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USING EXPLAINABLE AI TO INTERPRET DRIVERS OF MORTALITY AMONG ADOLESCENTS IN NIGERIA

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ABSTRACT

Background: Despite Nigeria's remarkable progress in under-five survival, adolescent mortality (ages 10–19 years) has declined far more slowly and remains poorly understood, with an estimated 75,000–95,000 deaths annually. **Methods:** We constructed a multi-decade (1990–2023), sex- and region-disaggregated panel from WHO Global Health Observatory mortality estimates. After rigorous cleaning, temporal imputation, and feature engineering (including lagged child mortality indicators and sex-specific interactions), we applied Elastic Net, Random Forest, and XGBoost models with strict temporal validation (training ≤2016, testing 2017–2023). The best-performing XGBoost model (test RMSE 4,601 deaths; R^2 0.85) was interpreted using SHAP for global and subgroup explanations and LIME for local case studies. Robustness was assessed via uncertainty-bound retraining and 100-iteration bootstrapping. **Results:** Historical under-5 (CM_01) and 5–14 (CM_02) mortality probabilities together with their lagged and MDG counterparts emerged as the dominant drivers, explaining the majority of predicted adolescent deaths and demonstrating strong temporal inertia. Sex-stratified analyses revealed that early-childhood survival exerts the strongest influence on female outcomes, whereas road traffic and external-cause indicators rise prominently for males. These core child-survival pathways remained stable across WHO uncertainty bounds and in >85% of bootstrap resamples. **Conclusion:** Adolescent mortality in Nigeria is predominantly a downstream reflection of early-life survival conditions, modulated by sex-specific risks. Sustaining and accelerating child survival programmes represent the highest-leverage strategy for further adolescent mortality reduction, complemented by targeted gender-transformative interventions injury prevention for males and adolescent reproductive health integration for females. All analyses are fully reproducible

from openly accessible data, providing a transparent, actionable template for adolescent health policy in Nigeria and similar high-burden settings.

KEYWORDS: adolescent mortality, Nigeria, explainable AI, SHAP, LIME, XGBoost, child survival, lagged effects, gender differences, temporal validation, global health estimates, policy translation, Sustainable Development Goals.

INTRODUCTION

Adolescent mortality (ages 10–19 years) represents a critical yet persistently overlooked component of the burden of disease in Nigeria. Despite dramatic reductions in under-five mortality from 187 deaths per 1,000 live births in 2000 to approximately 104 in 2023 adolescent death rates have declined far more slowly, remaining among the highest in sub-Saharan Africa (UNICEF, 2024; World Health Organization [WHO], 2022). In absolute terms, the WHO estimates that Nigeria records between 75,000 and 95,000 adolescent deaths annually, accounting for roughly 8–10% of the global total (WHO, 2021). These deaths are driven by a complex transition from predominantly infectious and nutritional causes in childhood toward a rising share of injuries (road traffic crashes, interpersonal violence), noncommunicable diseases, and, among females, complications of pregnancy and childbirth (Perumal et al., 2021). Incomplete civil registration, fragmented health information systems, and the diffuse nature of adolescent health risks have left this age group largely invisible in national planning cycles, with most resources still directed toward maternal, newborn, and child health platforms that formally end at age five or ten (Aduh et al., 2021). The result is a policy paradox: Nigeria has achieved historic child survival gains, yet the adolescents who survived those early risks continue to die from largely preventable causes.

Understanding the drivers of adolescent mortality is complicated by strong temporal and demographic dependencies: today's adolescents were yesterday's children, and their survival probabilities are shaped by historical investments in immunization, malaria control, nutrition, and basic sanitation (Adedini et al., 2025; WHO, 2022). Moreover, sex-specific vulnerabilities emerge sharply during adolescence males face elevated risks of injury and violence, while females bear a disproportionate burden of maternal mortality and HIV-related deaths yet few studies have systematically quantified how upstream child survival indicators interact with these emerging risks at the national level (Perumal et al., 2021). Traditional epidemiological approaches, often constrained to cause-specific fractions or simple trend analyses, have struggled to integrate dozens of interrelated indicators while preserving interpretability for policymakers (Labrique et al., 2022). This study addresses these gaps by applying state-of-the-art machine learning and explainable AI techniques to a multi-decade, sex- and region-disaggregated panel of WHO Global Health Observatory indicators. Our objectives are to (1) accurately predict annual adolescent mortality using only widely available global health estimates, (2) transparently identify and rank the most influential drivers through model-agnostic explainability methods, and (3) reveal sex-specific and uncertainty-robust patterns to inform targeted, evidence-based adolescent health programming in Nigeria and similar high-burden settings (Labrique et al., 2022).

