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RESEARCH

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Exploring the application of machine learning and SHAP explanations to predict health facility deliveries in Somalia

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Abstract

Background Health facility delivery is a critical strategy for reducing maternal and neonatal mortalities. In Somalia, maternal mortality remains alarmingly high due to socioeconomic disparities, geographic barriers, and limited healthcare infrastructure. Machine learning (ML) offers a novel approach for predicting health facility deliveries and identifying key determinants, enabling targeted interventions to improve maternal health outcomes.

Methods This study analyzed data from the 2020 Somalia Demographic and Health Survey (SDHS) involving 8,951 women aged 15–49 years. Seven ML algorithms, Random Forest, XGBoost, Gradient Boosting, Logistic Regression, Support Vector Machine, Decision Tree, and K-Nearest Neighbors, were evaluated for their ability to predict health facility deliveries. Model performance was assessed using the accuracy, precision, recall, F1-score, and AUROC. SHapley Additive exPlanations (SHAP) analysis was employed to interpret the relative importance of predictors, including wealth quintile, antenatal care (ANC) attendance, and residence type.

Results The Random Forest model achieved the highest performance, with an accuracy of 82%, a recall of 84%, and an AUROC of 0.89. XGBoost and Gradient Boosting followed with accuracies of 80% and 77%, respectively, and AUROC values of 0.89 and 0.86. Logistic regression and support vector machines demonstrated moderate performance (accuracy: 72%, AUROC: 0.80–0.81). SHAP analysis identified the wealth quintile as the most influential predictor, with women in the highest quintile being six times more likely to deliver in health facilities than those in the lowest quintile (AOR: 6.01; 95% CI: 4.04–8.94). ANC attendance and residence type were also significant contributors, with women attending four or more ANC visits (AOR: 4.82; 95% CI: 3.75–6.20) and urban residents were more likely to deliver in health facilities.

Conclusion Machine learning techniques, particularly Random Forest and SHAP analyses, offer robust tools for predicting health facility deliveries and identifying critical determinants. These findings underscore the potential of ML in designing targeted data-driven interventions to improve maternal health outcomes in Somalia.

Keywords Health facility delivery, Maternal health, Somalia, Machine learning, SHAP, Predictive modeling, Public health, SDHS

1 Introduction

Maternal mortality remains a pressing global health challenge, with an estimated 287,000 women dying annually due to pregnancy-related complications, many of which are preventable [1, 2]. Sub-Saharan Africa has the highest burden, accounting for nearly two-thirds of these deaths. Ensuring that women deliver in health facilities under the supervision of skilled birth attendants is one of the most effective strategies for reducing maternal and neonatal mortality [3, 4]. Health facility deliveries not only provide access to emergency obstetric care but also ensure the management of complications, such as postpartum hemorrhage, eclampsia, and obstructed labor [5, 6]. Despite these benefits, many women in low- and middle-income countries (LMICs), including Somalia, continue to deliver without professional medical assistance. This trend reflects persistent gaps in achieving universal health coverage for maternal care, influenced by socio-economic barriers, cultural norms, and inadequate healthcare systems [7–9]. Somalia faces significant challenges in maternal healthcare, contributing to one of the highest maternal mortality ratios in the world, estimated at approximately 692 deaths per 100,000 live births [10, 11]. Despite some progress in recent years, ongoing conflict, limited access to healthcare services, and low utilization of skilled birth attendants continue to affect maternal health outcomes in the country [11]. Decades of conflict and sociopolitical instability have severely weakened the country's healthcare infrastructure, limiting access to essential maternal health services. Geographic disparities exacerbate this issue, with women in rural and nomadic areas particularly disadvantaged due to long distances to health facilities and a lack of transportation. Cultural practices, limited female autonomy, and financial constraints deter women from seeking facility-based deliveries [12]. Consequently, efforts to improve maternal health outcomes in Somalia must address these barriers.

Existing literature identifies several key determinants of health facility delivery, including education, wealth, antenatal care (ANC) attendance, and residence type [13–15]. Educated women are more likely to seek facility-based deliveries because of their increased health literacy and autonomy in decision-making [14, 16]. Wealthier households often have better access to healthcare services, while urban residents benefit from closer proximity to health facilities than their rural or nomadic counterparts [17, 18]. Regular ANC attendance has also been linked to increased facility delivery as it serves as a critical point for educating women about the importance of skilled birth attendance [19]. While these factors are well documented in broader sub-Saharan Africa, their specific impact in Somalia, with its unique socio-political and cultural context, remains underexplored. Recent advancements in machine learning (ML) have created opportunities to address complex public health challenges, including those in maternal healthcare [20]. ML models offer several advantages over the traditional statistical methods [21]. They excel in analyzing large multidimensional datasets and identifying complex interactions between variables. For instance, ML models can account for nonlinear relationships and high-dimensional interactions, which are difficult to capture using conventional regression approaches [21, 22]. Additionally, the integration of interpretable frameworks, such as SHapley Additive exPlanations (SHAP), enables researchers to quantify the contribution of individual predictors to model outcomes, thus enhancing the utility of ML for decision-making [23–25]. In maternal health research, ML has been successfully applied to predict adverse pregnancy outcomes, assess ANC utilization, and identify the determinants of institutional deliveries [26–29]. Studies in similar contexts have demonstrated the utility of ML for identifying high-risk groups and informing targeted interventions. For example, ML approaches have revealed wealth and ANC attendance as consistent predictors of facility delivery in LMICs, emphasizing the potential of these methods to guide resource allocation and program design [29, 30]. Despite these advances, the application of ML in maternal healthcare in Somalia is limited. There is a critical need to leverage ML methods to predict health facility deliveries and to identify actionable predictors that can address geographic and socioeconomic disparities.

This study aimed to fill this gap by applying ML techniques to predict health facility deliveries among women in Somalia. Specifically, it evaluated the performance of seven ML algorithms, including Random Forest, XGBoost, and Logistic Regression, to identify the most effective predictive model. Additionally, SHAP analysis was employed to interpret the relative importance of predictors such as wealth, ANC attendance, and residence type. By integrating advanced ML methods, this study provides actionable insights for policymakers and healthcare providers to design targeted interventions that improve maternal healthcare utilization and reduce inequities. These findings are intended to contribute to the broader goal of enhancing maternal health outcomes in Somalia and similar contexts that face significant healthcare challenges.

2 Methods

2.1 Study setting, design and data source

Somalia, located in the Horn of Africa, has a rapidly growing population of approximately 18 million people as of 2023 [31]. The country experiences one of the highest fertility rates globally, with a total fertility rate of about 6.9 children per woman [32]. Despite efforts to strengthen maternal healthcare, access to facilities remains uneven, with most located in urban centers like Mogadishu, Hargeisa, and Garowe, leaving rural and nomadic populations with limited access due to distance and infrastructure challenges [33]. This disparity underscores the need for targeted maternal health interventions to address these unique challenges**.**

This study utilized secondary data from the 2020 Somalia Demographic and Health Survey (SDHS), a nationally representative household survey conducted by the Somalia Ministry of Health in partnership with international organizations. The SDHS employs a stratified, multistage random sampling approach to ensure diverse representations across various regions of Somalia. Data collection involved face-to-face interviews with women aged 15–49 years old. For this analysis, the Individual Record (IR) dataset was used to extract pertinent predictors and outcome variables, specifically focusing on women who reported their delivery location. The final sample included 8951 eligible women categorized according to their place of delivery.

2.2 Study variables

The primary outcome variable for this study was place of delivery, categorized as health facility-based (coded as'1') and home-based (coded as'0'). Health facility deliveries included births in government hospitals, referral health units, mobile clinics, other public health facilities, private hospitals or clinics, and various private medical centers. Conversely, home deliveries referred to births that occurred at the respondent's home or another residence.

