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Classification of Contraceptive Use among Women in Rwanda Using Machine Learning

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Research Article

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Abstract

Background

Rwanda has experienced a dramatic increase in contraceptive prevalence, rising from 10% to 58% between 2005 and 2020. Despite this progress, the complex socio-demographic factors influencing contraceptive choice among Rwandan women remain incompletely characterised. Traditional statistical methods struggle to capture the nonlinear interactions inherent in survey data. Machine learning (ML) offers a data-driven alternative that may reveal hidden patterns and improve predictive performance.

Methods

Using data from the 2020 Rwanda Demographic and Health Survey (RDHS), we applied five supervised ML classifiers, namely Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), and K-Nearest Neighbours (KNN), to classify current contraceptive use among women of reproductive age (15–49 years). The dataset comprised 8,824 observations with 57 features following pre-processing. We used all 57 features for model training; we then applied permutation feature importance (threshold > 0.003) to the tuned Decision Tree model to identify the top ten predictors. Grid Search Cross-Validation (GridSearchCV) was applied for hyperparameter optimisation.

Results

Prior to hyperparameter tuning, RF achieved the highest accuracy (81%), followed by LR and SVM (79% each), DT (74%), and KNN (68%). Following GridSearchCV optimisation, RF remained the strongest classifier overall (accuracy: 81%, ROC-AUC: 0.90), while the tuned DT model showed the largest improvement and reached comparable performance (accuracy: 80%, precision: 0.82, recall: 0.80, F1: 0.80, ROC-AUC: 0.87). Key predictors identified included: decision-making on contraceptive non-use, number of living children, side-effect counselling, respondent's age, recent sexual activity, husband's desire for children, partner's age, and fertility preference.

Conclusions

Random Forest achieved the strongest overall performance for predicting contraceptive use in the Rwandan DHS context, while hyperparameter-tuned Decision Trees performed comparably with an interpretable model structure. Permutation-based feature importance reveals actionable predictors, specifically fertility-related factors, partner factors, contraceptive decision-making, and side-effect counselling, that should inform targeted family planning interventions. ML-based predictive models represent a valuable complement to conventional epidemiological tools for reproductive health programme planning.

Background

Reproductive health is a cornerstone of sustainable development, encompassing an individual's capacity to determine the number and spacing of children [[1],[38]]. Family planning confers measurable benefits: reduced maternal mortality, improved child health outcomes, and enhanced socioeconomic well-being [[2],[4],[5],[6],[34],[36],[40]]. Rwanda has shown exceptional commitment to improving reproductive health. The contraceptive prevalence rate (CPR) among married women increased from 10% in 2005 to 58% in 2020, with modern method use predominating [[3]]. These gains reflect robust national policies, community health worker networks, and sustained political will [[7]]. Family planning also remains a regional programme priority in East and Southern Africa [[39]], and systematic measurement of programme results is central to managing national family planning programmes [[35]].

Despite this progress, the socio-demographic determinants of contraceptive choice remain heterogeneous and incompletely understood [[8],[9]]. Traditional regression-based approaches struggle to capture nonlinear, high-dimensional interactions in DHS survey data [[11],[12]]. Machine learning (ML) algorithms have emerged as powerful tools for classification and prediction in health research, capable of modelling complex relationships without a priori assumptions about data distributions [[13],[17]]. Such methods are increasingly applied to development questions in sub-Saharan Africa [[37]]. Prior applications in sub-Saharan Africa and South Asia have demonstrated the feasibility of ML-based classification of contraceptive use [[18],[19],[20],[22]], yet Rwanda-specific evidence using the most recent DHS data remains absent.

This study addresses that gap by evaluating the comparative performance of five supervised ML classifiers, specifically Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), and K-Nearest Neighbours (KNN), for predicting current contraceptive use among women in Rwanda using the 2020 RDHS. A secondary objective was to identify the most influential predictors through permutation feature importance analysis, generating evidence to inform policymakers and programme designers.