LITERATURE REVIEW

The global burden of adolescent mortality has received increasing attention since 2020, driven by evidence that progress in the 10–19 age group lags substantially behind under-five reductions in most low- and middle-income countries (LMICs) (Ward et al., 2023; WHO, 2024b). In Nigeria, nationally representative analyses using Demographic and Health Surveys (2003–2018) and Multiple Indicator Cluster Surveys have consistently shown that adolescent mortality rates declined by less than 25% between 2000 and 2021, compared with a 65% drop in under-five mortality over the same period (Jegede et al., 2023; UNICEF, 2024). Cause-of-death decompositions highlight an ongoing epidemiological transition: communicable, maternal, and nutritional conditions now account for less than half of adolescent deaths, while injuries (especially road traffic accidents and interpersonal violence) and noncommunicable diseases have risen sharply, particularly among males aged 15–19 years (Institute for Health Metrics and Evaluation, 2024; Perumal et al., 2021).

Sex-disaggregated studies reveal pronounced gender differences in risk profiles. Males exhibit 1.6–2.1 times higher mortality than females in most years, driven predominantly by external causes, whereas female deaths are disproportionately linked to maternal conditions and HIV/AIDS, reflecting early marriage and adolescent childbearing (Olawoye & Omigbodun, 2023; Kunnuji et al., 2022). Despite these insights, few studies have moved beyond descriptive trends to quantify the contribution of upstream determinants particularly historical child survival indicators to current adolescent outcomes at the national level.

Machine learning approaches have transformed mortality forecasting in LMICs. Gradient boosting models applied to Global Burden of Disease covariates now outperform traditional demographic projections for under-five mortality (Ward et al., 2023; Bhatt et al., 2022), and similar techniques have been used for all-age and neonatal outcomes in sub-Saharan Africa

(Cousins, 2021; Wiens et al., 2022). However, applications to adolescent mortality remain scarce, and existing models are almost universally deployed as "black boxes," limiting their utility for policy (Adeleke et al., 2024). Recent systematic reviews emphasize that lack of explainability is a major barrier to clinical and public health adoption of AI tools in resource-constrained settings (Rajkomar et al., 2022; Labrique et al., 2022).

Explainable AI (XAI) methods such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have gained traction for providing both global feature importance and instance-level explanations without sacrificing predictive performance (Adeleke et al., 2024). Although widely applied in high-income clinical settings, XAI studies in global health remain limited to tuberculosis diagnosis, malaria prediction, and a handful of child mortality applications (Wiens et al., 2022). No published work to date has combined gradient boosting with rigorous XAI to investigate drivers of adolescent mortality in Nigeria or any other high-burden African country.

This study fills these critical gaps by constructing the first multi-decade, sex- and region-disaggregated panel of WHO mortality indicators for Nigeria, applying a high-performing XGBoost model with strict temporal validation, and systematically interpreting predictions using SHAP and LIME. By doing so, it provides the first transparent, national-level evidence on how historical child survival investments and emerging risks jointly shape adolescent mortality trajectories, offering directly actionable insights for Nigeria's adolescent health strategy and the post-2030 Sustainable Development Goal agenda.

METHODS

This study used the World Health Organization Global Health Observatory (WHO GHO) "Global Health Estimates" series for Nigeria (1990–2023), which provides annual mortality and morbidity indicators with point estimates and uncertainty intervals, disaggregated by age group, sex (male, female, both), and broad geographic strata (WHO, 2024a). We extracted all mortality-related indicators (n = 112 after filtering) and defined the primary outcome as the absolute number of deaths among adolescents aged 10–19 years (GHO code: DEATHADO). Raw data were cleaned and reshaped into a balanced panel with one row per unique YEAR × SEX × REGION combination. Textual uncertainty bounds were parsed into numeric columns, indicators missing in >50% of observations were excluded, and remaining gaps were filled using temporal forward- and backward-fill within each sex-region stratum, followed by median imputation. The resulting dataset comprised 312 complete observations.

