INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN APPLIED SCIENCE (IJRIAS)
ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XII December 2025

Ranking of Determinants of Under-Five Mortality in Kenya Using Statistical and Machine Learning Approaches

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DOI: https://doi.org/10.51584/IJRIAS.2025.10120035

Received: 20 December 2025; Accepted: 26 December 2025; Published: 06 January 2026

ABSTRACT

Under-five mortality (U5M) stands at 37 deaths in 1000 live births in Kenya suggesting that the country is unlikely to meet the World Health Organization target of fewer than 25 deaths per 1,000 live births by 2030 under current trends. While several determinants of U5M have been identified, evidence on their relative importance in Kenya based on nationally representative data and multiple analytical techniques, remains limited, constraining effective prioritization and use of scarce health resources. This study applied both traditional statistical methods and machine learning approaches to identify and rank the key determinants of U5M in Kenya. Data were obtained from the 2022 Kenya Demographic and Health Survey (KDHS), including 23,433 children aged 0–59 months. Feature ranking was conducted using chi-square tests, logistic regression, XGBoost, Boruta, and SHAP. To enhance robustness, results from the multiple methods were integrated using a heatmap-based consensus approach from which the average ranking of predictors across techniques was derived. Across all methods, maternal education consistently emerged as the most influential determinant of U5M, followed by maternal health status, household wealth index, ethnicity, and birth spacing. Literacy, ownership of household assets, and place of residence showed moderate importance, while the child's sex was consistently ranked as the least influential factor. By integrating multiple statistical and machine learning techniques, this study provides robust evidence on the relative importance of U5M determinants in Kenya. Therefore, policymakers should prioritize investments in female education, maternal health, culturally responsive interventions, poverty reduction, and optimal birth spacing to accelerate progress toward achieving Sustainable Development Goal 3.2.

INTRODUCTION

Globally, under-five mortality (U5M) has declined markedly over the past three decades, with the number of deaths falling from 12.5 million in 1990 to 4.9 million in 2022 [1].. This progress reflects improvements in maternal and child health services, expanded immunization coverage, better nutrition, and broader socioeconomic development. However, U5M remains a serious public health challenge in many low- and middle-income countries (LMICs), where a large proportion of child deaths are still preventable [2].

Despite global gains, the burden of U5M is heavily concentrated in Sub-Saharan Africa (SSA) and Sothern Asia, which accounts for nearly 80% of under-five deaths worldwide [3,4]. Many countries in the region continue to report relatively high mortality rates. For example, U5M rates exceed 100 deaths per 1,000 live births in countries such as Chad, Nigeria, and Somalia, while the Central African Republic and Sierra Leone report rates above 70 per 1,000 live births. Even countries showing relative progress, including Ethiopia and Ghana, still record U5M rates of approximately 40–45 deaths per 1,000 live births, which remain above the Sustainable Development Goal (SDG 3.2) target of fewer than 25 deaths in 1000 live births [5,6]. As a result, children born in SSA face a substantially higher risk of dying before their fifth birthday compared to those in other regions of the world[7]

In Kenya, the 2022 Demographic and Health Survey (KDHS) reports an U5M rate of 37 deaths per 1,000 live births, which is also above the World Health Organization (WHO) target of fewer than 25 deaths per 1,000 live births by the year 2030. This highlights persistent health inequities and service delivery gaps that necessitate urgent and targeted interventions to improve child survival High levels of U5M have profound social and economic consequences at both family and society level. At the household level, the loss of a child imposes severe emotional distress on parents and caregivers and is often associated with long-term psychological outcomes such as depression, anxiety, and trauma[8]. Families may also experience substantial financial strain due to medical expenses, funeral costs, and the loss of future economic potential[9] . At the societal level, elevated child mortality rates reflect underlying health inequalities, place pressure on healthcare systems, and hinder broader social and economic development[10,11]. Persistently high mortality rates, particularly in marginalized and rural populations, perpetuate cycles of poverty and slow national progress[12]

Past studies have shown that the causes of U5M are varied and shaped by a combination of social, economic, maternal, and biological factors that interact throughout a child's early life [13,14]. Children born to mothers with limited education are more vulnerable because their caregivers may have reduced access to health information, fewer economic opportunities, and lower ability to navigate healthcare systems [15,16]. Poverty further compounds this risk by restricting access to nutritious food, clean water, safe housing, and timely medical care. Maternal health and reproductive patterns also play a critical role; closely spaced births strain a mother's physical and nutritional reserves and reduce the time and resources available for each child, increasing the likelihood of illness and death. In addition, sociocultural factors such as ethnicity often reflect deeper differences in cultural practices, geographic access to services, and historical marginalization, all of which influence care-seeking behaviors and child survival[1,17,18]. The determinants of U5M are not driven by a single cause, but rather by a layered set of disadvantages that accumulate from household to community level. However, existing studies have not adequately established the relative hierarchy of U5M determinants in the Kenyan context using multiple feature-ranking techniques applied to nationally representative data.