Methods

Data source and study population

This study used data from the 2020 Rwanda Demographic and Health Survey (2019–2020 RDHS), conducted by the National Institute of Statistics of Rwanda (NISR), the Ministry of Health (MOH), and ICF [[3]]. The RDHS is a nationally representative cross-sectional survey employing a two-stage stratified cluster sampling design. The study population comprised women of reproductive age (15–49 years) residing in Rwanda at the time of survey; the analytic sample was restricted to women who were ever married or in union, or recently sexually active (n = 8,824). Formal authorisation to use the dataset was obtained from the DHS Programme (*dhsprogram.com*). The Rwanda National Ethics Committee granted

ethics approval for the primary survey. No additional ethics approval was required for this secondary analysis of anonymised data.

Study design

This is a cross-sectional secondary data analysis, employing supervised machine learning classification methods.

Outcome variable

The dependent variable was *current contraceptive use*, defined as a binary outcome coded as 1 (currently using any contraceptive method) or 0 (not currently using). This variable was derived from the DHS standard recode variable *v312* (current use of family planning), recoded as a binary indicator following standard DHS recode procedures [[25]]. We deliberately combined modern and traditional methods into a single 'currently using' category for two reasons. First, the study objective was to classify contraceptive practice of any type rather than method choice; second, traditional-method users constituted only a small fraction of users (8.6%), too few to support a separate class without introducing severe imbalance. This binary formulation follows prior DHS-based ML studies [[18],[20]]. As a consequence, the identified predictors relate to contraceptive use in general and may not capture determinants that differentiate modern from traditional method choice; method-specific (multi-class) modeling is therefore identified as future work in the Discussion.

Independent variables

We extracted 65 candidate independent variables from the RDHS women's recode file, spanning socio-demographic characteristics, household factors, partner characteristics, reproductive history, health-system contact, and media exposure. After derivation of composite scores (family planning media exposure, number of children who have died, and attitude towards wife beating) and removal of their constituent items, the final model matrix comprised 57 features. Variables directly derived from the outcome were excluded to avoid information leakage. Table 1 presents the outcome and the top predictor variables identified by the analysis.

Table 1
Key independent variables included in the analysis

Variable	Category / Range	Role
Current contraceptive use	Binary: 0 = Not using, 1 = Using	Dependent
Decision maker for not using contraception	Categorical	Independent
Number of living children	Continuous	Independent
Told about contraceptive side effects	Binary: 0 = No, 1 = Yes	Independent
Respondent's current age	Continuous (years)	Independent
Number of sexual partners, incl. spouse (last 12 months)	Continuous	Independent
Recent sexual activity	Categorical	Independent
Husband's desire for children	Categorical	Independent
Husband/partner's age	Continuous (years)	Independent
Fertility preference	Categorical	Independent
Number of children under 5 in household	Continuous	Independent

Data acquisition and preprocessing

Data were obtained in SPSS format from the DHS Programme data repository [[25]]. Preprocessing was performed in Python 3.10 (Anaconda distribution) and included: (i) selection of eligible women-level records; (ii) exclusion of observations with > 30% missing values per case; (iii) imputation of remaining missing values using the median (continuous variables) and mode (categorical variables) strategies, consistent with established practice in DHS analysis [[26]]; (iv) one-hot encoding of nominal categorical variables; (v) normalisation of continuous variables using min-max scaling; and (vi) an 80:20 stratified train-test split to preserve class distribution.

Algorithm selection and training

Five supervised ML classifiers were selected based on their broad application in contraceptive use prediction studies [[17],[18],[19],[20],[22]]:

- Random Forest (RF): ensemble of decision trees using bootstrap aggregation and random feature subsets to reduce variance [13].
- Logistic Regression (LR): linear probabilistic model for binary outcomes, providing interpretable odds ratios [12].

- Support Vector Machine (SVM): margin-maximising classifier with a radial basis function (RBF) kernel [15].
- Decision Tree (DT): hierarchical recursive partitioning algorithm providing explicit decision rules [14], [31].
- K-Nearest Neighbours (KNN): non-parametric, instance-based classifier using Euclidean distance [16].

All models were implemented in Python using Scikit-learn (v1.3). Initial models were trained with default hyperparameters. Hyperparameter optimisation was subsequently performed using GridSearchCV with 5-fold stratified cross-validation [[27]]. For DT, parameters searched included *max_depth*, *min_samples_split*, and *min_samples_leaf*; for RF, *n_estimators* and *max_features*; for SVM, *C* and *gamma*; for KNN, *n_neighbors*.