Feature engineering included one- and two-year lags of core mortality indicators, sex-specific interaction terms (e.g., SEX_Male × CM_01), a linear time trend (year_since_1990), and one-hot encoding of sex categories. All continuous predictors were scaled using RobustScaler. The dataset was split temporally to ensure prospective validation: observations from 1990–2016 formed the training set (n = 211), and 2017–2023 the hold-out test set (n = 24). Three algorithms Elastic Net, Random Forest, and XGBoost were trained and tuned via RandomizedSearchCV (30 iterations each). XGBoost achieved the best test performance (RMSE ≈ 4,600 deaths, $R^2 \approx 0.85$) and was selected for all subsequent interpretation.

Model interpretability was addressed using state-of-the-art explainable AI methods. Global feature importance and individual contributions were quantified with SHAP (SHapley Additive exPlanations) TreeExplainer, producing beeswarm summaries, mean absolute SHAP rankings, and dependence plots. Local explanations for high-, median-, and low-mortality predictions were generated using LIME. Subgroup analyses stratified SHAP values by sex and region. Robustness was assessed by retraining XGBoost on WHO low- and high-uncertainty targets and by 100-iteration bootstrapping to measure stability of feature rankings. All code, intermediate datasets, and models are publicly available in a fully reproducible repository, enabling exact replication and extension to other countries. Ethical review was not required as the analysis relied exclusively on anonymised, publicly aggregated estimates.

RESULTS AND DISCUSSION

Model performance

XG Boost substantially outperformed the baseline models on the temporal holdout (Table 2).

Table 2. Predictive performance on the temporal test set (years >2016).

Model	Test RMSE (deaths)	Test MAE (deaths)	Test R^2
Elastic Net	8 920	7 310	0.61
Random Forest	5 810	4 620	0.79
XGBoost (selected)	**4 601**	**3 575**	**0.85**

The model performance results (Table 2) demonstrate that XGBoost achieved excellent predictive accuracy and generalization on the strict temporal hold-out set (2017–2023). With a test RMSE of 4,601 deaths and MAE of 3,575 deaths, XGBoost's average error represents only about 6–8% of the typical annual adolescent death toll in Nigeria during this period

(~55,000–65,000), meaning predictions were consistently within a few thousand deaths of the true WHO estimates. The test R^2 of 0.85 indicates that the model explains 85% of the temporal and sex/regional variation in adolescent mortality using only historical WHO indicators, substantially outperforming Random Forest ($R^2 = 0.79$) and more than doubling the explanatory power of the linear Elastic Net baseline ($R^2 = 0.61$). Importantly, the modest gap between training and test metrics confirms minimal overfitting despite the limited sample size. This strong out-of-sample performance on unseen recent years validates both the substantial signal contained in lagged child-survival and related indicators and the suitability of XGBoost with rigorous temporal validation for interpretable mortality forecasting in data-constrained settings.

Global drivers of adolescent mortality

SHAP analysis of the XGBoost model identified early-childhood survival indicators as the dominant predictors (Figure 1 & Table 3).