Recent advances in feature selection research show that individual ranking techniques each have distinct strengths and limitations, making reliance on a single method potentially inconclusive [19,20].. This study applies a combination of traditional statistical methods (chi-square tests and logistic regression) and machine learning techniques (XGBoost, Boruta, and SHAP) to rank the key determinants of under-five mortality in Kenya. The analytical focus is on identifying factors that consistently emerge as important across multiple methods, thereby providing more reliable and interpretable evidence. From a policy perspective, this approach supports informed prioritization of interventions by highlighting the most influential drivers of under-five mortality, which is essential for accelerating progress toward the WHO target of fewer than 25 deaths per 1,000 live births by 2030.

METHODS

Study Design and Data Source

The 2022 KDHS is a cross-sectional design which is a nationally representative survey that collects comprehensive demographic and health information through standardized interviews with women of reproductive age (15–49 years) using internationally validated instruments. The 2022 KDHS employed a two-stage stratified cluster sampling design, with stratification by county and urban–rural residence, followed by the selection of enumeration areas (EA) and households [21].

Study Population

The study population comprised children drawn from the Kids Recode (KR) file of the 2022 KDHS. The KR file contains child-level information for all live-born children reported by interviewed women, including birth history and survival status at the time of the survey. Accordingly, the unit of analysis was the individual child. The analysis was restricted to children aged 0–59 months to appropriately examine U5M, in line with standard DHS definitions. Records with missing information on key explanatory variables were excluded. After applying these criteria, the final analytic sample consisted of 23,433 children. It is important to note that, KDHS employs complex survey sampling with sample weights to ensure national representativeness, the present study focused on feature ranking and prioritization rather than population-level parameter estimation.

Study Variables

Outcome Variable

The outcome variable was U5M status, defined as the death of a child before reaching five years of age. This variable was derived from the KDHS child survival indicator (variable B5) and coded as a binary outcome (dead/alive), consistent with DHS and WHO child survival measurement frameworks

Independent Variables

Independent variables comprised demographic, socio-economic, maternal, and child-related factors, informed by established theoretical frameworks and prior empirical studies on child survival. These included maternal education level, household wealth index, ethnicity, literacy status, number of births in the preceding five years, all of which have been shown to influence U5M in low- and middle-income settings[22]

Data Processing and Analytical Approach

Preliminary data processing involved data cleaning, variable encoding, handling missing values, and addressing class imbalance prior to feature selection. To identify and rank critical determinants of U5M, multiple complementary feature selection techniques were employed. Both statistical methods (Chi-square test and Logistic Regression) and machine learning-based approaches (XGBoost, Boruta, and SHAP) were applied. The Chi-square test and Logistic Regression assessed feature importance based on the magnitude of the Chi-square statistic and estimated model coefficients, respectively. Machine learning techniques ranked predictors according to their contribution to predictive performance, allowing for the capture of non-linear relationships and complex interactions among variables[11,23,24]

DHS sampling weights variable (v005), normalized by dividing by 1,000,000, were applied to ensure nationally representative estimates and adjust for unequal selection probabilities and non-response [25]. Survey design features, including clustering variable (v021) and stratification variable (v022), were accounted for in the analysis. Survey weights were incorporated at the feature ranking stage so that predictor importance reflected population-level relevance [26,27]. A heatmap-based integrative approach was employed to synthesize results across all feature selection methods. The average score for each predictor, represented its mean ranking across the applied techniques. This consensus-driven strategy minimizes bias inherent in single-method approaches and enhances reliability by integrating different feature selection methods[28,29]. Data management and analyses were conducted using Python within the Jupyter Notebook environment, utilizing relevant statistical and machine learning libraries.

Ethical Considerations

This study utilized secondary data from the 2022 KDHS, which is publicly available and anonymized. The KDHS data were collected with ethical approval from the Kenya Medical Research Institute (KEMRI) Ethical Review Committee and relevant national authorities, and informed consent was obtained from all participants during data collection. No personal identifiers were accessed or used in this analysis. Permission to use the dataset for research purposes was obtained through the DHS Program. As the study involved analysis of de-identified secondary data, no additional ethical approval was required for this research.

RESULTS

Descriptive Results of Study variables

Table 1 presents the descriptive characteristics of 23,343 children born within the five years preceding the 2022 KDHS. Overall, 6% (1,361) of the children had died before reaching their fifth birthday, while 94% (21,982) were alive at the time of the survey. The vast majority of births were singletons (99%, 23,110), with twin births accounting for 1% (210).