The outcome classes were moderately imbalanced (58.4% users vs 41.6% non-users; majority-to-minority ratio 1.41:1). Because this imbalance is mild, synthetic minority oversampling (SMOTE) was not applied. Instead, stratification was used in both the 80:20 train-test split and the 5-fold cross-validation folds to preserve class proportions, and performance was assessed with class-sensitive metrics (precision, recall, F1-score and ROC-AUC) in addition to overall accuracy. A sensitivity analysis re-estimating the classifiers with inverse-frequency class weighting (class_weight = 'balanced' in Scikit-learn) changed accuracy and F1-score by less than 0.02 in all cases, indicating that the reported results are not driven by class imbalance.

Model evaluation

Model performance was assessed using five standard metrics [[28],[29],[30]]: accuracy (proportion of correct predictions), precision (positive predictive value), recall (sensitivity), F1-score (harmonic mean of precision and recall), and the area under the receiver operating characteristic curve (ROC-AUC). The first four metrics were computed from the confusion matrix; ROC-AUC was computed from predicted class probabilities (decision-function scores for SVM) and summarises discrimination between users and non-users across all classification thresholds. A heatmap confusion matrix was generated for each algorithm to visualise classification errors.

Feature importance analysis

We computed permutation feature importance for the tuned Decision Tree model. For each predictor, the variable was randomly permuted 30 times and the mean decrease in model accuracy was recorded. Features with a permutation importance score > 0.003 were retained as top predictors [[13]]. Results were visualised using horizontal bar plots in Matplotlib.

Results

Study population and contraceptive use distribution

The analytical sample comprised 8,824 women of reproductive age who were ever married or in union, or recently sexually active. The overall prevalence of current contraceptive use was 58.4%. Implants (24.7%) were the most commonly used modern method, followed by injectables (14.0%), pills (6.0%), and male condoms (3.4%). Traditional and folkloric methods accounted for 8.6% of users. Regional variation was observed: the Northern Province recorded the highest prevalence (63.1%), while Kigali City had the lowest (54.7%). Contraceptive use was markedly lower among women with no formal education (48.4%) than among women with primary or higher education (59–60%).

Machine learning model performance before hyperparameter tuning

Prior to hyperparameter optimisation, RF achieved the highest classification accuracy (81%), followed by LR and SVM (79% each), DT (74%), and KNN (68%). RF exhibited the best precision (0.82) and recall (0.81), reflecting its ensemble advantage in reducing overfitting. KNN performed the worst across all metrics, suggesting that distance-based classification is less suited to the high-dimensional, mixed-type DHS dataset. ROC-AUC followed the same ordering (RF: 0.90; LR: 0.88; SVM: 0.87; DT: 0.73; KNN: 0.72); the comparatively low AUC of the untuned DT reflects the near-binary probability estimates produced by a fully grown tree.

Model performance after hyperparameter tuning

Following GridSearchCV optimisation, the DT model showed by far the largest improvement, gaining approximately 6 percentage points over its baseline accuracy (0.74 to 0.80; precision: 0.82, recall: 0.80, F1: 0.80). RF (Tuned) remained the strongest overall classifier (accuracy: 0.81), essentially unchanged from its near-optimal default configuration. LR (Tuned) reached 0.79 and SVM (Tuned) 0.80 accuracy. KNN (Tuned) remained the weakest performer (accuracy: 0.70). ROC-AUC after tuning ranged from 0.74 (KNN) to 0.90 (RF); the tuned DT achieved an AUC of 0.87, the largest discrimination gain from tuning (+ 0.14) among all classifiers. Table 2 summarises performance metrics, including ROC-AUC, before and after tuning.

Table 2
Classification performance metrics before and after hyperparameter tuning

Algorithm	Acc (pre)	Prec (pre)	Rec (pre)	F1 (pre)	AUC (pre)	Acc (post)	Prec (post)	Rec (post)	F1 (post)	AUC (post)
Random Forest	0.81	0.82	0.81	0.80	0.90	0.81	0.82	0.81	0.80	0.90
Logistic Regression	0.79	0.79	0.79	0.79	0.88	0.79	0.79	0.79	0.79	0.88
SVM	0.79	0.80	0.79	0.79	0.87	0.80	0.80	0.80	0.79	0.87
Decision Tree	0.74	0.74	0.74	0.74	0.73	0.80	0.82	0.80	0.80	0.87
KNN	0.68	0.68	0.68	0.68	0.72	0.70	0.70	0.70	0.69	0.74

Acc accuracy, Prec precision, Rec recall, AUC area under the receiver operating characteristic curve; pre = before tuning, post = after tuning.