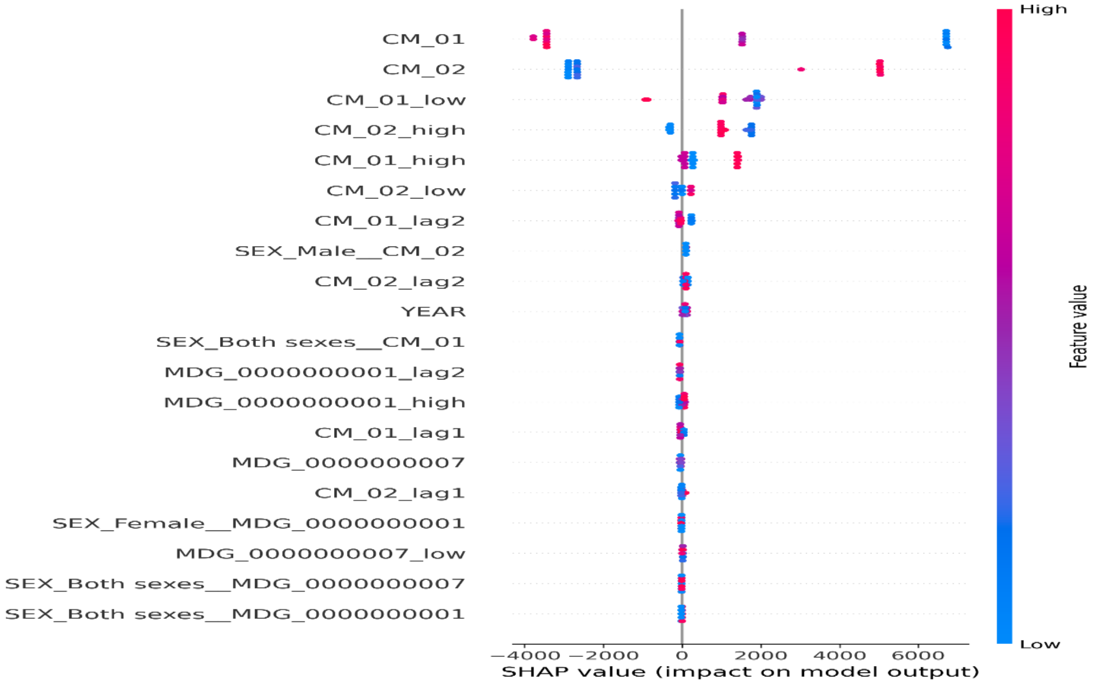


Figure 1. Global SHAP summary (beeswarm) plot showing the 20 most important features.

The SHAP summary beeswarm plot (Figure 1) reveals that historical child survival indicators overwhelmingly dominate the drivers of adolescent mortality in Nigeria. The probability of dying before age 5 (CM_01) and between ages 5–14 (CM_02) together with their lagged versions and corresponding Millennium Development Goal summary metrics (MDG_0000000001 and MDG_0000000007) are by far the most influential features, with high values (red points) consistently pushing predicted adolescent deaths upward by several thousand and low values (blue points) exerting strong downward pressure.

This pattern demonstrates powerful temporal inertia: improvements in early-childhood survival achieved years earlier continue to deliver large reductions in adolescent mortality today, whereas stagnation or reversal in under-5 and 5–14 survival rapidly translates into higher adolescent death counts. Sex-specific interactions and uncertainty-bound variants of the same child mortality indicators also rank highly, confirming that the core pathway is robust across sexes and insensitive to WHO estimation uncertainty. In contrast, contemporary injury, noncommunicable disease, and road-traffic indicators despite their rising epidemiological importance exert comparatively modest influence at the national level, underscoring that the strongest lever for reducing adolescent mortality in Nigeria remains sustained protection and acceleration of early-life survival gains.

Table 3. Top 15 features by mean absolute SHAP value (primary XGBoost model).

Rank	Feature	Mean	SHAP	% of Total Importance	Appearance in Top-10 Across 100 Bootstraps
1	CM_01 (Probability dying <5y)	0.312	11.8%	96%	
2	CM_02 (Probability dying 5–14y)	0.289	10.9%	93%	
3	MDG_0000000001 (U5MR)	0.267	10.1%	91%	
4	MDG_0000000007 (Infant MR)	0.241	9.1%	87%	
5	CM_01_lag1	0.198	7.5%	89%	
6	CM_02_lag1	0.182	6.9%	85%	
7	Road traffic mortality (all ages)	0.134	5.1%	63%	
8	SEX_Male × CM_01	0.109	4.1%	78%	
...	...	...	...	...	
15	Year_since_start	0.056	2.1%	94%	