The independent variables encompassed a range of sociodemographic characteristics, including age, educational attainment, marital status, wealth index, distance to a health facility, employment status, number of living children, frequency of antenatal care (ANC) visits, type of residence (urban, rural, or nomadic), and regional location. These predictors were selected based on established literature regarding their significance to maternal health behaviors, thereby providing a comprehensive overview of factors that may influence the likelihood of delivery in a health facility.

2.3 Data processing and analysis

We conducted data analysis using a mixed method approach. Initial exploratory data analysis and statistical evaluations were performed using STATA 17. Subsequently, the primary data analysis was carried out within the Python 3.10 environment using a Jupyter Notebook. This facilitated the utilization of powerful libraries, such as Pandas, NumPy, Scikit-learn, Matplotlib, SHAP, SciPy, and Seaborn. These libraries enable efficient data manipulation, exploration, visualization, model building, and feature importance assessment.

2.4 Data pre-processing

The raw SDHS data underwent rigorous preprocessing to ensure suitability for machine learning applications. Missing values were handled using multiple imputation with the predictive mean matching (PMM) technique to preserve dataset integrity and avoid loss of valuable information. Variables with excessive missingness were excluded, and outliers were treated using the interquartile range (IQR) method. This involves meticulous data cleaning to address inconsistencies, handle missing values, and identify and treat outliers. Additionally, feature engineering was employed to transform continuous variables into categorical variables where appropriate. This process enhances model interpretability and potentially improves model robustness by simplifying the relationships between predictors and outcomes.

2.5 Addressing class imbalance

Initial analysis revealed a class imbalance in the outcome variable, with facility-based deliveries being underrepresented. To mitigate this issue and enhance model performance, the synthetic minority oversampling technique (SMOTE) was employed with a 1:1 oversampling ratio. SMOTE addresses class imbalance by generating synthetic samples for the minority class (facility-based deliveries) through interpolation between the existing instances. This creates a more balanced dataset, enabling the model to learn effectively from both classes and potentially improving the predictive accuracy for the underrepresented class.

2.6 Feature selection

A thorough feature-selection process was conducted to identify the most relevant predictors of health facility deliveries. Exploratory data analysis (EDA) techniques, including descriptive statistics and visualizations, provide insights into variable distributions and associations with the outcome. Bivariate analysis was used to evaluate the associations of individual predictors with facility-based deliveries. To further refine the feature set, Recursive Feature Elimination (RFE) was applied to iteratively remove less significant predictors. Using the RFE, we selected 10 features for the final model after evaluating their importance to predictive performance. Cramer's V statistic was also used to assess correlations between predictors, minimizing multicollinearity and ensuring the robustness of the final feature set. This combination of statistical analysis, machine learning techniques, and a literature review yielded a comprehensive set of predictors for model development.

2.7 Feature importance

We assessed feature importance using SHapley Additive exPlanations (SHAP) values. SHAP provides a model-agnostic and consistent approach to explaining the contribution of each predictor variable to the model's predictions for facility-based deliveries. By assigning an importance score to each feature, SHAP offers valuable insights into the influence of each predictor on model output. This analysis allowed for a deeper understanding of the relative importance of the different factors in predicting early ANC initiation outcomes.

2.8 Model development

To predict facility-based deliveries, a comparative analysis of seven machine learning algorithms was conducted: Logistic Regression, Support Vector Machine (SVM), Decision Tree, Random Forest, K-Nearest Neighbors (KNN), Gradient Boosting, and XGBoost. Logistic Regression served as a baseline, whereas SVM effectively handled complex relationships. Decision Trees and Random Forest employed ensemble methods for improved accuracy. KNN classifies data based on their proximity to neighbors. Gradient Boosting and XGBoost iteratively built models for enhanced performance. By comparing the performance of these algorithms based on accuracy, precision, recall, F1-score, and ability to identify influential factors, we aimed to select the most effective model for predicting facility-based deliveries.

2.9 Model training and evaluation

To ensure a robust model performance, the dataset was split into training (80%) and testing (20%) sets. The models were trained on the training set and subsequently evaluated on the unseen test set using a comprehensive set of performance metrics including accuracy, precision, recall, F1-score, Area Under the Receiver Operating Characteristic Curve (AUROC), and confusion matrices. To further enhance the generalizability of the model and mitigate the risk of overfitting, stratified k-fold cross-validation was employed. This technique provides a more robust evaluation of model performance than a single train-test split by partitioning the data into k-folds ($k = 5$) and iteratively training and evaluating the model on each fold. Therefore, additional confidence intervals were not calculated.

2.9.1 Model selection

The model selection was based on a comprehensive evaluation of multiple performance metrics. The confusion matrix provided a detailed breakdown of the model predictions, categorizing them into true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). Accuracy, which represents the overall proportion of correct predictions, served as the primary measure. Precision indicates the proportion of true positive predictions among all predicted positive cases, while recall (sensitivity) measures the proportion of actual positive cases correctly identified. The F1-score, which balances precision and recall, provides a robust evaluation of model performance. By comparing these metrics across all seven machine learning algorithms, the model with the most favorable combination of performance metrics was selected as the optimal model for health-facility delivery.

3 Results

3.1 Sociodemographic characteristics

The study analyzed data from 8,951 women aged 15–49 years, and their sociodemographic characteristics are summarized in Table 1. The largest proportion of women were aged 25–29 years (27.4%), followed by those aged 20–24 years (20.3%), and 30–34 years (20.0%). The smallest group comprised women aged 45–49 years (2.3%). Most participants (83.7%) had no formal education, 12.0% had completed primary education, and only 1.2% had attained higher education. Most respondents were married (90.9%) and 93.3% were not currently employed.

Economic disparities were notable, with 24.4% of women in the lowest wealth quintile and 16.4% in the highest quintile. Regarding residence, 34.7% of the women lived in urban areas, 29.9% in rural areas, and 35.3% in nomadic settings. Furthermore, 63.9% of the respondents identified distance to a health facility as a significant barrier to accessing maternal healthcare.

3.2 Regional distribution of health facility deliveries

Regional disparities in health facility delivery were evident (Table 2, Fig. 1). Woqooyi Galbeed recorded the highest proportion of health facility deliveries (58%), followed by Banadir (40%) and Galgaduud (35%). Conversely, Bakool (2%) and Hiraan (5%) showed the lowest rates. Other regions, such as Sanaag and Sool, also exhibited low rates, with only 13% of deliveries occurring in health facilities. These findings underscore the significant geographic inequities in access to maternal healthcare services across Somalia.

