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Application of machine learning algorithms to model predictors of informed contraceptive choice among reproductive age women in six high fertility rate sub Sahara Africa countries

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Abstract

Introduction Informed contraceptive choice is declared when a woman selects a methods of contraceptive after receiving comprehensive information on available alternatives, side effects, and management if adverse effect happens. Access to contraceptive information is a fundamental right, crucial for reducing fertility and unintended pregnancies and related complications. Despite efforts to reduce fertility, Sub-Saharan Africa region is still accounts for over half of the global births due to low contraceptive use, high discontinuation rate, and unmet needs, often linked to uninformed contraceptive choice. While studies on informed contraceptive choice are available using classical regression analysis, the diverse nature of factors have not been systematically analyzed using machine learning algorithms. Hence, this study aimed to apply machine learning algorithms to model predictors of informed contraceptive choices among reproductive age women in six high fertility rate Sub Sahara Africa countries.

Methods This study used 11,706 weighted women aggregated from 6 high fertility rate countries in Sub Saharan Africa including Mali, Angola, Burundi, Nigeria, Gambia, and Burkina Faso, collected using stratified sampling techniques. Data cleaning, weighting, and descriptive statistical analyses were conducted using STATA version 17 and Excel 2019, while machine learning analysis was performed using Python 3.12. Furthermore, Random Forest, eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LGBM), Naïve Bayes, Decision Tree, Logistic Regression, and Adaptive Boosting (AdaBoost) were employed to predict informed contraceptive choice and to identify its predictors. Shapley Additive Explanations (SHAP) was used to assess the link between predictors and informed contraceptive choice. Accuracy and area under the curve (AUC), along with precision, recall, and F1 score, were used to evaluate the performance of the predictive models.

Results About 58% women receive informed choice of contraceptive methods, ranges 29% in Burundi to 77% in Burkina Faso. Moreover, the highest spatial clustering of informed choice of contraceptive methods cases was observed in Burkina Faso while the lowest is clustering was found in Angola. LGBM model achieved an accuracy of

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73%, area under the curve (AUC) of 0.80, precision of 71, and recall of 77. The SHAP analysis revealed that health facility visits within 12 months, religion, source of contraceptive, exposure to family planning message, mobile ownership, education, wealth index, under five children, residence, and total life time partner were the top ten predictors of informed contraceptive choice.

Conclusion Nearly six out of ten women received informed contraceptive choice, the magnitude is highest in Burkina Faso and lowest in Mali. Moreover, the highest spatial clustering of informed choice of contraceptive was observed in Burkina Faso while the lowest clustering was found in Angola. The LGBM classifier outperformed among machine learning algorithms and achieved 73% accuracy and an AUC of 0.80. Key factors influencing informed contraceptive choice were health facility visits, religion, contraceptive source, family planning messages, mobile ownership, education, wealth, residence, and lifetime partners. To enhance informed contraceptive choice, governments and policymakers should strengthen family planning education, expand healthcare services, and ensure equitable access to contraceptive information. Digital health solutions, especially mobile-based platforms, can also bridge information gaps. Integrating counseling into routine healthcare, training providers, and expanding mass media campaigns can enhance awareness. Engaging communities can help overcome social and religious barriers. Continuous monitoring and data-driven policy adjustments are essential for responsive interventions that address the evolving reproductive health needs in sub-Saharan Africa. Finally, we recommend that future research validate these findings using external data sources.

Keywords Informed contraceptive choice, Contraceptive, Six countries, High fertility, SSA, Machine learning algorithms, Prediction, Predictors

Introduction

Access to contraceptive methods is a core part of reproductive and sexual health services either to limit the number of children, or to delay the next birth Spacing following unprotected sexual intercourse [1–3]. Contraceptive service provision encompasses the services, policies, information, attitudes, practices, and commodities [4]. Access to contraceptive information and services is a fundamental human right and it is the fundamental aspects of the service [5], the quality of contraceptive information and services reinforces women freedom to determine the number and spacing of their children and offers a range of potential benefits, for both maternal and child health [3]. Informed choice of contraceptive is defined as when a woman selects a method after receiving comprehensive information on available alternatives contraceptive methods, side effects, and the management if anticipated side effect happened. If there are no contraindications, the choice of contraceptive methods is ultimately at the decision of the user [6]. Modern healthcare increasingly prioritizes patient preferences as a core component of person-centered and evidence-based care, recognizing patients as active partners in decision-making. Research shows that aligning treatment with patient values improves satisfaction, adherence, and clinical outcomes, especially in complex or chronic care settings. Incorporating these preferences not only enhances care quality but also upholds ethical principles of autonomy and respect [7–9]. Clients are entitled to make voluntary, informed decisions about contraceptive services based on options, knowledge, and comprehension [10]. Consequently, informed choice of contraceptive methods decreases the risk of contraceptive discontinuation [11, 12], and unintended pregnancies ultimately enhancing women's health and quality of life [13].

Evidences showed that countries in Sub Saharan Africa are providing contraceptive services without the optimal level of information about possible side effects, alternative methods and how to manage when the side effect happened. Although SSA countries are on an integrated effort to increase informed contraceptive choice, the level of informed choice of contraceptive remains very low [10, 14]. Moreover, country specific findings in Ethiopia [15] is reported a lower magnitude of informed contraceptive choice. Despite efforts to lower fertility rate, SSA still accounts more than half of the global births due to low contraceptive use. Niger, Democratic of Republic Congo, Mali, Chad, Angola, Burundi, Nigeria, Gambia, and Burkina Faso contributed a lot with their high fertility rates above 5.0 children per household, which is greater than SSA fertility rate (4.4) [16–18] and worldwide fertility rate (2.47) [19, 20]. This high fertility rate in the region and among the top ranked countries is resulted from non-use of contraceptive methods, unmet contraceptive need, discontinuation of contraceptive methods, and unintended pregnancies [21–30]. Evidences showed that the low level of contraceptive use and discontinuation from contraceptive use is highly interlinked with providing informed choice of contraceptives for users [14, 31–34].

Although studies are available on informed contraceptive choice and its determinant factors across SSA [14], the diverse nature of the determinant factors was not examined using machine learning algorithm which

is quite crucial in the case of large dataset [35]. Prior studies primarily relied on logistic regression and other conventional statistical methods. This study is aimed to apply machine learning algorithms to model predictors of informed contraceptive choices among reproductive age women amid countries with high fertility rate in SSA. Machine learning enhances predictive accuracy and effectively captures complex nonlinear relationships among multiple predictors. Practical studies demonstrate that machine learning offers powerful tools for analyzing intricate datasets and uncovering patterns that traditional statistical methods might overlooked. Understanding the key factors that influence informed contraceptive choice is essential for developing targeted and effective interventions. A tailored approach allows policymakers to focus on the most significant determinants, ensuring that programs and policies are aligned with the specific needs of different populations. By doing so, resources can be allocated more efficiently, interventions can be more impactful, and individuals can receive better-informed reproductive health support. This approach ultimately enhances the effectiveness of family planning programs and contributes to improved health outcomes.

Methodology

Study design and study period

Countries in Sub Sahara Africa region collaborate with international organizations, including the United Nations Population Fund (UNFPA), to conduct comprehensive Demographic and Health Surveys (DHS). These surveys are generally carried out every five years, with Mini-DHS surveys conducted every two to three years since 1990. The data was collected based on a cross section study design in each country. This study was conducted using a secondary analysis of data from Demographic and Health Surveys (DHS) that collected between 2015 and 2024. This study adopted a design science approach for further analysis of DHS data collected between 2015 and 2024 in SSA. Through this approach, the study aimed to contribute to both theory and practice by offering a novel solution to a specific problem [36].

Study area

SSA refers to the region of the African continent situated south of the Sahara Desert. These includes Central Africa, East Africa, Southern Africa, and Western Africa. The exact number of countries included in this region can vary depending on the defining organization. The International Monetary Fund (IMF) identifies 46 countries within SSA, while the World Population Review includes 51 countries. In 2023, the population of SSA was estimated approximately 1.26 billion. This figure is projected to increase to around 1.976 billion by 2043, driven primarily by high fertility rates. These demographic trends highlight the region's youthful population, with a significant proportion under the age of 15 https://www.statista.com/statistics/805605/total-population-sub-saharan-africa/. Countries such as Mali, Angola, Burundi, Nigeria, Gambia, and Burkina Faso, known for their high fertility rates, are the focus of this study, using data collected between 2015 and 2024 (Fig. 1) [19].

Source and study population

The source population comprises all women aged 15 to 49 years who are current users of contraceptive methods in the most recent DHS surveys across Sub-Saharan African countries. The study population includes women within the same age group who are current contraceptive users in the selected country within the region.

Dependent variable

The outcome variable, informed contraceptive choice, was measured dichotomously as "Yes" or "No." A woman was classified as having made an informed choice ("Yes") if she received information on at least one of the following: alternative contraceptive methods, potential side effects, or how to manage side effects. Conversely, if a woman did not receive any of this information, she is classified as "No."

Independent variable

The study encompassed a comprehensive range of variables, including demographic factors such as age, educational level, marital status, and religion, as well as socio-economic indicators such as sex of the household head, wealth index, and place of residence. Additionally, contextual factors like the year of the DHS survey and exposure to mass media were considered. The analysis also considered reproductive health-related factors, such as the desire to limit children, health facility visit within the past 12 months, sources of contraception, exposure to family planning messages, and access-related factors including distance to health facilities, permission to visit health facilities, and getting to go alone to health facility. Furthermore, the study incorporated indicators of family dynamics, including the number of children under the age of five, community health insurance, mobile phone ownership, internet use, and the total number of lifetime sexual partners.