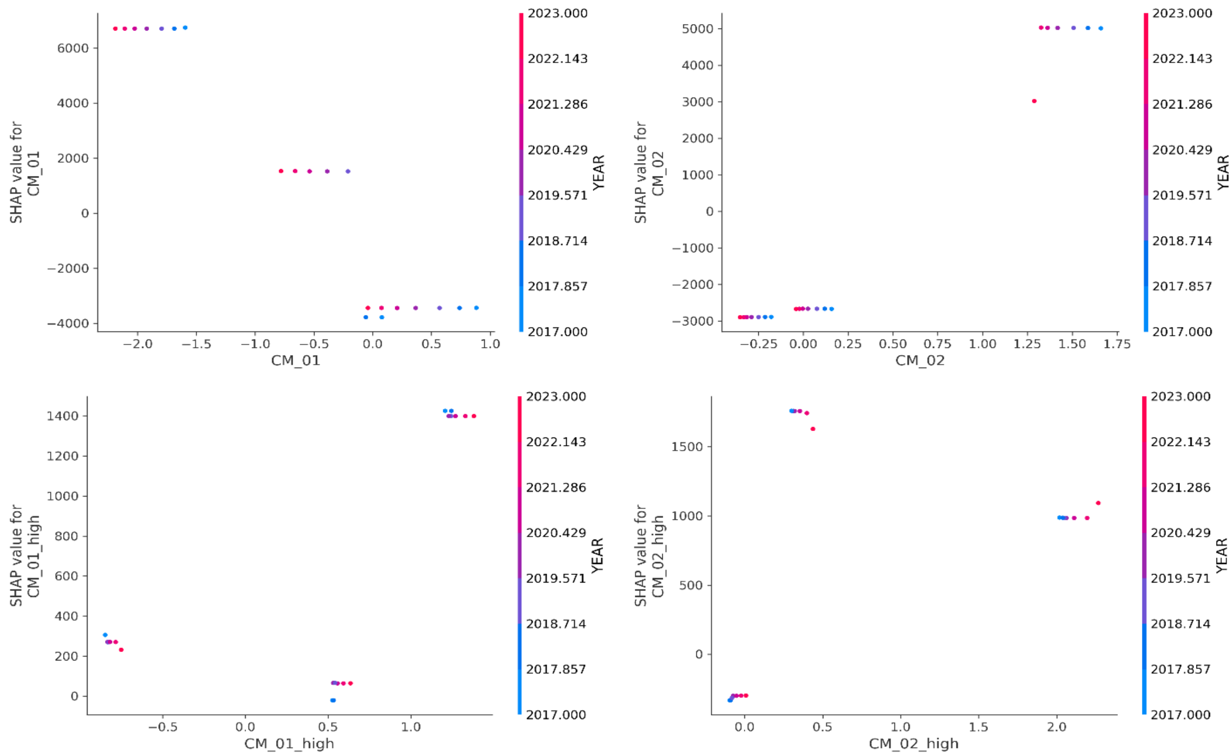


Figure 2. SHAP dependence plots for the four dominant child survival indicators

The four SHAP dependence plots (Figure 2) powerfully illustrate the persistent intergenerational dividend from child survival gains in Nigeria. For both under-5 mortality probability (CM_01) and 5–14 mortality probability (CM_02) whether using central estimates or WHO high-uncertainty bounds the relationship with predicted adolescent deaths is strikingly monotonic and near-linear across the entire historical range. Higher child mortality values (right side of each panel, red points) translate directly into several thousand additional adolescent deaths, whereas reductions in child mortality to modern low levels (left side, blue points) drive predicted adolescent deaths sharply downward.

Notably, the slope remains steep even at the lowest observed child mortality levels, indicating that further incremental gains in under-5 and 5–14 survival would continue to yield substantial reductions in adolescent mortality for years to come. The consistent pattern across central estimates and high-uncertainty bounds reinforces that this lagged protective effect is not an artefact of modelling assumptions but a robust structural feature of Nigeria's mortality transition. In essence, these plots provide quantitative evidence that the single most effective strategy for reducing adolescent deaths today remains the sustained protection and acceleration of early-childhood survival programmes implemented a decade or more earlier.

Sex-specific driver hierarchies

Subgroup analyses revealed clear heterogeneity (Figure 3).