3.3 Predictors of health facility delivery

Bivariate and multivariable logistic regression analyses were used to identify patterns influencing health facility delivery. Women with secondary education were nearly three times more likely to deliver in health facilities (AOR: 2.80, 95% CI: 1.99–3.95), while those with higher education were over four times more likely (AOR: 4.24, 95% CI: 2.16–8.32). The wealth quintile was another critical predictor: women in the highest wealth quintile were six times more likely to deliver in health facilities (AOR: 6.01, 95% CI: 4.04–8.94) than those in the lowest quintile. Antenatal care (ANC) attendance significantly influences delivery location. Women who attended four or more ANC visits were nearly five times more likely to be delivered in health facilities (AOR: 4.82, 95% CI:

Table 1 Sociodemographic characteristics

Variable	Weighted frequency	Percent (%)
Age in 5-year groups		
15–19	552	6.17
20–24	1817	20.31
25–29	2449	27.37
30–34	1791	20.02
35–39	1499	16.75
40–44	635	7.10
45–49	203	2.27
Education		
No Education	7492	83.70
Primary	1077	12.03
Secondary	273	3.05
Higher	109	1.22
Marital status		
Married	8133	90.86
Divorced	582	6.50
Widowed	236	2.64
Wealth quintile		
Lowest	2180	24.35
Second	1837	20.52
Middle	1676	18.73
Fourth	1792	20.02
Highest	1466	16.38
Distance to health facility		
Big problem	5721	63.94
Not a big problem	3226	36.06
Currently working		
Yes	599	6.69
No	8349	93.31
Number of living children		
0–1	36	2.33
2–3	302	19.51
4–5	440	28.47
6–7	457	29.55
8+	312	20.14
Births in last five years		
0	366	4.09
1	3045	34.01
2	3422	38.23
3	1807	20.19
4+	312	3.48
Residence		
Urban	3109	34.74
Rural	2683	29.98
Nomadic	3158	35.29
Region		
Awdal	758	8.47
Woqooyi Galbeed	536	5.99
Togdheer	282	3.15
Sool	701	7.83
Sanaag	910	10.17
Bari	557	6.23
Nugaal	985	11.00

Table 1 (continued)

Variable	Weighted frequency	Percent (%)
Mudug	1160	12.96
Galgaduud	970	10.84
Hiraan	597	6.67
Middle Shabelle	334	3.74
Banadir	482	5.39
Bay	87	0.97
Bakool	341	3.81
Gedo	105	1.18
Lower Juba	146	1.63

3.75–6.20) compared to those with fewer visits. Residence type also played a significant role, with urban women more likely to deliver in health facilities than rural (AOR: 0.71, 95% CI: 0.59–0.86) and nomadic women (AOR: 0.23, 95% CI: 0.16–0.32).

3.4 Model performance evaluation

Seven machine learning (ML) models were developed and evaluated for their ability to predict health facility deliveries. The models include Random Forest (RF), XGBoost, Gradient Boosting, Logistic Regression, Support Vector Machines (SVM), Decision Tree, and K-Nearest Neighbors (KNN) (Fig. 2). Their performance was assessed using key metrics, including accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUROC), as summarized in Table 3. The Random Forest model achieved the highest performance, with an accuracy of 82%, precision of 81%, recall of 84%, an F1-score of 82%, and AUROC of 0.89. XGBoost followed closely, with an accuracy of 80%, precision of 80%, recall of 82%, an F1-score of 81%, and AUROC of 0.89. Gradient Boosting also performed well, achieving an accuracy of 77%, a precision of 79%, a recall of 78%, an F1-score of 78%, and an AUROC of 0.86.

Logistic Regression and SVM demonstrated moderate performances, each with an accuracy of 72%. Logistic Regression achieved a precision of 72%, a recall of 71%, an F1-score of 71%, and an AUROC of 0.80, while SVM recorded a precision of 73%, a recall of 70%, an F1-score of 71%, and an AUROC of 0.81. Decision Tree and KNN were the least effective, with both models achieving accuracies below 70% and AUROCs of 0.75 and 0.74, respectively. The confusion matrix for the RF model (Fig. 3) provides further insight into its performance, revealing 1055 true positives (correctly predicted health facility deliveries) and 1157 true negatives (correctly predicted home deliveries). The RF model yielded 277 false positives (home deliveries incorrectly predicted as health facility deliveries) and 215 false negatives (health facility deliveries incorrectly predicted as home deliveries). These metrics highlight the ability of the RF model to balance sensitivity and specificity, making it the most robust predictor of health-facility delivery among all the evaluated models.

3.5 AUROC curve

The performance of the machine learning models was evaluated using the Area Under the Receiver Operating Characteristic Curve (AUROC) and confusion matrices. The AUROC curve (Fig. 4) provides a visual representation of the trade-off between the true positive rate (sensitivity) and false positive rate (1-specificity) for each model. The Random Forest (RF) model demonstrated the highest AUROC value of 0.89, indicating

Table 2 Bivariate and multivariable analysis of factors associated place delivery

Variable	Place of delivery		COR [95% C.I]	AOR [95% C.I]
	Home freq. (%)	Health facility freq. (%)		
Age in 5-year groups				
15–19 (Ref)	409 (74%)	142 (26%)	1	ref
20–24	1336 (74%)	480 (26%)	1.03[0.77–1.38]	0.87 [0.62–1.22]
25–29	1839 (75%)	609 (25%)	0.95[0.72–1.26]	0.79 [0.57–1.10]
30–34	1367 (76%)	423 (24%)	0.89[0.66–1.19]	0.72 [0.51–1.02]
35–39	1170 (78%)	328 (22%)	0.81[0.60–1.09]	0.65 [0.48–0.98]*
40–44	521 (82%)	114 (18%)	0.63[0.43–0.93]*	0.58 [0.37–0.90]*
45–49	168 (83%)	35 (17%)	0.60[0.34–1.05]	0.49 [0.25–0.98]*
Education				
No education (Ref)	6105 (81%)	1386 (19%)	1	ref
Primary	584 (54%)	492 (46%)	3.72[3.10–4.45]**	1.92 [1.55–2.38]**
Secondary	101 (37%)	171 (63%)	7.40[5.44–10.08]**	2.80 [1.99–3.95]**
Higher	26 (24%)	82 (76%)	13.58[7.32–25.19]**	4.24 [2.16–8.32]**
Marital status				
Married (Ref)	6264 (77%)	1867 (23%)	1	ref
Divorced	379 (65%)	202 (35%)	1.78[1.41–2.26]**	1.11 [0.84–1.47]
Widowed	172 (73%)	63 (27%)	1.24[0.84–1.81]	1.45 [0.94–2.25]
Wealth quintile				
Lowest (Ref)	2051 (94%)	128 (6%)	1	ref
Second	1656 (90%)	180 (10%)	1.74[1.22–2.47]**	1.71 [1.15–2.56]**
Middle	1272 (76%)	404 (24%)	5.06[3.71–6.91]**	2.36 [1.58–3.53]**
Fourth	1168 (65%)	623 (35%)	8.52[6.32–11.48]**	3.60 [2.42–5.37]**
Highest	669 (46%)	796 (54%)	18.95[14.03–25.60]**	6.01 [4.04–8.94]**
Distance to health facility				
Big problem (Ref)	4588 (80%)	1132 (20%)	1	ref
Not a big problem	2224 (69%)	1001 (31%)	1.82[1.60–2.09]**	1.09 [0.93–1.28]
Currently working				
Yes (Ref)	410 (69%)	188 (31%)	1	ref
No	6404 (77%)	1944 (23%)	0.66[0.52–0.84]**	0.99 [0.74–1.33]
Births in last five years				
0 (Ref)	289 (79%)	76 (21%)	1	1
1	2266 (74%)	778 (26%)	1.31[0.92–1.87]	1.45 [0.94—2.23]
2	2631 (77%)	790 (23%)	1.15[0.81–1.63]	1.28 [0.84—1.97]
3	1382 (76%)	424 (23%)	1.17[0.81–1.69]	1.13 [0.72—1.78]
4+	246 (79%)	65 (21%)	1.01[0.62–1.64]	0.96 [0.54—1.68]
ANC visits				
< =4 visit (Ref)	6474 (79.26%)	1694 (20.74%)	1	1
.= >4 visit	266 (35.19%)	490 (64.81%)	7.04 [6.00–8.25]**	4.82 [3.75—6.20]**
Residence				
Urban (Ref)	1868 (60%)	1240 (40%)	1	ref
Rural	1959 (73%)	723 (27%)	0.56[0.48–0.65]**	0.71 [0.59–0.86]**
Nomadic	2989 (95%)	169 (5%)	0.09[0.07–0.11]**	0.23 [0.16–0.32]**
Region				
Woqooyi Galbeed (Ref)	227 (42%)	308 (58%)	1 -	ref
Awdal	543 (72%)	208 (28%)	0.28 [0.19–0.40]**	0.80 [0.54–1.20]
Togdheer	205 (73%)	76 (27%)	0.28 [0.21–0.36]**	0.37 [0.27–0.50]**
Sool	610 (87%)	90 (13%)	0.11 [0.08–0.15]**	0.18 [0.13–0.26]**
Sanaag	795 (87%)	114 (13%)	0.11 [0.08–0.14]**	0.10 [0.07–0.14]**
Bari	448 (80%)	109 (20%)	0.18 [0.13–0.25]**	0.18 [0.12–0.27]**
Nugaal	770 (78%)	213 (22%)	0.20 [0.15–0.28]**	0.15 [0.14–0.28]**
Mudug	849 (73%)	311 (27%)	0.27 [0.20–0.36]**	0.23 [0.16–0.31]**
Galgaduud	626 (65%)	343 (35%)	0.40 [0.30–0.54]**	0.45 [0.32–0.63]**

