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Artificial intelligence-assisted decision support for postpartum family planning: a machine learning framework for personalized contraceptive recommendations in resource-limited settings

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Abstract

Background: For postpartum women, access to proper family planning methods in underserved regions is limited, which has contributed to the high rate of unwanted pregnancies and their associated sequelae. Despite efforts to curtail these challenges through the institution of the World Health Organization (WHO) medical eligibility criteria (MEC) provided guidance, their application in postpartum care is impeded by factors such as breastfeeding status, contraceptive availability, prior side effects, and privacy concerns.

Methods: This study instituted a comparative analysis featuring machine learning frameworks like logistic regression, Random Forest and XGBoost trained using a synthetic dataset of 8,000 anonymized postpartum records derived from a publicly available contraceptive method choice dataset and augmented with postpartum-related variables to achieve a prediction goal of seven WHO- approved contraceptive methods with the best performing model integrated with a Telegram bot for accessibility.

Results: The XGBoost model achieved the best performance with a test accuracy of 88.5% and a macro-averaged F1-score of 0.734, demonstrating balanced predictive performance across the seven contraceptive classes.

Conclusion: This study, as a proof of concept shows the urgency in using AI to combat lack of access to healthcare. Despite the excellent outcome, the need for further validation with real world data is imperative after which clinical deployment can be mooted. This model, if successfully deployed in clinical settings may support postpartum women in making informed decisions about their health, thereby contributing positively to maternal health especially in underserved regions. This study, though promising, is however limited by the use of synthetic data which can affect model performance on unseen dataset.

Keywords: Postpartum Family Planning, Machine Learning in Reproductive Health, Contraceptive Decision Support, WHO Medical Eligibility Criteria (MEC), Explainable Artificial Intelligence, Digital Health in Underserved Settings, Nigeria

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Background

Access to adequate and efficient family planning methods stems the tide of maternal and neonatal mortality worldwide [1]. Despite efforts made so far, the World Health Organization (WHO) reports that 1.9 billion women aged 15 - 49 years lived globally in 2021, of whom 1.1 billion required family planning, with 874 million using modern methods and 164 million experiencing unmet need [2]. In 2020, nearly 800 women died every day from avoidable pregnancy and childbirth complications around the world, and 540 of these deaths happened in the African region, which made up about two-thirds (69%) of global maternal deaths [3]. Among married or union women in Sub-Saharan Africa, the use of modern methods of contraception went up from 29% in 2015 to 34% in 2023, yet less than three out of five women in this group have their family planning needs met with modern methods [2].These wide disparities recorded in Sub-Saharan Africa can be attributed to barriers like lack of access, fear of side effects, cultural and religious opposition, leading to unplanned pregnancies, unsafe abortions, and maternal mortality which undermines the SDG 3.7 targets for universal reproductive healthcare [4,5].

Postpartum women are at a higher risk as fertility can return within weeks after delivery, yet statistically, the use of contraceptive methods remains low due to these aforementioned barriers [6]. Artificial intelligence (AI) and machine learning (ML) herald new avenues for personalized contraceptive counseling, data-driven decision making, personalized recommendations reflecting clinical inputs [7]. Ongoing efforts to address the gap in AI tools tailored towards contraceptive options are minimal or not well discussed as evident in the paucity of studies highlighting these events [8]. This study introduces a ML framework integrated with a Telegram bot for worldwide accessibility and designed to predict the best postpartum contraceptive method using demographics and clinical inputs consistent with the WHO medical eligibility criteria (MEC) [9].

The strong performance of this model on postpartum-related variables exemplifies its potential of utility over traditional approaches and can offer a scalable and compelling baseline for digital intervention in underserved regions if deployed successfully.

Methods

Study design and Dataset

This study is a retrospective analysis of a synthetic postpartum family planning dataset (n = 8000; 44 variables) derived from the publicly available Contraceptive Method Choice dataset [10] and augmented with postpartum-related variables to reflect clinical contexts, with each record anonymized and representing a woman within 12 months after delivery, which is consistent with the WHO MEC [9]. Key variables include age, weeks postpartum, breastfeeding, previous family-planning use, side effect history, fertility intent, privacy need, and preference for long-acting methods. Missing values were imputed with statistical methods prior to model training and evaluation. The dataset summary is provided in table 1.