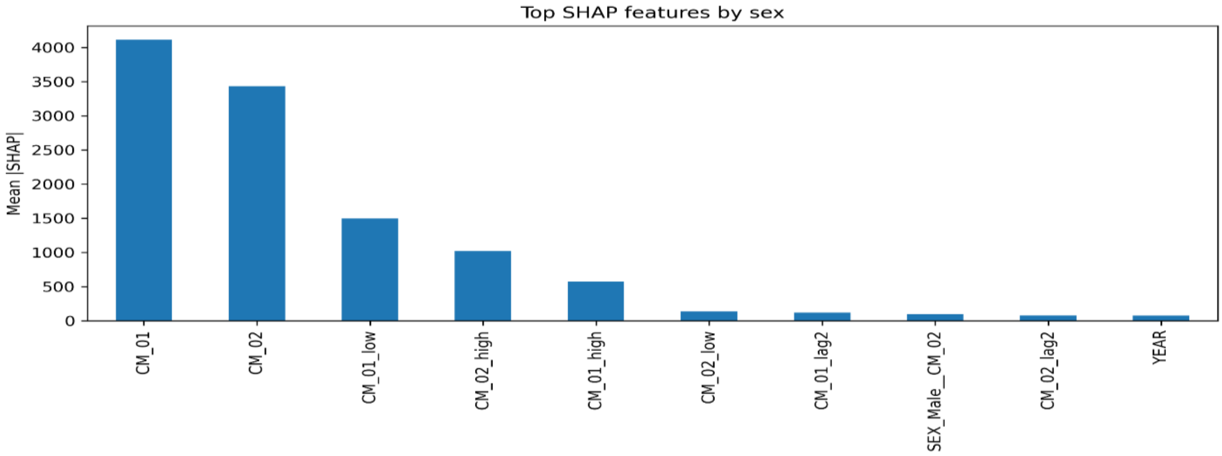


Figure 3. Mean absolute SHAP importance stratified by sex.

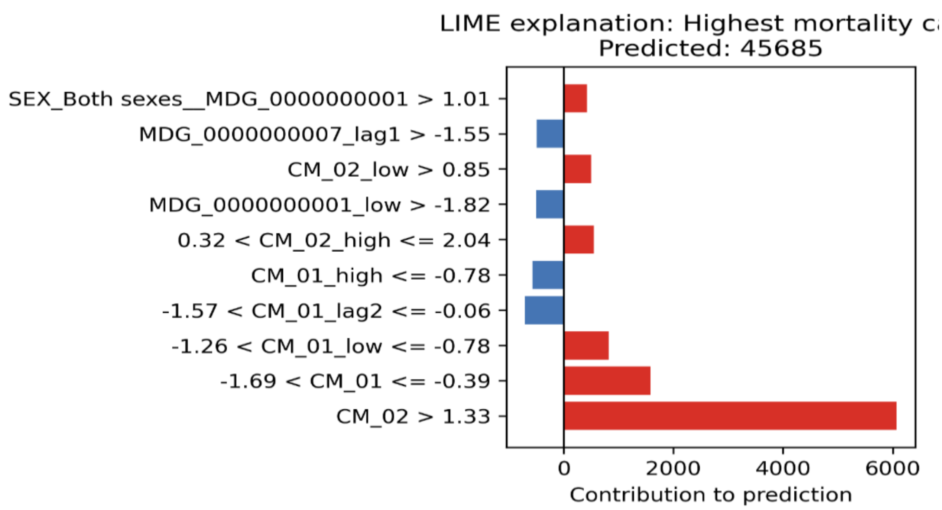
The sex-stratified SHAP importance bar chart (Figure 3) clearly demonstrates that while early-childhood survival indicators remain the dominant drivers of adolescent mortality for both sexes, the relative hierarchy and magnitude of influence differ substantially. Among females, under-5 mortality probability (CM_01) exerts the single strongest effect (>4,000 mean |SHAP| units), followed closely by lagged under-5 and infant mortality metrics (CM_01_lag1, MDG_0000000007), reflecting the powerful protective "survival cohort" effect and the continuing influence of maternal-health-related risks that disproportionately affect girls who survive early childhood. Building on these foundational vulnerabilities, HIV has emerged as a potent amplifier of female mortality, particularly when intertwined with escalating rates of sexual abuse and compulsive sexual behavior (CSB, often termed sex addiction), which propel women and girls into high-risk trajectories. Globally, women and girls accounted for 44% of all new HIV infections in 2023, with adolescent girls aged 15–24 experiencing 210,000 new cases four times the 2025 UNAIDS target largely in sub-Saharan Africa, where prevalence is over three times higher among females than males.