Sample size determination and sampling procedure

This study included a total of 11,706 weighted reproductive-age women from six Sub Sahara Africa countries. The households were selected using a stratified multistage cluster sampling technique. First, stratified random sampling was employed to select enumeration areas from national census regions (strata). Then, within these selected areas, households were randomly chosen for

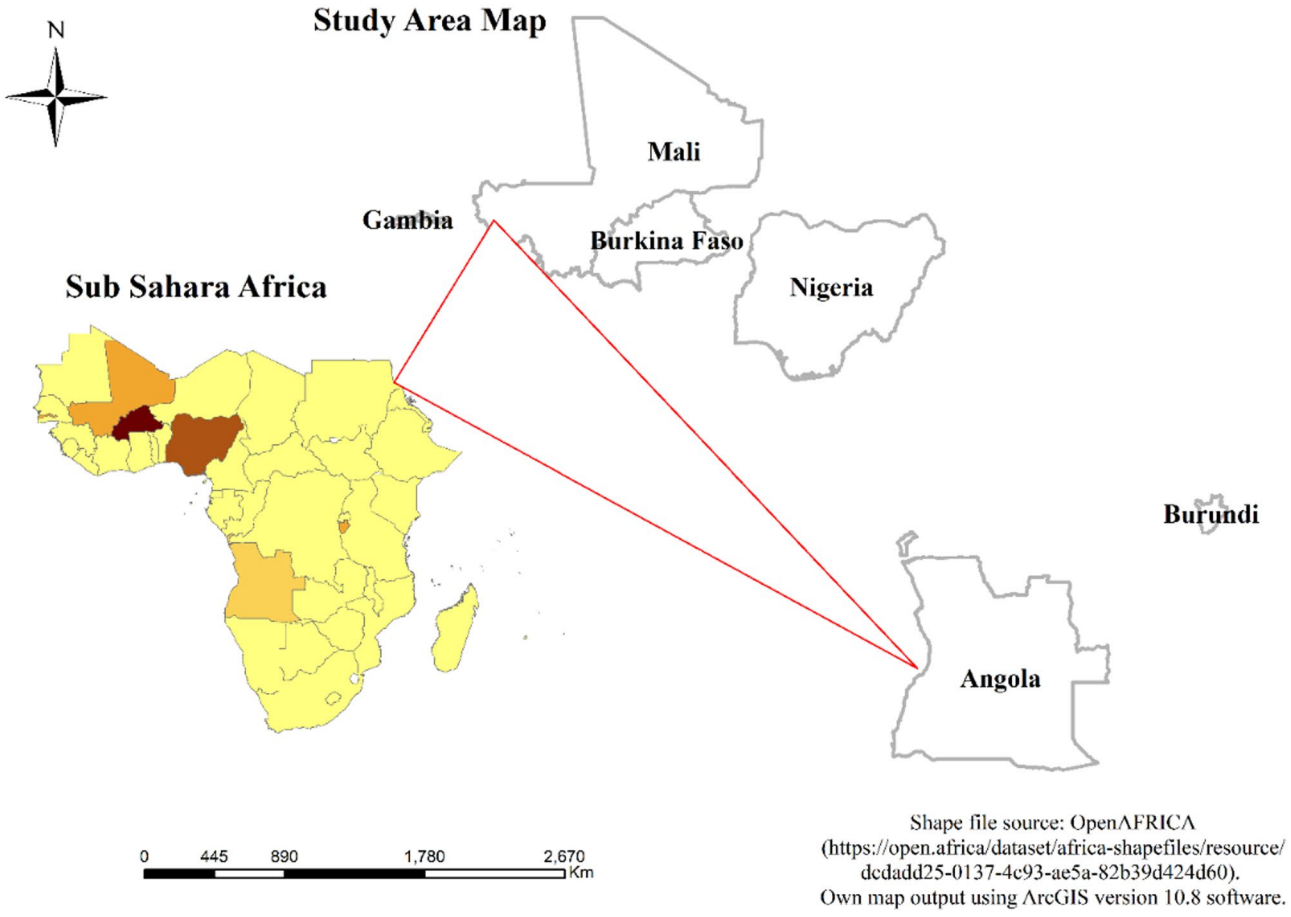

Fig. 1 Study area map of high fertility rate countries in SSA for informed contraceptive choice among reproductive age women

survey administration. The study utilized aggregated data from the most recent DHS dataset conducted in six Sub Sahara Africa countries between 2015 and 2024.

Data collection tool and procedures

The DHS employed five main questionnaires: the household questionnaire, the woman's questionnaire, the man's questionnaire, the biomarker questionnaire, and the health facility questionnaire. Survey methods, sampling strategies, questionnaires, and data collection procedures are standardized across all participating countries. Households and respondents were typically selected using a stratified two-stage cluster sampling technique. The woman's questionnaire was designed to gather data from all eligible women aged 15 to 49 on a range of topics, including maternal health and contraception. Information on informed contraceptive use is recorded in the individual record (IR) of the DHS survey.

Data management and analysis

STATA/MP version 17 and Microsoft Excel 2019 software were used to clean, extract, and weight the data. Prior to statistical analysis, the data were weighted using the sampling weight, which was calculated by dividing the women sample weight (v005) by 1,000,000 to ensure the survey's representativeness. Descriptive statistics were presented as frequencies, percentages, and text, through tables, graphs, and maps. An initial exploratory data analysis was performed to identify outliers, missing values, and assess data consistency.

Machine learning analysis was conducted using Python version 3.9 software. Missing values were addressed using the Simple Imputer with median imputation for numerical variables and mode imputation for categorical variables, while outliers were systematically identified and removed using the Local Outlier Factor, configured with a contamination parameter of 5% to reflect the expected proportion of anomalies in the dataset. Categorical variables were encoded as dummy variables via one-hot encoding, and numerical features requiring scale sensitivity were standardized using Z-score normalization. To mitigate class imbalance, the Synthetic Minority Over-Sampling Technique (SMOTE) was applied, adjusting the initial 4:6 minority-to-majority class ratio to a balanced 1:1 distribution prior to model training. Feature selection was conducted through a hybrid approach:

Recursive Feature Elimination (RFE) with logistic regression (L2 regularization) as the base estimator, iteratively removing 5 features per step. The optimal feature subset was determined by maximizing the AUC score across 5-fold cross-validation, ensuring relevance and reducing dimensionality. RFE was employed to eliminate irrelevant or redundant features, streamlining the model while preserving predictive accuracy.

Model selection and development

Seven classification algorithms namely AdaBoost Classifier, XGB Classifier, Random Forest (RF), Naïve Bayes, Light Gradient Boosting classifier (LGBM), Extreme Gradient Boosting (XGBoost), Decision Tree were selected to balance interpretability and predictive power [37–41]. Logistic regression served as a baseline for benchmarking, while ensemble methods (Random Forest, XGBoost, LGBM) were prioritized for their ability to model nonlinear relationships, handle high-dimensional data, and resist overfitting through bagging and boosting mechanisms. Simpler models (e.g., decision trees) were included to assess complexity trade-offs. To assess the performance of the model, we used an 80:20 train-test split, where 80% of the dataset was allocated for training and the remaining 20% for testing. The common k-fold cross validation methodology was used to ensure the performance of the model because the train-test split function method has the problem of either overfitting or under fitting on the dataset. The K-fold approach divides the dataset into 'K' sub-samples, one for testing and the remainder for training K times repeatedly. Hence, the ten-fold cross-validation performance measure is the average of the values computed in this loop [42]. In this study we utilized 10-fold cross validation. The outcome variable had two categories that were mutually exclusive for informed choice, the dataset used in the analysis fell under the category of binary classification. The performance of models was evaluated using accuracy, Area Under the Curve (AUC), Precision, Recall, and F1 score. These metrics provided a comprehensive evaluation of the models' accuracy, their ability to correctly classify instances, and their overall predictive power. This approach helps mitigate overfitting and provides a more reliable estimate of the model's generalization performance.

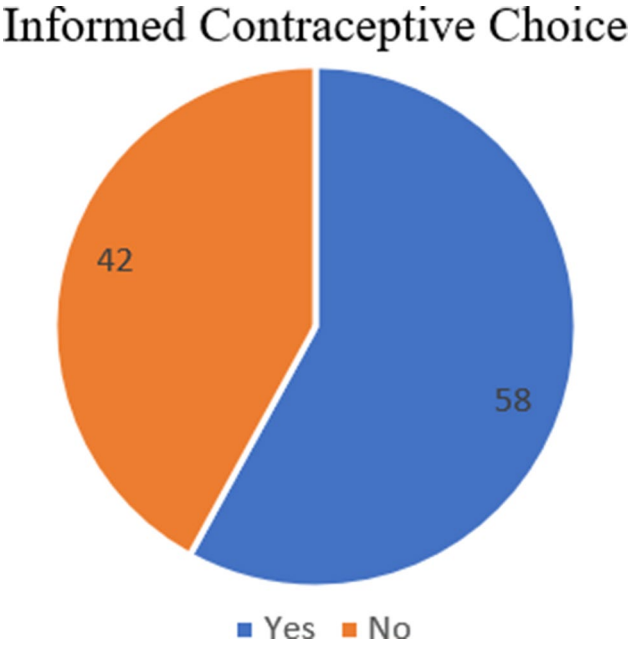

Fig. 2 The pooled prevalence of informed choice among women of high fertility rate countries in SSA

Performance metrics

To evaluate the effectiveness of the models, we used a comprehensive set of performance metrics, ensuring a balanced assessment of predictive accuracy and reliability. Accuracy was used as a general indicator of overall model performance, while precision, and recall, provided deeper insights, particularly in handling class imbalances. The area under the receiver operating characteristic curve (AUC-ROC) was also computed to measure the model's ability to distinguish between classes. These metrics collectively ensured a robust evaluation, highlighting both the strengths and potential limitations of each model in predicting informed choice.