Feature importance analysis

Permutation feature importance analysis (threshold > 0.003) applied to the tuned DT model identified ten key predictors of current contraceptive use, in descending order of importance: (1) decision maker for not using contraception; (2) number of living children; (3) having been told about contraceptive side effects; (4) respondent's current age; (5) number of sexual partners (including spouse) in the last 12 months; (6) recent sexual activity; (7) husband's desire for children; (8) husband/partner's age; (9) fertility preference; and (10) number of children under five in the household.

The three highest-importance features (permutation scores 0.05–0.08) contributed substantially more predictive power than the remaining seven (scores 0.01–0.02). The prominence of contraceptive decision-making and side-effect counselling underscores the role of the health system and of household decision dynamics in contraceptive behaviour. Fertility-related factors (number of living children, fertility preference) and partner-related factors (husband's desire for children, partner's age) also ranked highly, reflecting male partner influence on reproductive decisions documented in qualitative Rwandan research [[32],[23]].

Discussion

Principal findings

This study demonstrates that supervised ML classifiers can effectively classify current contraceptive use among Rwandan women using DHS data, with RF achieving 81% accuracy and a ROC-AUC of 0.90, and a hyperparameter-optimised DT model reaching comparable performance (80% accuracy; F1-score: 0.80; ROC-AUC: 0.87) while remaining fully interpretable. A key contribution is the empirical comparison

of five algorithms with systematic hyperparameter tuning, showing that algorithm selection and optimisation substantially affect predictive performance in this context.

Comparison with existing literature

The finding that RF performs best overall is consistent with observations in analogous Ethiopian DHS analyses [[18]]; Kebede et al. [[18]] reported RF superiority for unmet need prediction in Ethiopia. After GridSearchCV optimisation, however, the DT model closed most of the gap to RF, indicating that the performance advantage of ensemble methods is modest once simpler, interpretable models are properly tuned. The LR and SVM accuracy (0.79 baseline, 0.79–0.80 tuned) aligns with Bangladeshi DHS-based results (Haq et al. [[20]]). KNN's persistently low accuracy (0.68–0.70) mirrors findings from East Java province data [[21]] and likely reflects the algorithm's sensitivity to the high dimensionality and class imbalance in DHS datasets.

The identified predictors, including fertility and parity factors, partner characteristics, contraceptive decision-making, and health-system counselling, corroborate both quantitative epidemiological evidence [[9],[10],[24]] and qualitative Rwandan family planning research [[32],[23]]. The prominence of side-effect counselling as a predictor reinforces Rwanda's emphasis on the quality of family planning services and provider–client communication [[7]]. The prominence of respondent's age is likewise consistent with documented age-related barriers to sexual and reproductive health services, including HIV/AIDS services, among young people in Rwanda [[33]].

Strengths and limitations

Strengths include the use of nationally representative, high-quality DHS data; a systematic comparison of five established classifiers; application of GridSearchCV for hyperparameter optimisation; and the use of permutation-based feature importance for model interpretability. Limitations include: the cross-sectional design precluding causal inference; the binary outcome variable masking nuances in method mix; absence of external validation on a holdout DHS wave; potential residual confounding from unmeasured variables; and limited transparency of some of the algorithms evaluated. This transparency limitation is algorithm-specific: the final DT model is inherently interpretable, yielding explicit decision rules, and LR provides directly interpretable coefficients, whereas RF, SVM, and KNN operate as comparatively opaque ensemble, kernel-based, and instance-based methods whose individual predictions are less directly explainable. Future work should consider: multi-class outcome modelling (method-specific classification); longitudinal DHS data integration; Shapley Additive exPlanations (SHAP) values for enhanced model interpretability; and prospective validation in programme settings.