Table 1: Summary of demographic, clinical, behavioral, and service-related variables in the synthetic postpartum dataset (n = 8,000)

Variable type	Examples	Count / Range / Notes
Demographic	Age, Weeks PP (Postpartum), Education, Occupation	-18–49 years; ≤ 12 months postpartum.
Clinical	Sepsis, Preeclampsia, Hypertension, Diabetes, HIV, Anemia, Venous Thromboembolism (VTE) Risk, Postpartum Hemorrhage (PPH).	-Boolean indicators.
Behavioral / Reproductive	Breastfeeding, Previous Family Planning (FP), Previous Side Effects, Fertility Intent, Partner Support.	-Categorical / Boolean.
Preference & Service	Preference Long Acting, Privacy Need, Contraceptive Implant (Stock Implant), Progesterone-Only Pill (Stock POP) / Combined Oral Contraceptive (Stock COC), Stock IUD, Contraceptive Injection (Stock Inj), Condom (Stock Condom).	-Reflect user preference and method availability.
Target variable	Recommended method.	***Seven classes:** -IMP (48.9%); POP (24.5%); LAM (14.6%); IUD (4.0%); Condom (2.9%); INJ (2.7%); COC (2.4%).

*IMP: Implants (long-acting reversible contraception); POP: Progestin-only pills ("mini-pill"); LAM: Lactational amenorrhea method (temporary breastfeeding-based contraception); IUD: Intrauterine Device (Copper or Levonorgestrel-releasing); Condom: Male or Female condoms; INJ: Injectable contraceptives (e.g., Depo-Provera); COC: Combined oral contraceptive pills.

Data preprocessing

Variables were processed into numeric, Boolean, and categorical and rows with missing targets and imputed missing features were dropped. With the target labels having 7 classes for prediction: Implant (IMP), Progestin only pill (POP), Lactational amenorrhea method (LAM), Intrauterine device (IUD), Injectable contraceptive (INJ), Combined Oral Contraceptive (COC) which are WHO-approved contraceptive categories [11]. Train/test splits were 5000/3000 aligning with standard machine learning practice [12].

Feature ranking

For a better user experience on the Telegram bot, Extreme Gradient Boosting (XGBoost) was used to retain the top 7 ranked groups: previous family planning, preferred long-acting, stock implant, breastfeeding, privacy need, sepsis, stock progestin only pill. These will serve as the input features on the Telegram bot [13].

Model training and evaluation

A list of ML frameworks was considered for this study but the Logistic regression (LR), Random Forest (RF) and Extreme Gradient Boosting (XGBoost) were selected for comparative analysis on the basis of their high performance on structured data and low chances of overfitting [14]. The features below were utilized for each framework:

LR: Multinomial, max_iter = 1200, C =0.8

RF: 600 trees, min_samples_split = 3

XGB: tree_method = hist, n_estimators = 1200, learning_rate = 0.045, max_depth = 6, subsample/colsample_bytree = 0.9, reg_lambda = 1.5

Class weights were not applied during training as model robustness was handled via stratified splitting, macro-averaged metrics and performance evaluation across classes [15,16]. These features were integrated to reduce the chances of overfitting and to ensure a high accuracy level. For evaluation, the following metrics were used: accuracy, precision, recall, f1-score with the inclusion of data visualization modalities for explainable AI.

Accuracy refers to the proportion of correctly classified instances among all predictions. Precision represents the proportion of true positive predictions among all positive predictions made by the model. Recall (sensitivity) measures the proportion of actual positive cases correctly identified. The F1-score is the harmonic mean of precision and recall and provides a balanced metric for evaluating model performance, particularly in imbalanced datasets [17].

The model with the best performance was integrated with a Telegram bot to make it accessible worldwide especially in underserved regions where barriers to good healthcare exist.

Telegram bot integration

The XGBoost model was further integrated into a Telegram bot which provides real time interaction for accessibility and clinical utility using the python-telegram API (Application programming interface) [18].

Results

Model performance

The three models were trained using the same preprocessed data and feature set derived from the top seven predictors. The Logistic regression had the lowest validation level of 87%. This may be due to linear constraints while the Random forest had a slightly better performance achieving an accuracy level of 88%. This study adopted the XGBoost model with the highest validation accuracy of 90% for integration with the Telegram bot. The validation result is shown in table 2 below. The XGBoost model achieved a test accuracy of 88.5% and a macro-averaged F1-score of 0.734, indicating strong overall predictive performance and balanced classification across the seven contraceptive categories.

Class performance

The class metrics for the test set are shown in table 3. The XGBoost model performed best for Implant, POP, and LAM classes reflecting strong clinical significance and consistency as seen with a high level of precision, recall and F1 values recorded. Low recall value recorded for the INJ class can be attributed to limited training instances, which represents 2.7% of the dataset. These results show the potential of the model to accurately and transparently support individualized postpartum contraceptive counseling and planning.

Data visualization

This section outlines the visualization techniques employed by this study during training and evaluation of the model as shown in Figures1 - 3 below. The model assigns greatest importance to women's preference for long-acting contraception, followed by method availability, need for privacy, and postpartum timing, underscoring the central role of individual reproductive intent and service feasibility in postpartum family-planning decisions as shown in Figure 1.