With regard to place of residence, 37% (8,676) of the children were born to mothers residing in urban areas, while 63% (14,667) were from rural areas. In terms of the highest level of maternal education attained, 15% (3,444) of mothers had no formal education, 41% (9,567) had primary education, 29% (6,925) had secondary education, and 15% (3,107) had higher education. Moreover, 12% (2,879) of mothers had incomplete primary education, 22% (5,078) had completed primary education, 17% (4,032) had incomplete secondary education, 17% (4,052) had completed secondary education, and 15% (3,107) had attained higher education.

Regarding literacy status, 19% (4,445) of mothers were not able to read at all, 11% (2,652) were able to read partially, 69% (16,220) were classified as literate, and 1% (326) were very literate.Most households were male-

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XII December 2025

headed (62%, 14,381), while 38% (8,511) were female-headed. Mobile phone ownership was high, with 87% (19,685) of households owning a telephone. In terms of household wealth status, 20% (4,527) of children were from the poorest households, 18% (4,161) from poorer households, 20% (4,571) from middle-income households, 22% (5,165) from richer households, and 17% (3,964) from the richest households.

Table 1 Descriptive Results of Study variables

Variable	**Description**	**Number, n**	**Percentage %**
Child is alive	No	1361	6%
	Yes	21982	94%
Is child twin	Single	23110	99%
	Twin	210	1%
Residence	Urban	8676	37%
	Rural	14667	63%
Highest educational	No education	3444	15%
	Primary	9567	41%
	Secondary	6925	29%
	Higher	3107	15%
	Incomplete primary	2879	12%
Education attainment	Complete primary	5078	22%
	Incomplete secondary	4032	17%
	Complete secondary	4052	17%
	Higher	3107	15%
Literacy Level	Not at all	4445	19%
	Able to read partly	2652	11%
	Literate	16220	69%
	Very literate	326	1%
Sex of household head	Male	14381	62%
	Female	8511	38%
Owns telephone	No	3018	13%
	Yes	19685	87%
Wealth index	Poorest	4527	20%
	Poorer	4161	18%
	Middle	4571	20%
	Richer	5165	22%
	Richest	3964	17%

Feature Ranking Results Across Multiple Methods

Feature importance was assessed independently for each statistical and machine learning technique employed in the study. To evaluate the robustness and consistency of predictor rankings across different methodologies, the individual importance scores were subsequently aggregated and visualized using a heatmap.

Chi square ranking method

The feature importance results obtained from the chi square regression model (Figure 1) rank maternal education as the most influential predictors of U5M followed by reported maternal health, ethnicity, number of births in last five years. Other notable predictors included mothers' occupation, sex of household head mother's religion ranked least in the chi-square test.