Conclusions

This study demonstrates the comparative performance of five supervised ML classifiers for predicting current contraceptive use among Rwandan women of reproductive age. RF achieved the best overall classification performance (accuracy: 81%; ROC-AUC: 0.90), while the hyperparameter-optimised

Decision Tree model reached comparable performance (accuracy: 80%; F1: 0.80; ROC-AUC: 0.87) with an interpretable rule structure, highlighting the importance of systematic hyperparameter tuning. Permutation feature importance analysis identified ten actionable predictors, including fertility-related factors, partner-related factors, contraceptive decision-making, and side-effect counselling, that align with existing evidence and provide concrete targets for family planning programme design. ML-based classification models represent a valuable analytical complement to conventional epidemiological approaches for reproductive health surveillance in low- and middle-income country settings.

Declarations

Ethics approval and consent to participate

This study is a secondary analysis of publicly available, anonymised DHS data. Ethics approval for the 2019–2020 RDHS was granted by the Rwanda National Ethics Committee. Permission to use the dataset was obtained through the DHS Programme data request system (www.dhsprogram.com). Participant-informed consent was obtained by the original survey. No additional ethics approval was required for this secondary analysis.

Consent for publication

Not applicable.

Competing interests

The author declares no competing interests.

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No funding was received for this study.

Author Contribution

RH conceived the study, performed data acquisition and pre-processing, implemented and evaluated all machine learning models, interpreted results, and drafted the manuscript. The author read and approved the final manuscript. As this is a single-author study, the analysis code was not independently validated by a second analyst; the complete code and data-processing pipeline are available from the author to permit independent verification and reproduction of all results.

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Availability of data and materials

The datasets analysed are available from the DHS Programme data repository (https://dhsprogram.com/data/Using-Datasets-for-Analysis.cfm*)* upon registration and request. The analysis code is available from the corresponding author upon reasonable request.

References

1. Rwanda Ministry of Health. National Family Planning and Adolescent Sexual and Reproductive Health (FP/ASRH) Strategic Plan. Kigali: Ministry of Health; 2018.
2. World Health Organization. Packages of interventions for family planning, safe abortion care, maternal, newborn and child health. Geneva: WHO; 2010.
3. NISR, MOH, ICF. Rwanda Demographic and Health Survey 2019-2020. Kigali: NISR; 2021.
4. Ahmed S, Li Q, Liu L, Tsui AO. Maternal deaths averted by contraceptive use: an analysis of 172 countries. Lancet. 2012;380(9837):111–25.
5. Canning D, Schultz TP. The economic consequences of reproductive health and family planning. Lancet. 2012;380(9837):165–71.
6. Bloom DE, Canning D, Fink G, Finlay JE. Fertility, female labor force participation, and the demographic dividend. J Econ Growth. 2009;14(2):79–101.
7. Solo J. Family planning in Rwanda: how a taboo topic became priority number one. Afr J Reprod Health. 2012;2:1–14.
8. Brunie A, Tolley EE, Ngabo F, Wesson J, Chen M. Getting to 70%: barriers to modern contraceptive use for women in Rwanda. Int J Gynaecol Obstet. 2013;123(Suppl 1):e11–5.
9. Muhoza DN, Rutayisire PC, Umubyeyi A. Measuring the success of family planning initiatives in Rwanda: a multivariate decomposition analysis. J Popul Res. 2016;33(4):361–77.
10. Prata N, Fraser A, Huchko MJ, Gipson JD, Withers M, Lewis S, et al. Women's empowerment and family planning: a review of the literature. J Biosoc Sci. 2017;49(6):713–43.
11. Alpaydin E. Introduction to Machine Learning. 4th ed. Cambridge: MIT Press; 2020.
12. Shalev-Shwartz S, Ben-David S. Understanding Machine Learning: From Theory to Algorithms. Cambridge: Cambridge University Press; 2013.
13. Breiman L. Random forests. Mach Learn. 2001;45(1):5–32.
14. Breiman L, Friedman JH, Olshen RA, Stone CJ. Classification and Regression Trees. Boca Raton: CRC Press; 2017.
15. Cortes C, Vapnik V. Support-vector networks. Mach Learn. 1995;20(3):273–97.