Shapley additive explanations (SHAP)

The link between the predictors and the outcome variable was assessed using the Additive Explanations (SHAP) feature significance approach, which also assisted in identifying the independent factors that are most important for predicting informed contraceptive choice [43]. SHAP analysis uses a game theory framework to offer a global or local interpretation and explanation for any machine learning model's prediction [43].

Result

A total of 11,706 weighted respondents were included in this study. The largest survey sample was drawn from Burkina Faso 3489 (30%) and the least sample size was from Angola 834 (7%). Approximately 58% of women received informed contraceptive choice services (Fig. 2). In addition, the highest case of informed choice was clustered in Burkina Faso while the lowest is clustered in Angola (Fig. 3). Similarly, the highest proportion of informed contraceptive users was found in Burkina Faso with 2669 (77%) and the lowest proportion of informed contraceptive users was found in Burundi with 599 (29%) (Table 1).

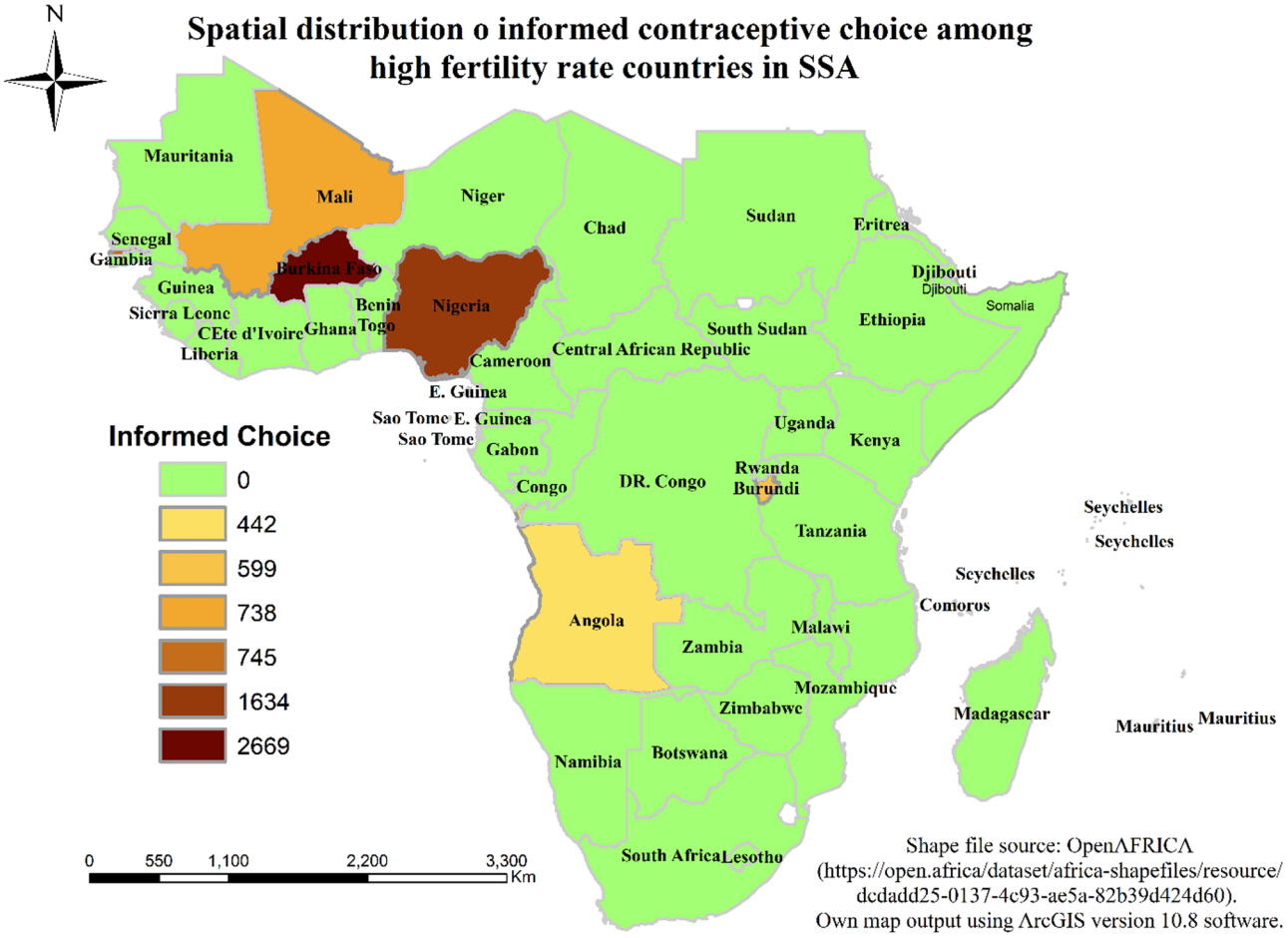

Fig. 3 The spatial distribution of informed contraceptive choice across high fertility rate countries in SSA

Table 1 Distribution of weighted sample and informed contraceptive choice of women across high fertility rate countries in SSA

SSA Countries	Informed choice		Weighted sample
	No	yes	
Angola	392(47)	442(53)	834(7)
Burkina Faso	820(23)	2669(77)	3489(30)
Burundi	1476(71)	599(29)	2075(18)
Gambia	541(42)	745(58)	1286(11)
Mali	754(51)	738(49)	1492(13)
Nigeria	895(35)	1634(65)	2529(22)
Total	4878(42)	6828(58)	11,706(100)

Sociodemographic characteristics

The majority of participants, 5298 (45.26%), were aged between 25 and 34 years, followed by those aged between 35 and 49 years, who accounted for 3789 (32.37%) participants. Approximately 5084 (43.43%) of the participants resided in urban areas. Similarly, the majority, 4873 (41.63%), had not received any form of formal education. The majority of respondents, 6,972 (59.56%), identified as Christians. A large proportion, 10,555 (90.16%), of respondents were married. Most participants, 10,898 (86.26%), lived in households where the male was the head. Additionally, a significant proportion, 7331 (62.63%), reported having had only one lifetime partner (Table 2).

Machine learning analysis

To assess the predictive ability of the models in predicting informed contraceptive choice, accuracy, AUC, precision, recall, and F1 score were compared across machine learning algorithms and a logistic regression baseline. The logistic regression model achieved modest performance (accuracy: 65%, AUC: 0.68), while the LGBM classifier emerged as the top performer with an accuracy of 73%, AUC of 0.80, precision of 71, and recall of 77. To ensure robustness, the models were rigorously evaluated using 10-fold cross-validation, which mitigates overfitting by averaging performance across multiple train-test splits. Cross-validation confirmed the stability of the machine learning models. Both XGBoost and LGBM maintained a comparable accuracy of 73%, mirroring their performance in the initial holdout validation (Table 3; Fig. 4).

Table 2 Socio-demographic characteristics of the study participants across high fertility rate countries in SSA

Independent Variables	Weighted frequency (%)	Informed Choice	
		No (%)	Yes (%)
Age			
15–24	2619(22.37)	1154(9.9)	1465(12.5)
25–34	5298(45.26)	2225(19.0)	3072(26.2)
35–49	3789(32.37)	1499(12.8)	2290(19.6)
Religion			
Christian	6972(59.56)	3071(26.2)	3893(33.3)
Assembly of God	1553(13.26)	519(4.4)	1034(8.8)
Universal	185(1.58)	77(0.7)	108(0.9)
Others	2996(25.60)	1203(10.4)	1793(15.3)
Wealth Index			
Poorest	1546(13.2)	679(5.8)	867(7.4)
Poorer	1814(15.5)	808(6.9)	1006(8.6)
Middle	2357(20.1)	1044(8.9)	1312(11.2)
Richer	2823(24.1)	1122(9.6)	1701(14.5)
Richest	3166(27.0)	1224(10.5)	1941(16.6)
Residence			
Urban	5084(43.43)	1920(16.4)	3164(27.0)
Rural	6622(56.57)	2958(25.3)	3664(31.3)
Contraceptive source			
Public	9791(83.64)	3714(31.7)	6077(51.9)
Private	1649(14.09)	994(8.4)	655(5.7)
Others	266(2.27)	170(1.5)	96(0.8)
Marital status			
Never in union	711(6.07)	344(2.9)	367(3.1)
Married	10,555(90.16)	4331(37.0)	6223(53.2)
Single	440(3.76)	203(1.7)	238(2.0)
Internet use			
No	9100(77.74)	3872(33.1)	5228(44.7)
Yes	2606(22.26)	1006(8.6)	1600(13.7)
Education			
No education	4873(41.63)	1950(16.7)	2923(25.0)
Primary	2522(21.55)	1238(10.6)	1284(11.0)
Secondary &higher	4311(36.82)	1690(14.4)	2621(22.4)
Desire to limit children			
Have another	7513(64.19)	3084(26.3)	4429(37.8)
Undecided	536(4.58)	194(1.7)	343(2.9)
No more	3656(31.24)	1600(13.7)	2056(17.6)
Exposed for family planning message			
No	5995(51.22)	2855(24.4)	3141(26.8)
Yes	5711(48.78)	2023(17.3)	3688(31.5)
Media exposure			
No	2645(22.59)	1308(11.2)	1337(11.3)
Yes	9061(77.41)	3570(30.5)	5491(47.0)
Mobile ownership			
No	3616(30.89)	1953(16.7)	1663(14.2)
Yes	8090(69.11)	2925(25.0)	5165(44.1)
Total life time partner			
One	7331(62.63)	3224(27.5)	4107(35.1)
Two and more	4375(37.37)	1654(14.1)	2721(23.3)
Health facility visit in the last 12 months			
No	7513(64.18)	3555(30.4)	3958(33.8)

