8], possibly due to our focus on married current users and survey-specific sampling. However, it remains lower than among older women, highlighting disparities driven by adolescents' limited autonomy and relational barriers [13, 37]. Regional clustering, visualized in Fig. 1, aligns with BDHS analyses showing southeastern divisions like Chittagong facing service inequities and conservative norms [38]. The finding is higher than in high-fertility Sub-Saharan African countries[24] but lower than in urban Kenya [39], reflecting Bangladesh's progress in FP programs amid persistent adolescent gaps.

Ten ML algorithms were trained on balanced and unbalanced datasets, with performance evaluated using accuracy, AUC, precision, recall, F1-score, Matthews Correlation Coefficient (MCC), and Cohen's Kappa. In the unbalanced dataset, several models achieved relatively high overall accuracy but showed poor sensitivity to the minority class (non-users), indicating majority-class bias. This is a common issue in health prediction problems where the outcome distribution is asymmetric, and it highlights why relying only on accuracy can be misleading [40]. After applying SMOTE, performance became more balanced, and ensemble models remained superior. XGBoost achieved the best overall composite performance across the evaluated metrics and also showed strong stability in k-fold cross-validation, a finding which aligns with a similar study on modern FP use among reproductive-age women in Ethiopia, where the XGBoost model outperformed other classifiers [41]. Our findings are consistent with evidence from other ML studies, in which XGBoost and Random Forest often outperform conventional classifiers in predicting FP-related outcomes such as modern FP non-use, optimal ANC utilization, or fertility preferences [3, 42, 43]. SMOTE addressed class imbalance by improving recall among the minority class (non-users), which is consistent with improvements in Ethiopian fertility models [29]. This robustness, with ensemble methods outperforming simpler classifiers such as Decision Tree (DT) or K-Nearest Neighbors (KNN), demonstrates machine learning's shift from linear assumptions in chi-square tests to capturing complex interactions [44]. Unlike logistic regression, which may fail due to multicollinearity and other statistical violations, ensemble methods effectively capture the complex, nonlinear interactions found in public health data, making them more reliable for prediction in this study [45].

Spousal co-residency emerged as the most influential determinant across Boruta selection, XGBoost importance, and SHAP analyses. Adolescents whose husbands lived outside Bangladesh had extremely low FP use, which is consistent with studies in Bangladesh [46] and India [47] that found reduced contraceptive uptake among women experiencing spousal separation due to migration. In contrast, research conducted in East Africa that employs machine learning methods identifies marital status (married vs. unmarried) as a significant predictor, rather than spousal co-residency [48]. This discrepancy is likely due to contextual differences in Bangladesh, where nearly all adolescents in the sample were married; spousal co-residency serves as a more informative marker of FP use than marital status alone. Adolescents residing with their husbands were significantly more likely to use modern family planning, a finding that was consistently prioritized across Boruta selection, XGBoost importance, and SHAP analyses. This is consistent with patterns in South Asia, where co-residency with husbands and, in some cases, with other family members such as mothers-in-law, is associated with higher use of modern contraceptive methods [49]. Adolescents who had ever given birth were substantially more likely to use modern FP, consistent with previous Bangladesh studies showing that contraceptive adoption often follows the first birth rather than preceding it [50, 51].

Joint decision-making for FP use showed a positive association with FP uptake, aligning with prior findings from Bangladesh and South Asia that emphasize the role of couple communication and shared authority [52–54]. This result is consistent with an ML-based FP study in East Africa that highlights women's autonomy and decision-making

power as key predictors, even though it modeled the non-use of family planning, unlike this study's focus on FP uptake [3]. Socioeconomic status also played an important role in modern FP use. Adolescents from wealthier households were more likely to use modern FP methods, while those in the lowest wealth quintile had lower uptake. This finding is consistent with previous studies in Bangladesh and Nigeria that demonstrate that economic disadvantage limits access to contraceptive services and information, thus reducing utilization [55, 56]. Although the bivariate association between wealth and FP use was marginal in this study, the SHAP results suggest that wealth interacts with other factors, such as geographic location and media exposure, in complex ways that may not be fully captured by traditional statistical tests.

