

Predicting Unmet Need for Family Planning Among Women of Reproductive Age in Zambia Using Explainable Machine Learning: Evidence from the 2024 DHS

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Research Article

Keywords:

Posted Date: September 29th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11018894/v1>

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Additional Declarations: No competing interests reported.

Abstract

Background.

Unmet need for family planning remains a major barrier to reproductive health in Zambia and across Sub-Saharan Africa, yet programmes still lack practical tools to identify women most likely to have unmet need using routinely available sociodemographic and reproductive health information. We aimed to develop and evaluate leakage-aware, explainable machine learning models that predict unmet need among women of reproductive age using nationally representative survey data aligned with SDG indicator 3.7.1.

Methods.

We analysed Individual Recode data from the 2024 Zambia Demographic and Health Survey (ZDHS). Women aged 15–49 years with classifiable unmet-need status ($n = 9,316$), including married or in-union and sexually active unmarried women, formed the analytic cohort. Unmet need followed the revised DHS algorithm. We excluded predictors that enter or closely reconstruct that algorithm and trained on 43 demographic and socioeconomic covariates to prevent label leakage. Logistic regression, random forest, XGBoost, and LightGBM were compared with Optuna tuning and SMOTE within cross-validation folds. The best random forest–XGBoost ensemble was evaluated on a locked 20% hold-out test set ($n = 1,864$). We reported discrimination, calibration, and decision-curve metrics and used SHAP values to summarise predictor contributions.

Results.

Unmet need affected 1,818 women (19.5%; DHS-weighted 19.4%). The ensemble achieved the highest hold-out performance (ROC-AUC 0.703, PR-AUC 0.384, Brier score 0.144). At the Youden threshold (0.201), sensitivity was 0.717 and specificity 0.589. After model fitting, currently working, place of residence, and mobile phone ownership contributed most to predictions. Provincial burden was higher in North Western, Northern, and Lusaka than in Central, Eastern, and Copperbelt provinces.

Conclusion.

Explainable machine learning can support moderate but trustworthy risk stratification for family planning programming in Zambia. Work status, geography, digital access, and provincial inequity offer actionable targets for FP2030 and SDG-aligned outreach, provided models are used for prioritisation rather than causal inference.

Introduction

Unmet need for family planning remains a central challenge for sexual and reproductive health worldwide. Among approximately 1.9 billion women of reproductive age in 2021, an estimated 1.1 billion had a need for family planning; of these, 874 million used a modern method while about 164 million had an unmet need for contraception^{1,2}. Global Burden of Disease analyses estimated 162.9 million women with unmet contraceptive need in 2019, over half in sub-Saharan Africa and South Asia³. Although the proportional share of unmet need has declined, absolute numbers remain high because of population growth¹. Unmet need contributes to unintended pregnancy, unsafe abortion, and preventable maternal morbidity and mortality^{4,5}, and it constrains women's educational and economic opportunities, especially among adolescents and young adults^{3,6,7}.

Progress toward universal access is monitored under Sustainable Development Goal (SDG) target 3.7, which calls for universal access to sexual and reproductive health-care services, including family planning, by 2030, and under SDG indicator 3.7.1—the proportion of women of reproductive age whose need for family planning is satisfied with modern methods^{1,2}. SDG target 5.6 further emphasises universal access to sexual and reproductive health and reproductive rights as part of gender equality⁸. The

Family Planning 2030 (FP2030) partnership continues this agenda by supporting country commitments to expand voluntary modern contraceptive use and to reduce unmet need in low- and middle-income settings^{9,10}. Critically, SDG monitoring of need satisfied is not limited to married women alone: sexually active unmarried women also contribute to national demand for family planning and to residual unmet need^{2,3}.

Sub-Saharan Africa bears a disproportionate share of unmet need. A meta-analysis of Demographic and Health Survey (DHS) data from 37 countries estimated that 22.9% of married women of reproductive age had unmet need for family planning across survey years spanning 1995–2020¹¹. Among young women, socioeconomic disadvantage, parity, marital status, and limited mass-media exposure remain important correlates of unmet need^{6,7,12}. Despite regional gains in modern contraceptive prevalence and demand satisfied, health systems must keep pace with a rapidly growing population of women and girls of reproductive age^{9,10}.

In Zambia, unmet need among currently married women declined from about 20% in the 2018 DHS to approximately 16% in the 2024 Zambia Demographic and Health Survey (ZDHS), with total demand for family planning among married women of 71% and 74% of that demand satisfied by modern methods^{13–15}. Modern contraceptive use among married women rose to 53% by 2024, yet substantial socioeconomic and geographic inequities persist¹³. Analyses of the 2018 ZDHS showed that age, parity, household wealth, and media-based family planning messages were significantly associated with unmet need¹⁵. Zambia's Integrated Family Planning Costed Implementation Plan (2021–2026) and FP2030 commitments explicitly link family planning to national development, SDG 3 and SDG 5, and improved data use for programme decision-making^{8,16}. Extending prediction beyond married women to all women with a classifiable unmet-need status, including sexually active unmarried women, better aligns analytic cohorts with universal-access framing under SDG 3.7¹⁷.

Most prior Zambian and regional evidence relies on logistic regression to identify determinants of unmet need^{6,7,15}. While informative, these models are primarily designed to estimate associations rather than to generate individual-level risk predictions for programme targeting. In addition, regression approaches may under-capture non-linear interactions among demographic, partner, access, and community factors. Recent studies in Ethiopia and East and West Africa have applied random forests, gradient boosting, and Shapley Additive Explanations (SHAP) to predict contraceptive outcomes and unmet need^{18–20}. Leakage-aware prediction using the newest ZDHS microdata, with transparent reporting and pre-specified exclusion of algorithm inputs that define the outcome, remains limited for Zambia—particularly for an all-women, classifiable-need cohort rather than a married-only sample.

This study addresses that gap by developing and internally validating explainable machine-learning models to predict unmet need among women of reproductive age with classifiable unmet-need status in the 2024 ZDHS (married/in-union and sexually active unmarried women), while excluding DHS algorithm-defining variables that would artificially inflate performance. By combining individual, partner, service and community factors with exploratory mutual-information screening, stratified descriptive analysis, SHAP-based interpretation, and a documented STROBE-style exclusion workflow, the study aims to generate actionable risk stratification to support Zambia's SDG 3.7, SDG 5.6, and FP2030 targeting of women at highest risk of unmet need.

Materials and methods

Study design and reporting standards

We conducted a secondary, cross-sectional prediction-model study using the nationally representative 2024 Zambia Demographic and Health Survey (ZDHS). Reporting followed Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis: Artificial Intelligence (TRIPOD + AI) guidance for development and internal validation of machine-learning classifiers, and Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) principles for participant selection, exclusions, and descriptive analyses. A signed pre-analysis protocol specified the outcome definition, leakage groups, primary metrics, and cohort eligibility before model training. Analyses were predictive rather than causal.

Data sources

The primary data source was the ZDHS 2024 Individual Recode (IR) file (ZMIR81FL), a complex survey of women aged 15–49 years. HIV blood-test results were merged from the Ancillary Recode (AR) file using household and line identifiers. Community-context variables were constructed as leave-in-cluster aggregates of wealth, secondary-or-higher education, and family-planning (FP) message exposure from IR variables. Geospatial covariates (travel time, elevation, malaria prevalence) were not included. Survey design variables (cluster, stratum, and women's sample weight) were retained for weighted prevalence and descriptive statistics; modelling used individual-level outcomes with stratified random splitting.

Participants, eligibility, and outcome

The analysis included women aged 15–49 years interviewed in the 2024 Zambia Demographic and Health Survey (ZDHS) Individual Recode dataset (ZMIR81FL). Eligibility was based on the revised DHS unmet need classification algorithm (variable v626a). Women with classifiable unmet need status (v626a = 1, 2, 3, 4, or 7) were eligible for analysis, comprising both currently married or in-union women and sexually active unmarried women. This approach is consistent with the revised DHS definition of unmet need and the Sustainable Development Goal (SDG) indicator for family planning among women of reproductive age. Women classified as never having had sexual intercourse (v626a = 0), not married with no recent sexual activity (v626a = 8), or infecund/menopausal (v626a = 9) were excluded.