Table 2 (continued)

Independent Variables	Weighted frequency (%)	Informed Choice	
		No (%)	Yes (%)
Yes	4193(35.82)	1323(11.3)	2870(24.5)
Household head sex			
Male	1098(86.26)	4118(35.2)	5980(51.1)
Female	1608(13.74)	760(6.5)	848(7.2)
Distance from health facility			
Big problem	3255(27.81)	1318(11.3)	1937(16.6)
Not a big problem	8451(72.19)	3560(30.4)	4891(41.8)
Getting permission to go health facility			
Big problem	1291(11.03)	573(4.9)	718(6.1)
Not a big problem	10,414(88.97)	4305(36.8)	6111(52.2)
Go alone to health facility			
Big problem	1482(12.66)	612(5.1)	870(7.3)
Not a big problem	10,224(87.34)	4266(36.5)	5958(50.1)
Health Insurance Coverage			
No	10,807(92.32)	4395(37.5)	6412(54.6)
Yes	899(7.68)	483(4.5)	416(3.4)
DHS survey upload year			
2016–2019	6931(59.21)	3517(30.0)	3413(29.2)
2020 = 2024	4775(40.79)	1361(11.6)	3415(29.2)
Number of under five children			
No children	401 (3.43)	192(1.7)	209(1.9)
One	1786(15.25)	753(6.5)	1033(8.9)
2–4	6111(52.21)	2542(21.8)	3570(30.1)
>=5	3408(29.11)	1391(11.9)	2016(17.2)

Importance feature selection

The key predictors of informed contraceptive choice were identified using the Light Gradient Boosting Machine (LGBM), with SHAP values computed to quantify each feature's contribution to the model predictions. The SHAP plot identified variables, including health facility visit within 12 months, source of contraception, mobile ownership, education, religion, exposure to family planning messages, residence, total lifetime partners, number of under-five children, and wealth index as a top ten predictors of informed contraceptive choice (Fig. 5).

Beeswarm plot

The beeswarm plot offers valuable insights into the relationship between features and the outcome variable. Each point in the plot represents a feature and its corresponding SHAP value. The position of the points relative to the vertical line at "0" SHAP value indicates the impact of the feature on the likelihood of informed choice. On the right side of the vertical line, where the SHAP values are positive, features contribute to an increased likelihood of informed choice. This is represented by the red line, indicating the category coded as "1" (i.e., informed choice Yes) or a high value. This means that increasing the value of these features tends to increase the predicted value of informed contraceptive choice. For example, increasing the values of health facility visit within 12 months, source of contraception, mobile ownership, education, religion, exposure to family planning messages, residence, total lifetime partners, number of under-five children, and wealth index had a significant positive impact on predicting informed choice towards Category "1", when these factors decrease, they have a corresponding influence toward category 0.

On the left side of the vertical line, where the SHAP values are negative, features are associated with a decreased likelihood of mothers who are not informed about family planning choices class 1. This is represented by the blue line, indicating the category coded as "0" (i.e., informed about contraceptive choices). Increasing the value of these features tends to decrease the predicted value of the target variable towards class 1 (Fig. 6).

Discussion

Informed choice of contraceptive methods is a crucial strategy to enhance the uptake of family planning services. When individuals have access to accurate, comprehensive, and unbiased information about various contraceptive methods including their benefits, potential side effects, and proper use they are more likely to choose

Table 3 Machine learning performance metrics to predict informed contraceptive choice among women across high fertility rate countries in SSA

Machine learning models	Dataset	Accuracy	AUC	Precision	Recall(Sensitivity)
Naïve Bayes	Unbalanced (%)	66	69	69	77
	Balanced (%)	65	69	64	71
Logistic regression	Unbalanced (%)	68	71	70	80
	Balanced (%)	67	72	67	70
LGBM classifier	Unbalanced (%)	69	73	71	79
	Balanced (%)	73	80	71	77
Decision Tree Classifier	Unbalanced (%)	60	58	65	68
	Balanced (%)	65	66	65	69
Random Forest Classifier	Unbalanced (%)	66	68	70	74
	Balanced (%)	71	77	71	73
XGBoost classifier	Unbalanced (%)	67	69	70	77
	Balanced (%)	73	79	72	77
AdaBoost Classifier	Unbalanced (%)	69	73	71	79
	Balanced (%)	71	77	72	72

and continue using a method that best suits their needs and lifestyle. Ensuring informed choice empowers individuals to make decisions aligned with their reproductive goals and overall well-being. When individuals receive clear and accessible contraceptive information, they can make confident and sustainable choices. Informed choice reduces uncertainty, enhances satisfaction, and promotes consistent use [34, 44–47]. This study aimed to model predictors of informed contraceptive choice among reproductive age women in Sub Sahara Africa with high fertility countries by the application of machine learning algorithms.

The pooled prevalence of informed choice of contraceptive methods among high fertility rate countries in SSA was 58% (95%CI: 57.4, 59.2%). The prevalence is higher in Burkina Faso and lower in Mali. Moreover, the highest spatial clustering of informed choice of contraceptive methods was observed in Burkina Faso while the lowest clustering was found in Angola. The finding is lower than a study findings conducted in Kenya [47]. The observed variation may be attributed to differences in study settings. In Kenya, the study was conducted in an urban setting, where increased access to information about contraceptive methods may have contributed to a higher prevalence of informed contraceptive choice. In contrast, our study included women from both urban and rural areas. On the other hand, the magnitude of informed contraceptive choice found in this study is higher than findings in SSA [14], India [48, 49], and in Ethiopia [15, 31]. The difference might be as a result of the difference in the study period and the study population. Moreover, this study was focused on high fertility rate countries in SSA and there might be a strategical intervention to mimic their population growth through informed contraceptive choice.

To predict informed contraceptive choice seven machine learning algorithms namely (Random Forest, XGBoost, LGBM, Naïve Bayes, Decision Tree, Logistic Regression, and AdaBoost was employed to predict informed contraceptive choice) were trained on balanced and imbalanced dataset and predicted informed contraceptive choice using unseen dataset. Classification accuracy, precision, recall, sensitivity and AUC scores were used to compare the performance of the seven machine learning models. The LGBM classifier was identified as the top performer with an accuracy of 73%, AUC of 0.80, precision of 71, and recall of 77 after a rigorously evaluation of models using 10-fold cross-validation to ensure robustness, which mitigates overfitting by averaging performance across multiple train-test splits. We applied the SMOTE balancing technique to address class imbalance, ensuring the model learned patterns from both the majority and minority classes while reducing prediction bias. SMOTE generated synthetic samples for the minority class, enhancing model generalization. Although the difference after balancing was minimal, we used the balanced dataset to further mitigate bias and improve the model's performance. XGBoost also maintained a comparable accuracy of 73% with LGBM that mirroring the high predictive performance of XGBoost in the initial holdout validation although LGBM outperformed by the rest machine learning performance metrics. As a result, the LGBM model was the best predictive models, and additional analysis to identify important features in predicting informed contraceptive choice was conducted after improving it for the optimal hyper parameters.

This method of analysis uncovers hidden patterns and complex relationships between the informed contraceptive choice and its determinant factors through identification of nonlinear interactions and dependencies that traditional methods may miss. Unlike conventional approaches that rely on predefined assumptions, this method of analysis can process large datasets and automatically detect associations across multiple variables. This leads to a deeper understanding of how factors interact, even in noisy or high-dimensional data.