Table 2 (continued)

Variable	Place of delivery		COR [95% C.I]	AOR [95% C.I]
	Home freq. (%)	Health facility freq. (%)		
Hiraan	567 (95%)	29 (5%)	0.04 [0.02–0.06]**	0.04 [0.02–0.06]**
Middle Shabelle	273 (82%)	61 (18%)	0.16 [0.11–0.24]**	0.18 [0.12–0.26]**
Banadir	291 (60%)	190 (40%)	0.48 [0.38–0.61]**	0.20 [0.15–0.27]**
Bay	69 (81%)	16 (19%)	0.18 [0.12–0.26]**	0.11 [0.07–0.17]**
Bakool	332 (98%)	8 (2%)	0.02 [0.01–0.03]**	0.04 [0.02–0.06]**
Gedo	85 (81%)	19 (19%)	0.17 [0.12–0.24]**	0.22 [0.15–0.32]**
Lower Juba	113 (78%)	32 (22%)	0.21 [0.15–0.30]**	0.13 [0.09–0.20]**

** p-value < 0.001; * p-value < 0.05

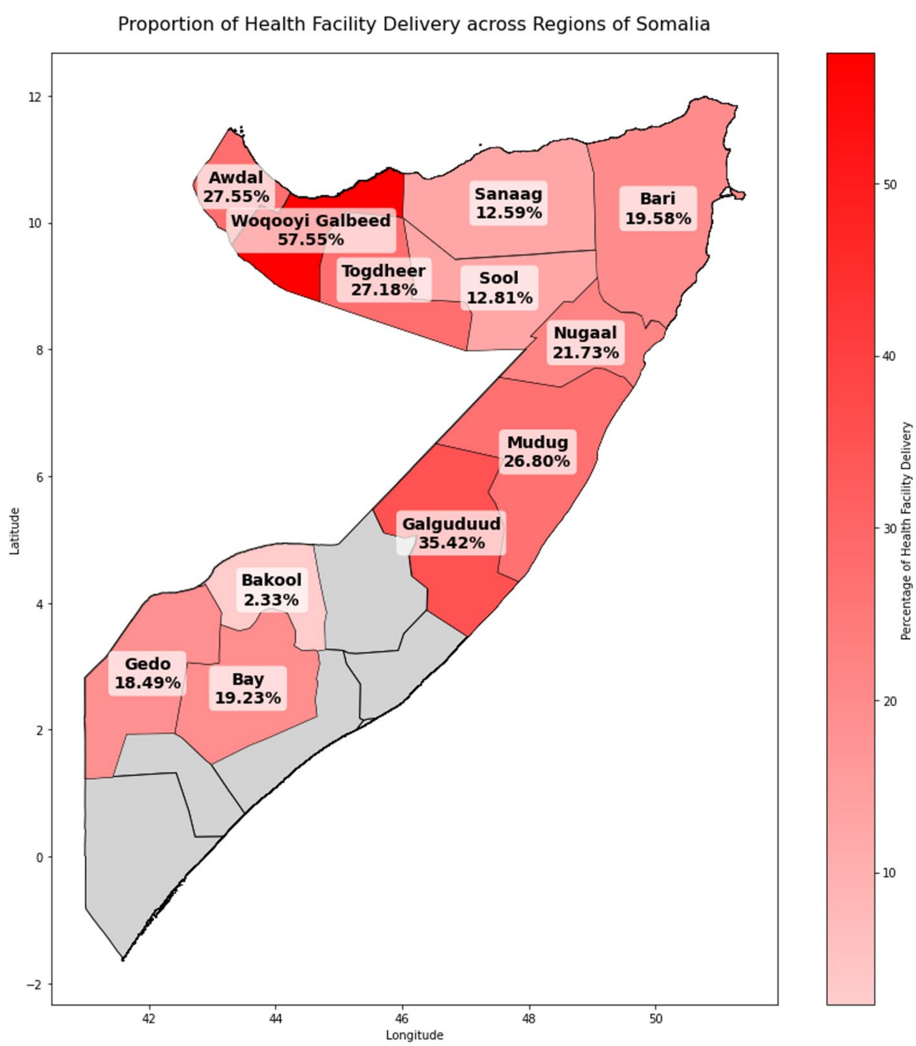

Fig. 1 Map of Somalia showing proportion of health facility delivery across the regions

excellent discriminative ability in predicting health facility delivery. This was closely followed by XGBoost with an AUROC of 0.89 and Gradient Boosting with an AUROC of 0.86. Other models, such as Logistic Regression and SVM, showed lower AUROC values of 0.80 and 0.81, respectively, suggesting relatively lower performance.

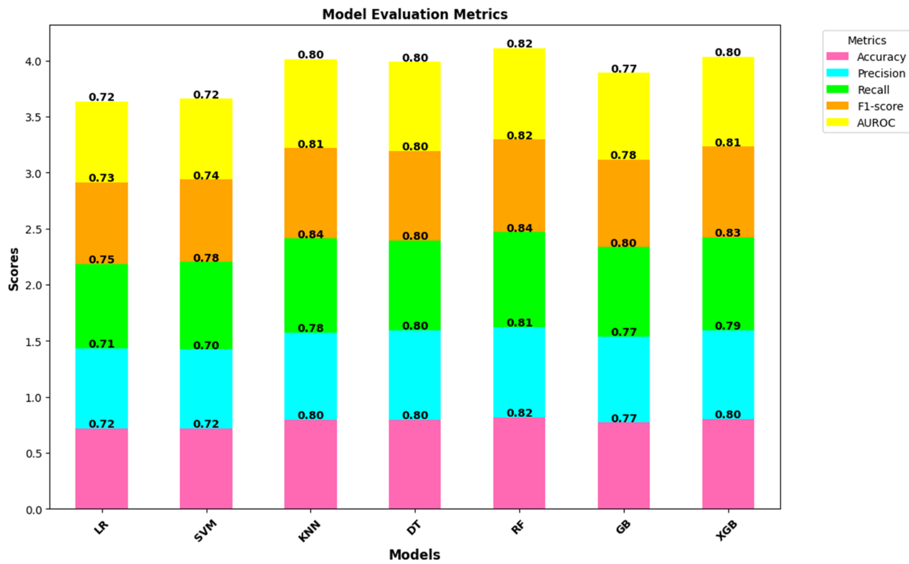

Fig. 2 Model evaluation metrics

Table 3 Model evaluation and confusion matrix

Evaluation metrics	**Models**						
	LR	**SVM**	**KNN**	**DT**	**RF**	**GB**	**XGB**
Accuracy	0.72	0.72	0.80	0.80	0.82	0.77	0.80
Precision	0.71	0.70	0.78	0.80	0.81	0.77	0.79
Recall	0.75	0.78	0.84	0.80	0.84	0.80	0.83
F1-score	0.73	0.74	0.81	0.80	0.82	0.78	0.81
AUROC	0.72	0.72	0.80	0.80	0.82	0.77	0.80
Confusion matrix							
TP	920	885	1005	1055	1055	998	1037
FP	412	447	327	277	277	334	295
FN	345	308	225	275	215	279	239
TN	1027	1064	1147	1097	1157	1093	1133

3.6 Feature importance analysis using SHAP

SHAP (SHapley Additive exPlanations) analysis was conducted to identify and interpret the most influential features affecting health facility delivery among women in Somalia. SHAP values provide a consistent, model-agnostic approach to explain the contribution of each predictor variable to the model's predictions. The beeswarm summary plot (Fig. 5) visually represents the distribution of the SHAP values for each feature, highlighting their overall impact on the model output.