The primary outcome was binary unmet need for family planning, defined according to the revised DHS algorithm. Women with unmet need for spacing or limiting births (v626a = 1 or 2) were coded as having unmet need (1), whereas women using contraception for spacing or limiting or those with no unmet need (v626a = 3, 4, or 7) were coded as having no unmet need (0). Participant selection and exclusions are summarised in the study flow diagram (Fig. 1).

Data sources

Individual-level demographic, reproductive, and household characteristics were obtained from the 2024 ZDHS Individual Recode file (ZMIR81FL). HIV serostatus (hiv03) was linked from the HIV testing dataset (ZMAR81FL) using the DHS-prescribed merge procedure. No geospatial datasets were incorporated into the present analysis.

Study sample

The initial study population comprised 13,951 interviewed women aged 15–49 years. After excluding women with non-classifiable unmet need status—never sexually active (n = 1,594), not married with no recent sexual activity (n = 2,110), and infecund or menopausal (n = 931); the final analytical sample consisted of 9,316 women with classifiable unmet need status as shown in Fig. 1.

Leakage control and predictors

Because unmet need (v626a) is constructed from contraceptive use, fertility preferences, pregnancy status, and fecundity pathways, predictors that enter or closely reconstruct that algorithm were banned a priori (Group A), including current method use, desire for children, ideal family size, pregnancy wantedness, and the outcome itself. An automated leakage audit blocked training if banned variables appeared in the feature matrix. Candidate predictors (Group C) spanned demographic, socioeconomic, household, partner, reproductive-history, health-service contact, FP mass-media exposure, care-seeking barriers, HIV status, union status, and cluster context domains. After pruning redundant near-duplicates (for example, continuous age when age group was retained), 43 predictors remained: 26 numeric or count variables and 17 categorical (factor) variables. Categorical predictors were one-hot encoded after mode imputation; continuous predictors were median-imputed within training folds only, expanding to approximately 144 model input columns after encoding.

Exploratory analysis and feature screening

Before modelling, we estimated unweighted and DHS-weighted prevalence of unmet need with Wilson and bootstrap confidence intervals, respectively. Table 1 compared socio-demographic characteristics by outcome using χ^2 tests (or Fisher's exact tests when sparse) for categorical variables and Mann–Whitney U tests for continuous variables. Spearman correlations summarised associations among numeric predictors. Mutual information (MI) with the binary outcome provided an exploratory univariate ranking; an MI threshold equal to the median of strictly positive MI scores flagged higher-signal predictors. MI screening informed descriptive interpretation and a pre-specified parsimonious sensitivity analysis; it did not redefine the primary 46-predictor set used for main models.

Model development, class imbalance, and validation

Data were split once into stratified training (80%) and hold-out test (20%) sets with a fixed random seed (42). All imputation, encoding, and synthetic minority oversampling (SMOTE) steps were fit inside scikit-learn / imbalanced-learn pipelines on training folds only. Candidate learners were logistic regression with class weights (interpretable linear baseline), random forest, gradient-boosted trees (XGBoost or HistGradientBoosting fallback), and LightGBM, plus a convex probability blend of random forest and boosting. Hyperparameters were tuned with Optuna (Tree-structured Parzen Estimator), maximising ROC-AUC under stratified cross-validation on the training set.

The primary reported analysis used an extended search (150 trials, five-fold CV); an earlier 60-trial, three-fold clean run produced nearly identical hold-out discrimination and served as a reproducibility check. Primary discrimination metrics on the untouched hold-out set were ROC-AUC and precision–recall AUC (PR-AUC). Classification metrics (accuracy, precision, recall/sensitivity, specificity, F1) used Youden's index to select the operating threshold. Calibration was summarised with the Brier score and reliability plots. Bootstrap resampling produced 95% confidence intervals for ROC-AUC, PR-AUC, and Brier score. A PSU-disjoint (cluster-separated) hold-out sensitivity assessed geographic generalisation. Parsimonious models restricted to the top 15 MI predictors and to predictors at or above the MI median threshold were refit with the same hyperparameters as a reviewer-oriented sensitivity analysis.

Explainability and provincial summaries

For the best hold-out model, we computed mean absolute SHAP values, permutation importance (average precision), and a Boruta-style confirmation screen on transformed features, triangulating influential predictors. Province-level weighted prevalence and mean predicted risk were summarised using the DHS province variable (v024). No geospatial covariates or GPS-based spatial analyses were included. Analyses used Python with open-source libraries for data management, modelling, and explanation.

Ethics

The analysis used de-identified, publicly available DHS datasets obtained under The DHS Program data-use terms; no additional primary data collection was undertaken. Findings are intended for risk stratification and programme targeting within Zambia's FP2030 and SDG frameworks and should not be interpreted as causal effects.

Results

Baseline characteristics

Table 1 shows participant characteristics. Women with unmet need ($n = 1,818$) differed from those without ($n = 7,498$) on multiple characteristics. Adolescents aged 15–19 years accounted for 21.3% of the unmet-need group versus 10.4% of the no-unmet-need group ($p < 0.001$). Women not married or not in union comprised 35.5% versus 24.2%, and never-in-union women 27.3% versus 13.4% (both $p < 0.001$). Not currently working was reported by 59.5% versus 47.1%, and nulliparity by 18.5% versus 9.6% (both $p < 0.001$). Mobile-phone ownership was lower (52.5% vs 60.2%) and any FP mass-media exposure was

lower (44.8% vs 50.1%) among women with unmet need (both $p < 0.001$). Urban residence did not differ significantly (39.9% vs 38.7%; $p = 0.353$).

Table 1
Participant characteristics stratified by unmet need.

Characteristic	Category	No unmet need (n = 7,498)	Unmet need (n = 1,818)	p-value
Age group	15–19	781 (10.4)	387 (21.3)	< 0.001
	20–24	1,554 (20.7)	348 (19.1)	
	25–29	1,585 (21.1)	274 (15.1)	
	30–34	1,397 (18.6)	236 (13.0)	
	35–39	1,050 (14.0)	225 (12.4)	
	40–44	785 (10.5)	210 (11.6)	
	45–49	346 (4.6)	138 (7.6)	
Marital/union status	Not married / not in union	1,812 (24.2)	646 (35.5)	< 0.001
	Married/cohabiting (currently in union)	5,686 (75.8)	1,172 (64.5)	
Union status (detail)	Never in union	1,003 (13.4)	496 (27.3)	< 0.001
	Currently married/in union	5,686 (75.8)	1,172 (64.5)	
	Formerly in union	809 (10.8)	150 (8.3)	
Marital status (detail)	Never in union	1,003 (13.4)	496 (27.3)	< 0.001
	Married	5,612 (74.8)	1,151 (63.3)	
	Living with partner	74 (1.0)	21 (1.2)	
	Widowed	102 (1.4)	25 (1.4)	
	Divorced	472 (6.3)	85 (4.7)	
	Separated	235 (3.1)	40 (2.2)	
Education	No education	546 (7.3)	172 (9.5)	0.001
	Primary	3,376 (45.0)	799 (43.9)	
	Secondary	3,063 (40.9)	754 (41.5)	
	Higher	513 (6.8)	93 (5.1)	
Residence	Urban	2,903 (38.7)	726 (39.9)	0.353
	Rural	4,595 (61.3)	1,092 (60.1)	
Wealth quintile	Poorest	1,711 (22.8)	447 (24.6)	0.015
	Poorer	1,595 (21.3)	422 (23.2)	
	Middle	1,613 (21.5)	341 (18.8)	
	Richer	1,387 (18.5)	347 (19.1)	
	Richest	1,192 (15.9)	261 (14.4)	
Currently working	Not working	3,531 (47.1)	1,081 (59.5)	< 0.001

Characteristic	Category	No unmet need (n = 7,498)	Unmet need (n = 1,818)	p-value
	Working	3,967 (52.9)	737 (40.5)	
Parity (living children)	0	717 (9.6)	336 (18.5)	< 0.001
	1	1,538 (20.5)	369 (20.3)	
	2+	5,243 (69.9)	1,113 (61.2)	
Owns mobile phone	No	2,983 (39.8)	864 (47.5)	< 0.001
	Yes	4,515 (60.2)	954 (52.5)	
HIV test result	Negative	6,423 (85.7)	1,582 (87.0)	0.022
	Positive	796 (10.6)	173 (9.5)	
	Missing/Indeterminate	124 (1.7)	19 (1.0)	
Any FP mass-media exposure	No	3,740 (49.9)	1,003 (55.2)	< 0.001
	Yes	3,758 (50.1)	815 (44.8)	
Age (continuous)	Mean (SD)	29.7 (8.2)	29.0 (9.7)	< 0.001
Living children	Mean (SD)	2.9 (2.1)	2.9 (2.5)	< 0.001
Cluster % poor	Mean (SD)	0.4 (0.4)	0.5 (0.4)	0.220
Cluster % secondary+ education	Mean (SD)	0.5 (0.3)	0.5 (0.3)	0.644
Cluster % FP exposure	Mean (SD)	0.5 (0.2)	0.5 (0.2)	< 0.001