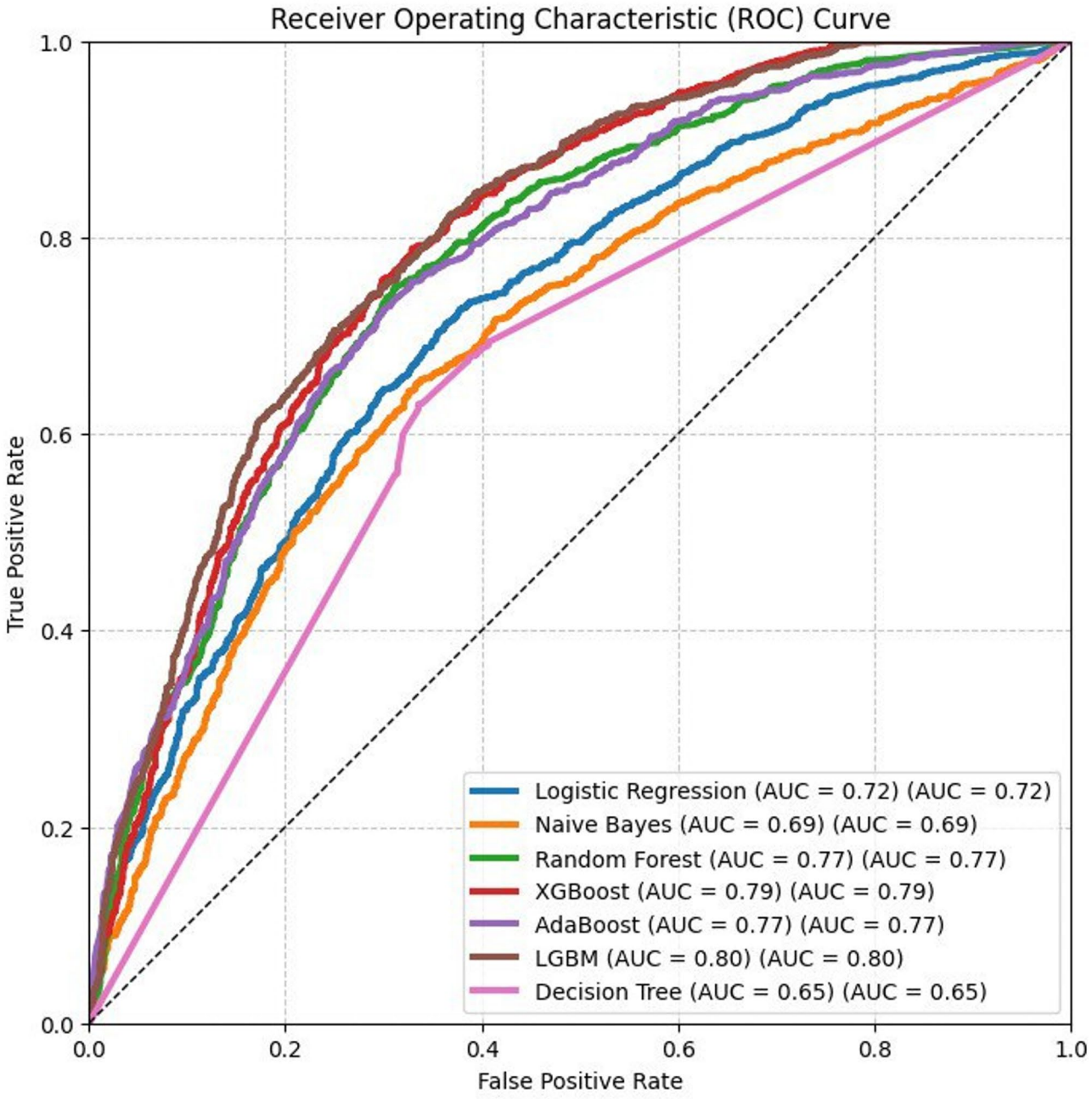

Fig. 4 AUC graph for machine learning algorithms utilized to predict informed contraceptive choice of women across high fertility rate countries in SSA

Moreover, machine learning analysis reveals trends, subgroup variations, and evolving influences that linear models might not capture and enhances data-driven decision-making, by providing more accurate predictions. Techniques like SHAP improve the interpretability of ML models, making the results more transparent and actionable. Accordingly, the SHAP analysis identified the top ten outperformed predictors of informed contraceptive choice. Accordingly, health facility visits within 12 months, religion, source of contraceptive, exposure to family planning message, mobile ownership, education, wealth index, under five children, residence, and total life time partner were the top ten predictors of informed contraceptive choice.

Health facility visit in the past 12 months is identified as a significant determinants of informed contraceptive choice which increases the likely hood of informed contraceptive choice uptake. Previous literatures conducted in SSA [50, 51] and Nigeria [52] also ensured the positive contribution of health facility visit to increase informed contraceptive choice uptake. Similarly, research findings conducted in Ethiopia [53] and Uganda [54] also

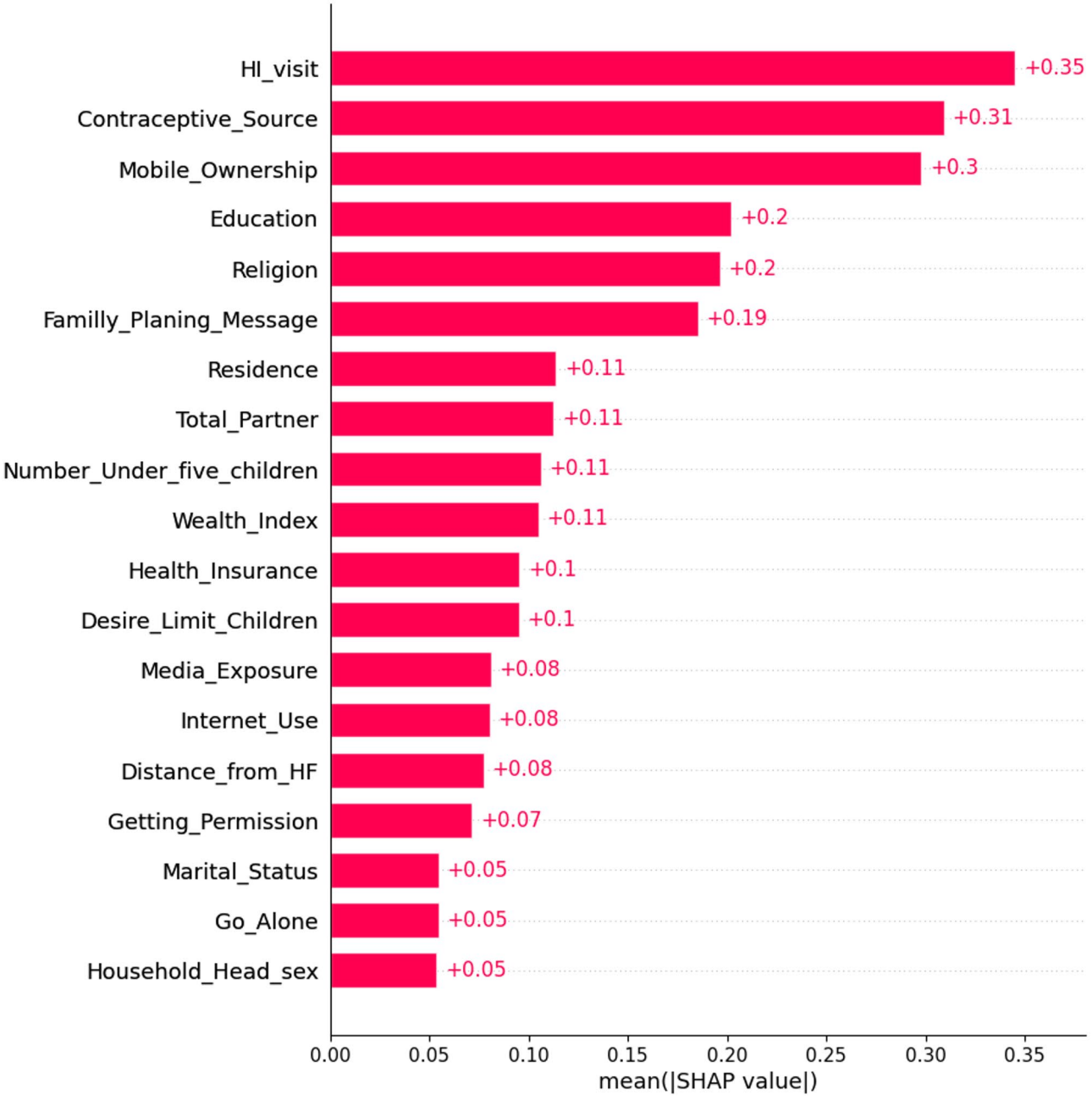

Fig. 5 Important features for informed contraceptive choice of women selected by light gradient boosting among high fertility rate countries in SSA

emphasized the increased likely hood of informed contraceptive choice resulted from prior health facility based in the postpartum period. Health facility visits play a vital role in increasing informed contraceptive choice by providing accurate information, fostering trust, integrating services, countering misinformation, and empowering women to take charge of their reproductive health. Many individuals in SSA lack reliable contraceptive knowledge, and facility-based counseling ensures they receive personalized guidance on available methods, effectiveness, and potential side effects [55, 56]. These visits also build trust between women and healthcare providers, making them more likely to accept contraceptive advice. Additionally, family planning is often integrated with maternal and child health services, such as antenatal and postnatal care, reducing missed opportunities for informed decision-making. Health facility visits further help dispel myths and misconceptions regarding contraception, addressing fears about infertility and side effects through evidence-based counseling. Moreover, they empower women by providing a safe space for confidential, unbiased discussions, enhancing their autonomy over