Exposure to media, particularly reading newspapers or magazines, was positively associated with the use of modern FP. Adolescents with no exposure to newspapers or magazines were less likely to use FP, whereas those with regular exposure had higher uptake. This aligns with prior evidence in Ethiopia, indicating that access to information through TV, radio, and magazines increases awareness of modern contraceptive options and improves informed decision-making [57]. Age differences were also observed in modern FP use among married adolescents. Although the chi-square test indicated no significant bivariate association between age group and modern FP use, Boruta feature selection and SHAP analysis identified age group as an important predictor, with the 15–17-year age group contributing positively to the predicted FP probability compared to 18–19-year-olds. Adolescents aged 15–17 years were more likely to use modern FP methods than those aged 18–19 years, after adjustment for other factors. This aligns with a systematic review in Bangladesh that found younger women utilize contraceptives more frequently than older women [58]. It also corresponds with DHS evidence from 2017–18, which indicates that younger contraceptive users (ages 15–24) are more likely to obtain methods from the private sector than older users [59].

Geographic variation in FP use remained pronounced in this study. Adolescents residing in Mymensingh and Rajshahi divisions had higher modern FP use than those in Chittagong, which consistently showed lower uptake. These findings are consistent with prior Bangladesh research showing persistent geographic inequalities in FP uptake across divisions, reflecting differences in service delivery, program intensity, infrastructure, and sociocultural norms [60, 61]. Participation in FP programs over the past three years had a modest effect on FP use. While program involvement contributed positively in the SHAP analyses, it did not emerge as a strong independent predictor in conventional regression models.

The integration of SHAP and Boruta allowed this study to move beyond prediction to interpretation. Similar to a recent ML study on modern FP outcome [3] SHAP revealed directional effects and interaction patterns not easily captured by traditional regression. The close alignment between SHAP-derived important predictors and survey-weighted logistic regression results supports the validity of the ML framework.

Strengths, limitations, and future directions

This study's strengths include the use of nationally representative adolescent data, applying major data preprocessing, systematic comparison of multiple ML models, explicit handling of class imbalance, and integration of SHAP analysis with regression validation. Limitations include the cross-sectional design, reliance on self-reported FP use, exclusion of unmarried adolescents, limited data on proximal determinants, and lack of external validation. Future research should incorporate longitudinal data, include proximal factors like autonomy and service quality, and apply deep learning.

Conclusion

This study applied and compared multiple machine learning classification models to predict modern family planning (FP) use and identify its key determinants among married adolescent women aged 15–19 years in Bangladesh using nationally representative BAHWS 2019–20 data. We used various machine learning classifiers, such as Logistic Regression, SVM, KNN, Decision Tree, Random Forest, Neural Network, and XGBoost. Ensemble-based approaches outperformed conventional classifiers, with XGBoost demonstrating the strongest and most stable predictive performance, achieving an accuracy of 76%, precision of 81.5%, recall of 86.5%, and an AUC-ROC of 72.9% after addressing class imbalance with SMOTE.

The findings indicate that modern FP use among married adolescents is primarily influenced by spousal co-residency, childbirth experience, decision-making authority for family planning, administrative division, age group, wealth status, and media exposure. Adolescents whose husbands were residing outside Bangladesh and those who had not yet given birth were substantially less likely to use modern FP methods. This study also revealed that adolescent girls from the poorest households and those with no exposure to newspapers or magazines were less likely to use modern FP methods. In contrast, adolescents who made joint family planning decisions with their husbands, belonged to wealthier households, and were exposed to newspapers or magazines were more likely to use modern family planning. In contrast, adolescents who engaged in joint decision-making with their husbands, were in the younger age group (15–17 years), and belonged to wealthier households, were significantly more likely to use modern FP. Geographic disparities were also evident, with higher FP use observed in Mymensingh and Rajshahi and lower use in Chittagong, Khulna, and Dhaka.