Exploratory predictor screening

Univariate mutual information identified Cohabitation duration, Marriage–first birth interval, Recent sexual activity, Marital status, Age group as the five highest-scoring predictors, led by Cohabitation duration (MI = 0.0167). The dotted line marks the median of strictly positive MI scores (0.0074); 15 of 43 predictors met or exceeded this threshold. Reproductive-history and union-related variables ranked above most FP-exposure and barrier items in this exploratory screen. (Fig. 2)

The heatmap displays Spearman ρ for 26 numeric predictors. The strongest pairwise associations included Cluster % secondary+ education–Cluster % poorer wealth ($\rho = -0.79$); Partner's age–Living children ($\rho = 0.70$); Partner's age–Age of household head ($\rho = 0.70$). Positive and negative correlations formed clusters among parity-related counts, partner-age variables, and cluster-context aggregates. (Fig. 3)

Hold-out model performance

On the hold-out set (n = 1,864), RF–XGBoost ensemble had the highest ROC-AUC (0.703), PR-AUC (0.384), and lowest Brier score (0.144). At the Youden threshold (0.201), sensitivity was 0.717, specificity 0.589, and F1-score 0.420. Logistic regression had ROC-AUC 0.685, sensitivity 0.503, and specificity 0.767. XGBoost and LightGBM matched at ROC-AUC 0.703. Results in Table 2 below.

Table 2
Hold-out performance at the Youden operating point

Model	ROC-AUC	PR-AUC	Accuracy	Precision	Recall	Sensitivity	Specificity	F1-score	Brier score	Youden threshold
Logistic regression	0.685	0.357	0.716	0.344	0.503	0.503	0.767	0.408	0.224	0.546
Random forest	0.689	0.383	0.740	0.372	0.484	0.484	0.802	0.421	0.148	0.309
XGBoost / LightGBM	0.702	0.375	0.584	0.288	0.769	0.769	0.539	0.419	0.144	0.172
RF–XGBoost ensemble	0.703	0.384	0.614	0.297	0.717	0.717	0.589	0.420	0.144	0.201

ROC curves separated models by discrimination: ensemble ROC-AUC 0.703, random forest 0.689, and logistic regression 0.685. PR-AUC values were 0.384 (ensemble), 0.383 (random forest), and 0.357 (logistic regression), all above the prevalence baseline (~ 19.5%). Tree-based models maintained higher recall at comparable thresholds than logistic regression. (Fig. 4)

At the Youden threshold (0.201) for the RF–XGBoost ensemble, the hold-out confusion matrix showed 261 true positives, 103 false negatives, 617 false positives, and 883 true negatives. Sensitivity was 0.717 and specificity 0.589. Accuracy was 0.614 and F1-score 0.420.

Calibration plots

Calibration plots compared observed unmet-need fractions with mean predicted probabilities across decile groups of predicted risk for each model on the hold-out set. Points lying on the 45° reference line indicate perfect calibration; systematic deviation above or below the line indicates over- or under-prediction within deciles. Tree ensembles and the RF–XGBoost ensemble showed tighter alignment between observed and predicted fractions than logistic regression across most of the risk distribution as shown in Fig. 5.

Isotonic recalibration was applied to the best model on the hold-out sample. The figures compares reliability curves before and after recalibration. Pre-recalibration probabilities from the ensemble showed moderate miscalibration at high predicted-risk deciles; post-isotonic curves moved closer to the diagonal reference, indicating improved agreement between predicted probabilities and observed unmet-need rates within calibration bins (Fig. 6).

Brier scores on the hold-out set ranged from 0.144 (RF–XGBoost ensemble) to 0.224 (Logistic regression). The RF–XGBoost ensemble, XGBoost, and LightGBM shared the lowest scores (~ 0.144), whereas logistic regression had the highest (0.224). Random forest scored 0.148. Lower Brier scores indicate better probabilistic calibration and sharper predictions on the 20% hold-out sample.

Decision-curve analysis (Fig. 7) plots net benefit across threshold probabilities for each model, with treat-all and treat-none reference strategies. On the hold-out set, tree-based models and the RF–XGBoost ensemble provided positive net benefit over treat-none across low-to-moderate threshold probabilities (0.05–0.30), exceeding logistic regression. At higher thresholds, net benefit declined and differences between models narrowed. Absolute net benefit values remained moderate, consistent with ROC-AUC near 0.70.

Sensitivity analyses

Table 3 shows bootstrap resampling (n = 1,000) of the hold-out set produced 95% confidence intervals for the RF–XGBoost ensemble: ROC-AUC 0.703 (95% CI 0.673–0.735); PR-AUC 0.382 (95% CI 0.338–0.440); Brier score 0.144 (95% CI 0.135–0.156). Logistic regression ROC-AUC was 0.686 (95% CI 0.662–0.711).

Table 3
Bootstrap 95% confidence intervals for hold-out discrimination and calibration

Model	ROC-AUC	PR-AUC	Brier score
Logistic regression	0.686 (0.662–0.711)	0.358 (0.309–0.404)	0.224 (0.218–0.230)
Random forest	0.689 (0.657–0.718)	0.381 (0.339–0.428)	0.148 (0.140–0.158)
XGBoost	0.702 (0.672–0.733)	0.374 (0.325–0.435)	0.144 (0.135–0.157)
LightGBM	0.702 (0.672–0.733)	0.374 (0.325–0.435)	0.144 (0.135–0.157)
RF–XGBoost ensemble	0.703 (0.673–0.735)	0.382 (0.338–0.440)	0.144 (0.135–0.156)

Explainability

The beeswarm plot displays SHAP values for the hold-out sample across the top 12 predictors in Fig. 8 below. Currently working, place of residence, and mobile-phone ownership showed the widest spread of positive and negative contributions. Recent sexual activity, province, and age group also contributed across multiple feature levels. Predictors with the largest mean absolute SHAP included Currently working, Place of residence, Owns a mobile phone, Recent sexual activity, Province.

Mean |SHAP| values aggregated to base predictors ranked currently working (0.770), place of residence (0.636), owns a mobile phone (0.520), recent sexual activity (0.282), and province (0.220) as the five largest contributors on the hold-out sample (figure not shown).

Permutation importance (mean decrease in average precision on the hold-out set) ranked currently working (0.185), place of residence (0.174), and owns a mobile phone (0.134) highest. Recent sexual activity (0.082), sex of household head (0.039), and age group (0.031) followed. Top values: Currently working (0.185); Place of residence (0.174); Owns a mobile phone (0.134) (not shown).

Provincial patterns

DHS-weighted unmet need prevalence varied across Zambia's ten provinces. The highest prevalences were in North Western (24.9%), Northern (22.5%), Lusaka (21.7%). The lowest were in Central (15.3%), Eastern (16.9%), Copperbelt (17.0%). The provincial range spanned 9.6 percentage points, from 15.3% to 24.9% (Fig. 9).

Mean predicted unmet-need risk on the hold-out sample ($n = 1,864$) varied by province. Highest mean predicted risks were in Lusaka (26.0%), North Western (25.6%), Western (24.7%). Lowest were in Copperbelt (19.1%), Central (19.3%), Luapula (20.9%). Provincial mean predicted risks ranged from 19.1% to 26.0%, mirroring but not identical to weighted observed prevalence rankings (not shown).