The wealth quintile emerged as the most critical predictor, with higher SHAP values indicating a strong positive contribution to the likelihood of delivery in a health facility. Residence type was the second most important feature, reflecting its significant influence on health-facility delivery predictions. Education level, antenatal care (ANC) visits, and regional variations were identified as key contributors. Features such as marital status, work status, and distance to a health facility showed moderate importance, while age and number of births in the last five years had a relatively smaller impact on model predictions.

The SHAP dot plot (Fig. 6) and bar plot (Fig. 7) further summarized the overall importance of each feature, providing a clear hierarchy of predictors. Overall, the SHAP

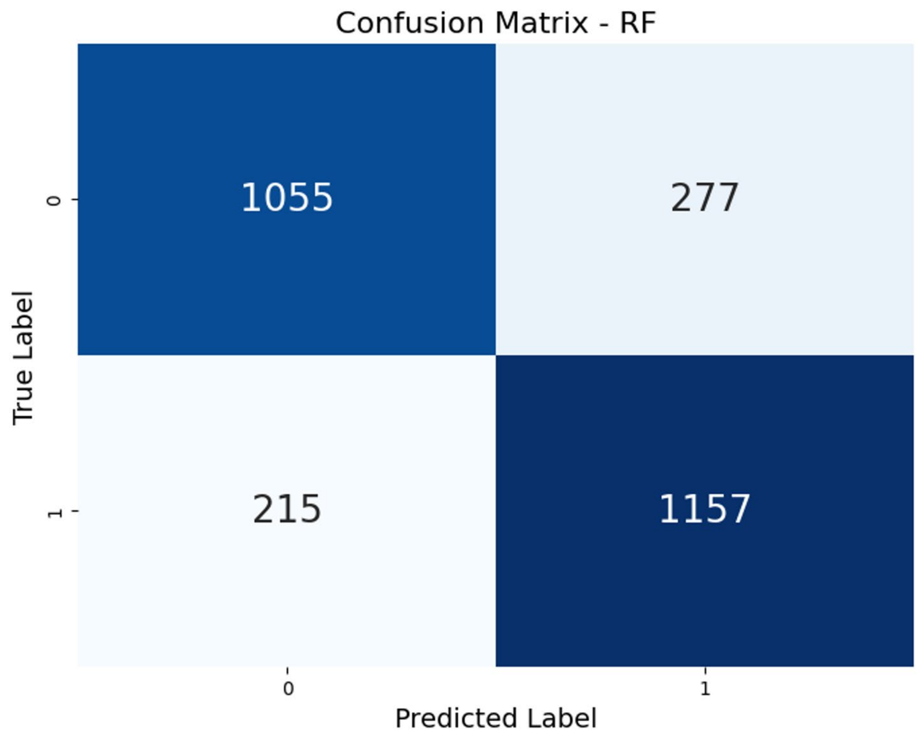

Fig. 3 Confusion matrix of random forest

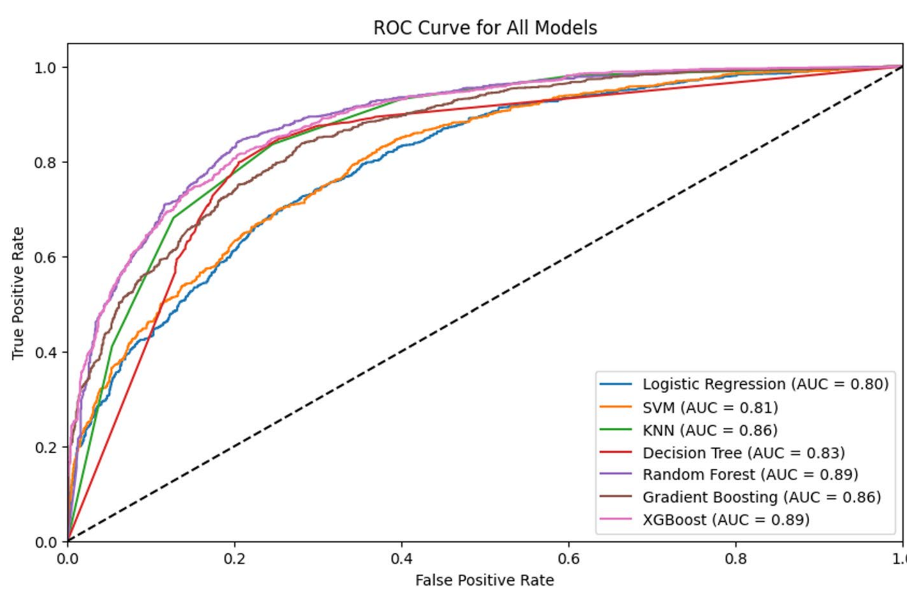

Fig. 4 AURCOC curve for all models

analysis emphasized the critical roles of socioeconomic factors, healthcare access, and geographic disparities in shaping maternal healthcare utilization in Somalia.

4 Discussion

This study demonstrates the application of machine learning (ML) techniques in predicting health facility deliveries among women in Somalia, highlighting the value of predictive modelling and feature interpretation through SHapley Additive exPlanations