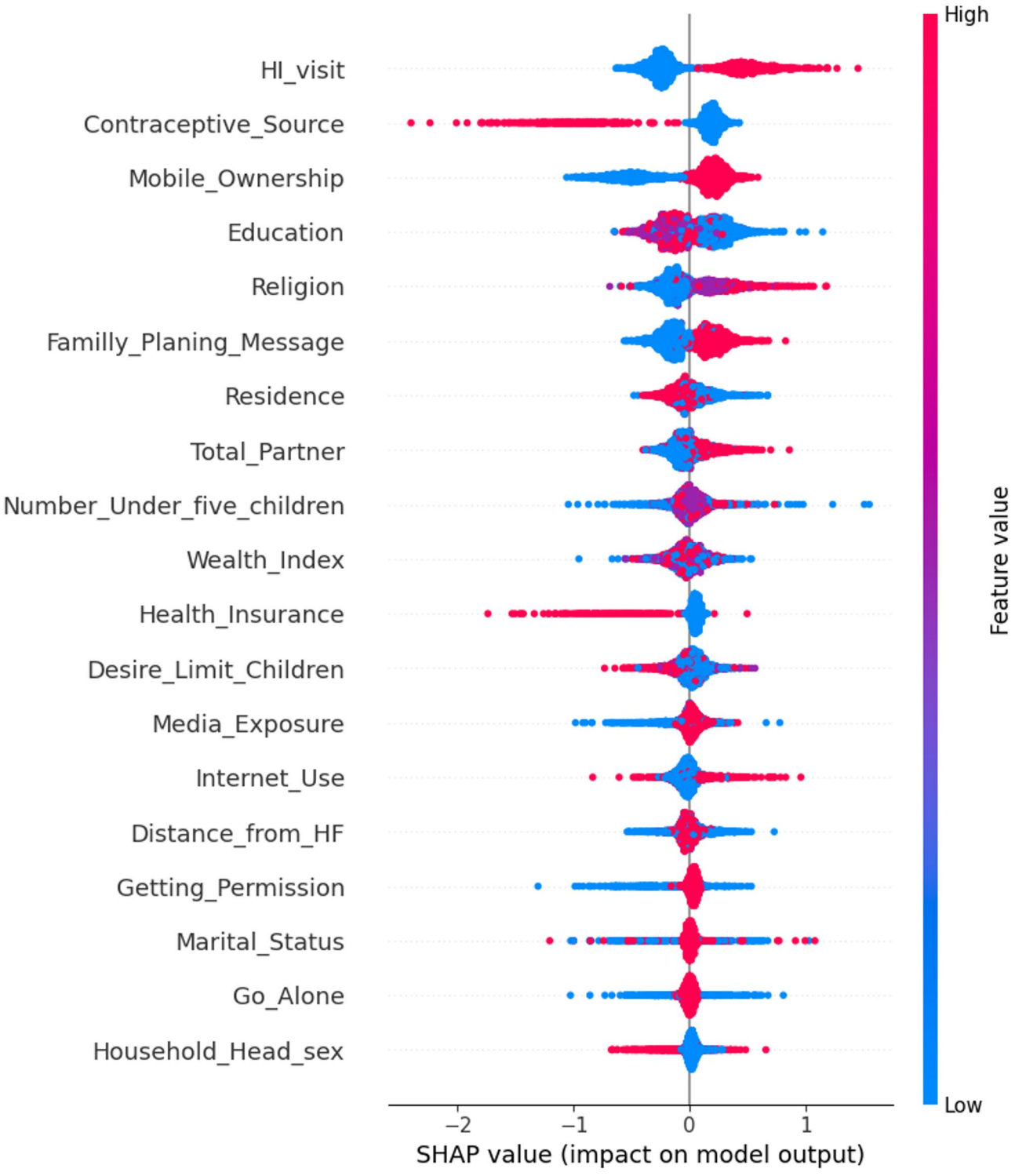

Fig. 6 Important features SHAP value impact to predict informed contraceptive choice of women across high fertility rate countries in SSA

reproductive choices. Ultimately, these visits increase the likely hood of informed contraceptive choice.

Likewise, the finding of this study shows that higher wealth status among participants increase the uptake of informed contraceptive choice. Previous literatures conducted in SSA [14] also supported the impact of economic status on the uptake of informed contraceptive choice. The finding emphasized women from lower middle and upper middle income level countries were more likely to involved with informed contraceptive choice.

One plausible explanation is that women from wealthier households often prioritize quality of life once their basic needs such as food, shelter, and healthcare are met. This financial security allows them the freedom and capacity to seek out and process health-related information more effectively. Consequently, they are more likely to actively participate in their reproductive health decisions, being better informed through interactions with healthcare professionals and exposure to various media outlets. This heightened awareness and access to information may lead to more autonomous and educated choices regarding contraceptive use.

Moreover, our study identified religious is as a significant predictor of informed contraceptive choice. Religion plays a significant role in shaping informed contraceptive choices among women of reproductive age in Sub-Saharan Africa (SSA). Religious beliefs often influence attitudes toward contraceptive use, method selection, and the availability of family planning information, with varying effects across different faith communities. In some cases, religious teachings may encourage the use of contraceptives, while in others, they may discourage it, creating barriers to accessing family planning services. For instance, in Sierra Leone, Catholic leaders oppose modern contraceptives based on religious convictions, while Pentecostal and some Muslim leaders accept their use under specific conditions [57]. In Uganda, both Christian and Muslim leaders tend to discourage the use of modern contraceptives, advocating for natural methods like abstinence instead [58]. Understanding these diverse religious perspectives is critical to promoting informed contraceptive decisions. By engaging religious leaders in educational efforts, addressing gender dynamics, and bridging gaps between religious views and modern family planning practices, it is possible to improve reproductive health outcomes and ensure that women have access to the information and support needed to make informed contraceptive choice.

Similarly, women with higher education level are more likely to receive informed contraceptive choice, which is consistent with prior studies [14, 15]. This might be education prepares individuals with the requisite knowledge and skills so that they can make informed decisions that positively impact their health. Education is the most important weapon to battle and being curious about the health and related choices of the women. Moreover, educated women can comprehend and retained the information received from different sources and would explore more about family planning methods while they are in front of the health care providers. Likewise, women from urban residents were high likely to receive informed contraceptive choice, which is consistent with prior studies [15]. This might have explained urban residents have many media channels that increase their knowledge about contraceptive methods and they will explore more while they are intended to receive. Rural areas in Sub-Saharan Africa often grapple with poorly equipped healthcare facilities, which significantly hinders the availability of facilities to enhance their women informed contraceptive choice. Even when facilities are present, finding skilled healthcare personnel in rural settings remains a challenge. Additionally, healthcare facilities in rural regions are typically centralized, making them difficult to access for many women, thereby contributing to the low level of informed choice.

On the other hand, exposure to family planning message is identified as a significant predictor of informed contraceptive choice among reproductive age women. Previous literatures conducted in SSA [50, 59] and Ethiopia [60] also supported this finding. This might be because women who have information about family planning methods could assert additional information to convince themselves. As a result, they will comprehend the provided detail or would seek information intentionally and going to be informed the details of methods and side effects. Similarly, source of contraceptive also identified as a significant determinant of informed contraceptive choice, those who receive their contraceptive from public health organizations is high likely to be informed about the available methods, the possible side effects, and what they could did if side effect happened. The finding is consistent with previous literatures from Ethiopia [15] and SSA [14]. This might be due to the fact that government health facilities may have family planning guidelines and equipped with trained providers for counseling about the components of informed choice. Moreover, private health facilities are commercial, they could have inadequate time to provide detailed information about the service they are providing to their clients who receive contraceptive methods.

Moreover, Mobile phone ownership also significantly contribute to informed contraceptive choice of a woman. The finding is consistent with previous published literatures [14], mobile phone ownership could facilitate the communication process for consultation and the information delivery via text, phone calls, and browsing on the web. This in turn facilitates their comprehension of messages to clearly articulated the messages from health care providers and has a chance to contact the health care provider after leaving the health facility [61]. Accordingly, the chance of being informed among mobile owners would be enhanced significantly. In addition, women who had mobile phone could have retained information about different types of contraceptive methods and their side effects that enabled them to make an informed choice [62].

Similarly, total life time partner also identified as a significant predictor of receiving informed contraceptive

choice among reproductive age women. The number of lifetime sexual partners serves as a significant predictor of informed contraceptive choices, influenced by increased exposure to reproductive health information, heightened awareness of contraception-related risks, and a greater likelihood of seeking and utilizing contraceptive methods. This heightened awareness and experience facilitate more informed decision-making regarding contraception, especially among individuals who perceive themselves at higher risk of unintended pregnancies and sexually transmitted infections [63, 64]. However, the relationship between the number of lifetime sexual partners and contraceptive use is also shaped by socioeconomic, cultural, and gender factors, which can either support or hinder an individual's ability to make informed reproductive health decisions. Lastly, total life time partner and number of under five children also identified as a significant determinant of receiving informed choice among reproductive age women. The number of under-five children a woman has significantly influences her informed contraceptive choices, driven by desires to space or limit pregnancies, improve maternal and child health, and manage socioeconomic pressures. Women with multiple young children often recognize the practical implications of expanding their families and may be motivated to seek contraception to ensure better health outcomes for themselves and their existing children. This awareness, coupled with increased access to family planning services, healthcare visits, and empowerment, can lead to more informed decisions about contraceptive methods [65–67].

Limitations and strengths of the study

This primary strength of this study is utilization of a large, nationally representative sample sizes. Moreover, the application of machine learning models uncovers hidden patterns and complex relationships that traditional methods might miss by identifying nonlinear interactions across multiple variables. Unlike conventional approaches, machine learning processes large datasets and detects associations automatically, revealing trends and subgroup variations that linear models may overlook. Algorithms like decision trees, XGBoost, LGBM, AdaBoost, and ensemble learning help identify how social, economic, and behavioral factors shape outcomes. Techniques like SHAP improve model interpretability, making the results more transparent and actionable. Ultimately, machine learning enhances data-driven decision-making, providing more accurate predictions. The researchers used SHAP and other methods to assess the relative significance of each predictor and understand their contribution to the model's predictions.