Discussion

Our study yields six principal findings. First, leakage aware machine learning can discriminate unmet need among women with classifiable need status in the 2024 Zambia Demographic and Health Survey, but performance is moderate rather than high: our best hold out model, an RF XGBoost ensemble, reached a ROC AUC of 0.703 on $n = 9,316$ women with classifiable need status. Second, unmet need remains common in this national classifiable cohort, affecting about one in five women, in line with pooled DHS evidence that need persists across Sub Saharan Africa¹¹. Third, our lower headline discrimination relative to recent machine learning work is expected and more defensible because we used a locked hold out test set and excluded predictors that enter or closely reconstruct the DHS unmet need algorithm^{19,21}. Fourth, after model fitting, currently working, place of residence, and mobile phone ownership were the leading SHAP drivers, pointing to work status, geography, and digital access as actionable correlates rather than algorithm inputs²². Fifth, provincial inequity persists, with higher burden in North Western, Northern, and Lusaka relative to Central, Eastern, and Copperbelt²³. Sixth, the practical use of our models is risk stratification for FP2030 and SDG 3.7 programming, not causal inference about why individual women have unmet need^{24,25}.

Pooled DHS meta analyses estimate unmet need near 23 percent among married women in Sub Saharan Africa¹¹. In Zambia, 2018 DHS work reported about one in five married women with unmet need¹⁵, with lasting inequality by wealth and place through 2018²³ and higher need linked to rural residence and migration²⁶. Employment and household structure predict unmet need among young women across the region⁷. A study from Ethiopia reported random forest AUC near 0.93 for PMA under cross validation after balancing¹⁹. Other DHS machine learning studies in East and West Africa report high AUC from cross validation and predictors closer to contraceptive pathways, including continuation, informed choice, and intention models^{18,20,27,28}. We analysed all women aged 15 to 49 with classifiable need status, including sexually active women not in union, matching SDG 3.7.1 framing^{25,29,30}, and excluded contraceptive use, fertility preference, pregnancy, and infecundity markers from the revised unmet need algorithm³¹. Our hold out AUC near 0.70 is a credible ceiling under leakage control, consistent with TRIPOD + AI, PROBAST, and external validation guidance^{21,32,33}. In Zambia, our contribution is a leakage aware, explainable 2024 ZDHS model with hold out evaluation, calibration plots, and decision curve analysis that reports net benefit alongside discrimination.

After model fitting, currently working, place of residence, and mobile phone ownership ranked highest on mean absolute SHAP contribution²². The predictive importance of these predictors aligns with previous studies linking employment, empowerment and digital access with unmet need. Residence effects mirror Zambia and spatial Ghana evidence that geography shapes access^{15,26,38}. Mutual information instead ranked cohabitation duration, marriage to first birth interval, and recent sexual activity highest, showing that univariate association and model importance differ. Complemented by existing interventions, the findings of these risk stratification analyses can guide programmes in targeting populations with unmet need who may benefit from intensified engagement. Evidence-based approaches include integration of family planning into maternal health services, community health worker outreach, geographically targeted strengthening of service availability and digital channels for phone owners while maintaining non-digital options^{35,37,39}. These markers are observable in routine surveys and programme registers, making them suitable for risk stratification even when causal pathways remain unclear. SHAP values guide targeting, not causal claims.

For Zambia's health sector, our findings support practical risk stratification rather than claims of near perfect prediction. Managers can combine province maps with individual scores to prioritise North Western, Northern, and Lusaka. Community teams can intensify counselling for women not working, in higher risk settings, or without phones, consistent with Zambia evidence on media, service contact, and health system barriers^{15,23,39}. Because discrimination is moderate, threshold choice should follow calibration and decision curve analysis, not accuracy alone^{21,40,41}. Lower thresholds favour case finding when outreach capacity is ample; higher thresholds conserve counselling time when resources are scarce. Models should complement FP2030 commodity and quality work, not replace clinical judgement^{30,42,43}.

Unmet need and demand satisfied by modern methods anchor SDG targets 3.7 and 5.6 and the FP2030 agenda^{25,29,30}. FP2030 monitoring shows uneven contraceptive equity across partner countries²⁴, and global analyses show persistent need in Sub Saharan Africa^{11,43,44}. Zambia has expanded modern use yet inequality by wealth and place remains^{15,23}. Policy reviews frame voluntary family planning as a development pillar⁴². Our 2024 analysis confirms the gap among women with classifiable need status, including those not in union. National monitoring should report SDG 3.7.1 cohorts beyond married women²⁵; dashboards can blend risk scores with service data; and digital and facility strategies must reach women flagged by phone and residence gaps so that FP2030 gains do not exclude rural or digitally marginalised groups^{24,35,37}.

Research and policy implications

Future studies should externally validate our hold out model in later ZDHS rounds and neighbouring countries under the same leakage rules, following TRIPOD + AI and PROBAST standards. Incorporating additional variables such as contraceptive commodity availability, geospatial accessibility and community health worker coverage may improve predictive performance and programme relevance. Policy makers should treat explainable risk scores as one input to equity focused allocation of commodities, community health worker visits, and workplace outreach linked to employment patterns^{7,26,39}. Implementation

studies should assess whether risk-based targeting improves identification of women with unmet need and supports efficient resource allocation. Digital messaging should expand among phone owners while parallel non digital channels serve women without phones^{35,36}. Reporting standards for DHS machine learning should require leakage audits, hold out validation, calibration, and decision curve metrics before headline AUC supports programme claims^{19,40,41}.

Limitations

Our study has limitations. The design is cross sectional, so we cannot claim that working status, residence, or phone ownership cause unmet need. DHS cluster coordinates are displaced, which limits fine scale spatial inference, and our primary models did not use geospatial covariates despite geographic inequity in the outcome. Class imbalance near 20 percent events and moderate discrimination mean that operating point choice strongly affects sensitivity and specificity, and miscalibration can mislead risk based decisions if thresholds are chosen from discrimination alone. We report Youden based thresholds, which may differ from programme preferred trade offs. Extended hyperparameter search may yield small gains but is unlikely to approach cross validated AUC near 0.93 reported elsewhere without relaxing leakage constraints. External validation in future surveys remains needed.

Conclusions

Our leakage aware analysis of the 2024 ZDHS shows that explainable machine learning can support risk stratification for unmet need in Zambia with moderate but trustworthy hold out performance (ROC AUC 0.703). Relative to other Sub Saharan Africa applications reporting much higher AUC under less restrictive predictors and cross validation, we prioritise defensible hold-out evaluation and SDG aligned cohort definition. Work status, residence, mobile phone ownership, and provincial inequity may help guide targeted outreach through evidence-based family planning interventions to close remaining FP2030 and SDG gaps without mistaking prediction for causation.

Abbreviations

- AUC**
Area under the receiver operating characteristic curve
- DHS**
Demographic and Health Survey
- FP2030**
Family Planning 2030 partnership
- MI**
Mutual information
- PMA**
Performance Monitoring for Action
- PR AUC**
Area under the precision recall curve
- RF**
Random forest
- ROC**
Receiver operating characteristic
- SDG**
Sustainable Development Goal
- SHAP**
SHapley Additive exPlanations
- SSA**
Sub Saharan Africa

STROBE

Strengthening the Reporting of Observational Studies in Epidemiology

TRIPOD + AI

Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis, artificial intelligence extension

XGBoost

Extreme Gradient Boosting

ZDHS

Zambia Demographic and Health Survey

Declarations

Ethics approval and consent to participate

Our study is a secondary analysis of deidentified, publicly available DHS datasets obtained under The DHS Program data use terms. The original ZDHS 2024 survey obtained informed consent from participants under protocols approved by the appropriate national ethics bodies and ICF Institutional Review Board, as described in DHS Program documentation. No additional primary data collection involving human participants was conducted for this analysis.

Consent for publication

Not applicable. The manuscript does not contain individual person identifiable data.

Availability of data and materials

The 2024 Zambia DHS Individual Recode and related files are available from The DHS Program upon registration (<https://dhsprogram.com>). Analysis code and derived tables and figures supporting this manuscript are available in the project repository accompanying submission.

Competing interests

The authors declare that they have no competing interests.

Funding

This project is part of the EDCTP3 programme supported by the European Union (grant number 101145636-SOFAR-HORIZON-JU-GH-EDCTP3-2023-01)

Authors' contributions

SM, TM Conceptualization; SM - Data curation; SM, TM - Formal analysis; GM - Methodology; SM, TM, GM - Writing original draft; GM - Writing review and editing; GM - Supervision; GM - Project administration.

Acknowledgements

We thank The DHS Program and the Zambia Statistics Agency for access to the 2024 ZDHS datasets. The views expressed are those of the authors and do not necessarily reflect those of The DHS Program or the Government of Zambia.