The consistency among machine learning, SHAP analysis, and multivariable logistic regression strengthens the validity of these findings and demonstrates that ensemble machine learning models, particularly XGBoost, are effective at identifying specific risk factors among adolescents using modern family planning and provide valuable evidence for targeted interventions. Policymakers and program planners should consider these findings when designing adolescent-focused family planning strategies, with particular attention to adolescents affected by spousal separation, limited decision-making power, and regional and socioeconomic inequalities. Strengthening targeted approaches is essential to expanding equitable access to modern family planning services and achieving Sustainable Development Goal (SDG) target 3.7 in Bangladesh.

Declarations

Ethics approval and consent to participate

This study used secondary, publicly available data. Ethical approval for the original survey was obtained from the relevant authorities. Therefore, additional ethical approval and informed consent were not required for this study.

Consent for publication

Not applicable.

Availability of data and materials

The data utilized in the current research can be accessed without registration at the UNC Dataverse (<https://dataverse.unc.edu/>).

Competing interests

The authors have declared that no competing interests exist.

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Authors' information

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Figures

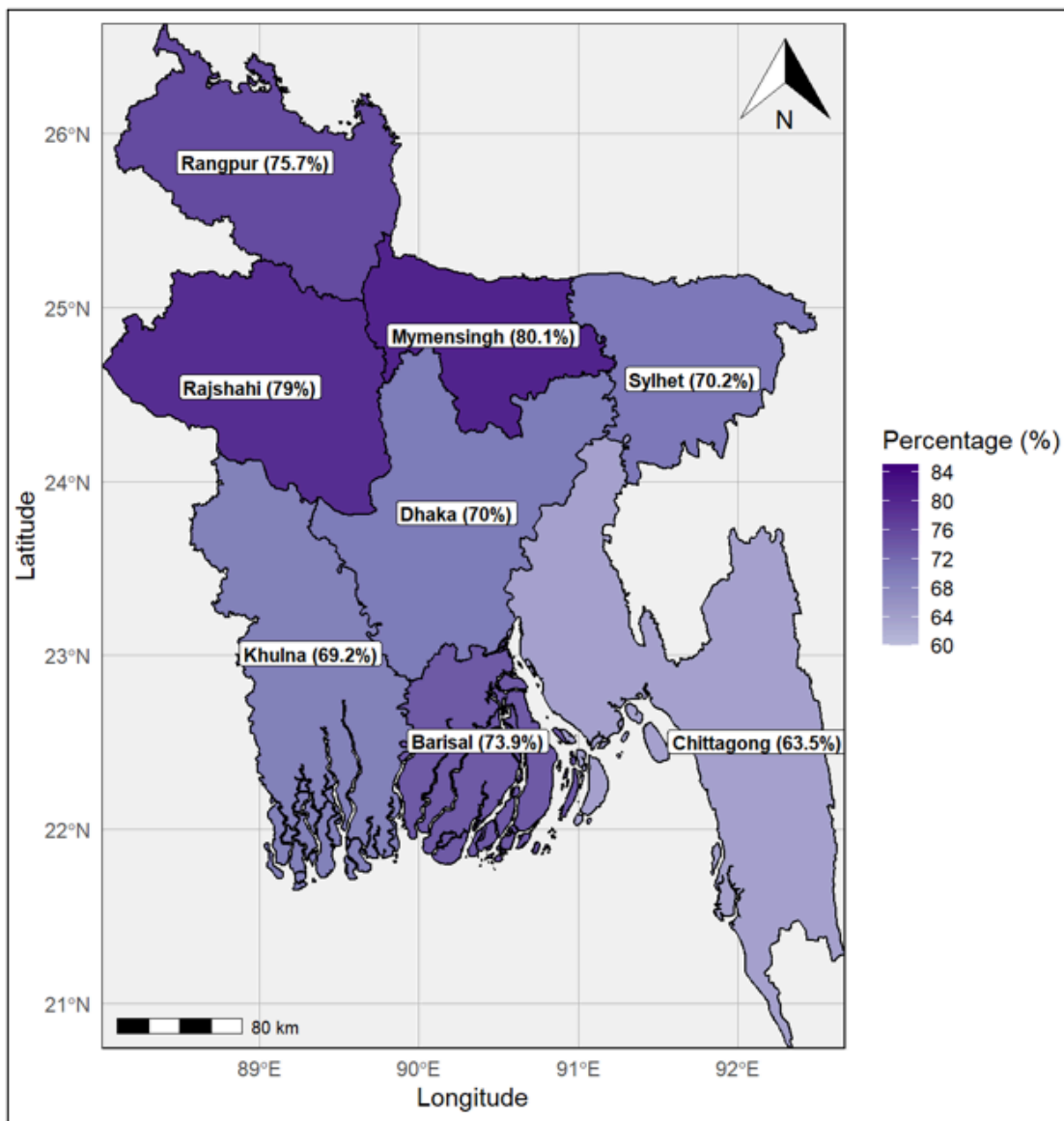


Figure 1

Geographical distribution of modern family planning method use among married adolescent women in Bangladesh.

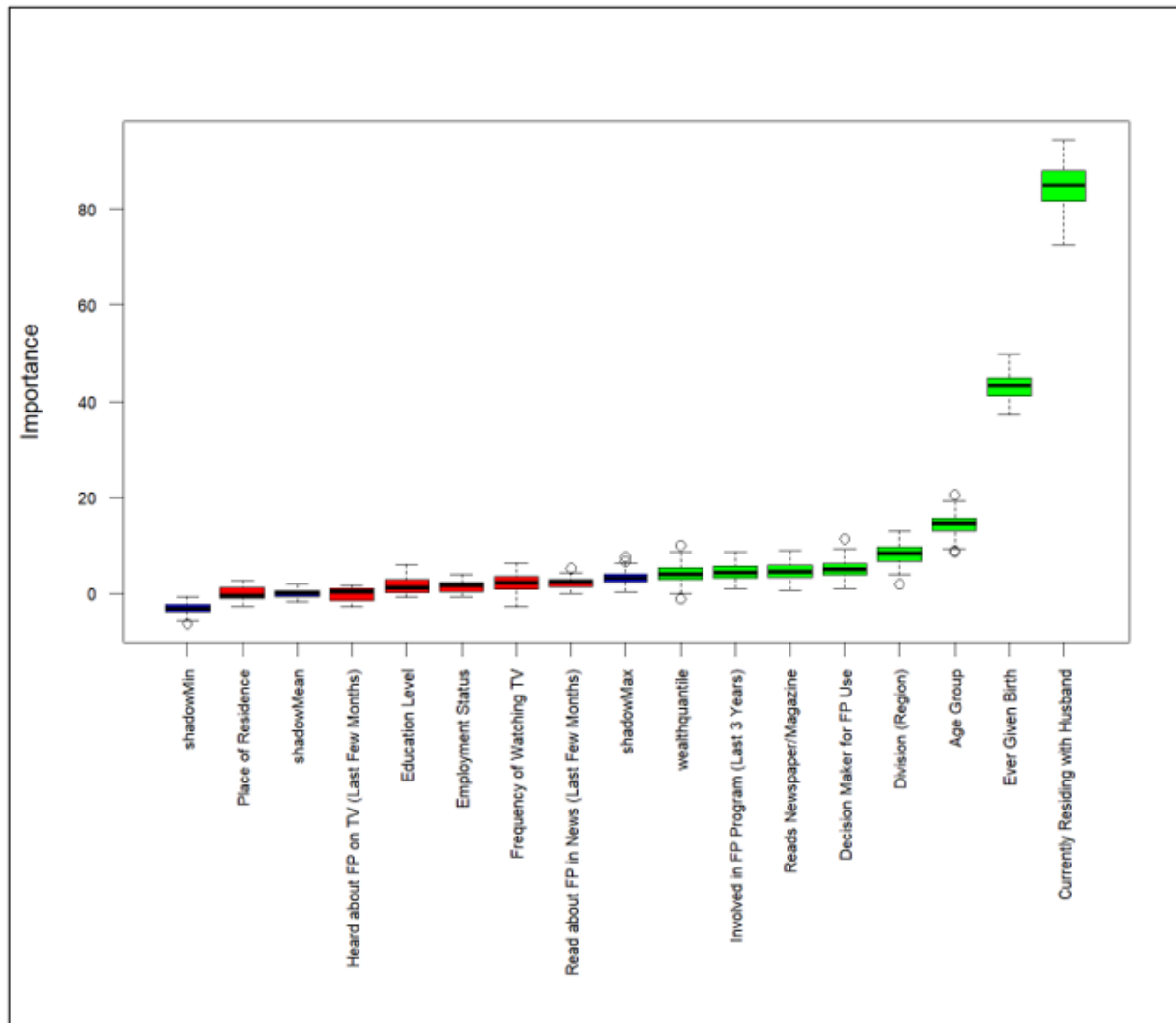


Figure 2

Feature selection using the Boruta algorithm.