Despite the wide nature and high sample size of this study, the study has limitations, such as proximal determinants of informed contraceptive choice such as decision autonomy, intention to use contraceptives, efficiency of health care professionals to provide counseling service, perceived side effects and health concerns, health system related factors such as accessibility and integration with cultural norms were not included due to a significant missing value and DHS has not collected some of the proximal determinants. Although we had conducted 10-fold cross validation to ensure the prediction is valid, we had not conducted external validation using external dataset.

Conclusion

This study highlights the growing role of machine learning in advancing reproductive health by effectively predicting informed contraceptive choice among women in high-fertility countries in Sub-Saharan Africa (SSA). The prevalence of informed contraceptive choice was found to be 58%, with significant variations across countries, the highest in Burkina Faso and the lowest in Mali. Moreover, the highest spatial clustering of informed choice of contraceptive methods was observed in Burkina Faso while the lowest clustering was found in Angola. The LGBM classifier demonstrated the highest predictive power, achieving 73% accuracy and an AUC of 0.80, precision of 71, and recall of 77.

Factors influenced informed contraceptive choice, was identified through the comprehensive analysis LGBM classifier. Accordingly, health facility visits, religion, contraceptive source, exposure to family planning messages, mobile phone ownership, education, wealth status, residence, and total life time partner were identified as top ranked factors that determined the uptake of informed contraceptive choice. These determinants highlight the interplay of socioeconomic, demographic, and policy-related factors in shaping informed contraceptive decisions. To enhance informed contraceptive choice, governments, policymakers, and healthcare organizations should prioritize strengthening family planning education, expanding healthcare services, and ensuring equitable access to contraceptive information.

Digital health interventions, particularly mobile-based platforms, can bridge information gaps and facilitate decision-making, especially in underserved rural areas. Additionally, integrating informed contraceptive choice counseling into routine healthcare services is essential to ensure that all women receive comprehensive and accurate information about contraceptive options. Healthcare providers should be adequately trained to deliver high-quality counseling, addressing potential concerns and misconceptions regarding contraceptive methods. Mass media campaigns should be expanded to raise awareness about the importance of informed contraceptive choice. These campaigns should be tailored to cultural

and linguistic contexts to effectively reach diverse populations. Community engagement programs can also play a crucial role in addressing social and religious barriers by involving community leaders, educators, and health advocates. Efforts should also focus on improving healthcare infrastructure, particularly in rural and underserved areas, by ensuring the availability of contraceptive supplies and enhancing the quality of services. Governments should allocate sufficient resources to support family planning programs and ensure that cost is not a barrier to accessing contraceptive services. Finally, continuous monitoring and evaluation of family planning initiatives should be implemented to assess their effectiveness and identify areas for improvement. Data-driven decision-making should guide policy adjustments, ensuring that interventions remain responsive to evolving reproductive health needs in SSA. Finally, we recommend that researchers should further validate these findings using external data sources.

Abbreviations

DHS	Demographic and health survey
UNFPA	United Nations Population Fund
IMF	International Monetary Fund
IR	Individual record
AUC-ROC	Area under the receiver operating characteristic curve
SMOTE	Synthetic Minority Over-Sampling Technique
LGBM	Light Gradient Boosting classifier
XGBoost	Extreme Gradient Boosting
AUC	Area Under the Curve
SHAP	SHapley Additive exPlanations
RFE	Recursive Feature Elimination

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Author contributions
All authors agreed to be responsible for all elements of the work and, including M, MS: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, writing original draft, Writing review & editing. LY: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, writing original draft, Writing review & editing. BS: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, writing original draft, Writing review & editing. MH: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, writing original draft, Writing review & editing. T, EA: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, writing– original draft, Writing– review & editing. All authors made a significant contribution to the work reported.

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Data availability
The datasets used during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The study was a secondary data analysis based on the publicly available DHS data, thus ethical approval and participant consent were not necessary. The IRB-approved procedures for DHS public-use datasets do not in any way allow respondents, households, or sample communities to be identified. There are no names of individuals or household addresses in the data files. Under the MEASURE DHS Program, respondents' privacy is well secured. The confidentiality of respondents is protected by the MEASURE DHS Program. The MEASURE DHS Program website (https://dhsprogram.com/data/dataset_admin/index.cfm) is where we found the dataset. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki, ensuring that all procedures respected participants' rights, autonomy, and well-being.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Consent to participate
The study was conducted in accordance with the ethical principles of the Declaration of Helsinki, ensuring that all procedures respected participants' rights, autonomy, and well-being.

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References

1. Bongaarts J. The impact of family planning programs on unmet need and demand for contraception. Stud Fam Plann. 2014;45(2):247–62.
2. Westoff CF. The potential demand for family planning: a new measure of unmet need and estimates for five Latin American countries. Int Fam Plan Perspect. 1988:45–53.
3. Ali M, Tran NT. Defining counselling in contraceptive information and services: outcomes from an expert think tank. Br Med J Publishing Group; 2022. pp. 79–81.
4. Bakamjian L, Harper P, Association for Voluntary Surgical Contraception (US). Family planning counseling: an international conference. AVSC News. 1992;30(2):1–2.
5. Rimon JG, Tsui AO. Regaining momentum in family planning. Global Health: Sci Pract. 2018;6(4):626–8.
6. Kamalam S. Fp Summit-India's vision fp 2020. TNNMC J Community Health Nurs. 2020;8(2):41–5.
7. Tringale M, Stephen G, Boylan A-M, Heneghan C. Integrating patient values and preferences in healthcare: a systematic review of qualitative evidence. BMJ Open. 2022;12(11):e067268.
8. Swift JK, Mullins RH, Penix EA, Roth KL, Trusty WT. The importance of listening to patient preferences when making mental health care decisions. World Psychiatry. 2021;20(3):316.
9. Lindhiem O, Bennett CB, Trentacosta CJ, McLear C. Client preferences affect treatment satisfaction, completion, and clinical outcome: a meta-analysis. Clin Psychol Rev. 2014;34(6):506–17.
10. Loaiza E, Liang M, Snow R, editors. Informed choice for modern contraceptive use: evidence from 24 countries served by the UNFPA supplies programme. Population Association of America meeting; 2016.