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Figures

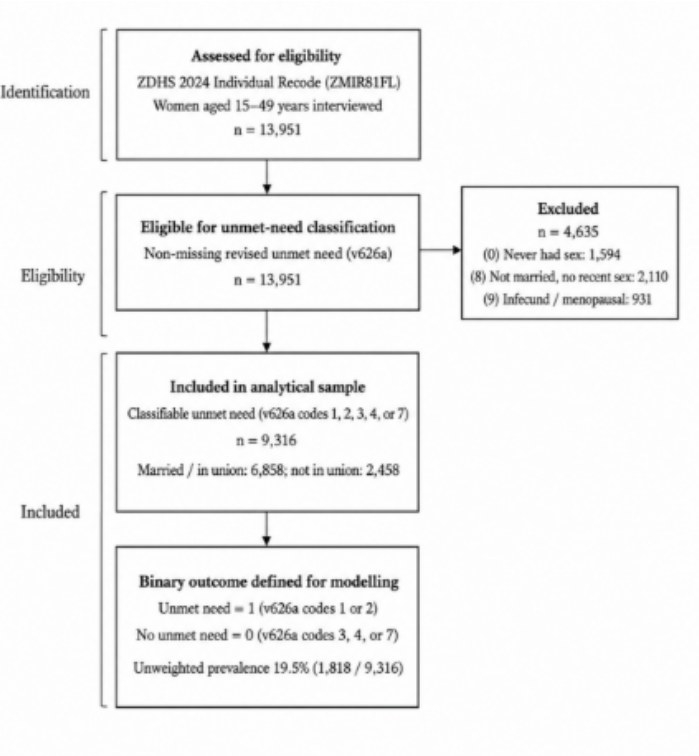


Figure 1

STROBE participant flow showing exclusions to the analytical cohort (n = 9,316)