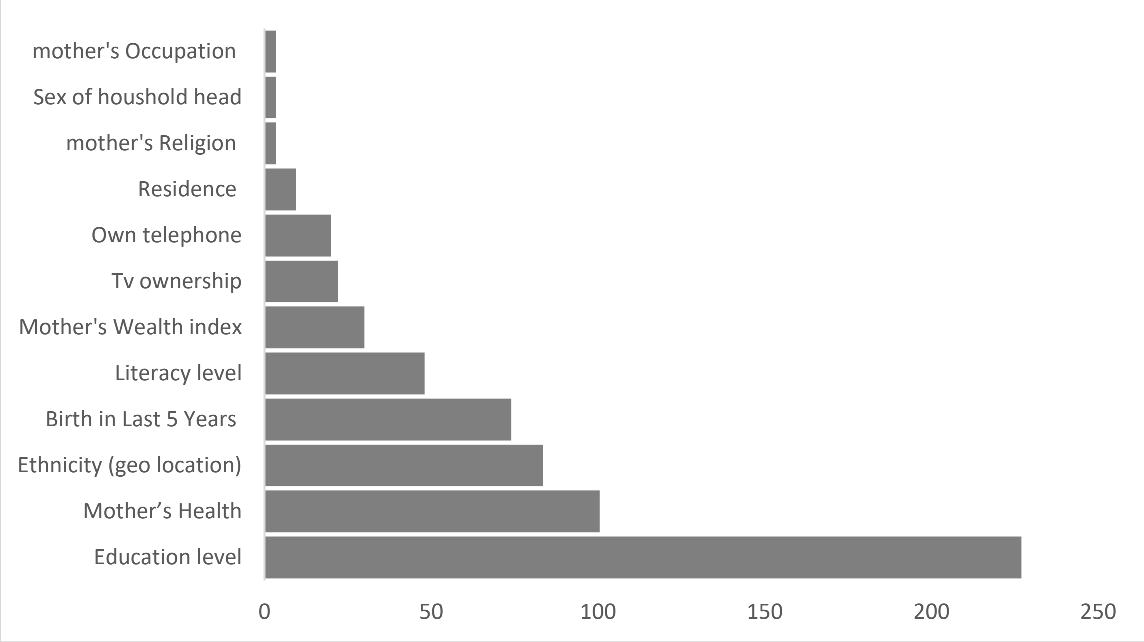

Figure 1: Feature Ranking of U5M by Chi Square Method

Logistic regression ranking

The feature importance results obtained from the logistic regression model (Figure 2) indicate that maternal health status and maternal education were the most influential predictors of U5M. Other notable predictors included mobile phone ownership, sex of the household head, and maternal literacy. In contrast, variables such as ethnicity and the number of births in the last five years exhibited relatively lower importance within the logistic regression framework.

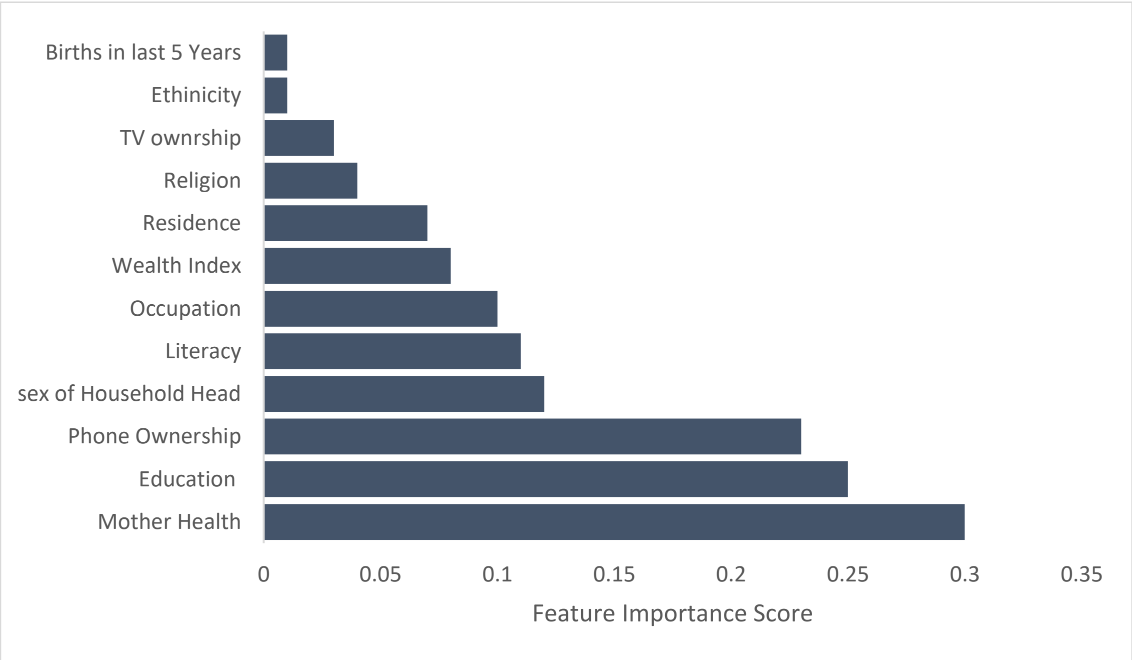

Figure 2: Feature Ranking of U5M by Logistic Regression

XGBoost ranking

The XGBoost model produced a distinct ranking pattern (Figure 3), with ethnicity, maternal education, and household wealth index emerging as the most influential predictors of U5M. Reproductive health indicators, particularly birth spacing, as well as maternal health variables, also ranked highly. Variables related to household assets and place of residence demonstrated moderate to lower importance in the model.