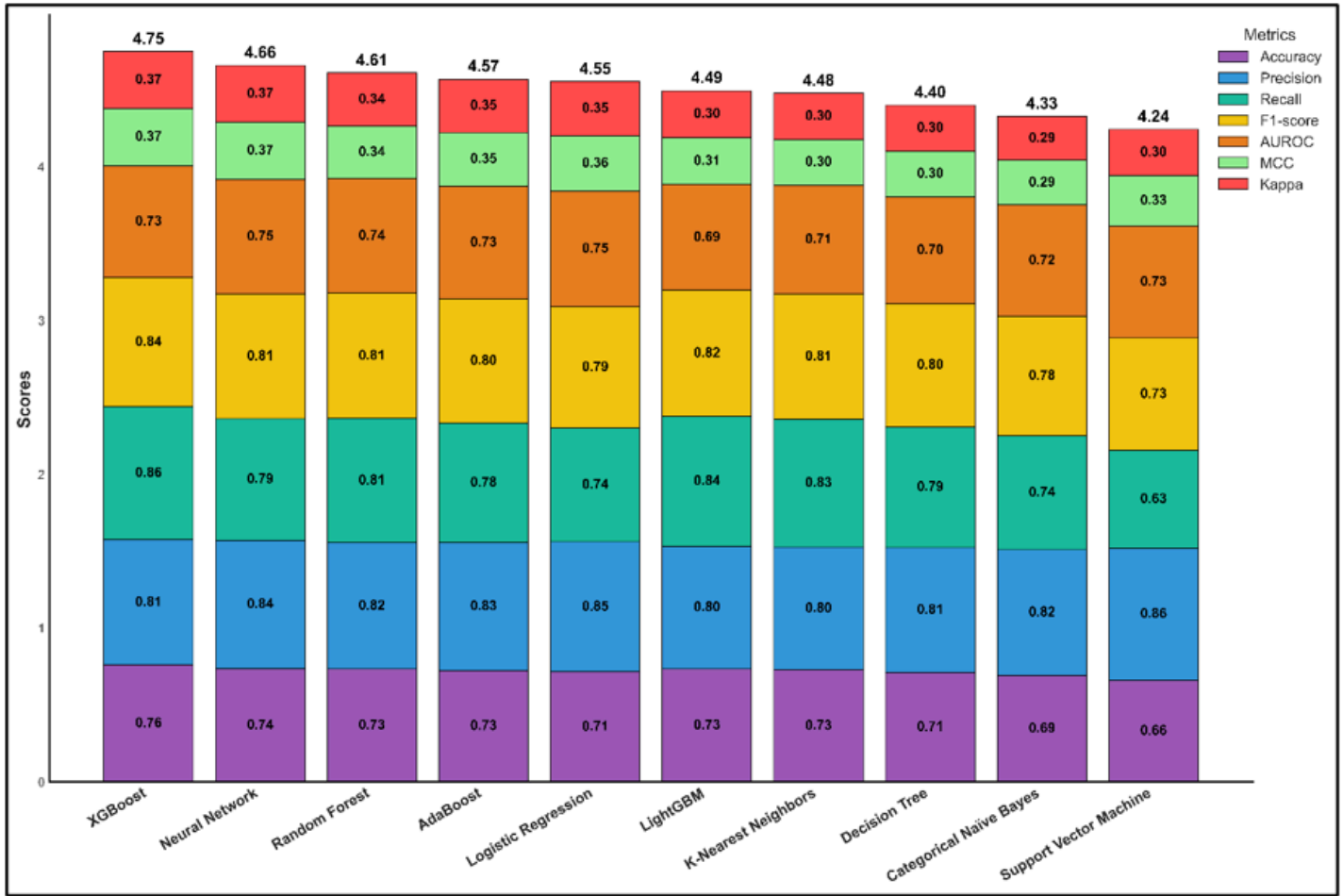


Figure 3

Comparison of model performance metrics (accuracy, precision, recall, F1-score, AUC, MCC, and Kappa) for SMOTE-balanced data.