Table 2: Comparative validation and test performance of logistic regression, random forest, and XGBoost models

Model	Validation Accuracy	Validation F1 (Macro)	Test Accuracy	Test F1 (Macro)
Logistic Regression	0.874	0.629	—	—
Random Forest	0.888	0.709	—	—
XGBoost	**0.901**	**0.739**	**0.885**	**0.734**

Table 3: Class-level precision, recall, f1-score, and support for the XGBoost model on test data

Classes	Precision	Recall	F1-score	Support
COC	0.62	0.59	0.60	58
Condom	0.87	0.79	0.83	76
Implant (IMP)	**0.94**	**0.96**	**0.95**	1,469
Injectable (INJ)	0.37	0.19	0.25	94
Intrauterine Device (IUD)	0.71	0.82	0.76	124
Lactational Amenorrhea Method (LAM)	**0.84**	**0.90**	**0.87**	465
Progestin-Only Pill (POP)	**0.90**	**0.86**	**0.88**	712

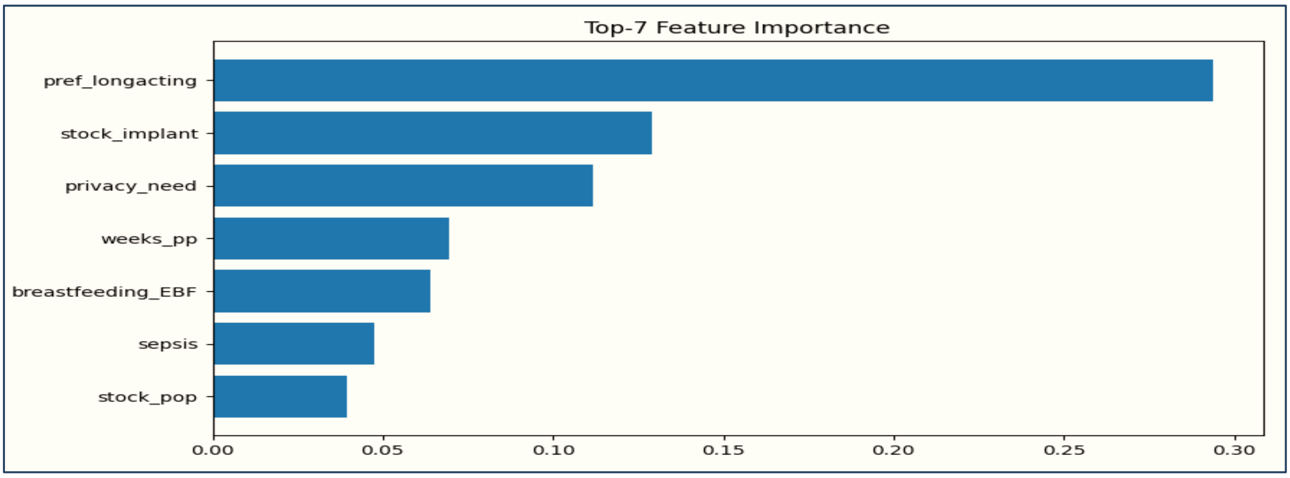

Figure 1: Top Seven Feature Importance.

The low correlations observed among predictors indicate minimal multicollinearity, suggesting that each feature contributes independent clinical information to the model's decision-making process as shown in Figure 2.

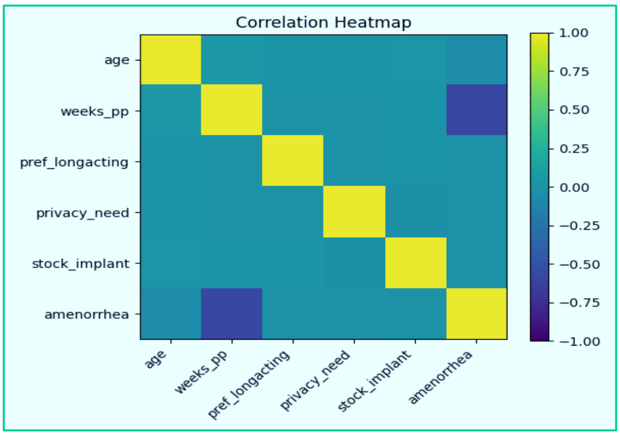

Figure 2: Correlation Heatmap

The confusion matrix demonstrates strong method-specific classification performance, with high accuracy for implants, injectables, lactational amenorrhea (LAM), and progestin-only pills (POP), indicating reliable differentiation among postpartum contraceptive options as shown in Figure 3.