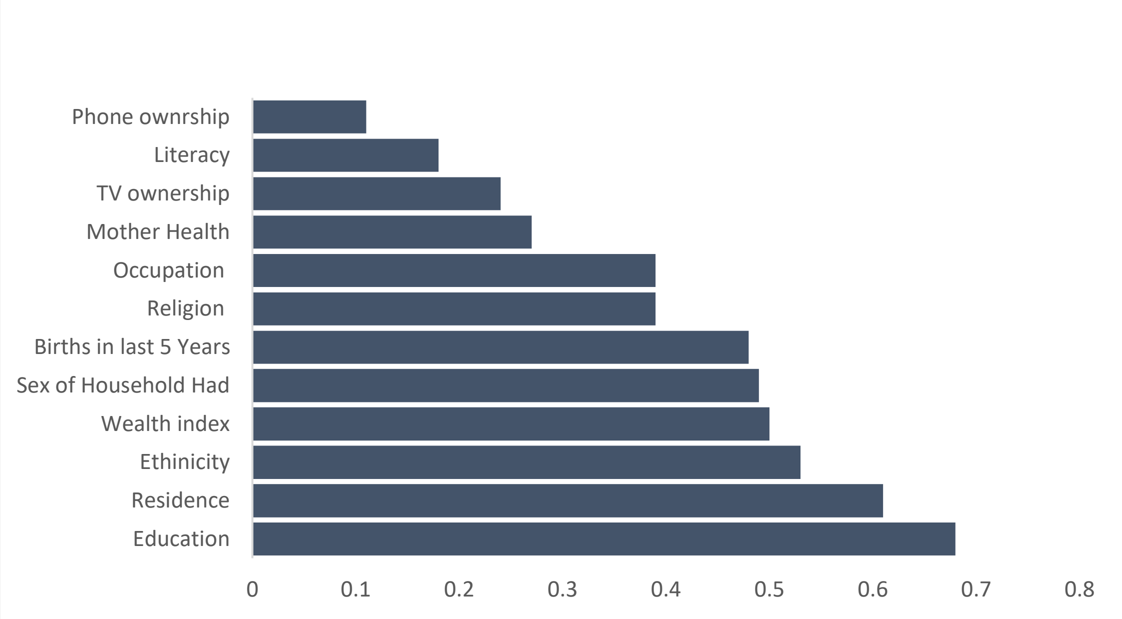

Figure 3: Feature Ranking of U5M by XGBoost

Boruta ranking

The Boruta feature selection results (Figure 4) identified maternal education, household wealth index, and literacy as the dominant predictors of U5M. Notably, ownership of a television and urban residence gained relative importance under this method. Conversely, maternal health status, which ranked highly in the logistic regression model, showed comparatively lower importance in the Boruta results.

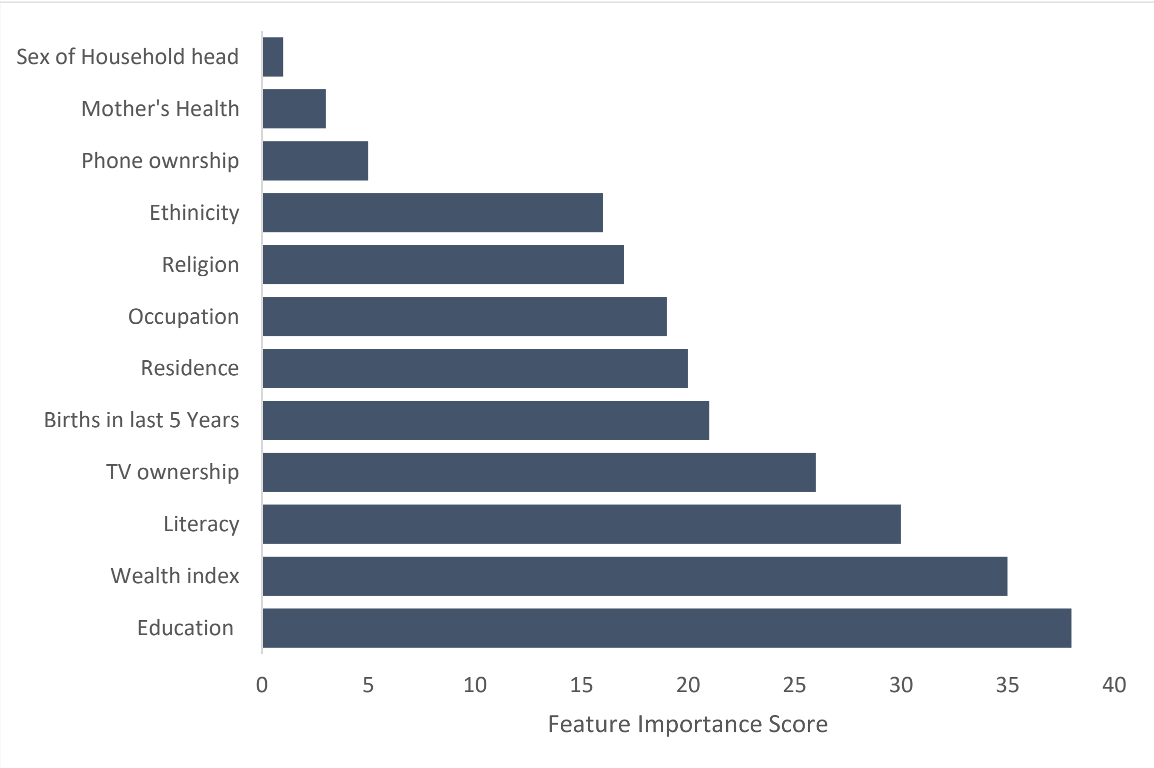

Figure 4: Feature Ranking of U5M by Boruta

SHAP values ranking

The SHAP-based analysis (Figure 4) identified maternal education, place of residence, and ethnicity as the strongest contributors to U5M risk. The SHAP results showed partial alignment with other methods while also highlighting differences in the relative positioning of predictors such as sex of household head and birth spacing.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XII December 2025