Top predictors by mutual information

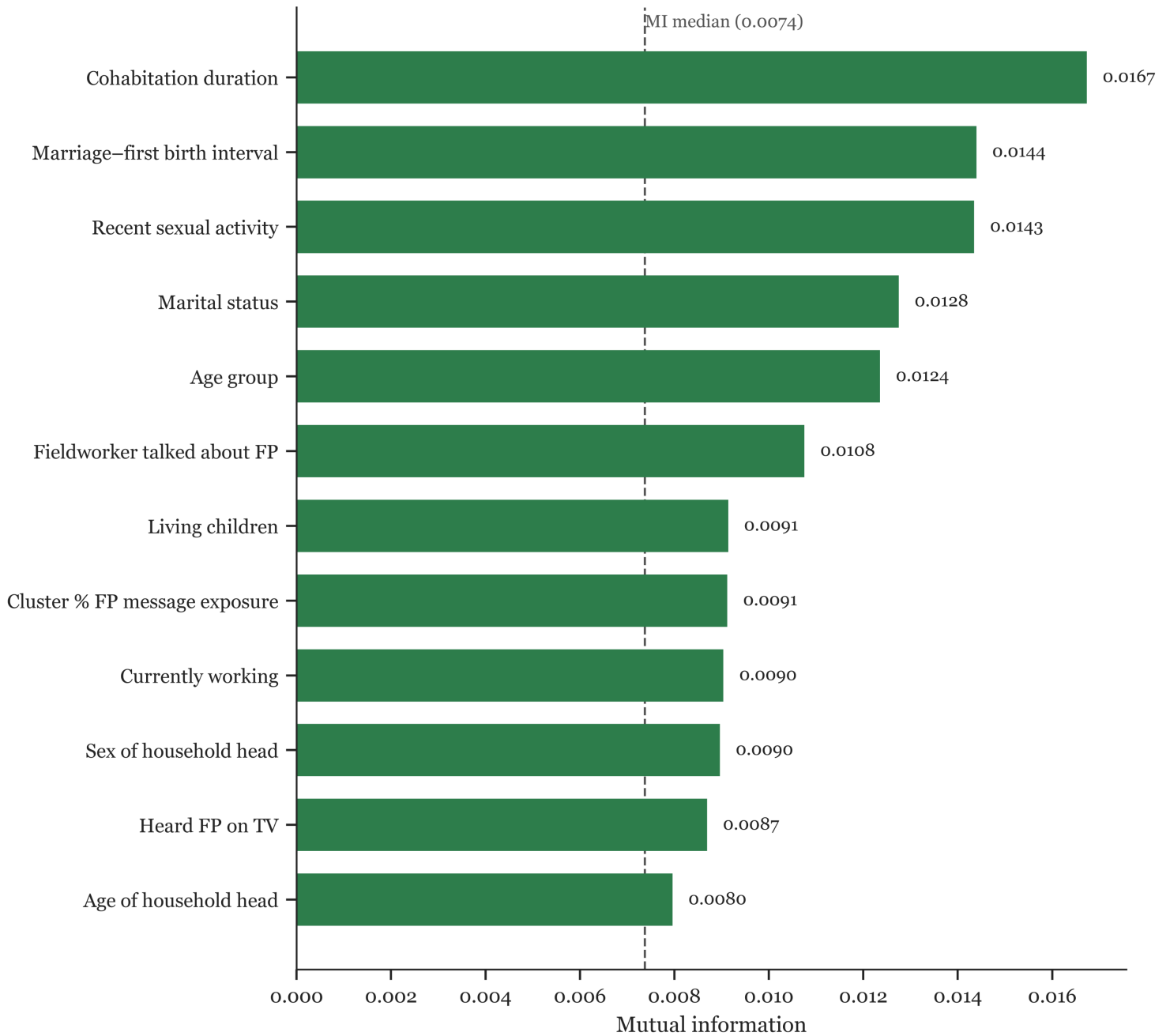


Figure 2

Top 12 predictors by mutual information with unmet need

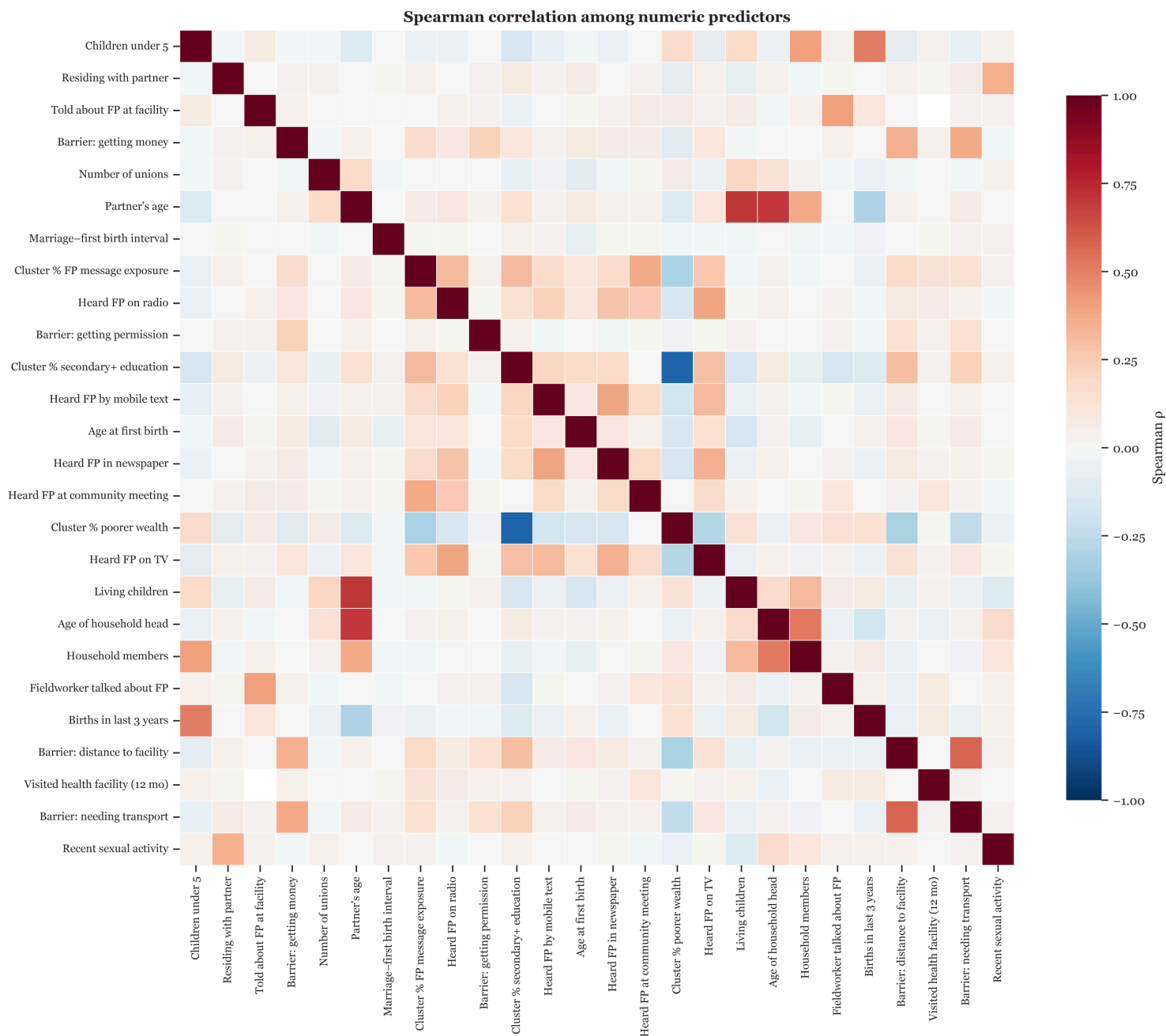


Figure 3

Spearman correlation among numeric predictors

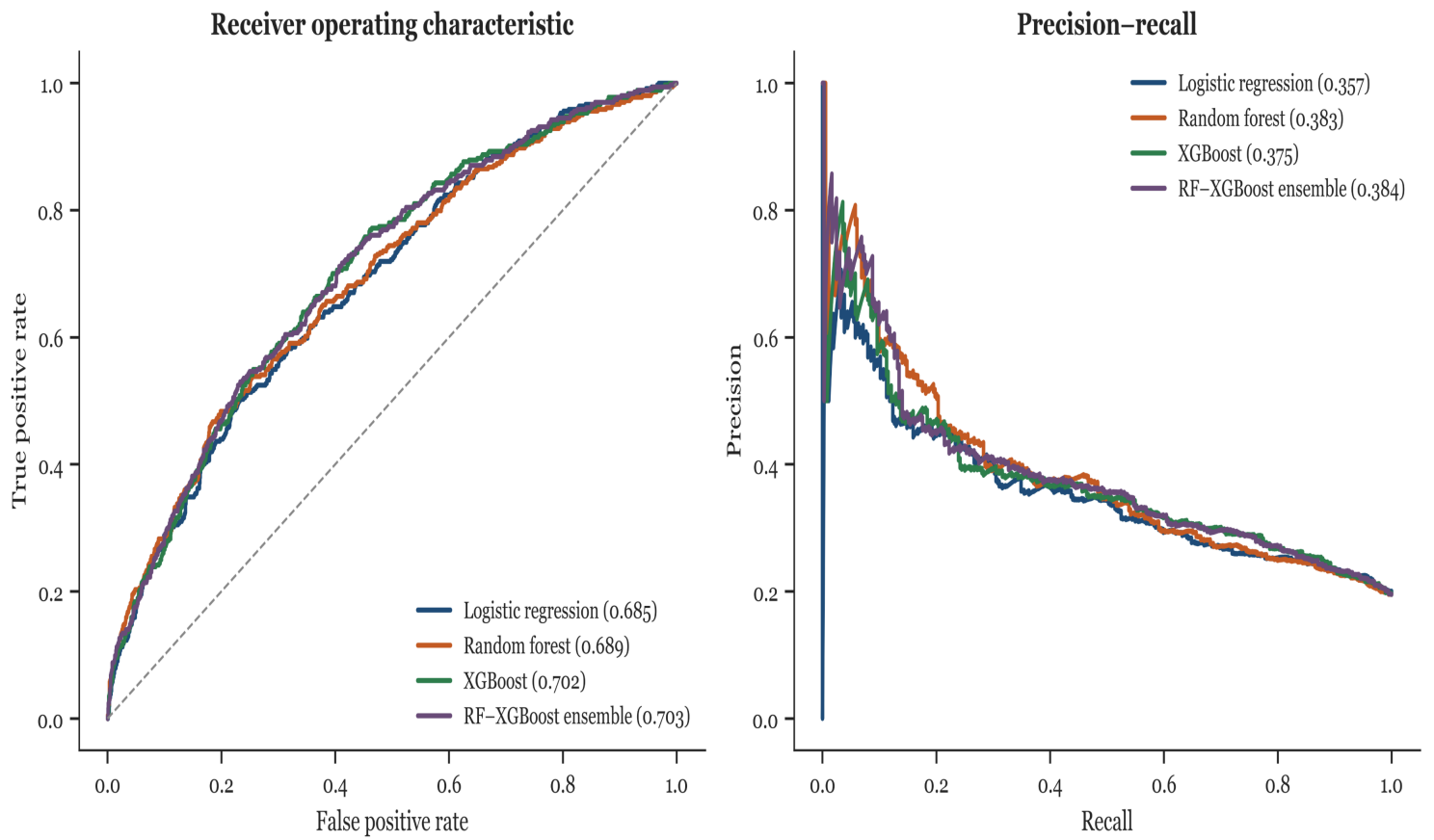


Figure 4

Receiver operating characteristic and precision-recall curves (hold-out, n = 1,864)

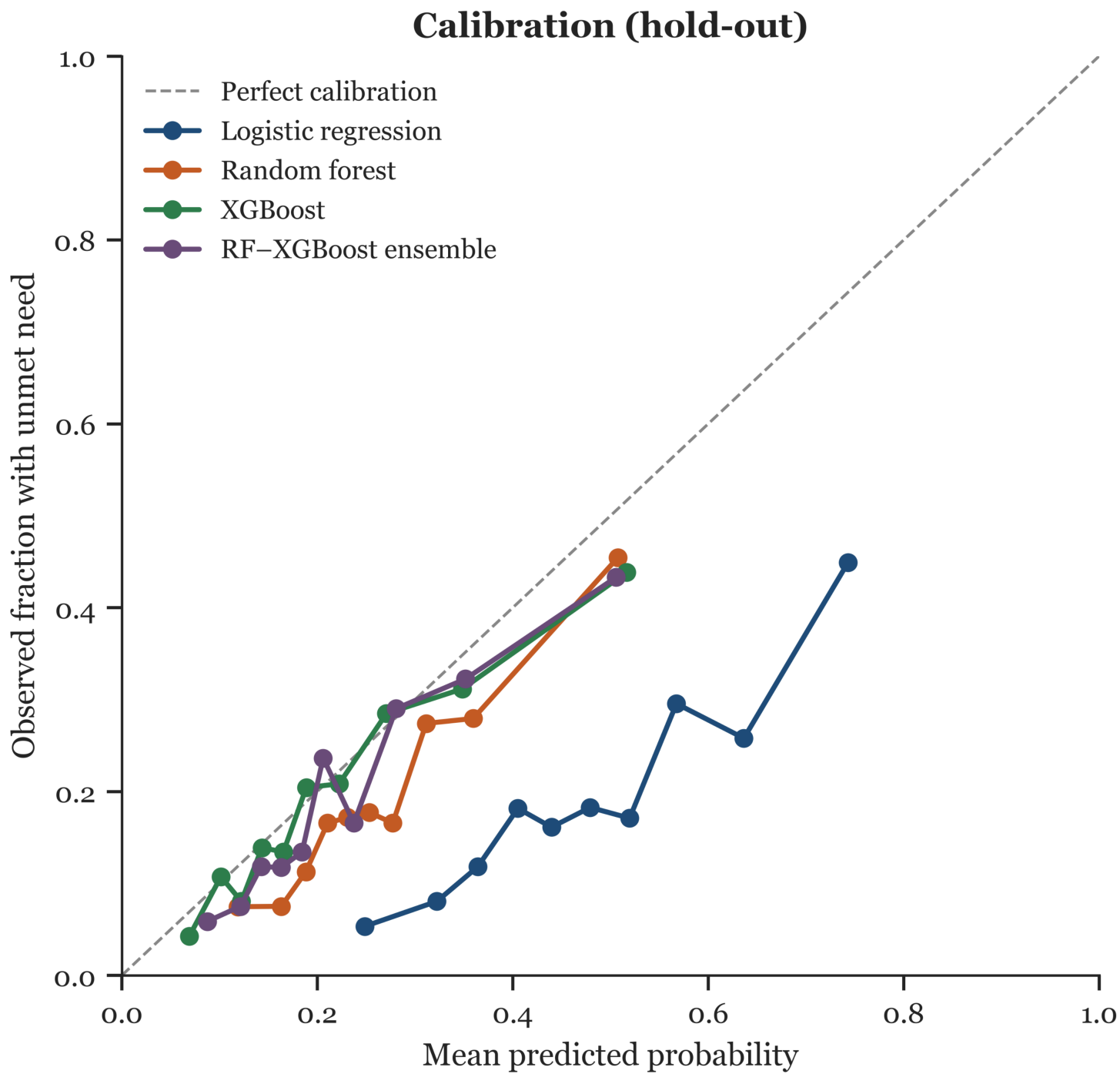


Figure 5

Calibration curves on the hold-out set

Calibration (hold-out)