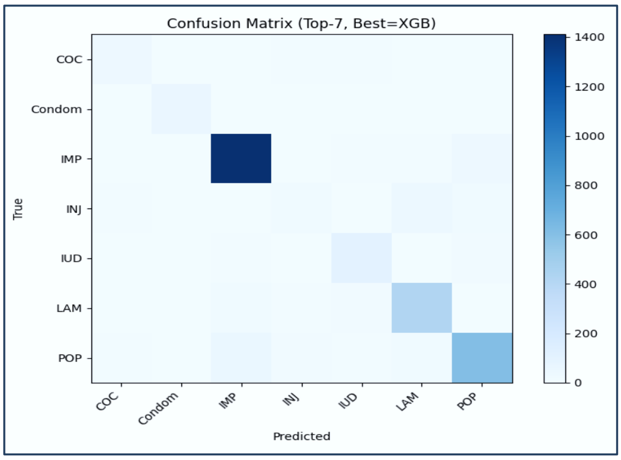

Figure 3: Confusion Matrix

Discussion

This study presents a high-performing ML model designed to provide postpartum contraceptive decision support. The XGBoost model delivered a strong overall performance with 88.5% test accuracy across the seven WHO-approved contraceptive methods with a distinctive ability for the IMP, POP and LAM classes which are common family planning methods recommendations. The successful integration of clinical and demographic variables highlights strong potential for AI-assisted decision-support system which can enhance personalization of postpartum family planning methods in underserved regions.

Comparison with traditional methods and Other Studies

1) Traditional postpartum family planning methods rely primarily on guidelines like the WHO's MEC wheel and decision-making tool for family planning. These guidelines are rigid in structure and does not take into consideration factors like stock availability, side effects, privacy concerns, whereas the model takes into cognizance these factors which gives it an edge, if utilized in clinical settings. Recent studies have explored the benefits of AI integration into the prediction of suitable family planning methods. A study developed a LGBM model which achieved an accuracy of 73% [19] as against the model developed by this study with an accuracy of 88.5%, showing better performance. Another study used machine learning to determine use of IUD but could not factor in other family planning methods [20] in comparison with this study that is more encompassing with the integration of features that makes prediction beyond a single method. Furthermore, another study was found to have used machine learning to explore unmet needs for family planning and developed a model using a Random forest framework with an accuracy level of 85% [21] compared with the model developed by this study which showed better performance and more potential for clinical utility. The integration of this model with a Telegram bot increases its potential for clinical utility and future deployment. This also increases its novelty and gives a strong pedestal for future studies to build on.

Limitations of study

This study is limited by the use of synthetic datasets for both model training, evaluation and testing. It is imperative for further model iteration be performed on real world dataset to assess clinical utility and potential for deployment as this study stands as a proof of concept. The model recorded a very low recall value (0.19) which may be due to class imbalance which this study acknowledges as a limitation. Future works can utilize a real-world dataset for model training. The lack of external validation also poses a limitation to this study and future works can validate this model with an external dataset to ascertain model generalizability.

Future Works

A more robust validation with a diverse dataset to ensure model generalizability. Clinical trials with postpartum patients in primary health centers. Transitioning from Kaggle to a cloud storage that can guarantee a 24-hour run time.

Conclusion

This proof-of-concept study demonstrates the potential of artificial intelligence to support postpartum family planning decision-making in underserved settings. The XGBoost model achieved strong predictive performance across seven WHO-approved contraceptive categories. Although the results are promising, further validation using real-world clinical datasets is necessary prior to deployment. If successfully implemented, this AI-assisted decision support system may enhance informed contraceptive choices and contribute positively to maternal health outcomes in resource-limited regions.

Abbreviation

AI: Artificial Intelligence; COC: Combined Oral Contraceptive HIV: Human Immunodeficiency Virus; IMP: Implant; INJ: Injectable Contraceptive; IUD: Intrauterine Device; LAM: Lactational Amenorrhea Method; LR: Logistic Regression; MEC: Medical Eligibility Criteria; ML: Machine Learning; POP: Progestin-Only Pill; RF: Random Forest: SDG: Sustainable Development Goal; WHO: World Health Organization; XGB:

Extreme Gradient Boosting; XGBoost: Extreme Gradient Boosting.

Declaration

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Availability of data and materials
Data will be available by emailing drmichael17@gmail.com

Authors' contributions
Babatunde Ogunmiloro (BO) is the principal investigator of the research. The author had read and agreed to the published version of the manuscript.

Ethics approval and consent to participate
I conducted the research following the declaration of Helsinki. The datasets used for this study are synthetic and do not reveal any patient identity.

Consent for publication
Not applicable

Competing interest
The author declares that he has no competing interests.

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