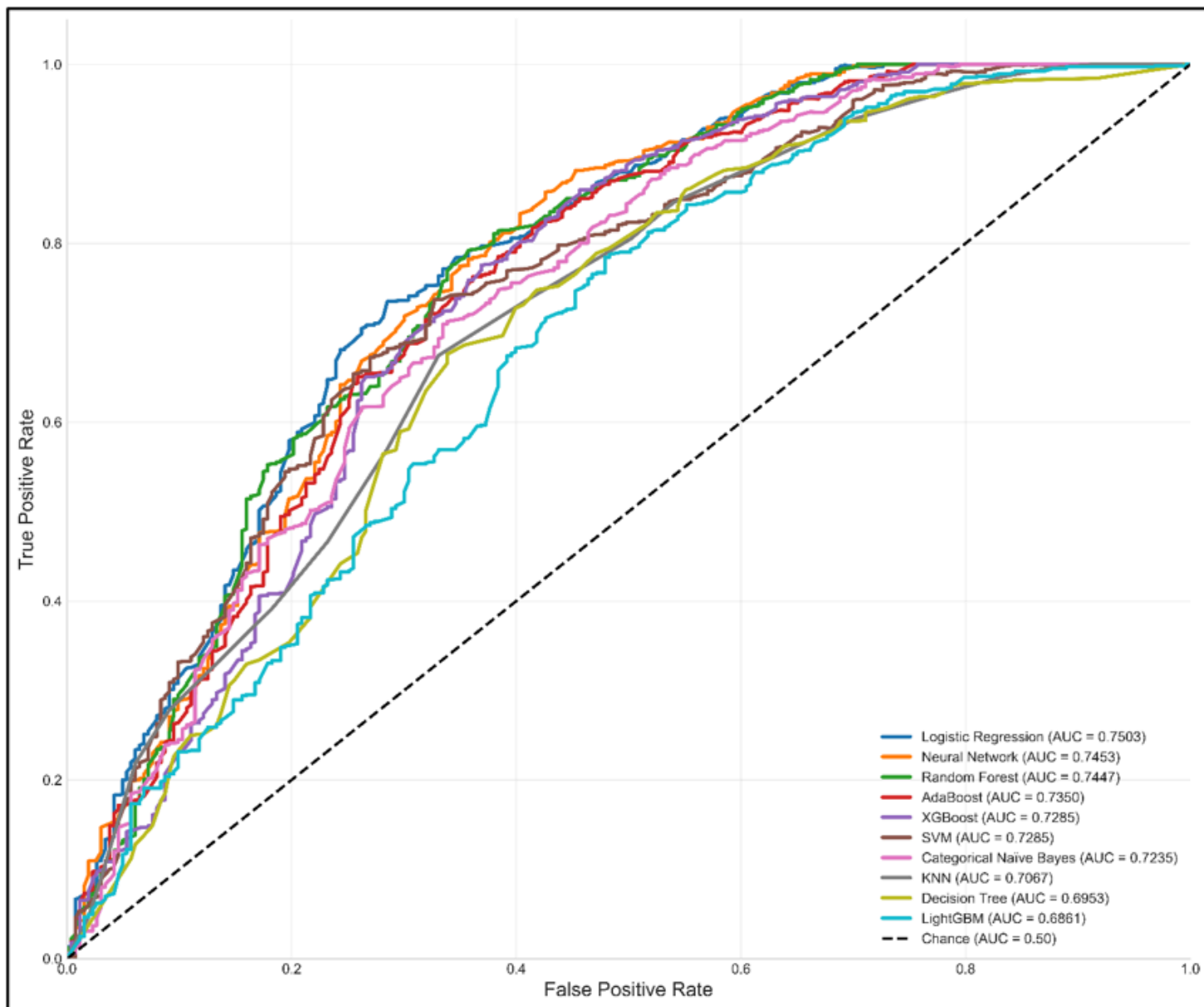


Figure 4

ROC curves of selected machine learning models for predicting modern family planning use.