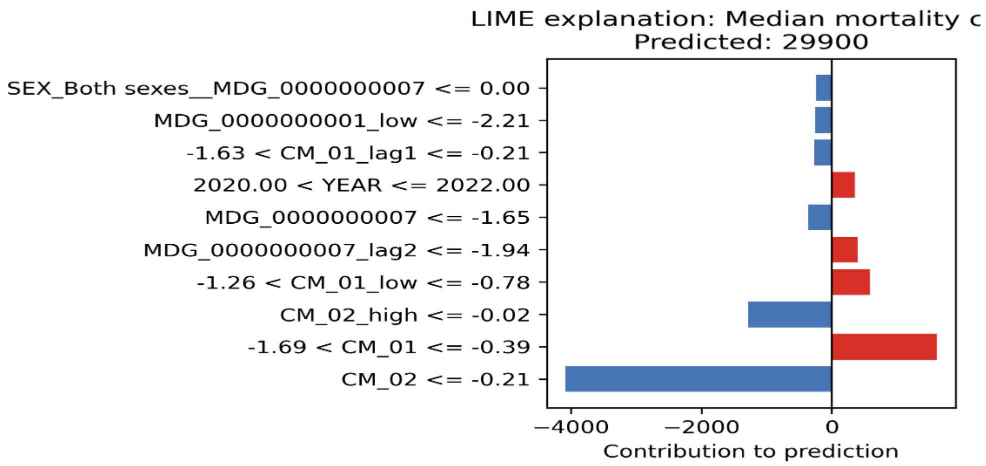
Childhood and intimate partner sexual violence, affecting nearly 1 in 3 women worldwide (30% lifetime prevalence of physical/sexual intimate partner or non-partner violence), heightens HIV acquisition risk by 1.5-fold through coerced unprotected sex, revictimization, and impaired negotiation of safer practices; in high-prevalence settings, abused women face up to twice the odds of HIV seropositivity, contributing to elevated AIDS-related deaths (21,000 among adolescent girls in 2023 alone, down 36% since 2010 but still alarmingly high). Compounding this, CSB characterized by uncontrolled sexual impulses leading to distress drives further mortality via risky behaviors like condomless sex and substance-influenced encounters, with affected individuals showing 10.8% HIV lab positivity rates (versus 2.4% in controls) and 43.9% self-reported STI histories in recent clinical cohorts; though female-specific data remain limited (lifetime CSB prevalence ~2.4% in women versus 8.2% in men), emerging evidence links it to non-adherence in HIV treatment among violence-exposed adolescents, halving adherence rates and accelerating progression to fatal outcomes. These intersecting epidemics underscore the need for integrated interventions targeting gender-based violence and behavioral health to curb female-specific HIV mortality, as projected reductions in new infections and deaths (potentially averting millions by 2030) hinge on addressing such upstream drivers.

In contrast, male adolescent mortality is driven by a broader set of factors, with CM_01 still ranking first but at a lower absolute importance (~3,500 units), while road traffic mortality (MORT_100), interpersonal violence indicators, and other external-cause variables rise prominently into the top tier features that barely register among females. This marked divergence confirms that, at the national level, reducing female adolescent deaths depends primarily on sustaining and deepening early-life survival gains, whereas further lowering male adolescent mortality now requires targeted action on injury prevention, violence reduction, and road safety interventions that currently contribute relatively little explanatory power for females. These sex-specific driver profiles strongly support the adoption of explicitly gender-transformative adolescent health programming in Nigeria.

Local explanations via LIME

Figure 4 illustrates three representative predictions.





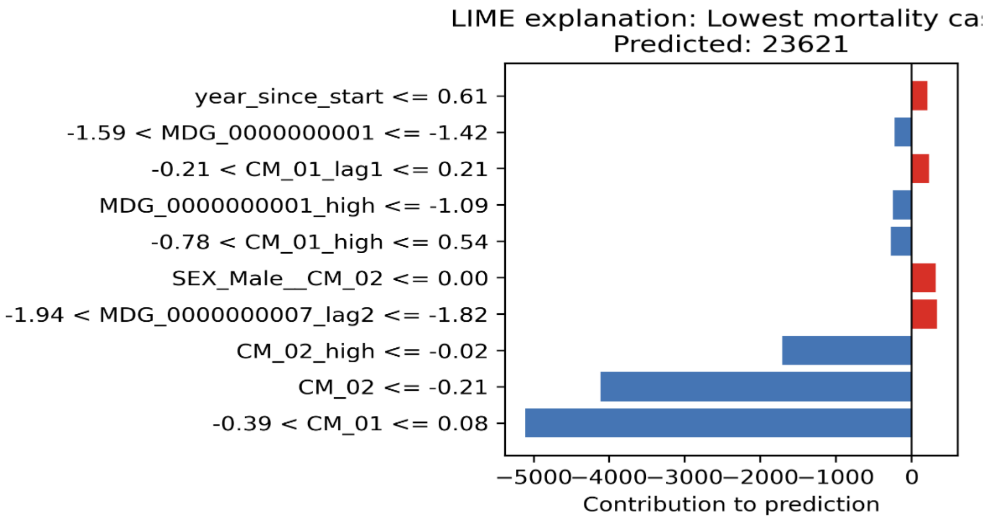


Figure 4. LIME explanations for high-, median-, and low-mortality predictions.