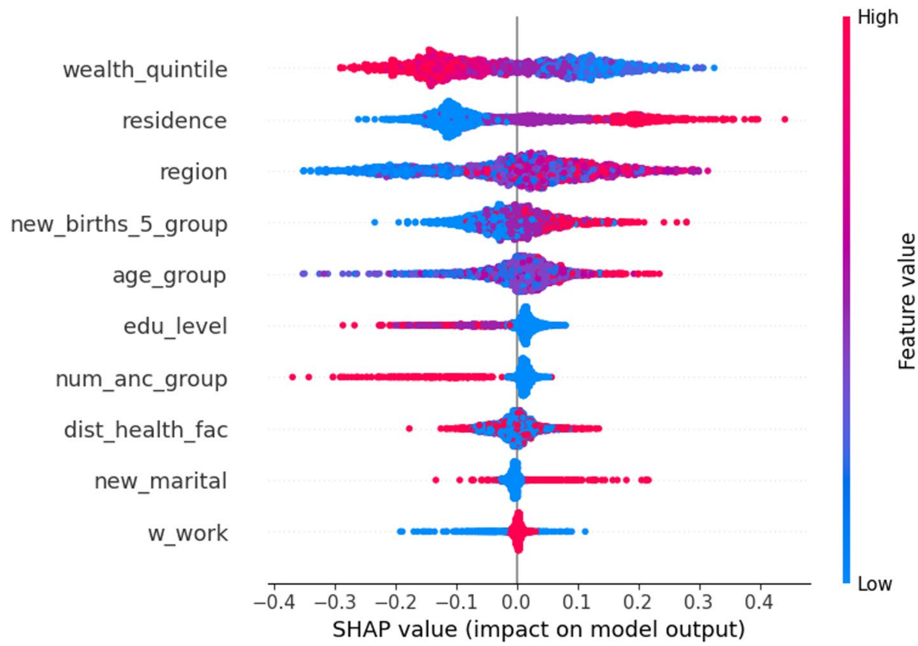

Fig. 5 Beeswarm summary plot

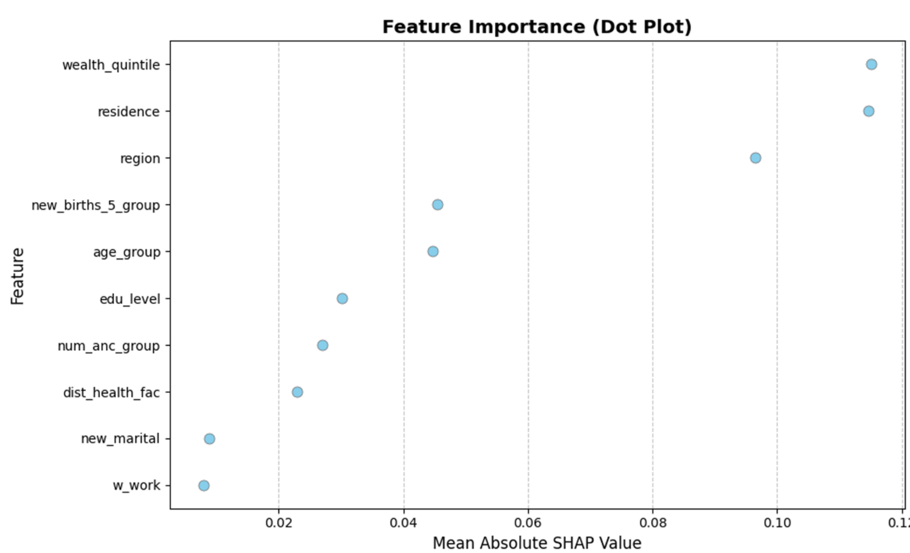

Fig. 6 SHAP dot plot of features importance

(SHAP). Among the seven ML models, Random Forest (RF) emerged as the most effective, with an accuracy of 82%, precision of 81%, recall of 84%, and AUROC of 0.89. These metrics underscore the model's ability to generate balanced and reliable predictions, outperforming XGBoost (accuracy: 80%, AUROC: 0.89) and Gradient Boosting (accuracy: 77%, AUROC: 0.86). SHAP analysis identified wealth quintile as the most influential predictor, with women in the highest wealth quintile being six times more likely to deliver in health facilities than those in the lowest quintile (AOR: 6.01; 95% CI: 4.04–8.94). This finding aligns with prior evidence that financial capacity significantly affects healthcare access and utilization [34, 35]. The ability of the RF model to detect and prioritize wealth

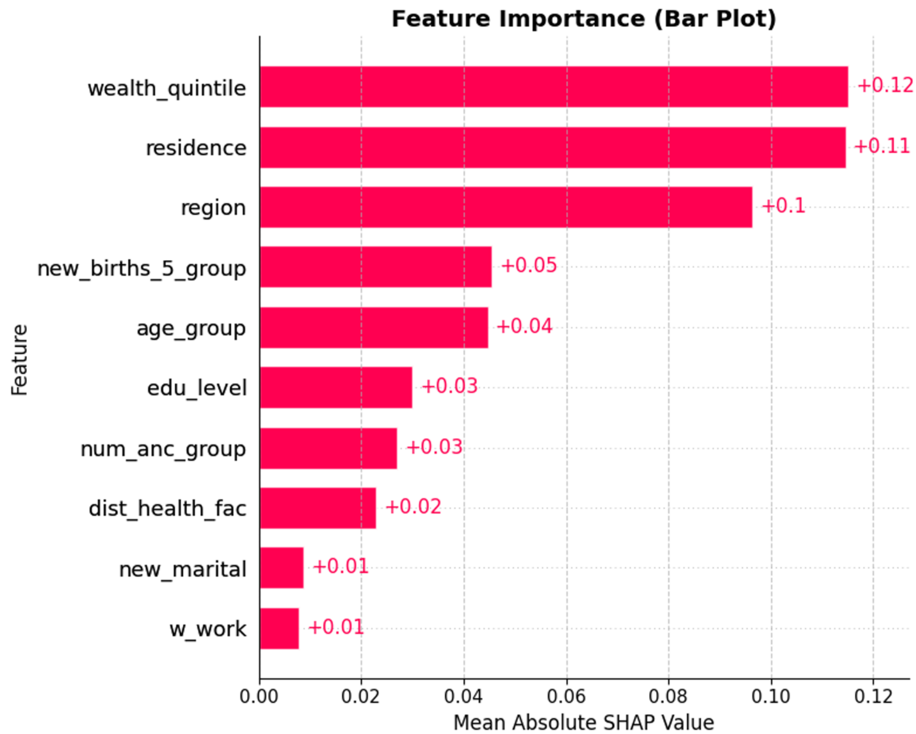

Fig. 7 SHAP bar plot of feature importance

as a critical determinant highlights its practical utility in informing targeted maternal health interventions [36].

Antenatal care (ANC) attendance was another pivotal predictor revealed through both the regression and SHAP analyses. Women who attended four or more ANC visits were nearly five times more likely to deliver at health facilities (AOR: 4.82; 95% CI: 3.75–6.20). This reinforces ANC's well-established role as an entry point for institutional deliveries and maternal health improvements [37, 38]. Geographic disparities in facility-based deliveries were also significant, with Woqooyi Galbeed reporting the highest facility delivery rate (58%) and Bakool the lowest (2%). These variations reflect differences in healthcare infrastructure and accessibility [39]. The ability of the RF model to integrate geographic factors underscores its adaptability to complex maternal health datasets [40, 41]. Interestingly, simpler models such as Decision Tree and K-Nearest Neighbors (KNN) underperformed, with accuracies below 70% and AUROC values of 0.75 and 0.74, respectively. This contrast underscores the advantage of ensemble models, such as RF, in minimizing overfitting and better handling complex predictor interactions [42, 43]. Additionally, preprocessing techniques, including the Synthetic Minority Oversampling Technique (SMOTE), played a key role in addressing class imbalance between home and facility deliveries. By generating synthetic samples for the underrepresented class, SMOTE helped RF maintain high recall for facility deliveries (84%), ensuring balanced model performance.

The SHAP summary plot visually emphasized the hierarchical importance of predictors, with wealth, ANC attendance, and residence type ranking the highest. Urban women were significantly more likely to deliver in facilities (AOR: 1.45; 95% CI: 1.17–1.78), whereas nomadic women were disadvantaged (AOR: 0.23; 95% CI: 0.16–0.32). These insights demonstrate ML models' ability to uncover actionable predictors and guide equity-focused health interventions [44–46]. Several studies have applied ML techniques to maternal health, particularly in predicting pregnancy risks, antenatal care utilization, and institutional deliveries [20, 26, 28, 29, 36]. For instance, studies in Nigeria and Ethiopia have used ML to identify determinants of facility-based deliveries, emphasizing socioeconomic factors such as wealth status and ANC attendance [20, 29, 30]. Our study aligns with these findings, reinforcing the role of economic and healthcare access disparities in maternal health outcomes. However, unlike prior research that primarily relied on logistic regression, our study employs tree-based and ensemble methods, such as RF and XGBoost, which enhance predictive power and model interpretability [22, 26, 47]. The integration of SHAP enhances explainability, allowing for detailed insights into predictor influence [24, 48]. These findings highlight ML's potential to complement traditional public health strategies by identifying high-risk groups and informing targeted interventions.