16. Altman NS. An introduction to kernel and nearest-neighbor nonparametric regression. Am Stat. 1992;46(3):175–85.
17. Hailemariam T, Gebregiorgis A, Meshesha M, Mekonnen W. Application of data mining to predict the likelihood of contraceptive method use among women aged 15–49: case of 2005 demographic health survey data. J Health Med Inform. 2017;8(3):274.
18. Kebede DS, Niguse Mamo D, Bashir Adem J, Ewunu Semagn B, Damtew Walle A. Machine learning modeling for identifying predictors of unmet need for family planning among married/in-union women in Ethiopia. PLOS Digit Health. 2023;2(10):e0000345.
19. Maulana DFY, Ruldeviyani Y, Sensuse DI. Data mining classification approach to predict the duration of contraceptive use. In: Proceedings of the 2020 5th International Conference on Informatics and Computing (ICIC). IEEE; 2020.
20. Haq I, Hossain MI, Rahman MM, Methun MIH, Talukder A, Habib MJ, et al. Machine learning algorithm-based contraceptive practice among ever-married women in Bangladesh: a hierarchical machine learning classification approach. London: IntechOpen; 2022.
21. Ibad M, Lutfiya I, Handayani D, Fasya AHZ, Herowati D, Sari MP. Classification analysis using decision tree on factors that influence the selection of contraception equipment in East Java Province. AIP Conf Proc. 2023;2595(1).
22. Letta A, Achamyeleh B. Designing a predictive model for the likelihood of contraceptive method usage in Ethiopia. Cosmos J Eng Technol. 2022;6(2):1001.
23. Doyle K, Levtov RG, Barker G, Bastian GG, Bingenheimer JB, Kazimbaya S, et al. Gender-transformative Bandebereho couples' intervention to promote male engagement in reproductive and maternal health and violence prevention in Rwanda: findings from a randomized controlled trial. PLoS ONE. 2018;13(4):e0192756.
24. Ndahindwa V, Kamanzi C, Semakula M, Abalikumwe F, Hedt-Gauthier B, Thomson DR. Determinants of fertility in Rwanda in the context of a fertility transition: a secondary analysis of the 2010 DHS. Reprod Health. 2014;11(1):87.
25. ICF. Demographic and Health Surveys Standard Recode Manual for DHS 7. Rockville: USAID; 2018.
26. Ibrahim JG, Chu H, Chen MH. Missing data in clinical studies: issues and methods. J Clin Oncol. 2012;30(26):3297–303.
27. Hastie T, Tibshirani R, James G, Witten D. An Introduction to Statistical Learning. 2nd ed. New York: Springer; 2021.
28. Sokolova M, Lapalme G. A systematic analysis of performance measures for classification tasks. Inf Process Manag. 2009;45(4):427–37.
29. Powers DM. Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. arXiv:2010.16061 [cs.LG]. 2020.
30. Ting KM. Confusion matrix. In: Sammut C, Webb GI, editors. Encyclopedia of Machine Learning. New York: Springer; 2011. p. 209.

31. Quinlan JR. Induction of decision trees. Mach Learn. 1986;1(1):81–106.
32. Farmer DB, Berman L, Ryan G, Habumugisha L, Basinga P, Nutt C, et al. Motivations and constraints to family planning: a qualitative study in Rwanda's Southern Kayonza District. Glob Health Sci Pract. 2015;3(2):213–27.
33. Binagwaho A, Fuller A, Kerry V, Dougherty S, Agbonyitor M, Wagner C, et al. Adolescents and the right to health: eliminating age-related barriers to HIV/AIDS services in Rwanda. AIDS Care. 2012;24(7):936–42.
34. Rutstein SO. Effects of preceding birth intervals on neonatal, infant and under-five years mortality and nutritional status in developing countries: evidence from the DHS. Int J Gynaecol Obstet. 2005;89(Suppl 1):S7–24.
35. Butler AS, Clayton EW. A Review of the HHS Family Planning Program: Mission, Management, and Measurement of Results. Washington DC: National Academies Press; 2009.
36. Singh S, Darroch JE, Ashford LS. Adding It Up: The Costs and Benefits of Investing in Sexual and Reproductive Health 2014. New York: UNFPA; 2014.
37. Otchia C, Asongu S. Industrial growth in sub-Saharan Africa: evidence from machine learning with insights from nightlight satellite images. SSRN Electron J. 2019.
38. World Health Organisation. Sexual and Reproductive Health and Research (SRH). Geneva: WHO; 2021.
39. UNFPA East and Southern Africa. UNFPA ESARO Family Planning. Nairobi: UNFPA; 2022.
40. Centers for Disease Control and Prevention. Ten great public health achievements—United States, 2001–2010. MMWR Morb Mortal Wkly Rep. 2011;60(19):619–23.