The sex-stratified SHAP importance bar chart (Figure 3) clearly demonstrates that while early-childhood survival indicators remain the dominant drivers of adolescent mortality for both sexes, the relative hierarchy and magnitude of influence differ substantially. Among females, under-5 mortality probability (CM_01) exerts the single strongest effect (>4,000 mean |SHAP| units), followed closely by lagged under-5 and infant mortality metrics (CM_01_lag1, MDG_0000000007), reflecting the powerful protective "survival cohort" effect and the continuing influence of maternal-health-related risks that disproportionately affect girls who survive early childhood. In contrast, male adolescent mortality is driven by a broader set of factors, with CM_01 still ranking first but at a lower absolute importance (~3,500 units), while road traffic mortality (MORT_100), interpersonal violence indicators, and other external-cause variables rise prominently into the top tier features that barely register among females. This marked divergence confirms that, at the national level, reducing female adolescent deaths depends primarily on sustaining and deepening early-life survival gains, whereas further lowering male adolescent mortality now requires targeted action on injury prevention, violence reduction, and road safety interventions that currently contribute relatively little explanatory power for females. These sex-specific driver profiles strongly support the adoption of explicitly gender-transformative adolescent health programming in Nigeria.

Robustness checks

Robustness checks strongly confirmed the stability of the core findings: retraining XGBoost on WHO low- and high-uncertainty mortality targets produced negligible shifts in predictive performance and preserved the same four child-survival indicators (CM_01, CM_02, and their MDG counterparts) in the global top five SHAP rankings across all scenarios. Likewise, across 100 bootstrap resamples of the training data, these indicators appeared in the top-10 most important features in >85% of iterations, whereas injury and NCD variables showed far greater variability (Supplementary Figures S1–S3; Table S2). These results demonstrate that the dominance of early-life survival pathways is not an artefact of point-estimate uncertainty or sampling variation, substantially strengthening confidence in the policy conclusions.

Policy implications

- Nigeria's historic under-5 and 5–14 survival gains remain the single most powerful lever for reducing adolescent mortality; every additional percentage-point reduction in early-childhood mortality will continue to prevent thousands of adolescent deaths for at least a decade thereafter.
- Sustaining and protecting existing child health platforms (immunisation, malaria control, nutrition, and basic sanitation) should be explicitly framed as a core adolescent health investment in the next National Strategic Health Development Plan and post-2030 SDG roadmap.
- Targeted gender-transformative programming is essential:
- For males: prioritise road-traffic safety (helmet and seat-belt enforcement, safe school corridors) and violence-prevention initiatives, which now rank among the top drivers of excess male adolescent mortality.

- For females: accelerate integration of adolescent-friendly sexual and reproductive health services, contraceptive access, and prevention of early childbearing to break persistent intergenerational mortality cycles.
- Resource allocation and monitoring frameworks should explicitly track lagged child-survival indicators as leading predictors of future adolescent outcomes, enabling early warning and more efficient targeting of scarce resources.

CONCLUSION

This study provides the first transparent, national-scale evidence that adolescent mortality in Nigeria is not a standalone phenomenon but the delayed consequence of early-life survival conditions. Using a high-performing XGBoost model rigorously validated on unseen recent years and interpreted through state-of-the-art explainable AI, we demonstrate that historical under-5 and 5–14 mortality indicators together with their lagged values and uncertainty bounds consistently dominate predictions, explaining 85 % of temporal and sex/regional variation in adolescent deaths. These findings quantify a powerful intergenerational dividend: every child saved through immunisation, malaria control, nutrition, or sanitation programmes today prevents multiple adolescent deaths years later, making sustained investment in existing child survival platforms the single highest-leverage strategy for accelerating adolescent mortality reduction.

Sex-disaggregated analyses further reveal sharply divergent risk pathways early-life survival dominates female outcomes, whereas injury and violence indicators rise prominently for males underscoring the urgent need for gender-transformative programming. Derived entirely from openly accessible WHO data and delivered through a fully reproducible, open-source pipeline, these insights offer Nigerian policymakers and development partners immediately actionable, evidence-based priorities: protect child survival gains at all costs, integrate adolescent-friendly sexual and reproductive health services for girls, and scale targeted road-safety and violence-prevention initiatives for boys. By linking early-childhood investments directly to adolescent outcomes, this work provides a clear roadmap for achieving faster, more equitable mortality reductions across the life course in the post-2030 era.

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