Policymakers should leverage these tools to identify high-risk groups, such as women in lower-wealth quintiles and nomadic communities and prioritize tailored programs to address their unique barriers. Expanding access to maternal healthcare services in underserved regions, such as Bakool and other low-performing areas, is critical to bridging geographic disparities. Given the strong association between wealth and facility-based deliveries, targeted financial interventions such as conditional cash transfers, maternal health insurance subsidies, or transport vouchers could help mitigate economic barriers [34]. Strengthening ANC programs is also essential, as frequent ANC visits strongly predict facility deliveries. This can be achieved through mobile health clinics, community-based ANC outreach, and digital health solutions that provide appointment reminders and maternal health education [19]. Geographic disparities in health facility utilization further highlight the need for expanding maternal health services in rural and nomadic regions. Establishing maternity waiting homes, increasing the deployment of skilled birth attendants, and enhancing transportation support systems could help bridge access gaps [7]. By integrating ML-based predictive tools into maternal health policies, governments and healthcare organizations can better identify at-risk populations, allocate resources, and implement data-driven interventions that improve maternal and neonatal health outcomes [41].

5 Conclusion

Machine learning techniques, particularly Random Forest and SHAP analyses, provide robust tools for predicting health facility deliveries and identifying critical determinants. This study demonstrated the effectiveness of ML in offering both accurate predictions and interpretable insights, highlighting the wealth quintile, ANC attendance, and residence type as key predictors. Geographic disparities underscore the importance of tailored interventions to address inequities in maternal health care access across Somalia.

6 Limitations

Although the ML models provided robust predictions, this study has several limitations. The use of cross-sectional data restricts causal inferences regarding predictors and health facility delivery. Future research should incorporate longitudinal datasets to track women's healthcare-seeking behaviors over time and establish temporal associations. The reliance on self-reported data on ANC visits and delivery locations may introduce recall bias. Integrating real-time hospital records, electronic health systems, or mobile health applications could enhance data accuracy and reduce recall bias in future studies. Additionally, the lack of external validation restricts the generalizability of findings beyond Somalia. To address this, ML models should be tested on similar datasets from other low-resource settings to assess their robustness and applicability. Lastly, while SHAP analysis enhances model interpretability, ML algorithms can still be complex for direct integration into routine maternal health decision-making. Developing user-friendly ML dashboards and training healthcare professionals in ML-assisted decision-making could facilitate practical adoption in maternal health programs.

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Author contributions
JS conceptualized the study, designed the methodology, performed data analysis, visualized the results, and wrote the manuscript. SH and MMA contributed by providing critical reviews and editing the manuscript. AA and JHM offered additional insights and technical support during the manuscript preparation. All authors have reviewed and approved the final version of the manuscript.

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Data availability
The SDHS dataset is publicly available through the DHS Program website (https://dhsprogram.com/) upon request. While the data are in the public domain, access may be subject to registration and adherence to the DHS Program's data use policies. Information on accessing the data can also be found on the Somali Bureau of Statistics website (https://nbs.gov.so/).

Declarations

Ethics approval and consent to participate
This study employed secondary data from the 2020 Somalia Demographic and Health Survey (SDHS). The SDHS was conducted in accordance with international ethical standards, and ethical approval for the primary data collection was granted by the ICF Institutional Review Board (IRB) and the Somalia Ministry of Health. As this secondary analysis used fully anonymized data, no additional ethical approval was required.

Competing interests
The authors declare that they have no conflicts of interest.

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References

1. Adeyemo MO, Olaogun MS, Alawode GO, Idoko SO, Ijeoma JI. Review of policy initiatives on maternal mortality in Nigeria. Int J Res Innov Soc Sci. 2024;8(11):1710–8.
2. Organization WH. Trends in maternal mortality 2000 to 2020: estimates by WHO, UNICEF, UNFPA, World Bank Group and UNDESA/Population Division [Internet]. World Health Organization; 2023 [cited 2024 Nov 19]. Available from: https://books.google.com/books?hl=en&lr=&id=6WnWEAAAQBAJ&oi=fnd&pg=PR17&dq=Trends+in+maternal+mortality+2000+to+2020+-+IRIS&ots=93UHeN2q-H&sig=-iwGZYpehKeoXnuDp9BknFbhNkE
3. Newborn mortality [Internet]. [cited 2024 Dec 31]. Available from: https://www.who.int/news-room/fact-sheets/detail/newborn-mortality
4. Gliozheni O, Gliozheni E. Some Solutions to Reduce Maternal Mortality. Orion [Internet]. 2020 [cited 2024 Dec 31];14(1). Available from: https://www.ijhns.com/abstractArticleContentBrowse/DSJUOG/18925/JPD/fullText
5. Birabwa C, Beňová L, van Olmen J, Semaan A, Waiswa P, Banke-Thomas A. Emergency Obstetric Care Access Dynamics in Kampala City, Uganda: Analysis of Women's Self-Reported Care-Seeking Pathways. Glob Health Sci Pract. 2024;12(6): e2400242.
6. Khanam R, Baqui AH, Syed MIM, Harrison M, Begum N, Quaiyum A, et al. Can facility delivery reduce the risk of intrapartum complications-related perinatal mortality? Findings from a cohort study. J Glob Health. 8(1):010408.
7. Jaca A, Malinga T, Iwu-Jaja CJ, Nnaji CA, Okeibunor JC, Kamuya D, et al. Strengthening the Health System as a Strategy to Achieving a Universal Health Coverage in Underprivileged Communities in Africa: A Scoping Review. Int J Environ Res Public Health. 2022;19(1):587.
8. Ahmed S, Chase LE, Wagnild J, Akhter N, Sturridge S, Clarke A, et al. Community health workers and health equity in low- and middle-income countries: systematic review and recommendations for policy and practice. Int J Equity Health. 2022;21(1):49.
9. Abubakar I, Dalglish SL, Angell B, Sanuade O, Abimbola S, Adamu AL, et al. The Lancet Nigeria Commission: investing in health and the future of the nation. Lancet. 2022;399(10330):1155–200.