11. Polis C, Bradley SE, Bankole A, Onda T, Croft TN, Singh S. Contraceptive failure rates in the developing world: an analysis of demographic and health survey data in 43 countries. 2016.
12. Ali MM, Cleland JG, Shah IH, Organization WH. Causes and consequences of contraceptive discontinuation: evidence from 60 demographic and health surveys. 2012.
13. Fotso JC, Izugbara C, Saliku T, Ochako R. Unintended pregnancy and subsequent use of modern contraceptive among slum and non-slum women in Nairobi, Kenya. BMC Pregnancy Childbirth. 2014;14:1–10.
14. Tsega NT, Haile TT, Asratie MH, Belay DG, Endalew M, Aragaw FM, et al. Pooled prevalence and determinants of informed choice of contraceptive methods among reproductive age women in Sub-Saharan Africa: A multilevel analysis. Front Public Health. 2022;10:962675.
15. Tareke AA, Takele BA, Ahmed MH, Tegegne MD, Eshetu HB. Urban-rural inequalities and Spatial arrangement of informed choice of family planning in Ethiopia: further analysis of 2016 Ethiopian demographic health survey. PLoS One. 2023;18(8):e0289099.
16. Bhattacharjee NV, Schumacher AE, Aali A, Abate YH, Abbasgholizadeh R, Abbasian M, et al. Global fertility in 204 countries and territories, 1950–2021, with forecasts to 2100: a comprehensive demographic analysis for the global burden of disease study 2021. Lancet. 2024;403(10440):2057–99.
17. Bayoumi RR, Hurt L, Zhang N, Law YJ, Venetis C, Fatem HM, et al. A critical systematic review and meta-analyses of risk factors for fertility problems in a globalized world. Reprod Biomed Online. 2024;48(3):103217.
18. Mburu G, Kiarie J, Allotey P. Towards a nuanced view and response to global fertility trends. Lancet. 2024;403(10440):1953–6.
19. Negash WD, Kefale GT, Belachew TB, Asmamaw DB. Married women decision making autonomy on health care utilization in high fertility sub-Saharan African countries: A multilevel analysis of recent demographic and health survey. PLoS ONE. 2023;18(7):e0288603.
20. Tesfa D, Tiruneh SA, Gebremariam AD, Azanaw MM, Engidaw MT, Kefale B, et al. The pooled estimate of the total fertility rate in sub-Saharan Africa using recent (2010–2018) demographic and health survey data. Front Public Health. 2023;10:1053302.
21. Mulugeta SS, Muluneh MW, Belay AT, Yalew MM, Agegn SB. Reason and associated factors for nonuse of contraceptives among Ethiopian rural married women: a multilevel mixed effect analysis. SAGE Open Nurs. 2023;9:23779608221150599.
22. Mekonnen W, Worku A. Determinants of fertility in rural Ethiopia: the case of Butajira demographic surveillance system (DSS). BMC Public Health. 2011;11:1–6.
23. Hailemariam A. An overview of the determinants of high fertilily in Ethiopia. Ethiop J Dev Res. 1992;14(2):1–30.
24. Götmark F, Andersson M. Human fertility in relation to education, economy, religion, contraception, and family planning programs. BMC Public Health. 2020;20:1–17.
25. Bradley SE, Schwandt H, Khan S. Levels, trends, and reasons for contraceptive discontinuation. DHS Anal Stud. 2009;20.
26. Machiyama K, Casterline JB, Mumah JN, Huda FA, Obare F, Odwe G, et al. Reasons for unmet need for family planning, with attention to the measurement of fertility preferences: protocol for a multi-site cohort study. Reproductive Health. 2017;14:1–11.
27. Bradley SE, Casterline JB. Understanding unmet need: history, theory, and measurement. Stud Fam Plann. 2014;45(2):123–50.
28. Eisenberg L, Brown SS. The best intentions: Unintended pregnancy and the well-being of children and families. 1995.
29. Ventura SJ, Mosher WD, Curtin SC, Abma JC, Henshaw S. Trends in pregnancy rates for the united States, 1976-97: an update. Natl Vital Stat Rep. 2001;49(4):1–9.
30. Coulson J, Sharma V, Wen H. Understanding the global dynamics of continuing unmet need for family planning and unintended pregnancy. China Popul Dev Stud. 2023;7(1):1–14.
31. Handebo S. Informed choice of contraceptive methods among women in Ethiopia: further analysis of the 2016 Ethiopian demographic health survey. Open Access J Contracept. 2021:83–91.
32. Dau H, Kakaire O, Karim ME, Nakisige C, Vidler M, Payne BA, et al. Understanding the association between informed choice and long-term reversible contraception among Ugandan women: findings from the 2016 demographic health survey. Int J Gynecol Obstet. 2023;160(3):978–85.
33. Lozano F, Velásquez A, Marrugo M, Torres L. Impact of contraception counseling on choice of combined hormonal methods in Colombia. Revista Panam De Salud Publica = Pan Am J Public Health. 2015;37(6):395–401.
34. D'Souza P, Bailey JV, Stephenson J, Oliver S. Factors influencing contraception choice and use globally: a synthesis of systematic reviews. Eur J Contracept Reproductive Health Care. 2022;27(5):364–72.
35. Chen JH, Asch SM. Machine learning and prediction in medicine—beyond the peak of inflated expectations. N Engl J Med. 2017;376(26):2507.
36. Holmström J, Ketokivi M, Hameri AP. Bridging practice and theory: A design science approach. Decis Sci. 2009;40(1):65–87.
37. Wyner A, Olson M, Bleich J, Mease D. Explaining the success of adaboost and random forests as interpolating classifiers. ArXiv. 2015;abs/1504.07676.
38. Irmalasari I, Dwiyanti L. Algorithm Analysis of Decision Tree, Gradient Boosting Decision Tree, and Random Forest for Classification (Case Study: West Java House of Representatives Election 2019). 2023 International Conference on Electrical Engineering and Informatics (ICEEI). 2023:1–5.
39. Dev V, Eden M. Gradient boosted decision trees for lithology classification. Computer Aided Chemical Engineering; 2019.
40. Basha S, Rajput D, Vandhan V. Impact of gradient ascent and boosting algorithm in classification. Int J Intell Eng Syst. 2018;11:41–9.
41. Azmi SS, Baliga S. An Overview of Boosting Decision Tree Algorithms utilizing AdaBoost and XGBoost Boosting strategies. 2020.
42. Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: machine learning in Python. J Mach Learn Res. 2011;12:2825–30.
43. Bifarin OO. Interpretable machine learning with tree-based Shapley additive explanations: application to metabolomics datasets for binary classification. PLoS ONE. 2023;18(5):e0284315.
44. Mruts KB, Tessema GA, Dunne J, Gebremedhin AT, Scott J, Pereira GF. Does family planning counselling during health service contact improve postpartum modern contraceptive uptake in Ethiopia? A nationwide cross-sectional study. BMJ Open. 2022;12(5):e060308.
45. Cavallaro FL, Benova L, Owolabi OO, Ali M. A systematic review of the effectiveness of counselling strategies for modern contraceptive methods: what works and what doesn't? BMJ Sex Reproductive Health. 2020;46(4):254–69.
46. D'Souza P, Phagdol T, D'Souza SR, Anupama D, Nayak BS, Velayudhan B, et al. Interventions to support contraceptive choice and use: a global systematic map of systematic reviews. Eur J Contracept Reproductive Health Care. 2023;28(2):83–91.
47. Feeser K, Chakraborty NM, Calhoun L, Speizer IS. Measures of family planning service quality associated with contraceptive discontinuation: an analysis of measurement, learning & evaluation (MLE) project data from urban Kenya. Gates Open Res. 2020;3:1453.
48. Jain AK. Information about methods received by contraceptive users in India. J Biosoc Sci. 2017;49(6):798–810.
49. Pradhan MR, Patel SK, Saraf AA. Informed choice in modern contraceptive method use: pattern and predictors among young women in India. J Biosoc Sci. 2020;52(6):846–59.
50. Mohammed A, Donkoh IE, Aboagye RG, Ahinkorah BO, Seidu A-A. Access to quality contraceptive counselling among adolescent girls and young women in sub-Saharan Africa. Contracept Reproductive Med. 2024;9(1):16.
51. Adu-Gyamfi R, Enos J, Yeboah DO, Torpey K. Theory-based determinants of modern contraceptive use in sub-Saharan Africa: an analysis of demographic and health surveys. MedRxiv. 2022:2022.07. 20.22277859.
52. Ajayi AI, Adeniyi OV, Akpan W. Maternal health care visits as predictors of contraceptive use among childbearing women in a medically underserved state in Nigeria. J Health Popul Nutr. 2018;37:1–10.
53. Samuel B, Tsegaye B, Dulla D, Aynalem A, Israel E, Gebrie M. Informed choice and its associated factors among women received immediate postpartum long-acting reversible contraceptives at public hospitals in Sidama regional State, Ethiopia, 2022. Contracept Reproductive Med. 2023;8(1):32.
54. Nakiwunga N, Kakaire O, Ndikuno CK, Nakalega R, Mukiza N, Atuhairwe S. Contraceptive uptake and associated factors among women in the immediate postpartum period at Kawempe hospital. BMC Womens Health. 2022;22(1):281.
55. Zimmerman LA, Yi Y, Yihdego M, Abrha S, Shiferaw S, Seme A, et al. Effect of integrating maternal health services and family planning services on postpartum family planning behavior in Ethiopia: results from a longitudinal survey. BMC Public Health. 2019;19:1–9.
56. Roro MA, Adinew YM, Yimer SS, Gizaw NF, Estifanos AS, Mohammed JK, et al. Integration of family planning into the primary health care in Ethiopia: results from National assessment. Reproductive Health. 2024;21(1):174.
57. Yillah RM, Bull F, Sawaneh A, Reindorf B, Turay H, Wurie HR, et al. Religious leaders' nuanced views on birth spacing and contraceptives in Sierra Leone-qualitative insights. Contracept Reproductive Med. 2024;9(1):40.

58. Namanda C, Atuyambe L, Ssali S, Mukose A, Tumwesigye NM, Makumbi FE, et al. A qualitative study of influences on the uptake of contraceptive services among people of reproductive age in Uganda. BMC Womens Health. 2023;23(1):130.
59. Iacoella F, Gassmann F, Tirivayi N. Which communication technology is effective for promoting reproductive health? Television, radio, and mobile phones in sub-Saharan Africa. PLoS ONE. 2022;17(8):e0272501.
60. Sully EA, Biddlecom A, Darroch JE, Riley T, Ashford LS, Lince-Deroche N et al. Adding it up: investing in sexual and reproductive health 2019. 2020.
61. Dagnew B, Teshale AB, Dagne H, Diress M, Tesema GA, Dewau R, et al. Individual and community-level determinants of knowledge of ovulatory cycle among women of childbearing age in Ethiopia: A multilevel analysis based on 2016 Ethiopian demographic and health survey. PLoS ONE. 2021;16(9):e0254094.
62. Yeboah A, Yaw D, Gyamfuah A. Influence of multiple media channels on adolescents' knowledge and intentions to use contraceptives: a quantitative study of amasaman, the capital of ga west district assembly in Ghana. Huria: Journal of the Open University of Tanzania. 2017;24(1):92–106.
63. Cornelius T, Kershaw T. Perception of partner sexual history: effects on safe-sex intentions. Health Psychol. 2017;36(7):704.
64. Joffe GP, Foxman B, Schmidt AJ, Farris KB, Carter RJ. Multiple partners and partner choice as risk factors for sexually transmitted disease among female college students. Sex Transm Dis. 1992;19(5):272–8.
65. Abebe Y, Berhanu RD, Kajela L, Bayane YB. Association between women empowerment and contraceptive utilization in Ethiopia. Women's Health. 2024;20:17455057241310641.
66. Yaya S, Uthman OA, Ekholuenetale M, Bishwajit G. Women empowerment as an enabling factor of contraceptive use in sub-Saharan Africa: a multilevel analysis of cross-sectional surveys of 32 countries. Reproductive Health. 2018;15:1–12.
67. Anbesu EW, Alemayehu M, Asgedom DK, Jeleta FY. Women's decision-making power regarding family planning use and associated factors in Ethiopia: a systematic review and meta-analysis. SAGE Open Med. 2023;11:20503121231162722.

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