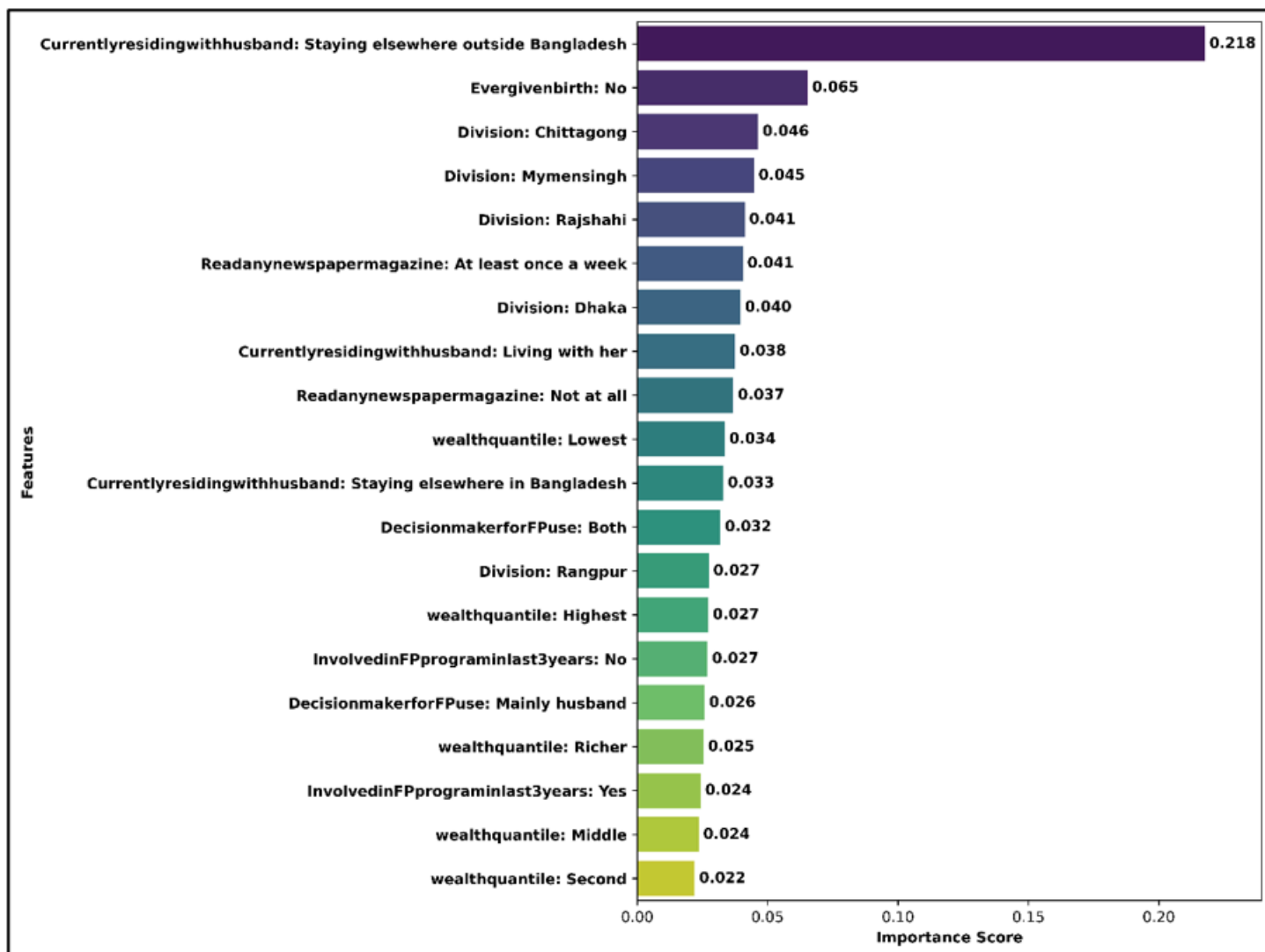


Figure 5

Important determinants selected by XGBoost model.