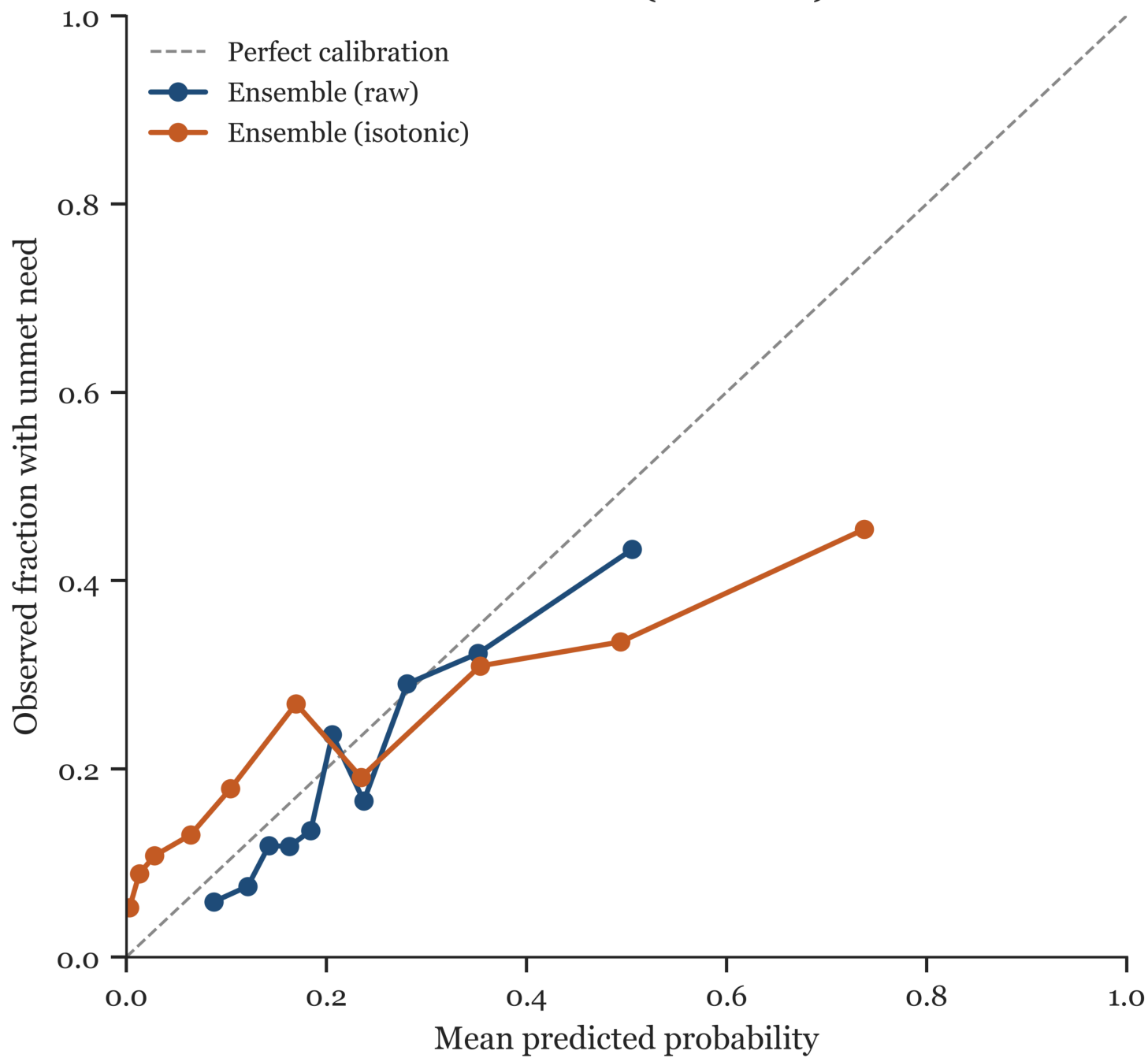


Figure 6

Calibration before and after isotonic recalibration

Decision-curve analysis (hold-out)