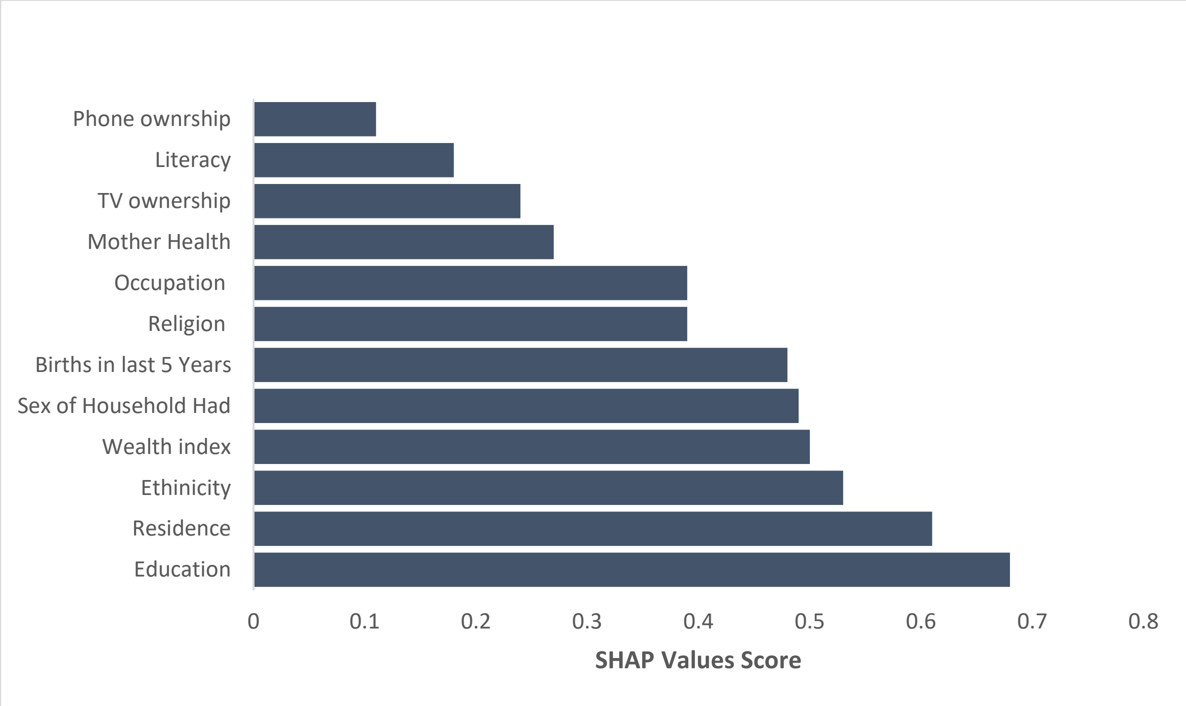

Figure 4: Feature Ranking of U5M by SHAP Method

Heatmap visual and overall ranking

Figure 5 presents a heatmap summarizing the relative importance of predictors across all the five methods considered. The results demonstrate a high degree of consistency in the identification of key predictors, with maternal education, household wealth index, ethnicity, place of residence, and birth spacing consistently ranked among the most influential determinants of U5M.