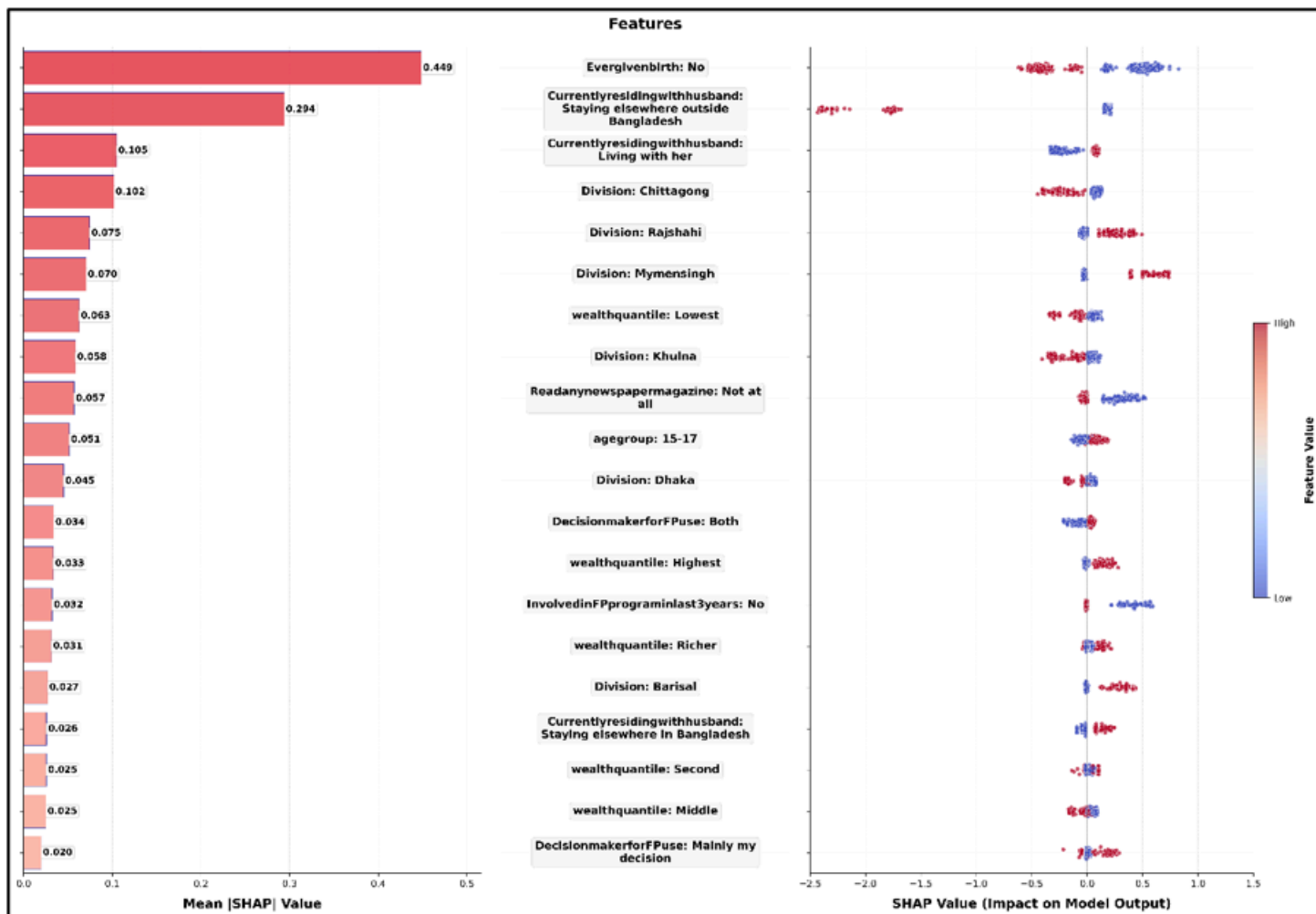


Figure 6

Combined feature importance (left) and SHAP summary (right) plots from the XGBoost model showing the top 20 predictors.

Supplementary Files

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- [SupplementaryTables.docx](#)