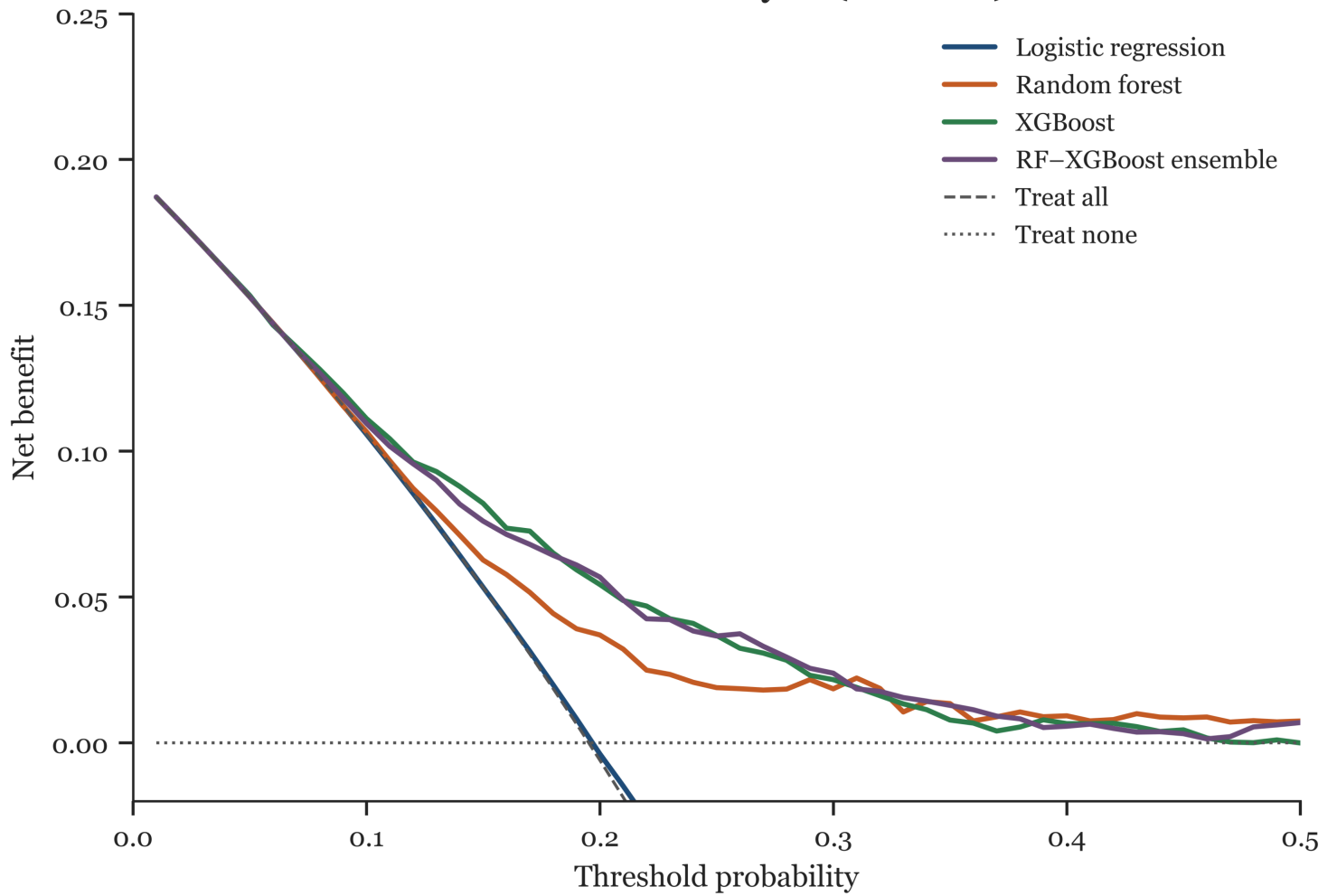


Figure 7

Decision-curve analysis on the hold-out set

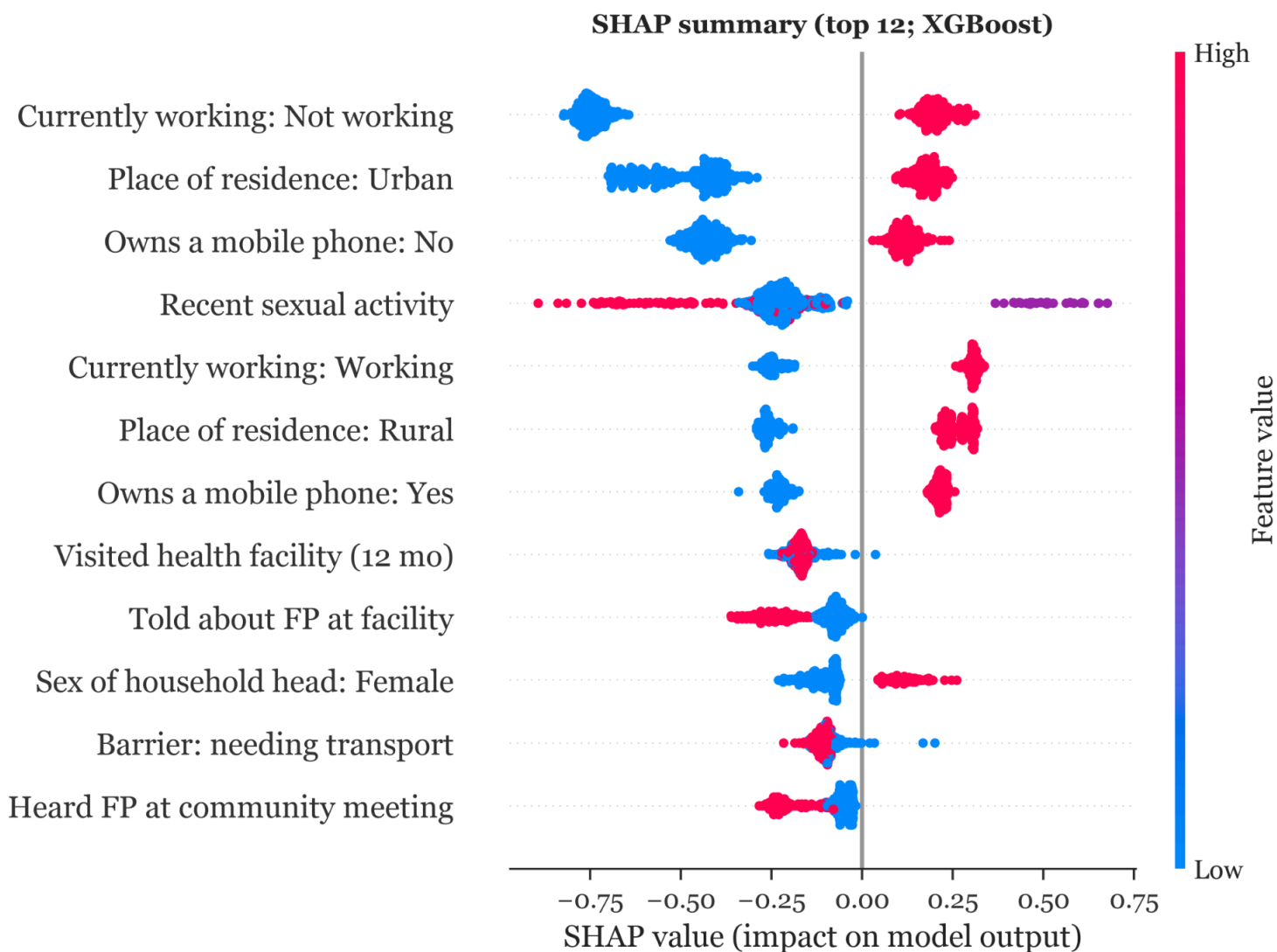


Figure 8

SHAP beeswarm plot (top 12 predictors; hold-out sample).

DHS-weighted unmet need by province

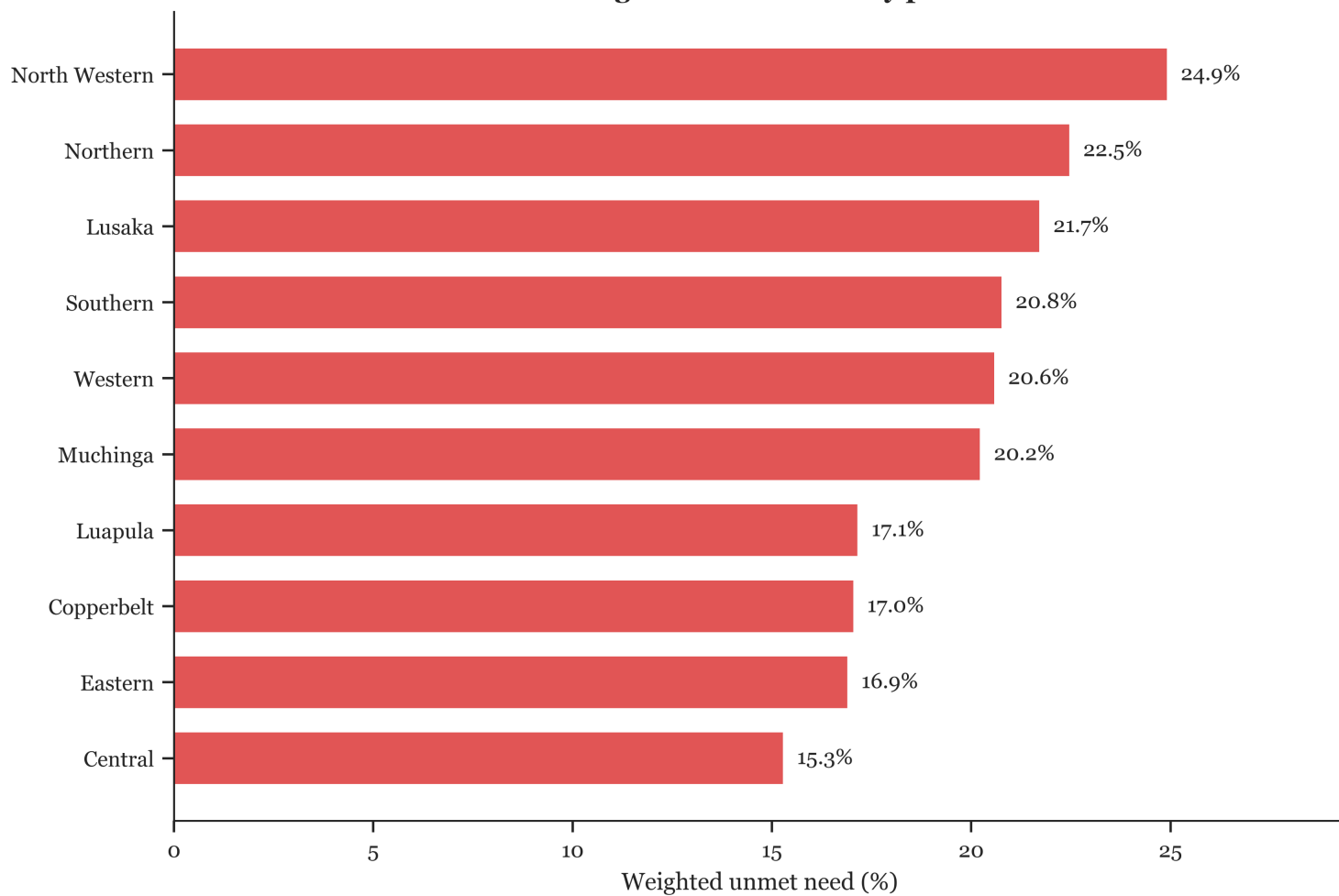


Figure 9

DHS-weighted unmet need prevalence by province.