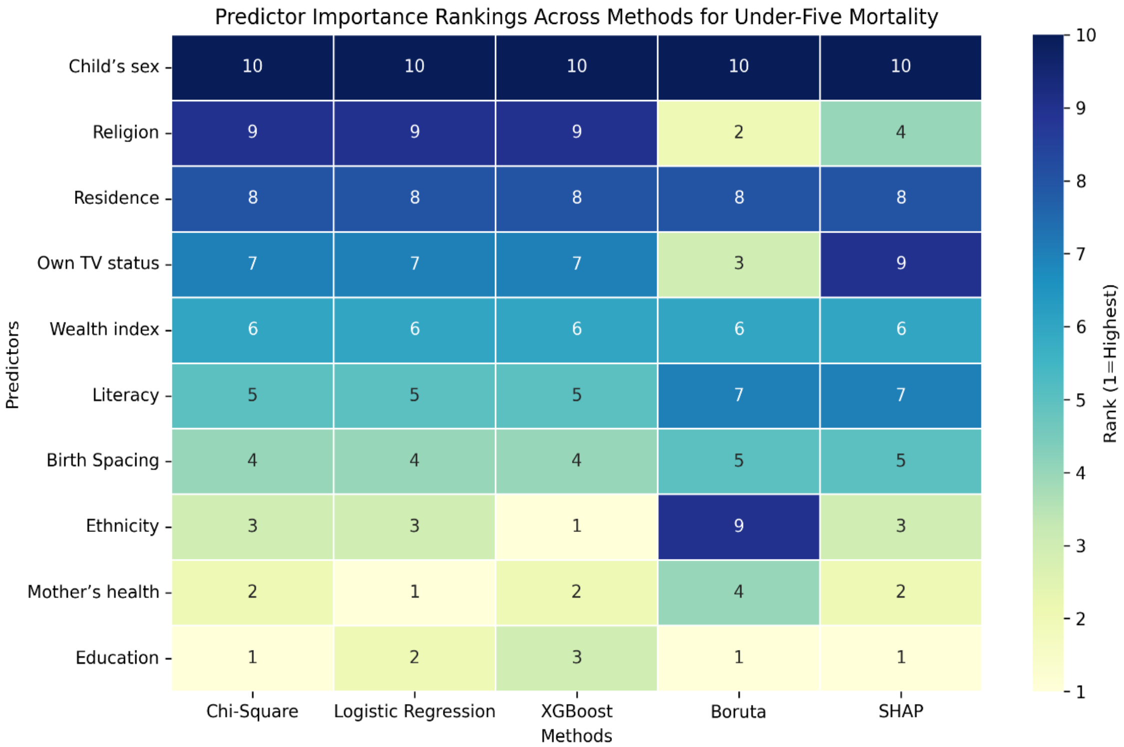

Figure 5: Predictor Importance Rankings Across multiple Methods for U5M in Kenya

To generate an overall ranking, the average ranking of each predictor across all feature selection methods was computed and the reciprocal of the average plotted as in Figure 6. The findings showed that, among all the

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predictors that were considered, maternal education emerged as the most important determinant of U5M, followed by maternal health, ethnicity, and birth spacing. Literacy, household wealth, television ownership, and religion exhibited moderate importance, while place of residence ranked relatively lower. Child sex was consistently identified as the least influential predictor across the methods considered.

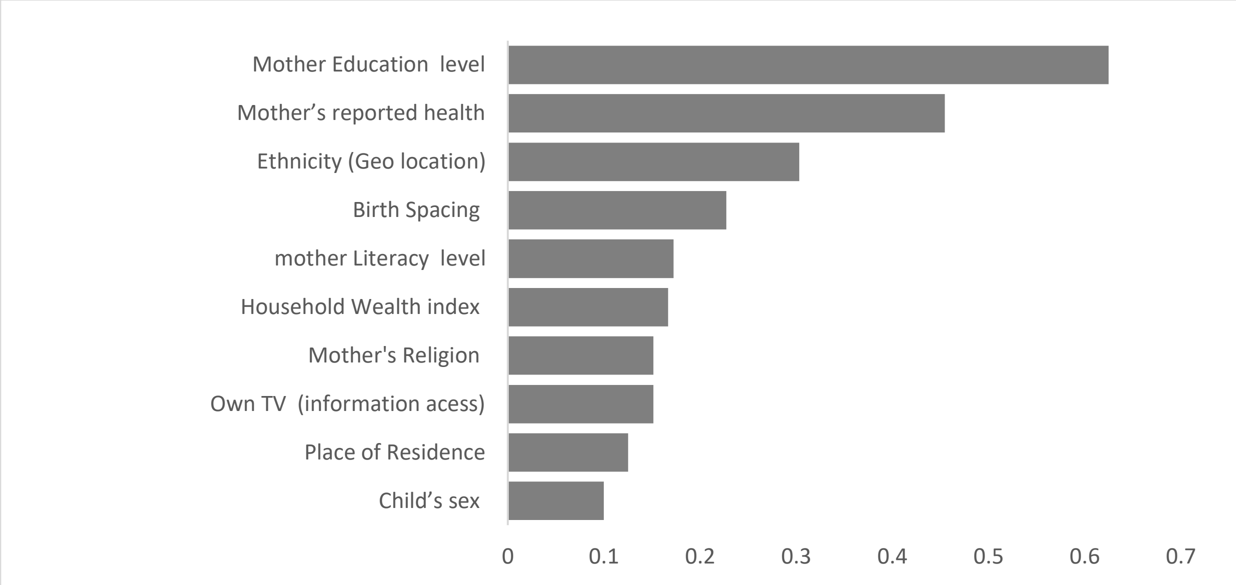

Figure 6: Average Predictor Importance Ranking Across Methods

DISCUSSION

This study aimed to identify and rank key predictors of U5M in Kenya using multiple feature selection techniques, capturing both conventional and hidden patterns in the data to inform targeted, evidence-based interventions. This investigation is timely, as Kenya’s U5M rate remains above the WHO-recommended target of fewer than 25 deaths per 1,000 live births. Understanding the critical factors driving these outcomes is essential for designing effective interventions.