10. UNFPA Somalia [Internet]. [cited 2024 Dec 31]. Renewing the fight against maternal and new-born mortality in Somalia. Available from: https://somalia.unfpa.org/en/news/renewing-fight-against-maternal-and-new-born-mortality-somalia
11. Aweis A, Osoble AH, Mohamed SA, Aweis A. Obstetric transition: trends in maternal mortality in Somalia over the last two decades. Int Health. 2024. https://doi.org/10.1093/inthealth/ihad121.
12. Dahab R, Sakellariou D. Barriers to accessing maternal care in low income countries in Africa: a systematic review. Int J Environ Res Public Health. 2020;17(12): 4292.
13. Mugambe RK, Yakubu H, Wafula ST, Ssekamatte T, Kasasa S, Isunju JB, et al. Factors associated with health facility deliveries among mothers living in hospital catchment areas in Rukungiri and Kanungu districts, Uganda. BMC Pregnancy Childbirth. 2021;21(1): 329.
14. Mugambe RK, Yakubu H, Wafula ST, Ssekamatte T, Kasasa S, Isunju JB, et al. Factors associated with health facility deliveries among mothers living in hospital catchment areas in Rukungiri and Kanungu districts, Uganda. BMC Pregnancy Childbirth. 2021;21: 329.
15. Etokidem A, Agbor I, Isika A, Ago B, Mkpanam N. Predictors of utilization of facility-based ante-natal care and delivery services in a Nigerian rural community. Afr Health Sci. 2022;22(1):139.
16. Olwanda E, Opondo K, Oluoch D, Croke K, Maluni J, Jepkosgei J, et al. Women's autonomy and maternal health decision making in Kenya: implications for service delivery reform–a qualitative study. BMC Womens Health. 2024;19(24):181.
17. Chen X, Orom H, Hay JL, Waters EA, Schofield E, Li Y, et al. Differences in rural and urban health information access and use. J Rural Health. 2019;35(3):405–17.
18. Wulifan JK, Dordah AD, Sumankuuro J. Nomadic pastoralists' experience accessing reproductive and maternal healthcare services in low and middle-income countries: a contextual scoping review. Pastoralism. 2022;12(1):47.
19. Abdus-Salam RA, Mark T, Agboola AD, Babawarun T. Healthcare financing for antenatal care and delivery services in a tertiary health facility in South-West Nigeria. Ann Ibadan Postgrad Med. 2021;19(1):56–62.
20. Mennickent D, Rodríguez A, MaC O, Riedel CA, Castro E, Eriz-Salinas A, et al. Machine learning applied in maternal and fetal health: a narrative review focused on pregnancy diseases and complications. Front Endocrinol. 2023;14:1130139.
21. Ley C, Martin RK, Pareek A, Groll A, Seil R, Tischer T. Machine learning and conventional statistics: making sense of the differences. Knee Surg Sports Traumatol Arthrosc. 2022;30(3):753–7.
22. Kalantari E, Gholami H, Malakooti H, Eftekhari M, Saneei P, Esfandiarpour D, et al. Evaluating traditional versus ensemble machine learning methods for predicting missing data of daily PM10 concentration. Atmos Pollut Res. 2024;15(5): 102063.
23. Ning Y, Ong MEH, Chakraborty B, Goldstein BA, Ting DSW, Vaughan R, et al. Shapley variable importance cloud for interpretable machine learning. Patterns [Internet]. 2022 [cited 2024 Dec 31];3(4). Available from: https://www.cell.com/patterns/fulltext/S2666-3899(22)00025-3
24. Feretzakis G, Sakagianni A, Anastasiou A, Kapogianni I, Bazakidou E, Koufopoulos P, et al. Integrating Shapley values into machine learning techniques for enhanced predictions of hospital admissions. Appl Sci. 2024;14(13): 5925.
25. Tadese ZB, Hailu DT, Abebe AW, Kebede SD, Walle AD, Seifu BL, et al. Interpretable prediction of acute respiratory infection disease among under-five children in Ethiopia using ensemble machine learning and Shapley additive explanations (SHAP). Digit Health. 2024;10: 20552076241272739.
26. Fredriksson A, Fulcher IR, Russell AL, Li T, Tsai YT, Seif SS, et al. Machine learning for maternal health: predicting delivery location in a community health worker program in Zanzibar. Front Digit Health. 2022;4: 855236.
27. Owusu-Adjei M, Ben Hayfron-Acquah J, Gaddafi AS, Frimpong T. An AI-based approach to predict delivery outcome based on measurable factors of pregnant mothers. medRxiv. 2024;2024–06.
28. Walle AD, Kebede SD, Adem JB, Gebreegziabher Z, Mamo D. Machine learning algorithm to predict determinants of home delivery after ANC visit among reproductive age women in East Africa: Using SHAP. 2024 [cited 2024 Dec 31]; Available from: https://www.researchsquare.com/article/rs-4223378/latest
29. Sani J, Ahmed MM, Oluyomi AO. Exploring machine learning algorithms for predicting early antenatal care initiation at first trimester among reproductive women in Nigeria. 2024 [cited 2024 Nov 24]; Available from: https://www.researchsquare.com/article/rs-5321613/latest
30. Njagi CO. Predicting Antenatal Care (ANC) Visits using machine learning algorithms [Internet] [PhD Thesis]. University of Nairobi; 2022 [cited 2024 Dec 31]. Available from: http://erepository.uonbi.ac.ke/handle/11295/164115
31. WHO, Somalia, Population. datadot. [cited 2025 Mar 7]. Somalia. Available from: https://data.who.int/countries/706
32. World Population Dashboard -Somalia| United Nations Population Fund [Internet]. [cited 2025 Mar 7]. Available from: https://www.unfpa.org/data/world-population/SO
33. Sheikh NS, Hussein AM, Mohamed SS, Gele A. Does living in major towns favor institutional delivery in Somalia? Front Global Women's Health. 2024;5:1216290.
34. Adams A, Kluender R, Mahoney N, Wang J, Wong F, Yin W. The impact of financial assistance programs on health care utilization: evidence from kaiser permanente. Am Econ Rev Insights. 2022;4(3):389–407.
35. Bintabara D, Mwampagatwa I. Socioeconomic inequalities in maternal healthcare utilization: an analysis of the interaction between wealth status and education, a population-based surveys in Tanzania. PLOS Glob Public Health. 2023;3(6): e0002006.
36. Al Mashrafi SS, Tafakori L, Abdollahian M. Predicting maternal risk level using machine learning models. BMC Pregnancy Childbirth. 2024;24(1):820.
37. Mwenebanda E, Machado A, Patel AI, Nyondo-Mipando AL, Chiumia IK. Factors influencing antenatal care attendance in the eight contact era policy: a case of selected maternal health service facilities in Blantyre, Malawi. BMC Pregnancy Childbirth. 2024;24(1):704.
38. Sani J, Ahmed A, Wagini Hassan A, Wali I, Bashir A, Danjuma A. Disparities in optimal antenatal care visits among women in north-western states of Nigeria. 2024 Nov 24;2024
39. Afolabi RF, Salawu MM, Bamgboye EA, Bello S, Adebowale AS, Dairo MD, et al. Regional differences in the utilisation of antenatal care and skilled birth attendant services during the COVID-19 pandemic in Nigeria: an interrupted time series analysis. BMJ Glob Health. 2023;8(10): e012464.
40. Prathap KR, Bhavani R. Study comparing classification algorithms for loan approval predictability (Logistic Regression, XG boost, Random Forest, Decision Tree). J Surv Fisheries Sci. 2023;10(1S):2438–47.

41. Wallkulle T. Exploring the importance of women's educational attainment in HIV risk prediction: a comparative study of logistic regression, random forest and XGBoost [Internet]. 2023 [cited 2024 Oct 30]. Available from: https://www.diva-portal.org/smash/record.jsf?pid=diva2:1763928
42. Khan AA, Chaudhari O, Chandra R. A review of ensemble learning and data augmentation models for class imbalanced problems: combination, implementation and evaluation. Expert Syst Appl. 2024;15(244): 122778.
43. Kigo SN, Omondi EO, Omolo BO. Assessing predictive performance of supervised machine learning algorithms for a diamond pricing model. Sci Rep. 2023;13(1): 17315.
44. Olawade DB, Wada OJ, David-Olawade AC, Kunonga E, Abaire O, Ling J. Using artificial intelligence to improve public health: a narrative review. Front Public Health. 2023;11: 1196397.
45. Rubinger L, Gazendam A, Ekhtiari S, Bhandari M. Machine learning and artificial intelligence in research and healthcare. Injury. 2023;54:S69-73.
46. Hamilton AJ, Strauss AT, Martinez DA, Hinson JS, Levin S, Lin G, et al. Machine learning and artificial intelligence: applications in healthcare epidemiology. Antimicrob Steward Healthc Epidemiol. 2021;1(1): e28.
47. Che D, Liu Q, Rasheed K, Tao X. Decision tree and ensemble learning algorithms with their applications in bioinformatics. In: Arabnia HR, Tran QN, editors. Software Tools and Algorithms for Biological Systems [Internet]. New York, NY: Springer New York; 2011 [cited 2024 Oct 18]. p. 191–9. (Advances in Experimental Medicine and Biology; vol. 696). Available from: http://link.springer.com/https://doi.org/10.1007/978-1-4419-7046-6_19
48. Ponce-Bobadilla AV, Schmitt V, Maier CS, Mensing S, Stodtmann S. Practical guide to SHAP analysis: Explaining supervised machine learning model predictions in drug development. Clin Transl Sci. 2024;17(11): e70056.

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