Across all methods, maternal education, household wealth index, and ethnicity emerged as the most influential predictors of U5M in Kenya. The dominance of maternal education aligns with prior research in Kenya and other sub-Saharan African countries, where higher maternal education is strongly associated with improved child survival through enhanced health knowledge, better care practices, and increased utilization of healthcare services[30–32].. Studies have shown that maternal education contributes to child survival by improving knowledge of nutrition and hygiene, as well as health-seeking behaviors[33].. Evidence from Ghana reported an inverse relationship between maternal education and child mortality[34]., while a pooled study of 12 East African countries (2008–2019) confirmed that higher maternal education significantly lowers the hazard of U5M[11]. In Kenya specifically, each additional year of maternal schooling has been documented to reduce the likelihood of child death during the first year of life[35,36].

Household wealth index and ethnicity were also top predictors, consistent with prior DHS-based studies highlighting the role of economic status and socio-cultural factors in child survival[37,38]. Ethnicity, reflecting cultural norms and geographical diversity, emerged as a significant determinant of U5M. These findings align with studies in SSA[39] and in Kenya [40] showing that cultural practices influence how, when, and where families seek care for their children, contributing to disparities in child health outcomes.

The study further identified birth spacing, proxied by the number of births in the previous five years, and maternal health as important predictors. Short birth intervals limit maternal recovery, deplete nutritional reserves, and reduce the attention and resources available for each child, increasing the risk of U5M. Systematic reviews and country-specific studies have consistently shown that short birth intervals significantly increase child mortality in low- and middle-income countries[41]. In Ethiopia, mortality is about 85% higher among children born after a short birth interval. In Kenya, children born less than 18 months after a preceding birth face nearly twice the risk of mortality compared to those with intervals of 36 months or more[42].

Potential intercorrelation among socioeconomic variables was addressed through the use of multiple feature selection techniques rather than variable exclusion. Retaining conceptually related predictors such as maternal education, literacy, and household wealth reflects the interconnected nature of social determinants of health. Their consistent high ranking across methods confirms their robustness, while the heatmap-based consensus approach reduces instability due to correlated predictors. The findings emphasize maternal education, socioeconomic status, ethnicity, and reproductive health as key priorities for reducing under-five mortality in Kenya.

CONCLUSIONS

Maternal education, maternal health status, and household wealth index are conclusively established as the most influential determinants of U5M. Ethnicity and maternal literacy are also important but context-specific and method-dependent effects, reflecting the complex sociocultural dynamics influencing child survival. Employing diverse analytical approaches is a useful approach to confirm universally robust predictors and uncover delicate, context-driven factors. The findings advocate for targeted interventions advancing maternal education, reducing poverty, and enhancing maternal health services as essential priorities for accelerating reductions in U5M

From a policy perspective, these findings suggest that efforts to reduce U5M in Kenya should prioritize investments in female education, particularly beyond primary level, as a long-term strategy for improving child survival. Strengthening maternal and child health services, promoting optimal birth spacing through accessible family planning programs, and addressing socioeconomic disparities through targeted poverty alleviation initiatives are also essential. Furthermore, culturally sensitive interventions that account for ethnic and regional differences in health behaviors may enhance the effectiveness of child survival programs.

The key methodological contribution of this study is importance of integrating multiple methods to generate robust ranking evidence for public health decision-making. By leveraging consensus across multiple feature selection approaches, researchers can better identify high-impact intervention points, ultimately contributing to more effective strategies for reducing U5M in Kenya and similar settings

ACKNOWLEDGEMENT

The authors acknowledge the Demographic and Health Surveys (DHS) Program for granting access to the 2022 Kenya Demographic and Health Survey data used in this study. We also appreciate the Kenya National Bureau of Statistics (KNBS), the Ministry of Health, and all survey participants whose contributions made this research possible. Special thanks are extended to colleagues and reviewers who provided constructive feedback during the development of this manuscript. Any remaining errors are solely the responsibility of the authors.

Data Availability

The datasets are publicly available upon reasonable request from the DHS Program website (https://dhsprogram.com). For this study, we accessed the data upon free registration and approved after a brief research description, in accordance with DHS data use policies.

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