World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(RESEARCH ARTICLE)

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Fitting Cox proportional hazard models to identify mortality predictors during pregnancy and postpartum periods

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World Journal of Advanced Research and Reviews, 2025, 26(03), 027–047

Publication history: Received on 22 April 2025; revised on 30 May 2025; accepted on 02 June 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.26.3.2152

Abstract

Maternal mortality remains a major global health challenge, particularly in low- and middle-income countries, where pregnancy and postpartum periods are associated with elevated risks of death due to both obstetric and non-obstetric complications. To identify predictors of mortality during these critical periods, this study employs Cox proportional hazards models, a robust survival analysis technique suited for time-to-event data. The objective is to evaluate time-dependent risks and determine significant covariates that influence maternal survival from conception through the first six weeks postpartum. Using longitudinal data from national reproductive health surveillance systems and hospital-based cohorts, we assess various socio-demographic, clinical, and obstetric factors, including age, parity, antenatal care utilization, mode of delivery, pre-existing conditions, and obstetric complications. The Cox model accommodates censoring and permits the estimation of hazard ratios (HRs), quantifying the relative risk of mortality associated with each predictor while adjusting for confounders. Our findings highlight critical predictors of maternal mortality, including advanced maternal age, delayed antenatal care, hypertensive disorders, cesarean delivery, and postpartum hemorrhage. Interaction terms and stratified analyses further reveal context-specific risk amplifiers, such as rural residence and limited health facility access. Proportional hazard assumptions are verified using Schoenfeld residuals and time-varying covariate assessments to ensure model validity. By identifying and quantifying key mortality predictors, this research offers valuable insights for targeted clinical interventions and policy-level strategies aimed at reducing maternal deaths. The integration of survival modeling into maternal health research enhances our understanding of temporal risk dynamics and supports evidence-based improvements in perinatal care delivery systems.

Keywords: Maternal mortality; Pregnancy outcomes; Cox proportional hazards model; Survival analysis; Postpartum risk factors; Mortality predictors

1. Introduction

1.1. Global Burden of Maternal Mortality and Epidemiological Context

Maternal mortality remains one of the most pressing global health challenges of the 21st century, despite notable progress in reducing its incidence. According to the World Health Organization, approximately 287,000 women died from pregnancy-related causes in 2020, with 95% of these deaths occurring in low- and middle-income countries [1]. These statistics underscore the persistent inequality in maternal health access and outcomes, often driven by systemic failures in healthcare delivery, education, and socio-political infrastructure [2].

Sub-Saharan Africa and South Asia account for nearly 86% of maternal deaths globally, revealing stark geographic disparities [3]. Within these regions, rural populations, young mothers, and those with limited antenatal care access are

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at particularly high risk. The causes of maternal mortality are multifactorial—ranging from direct obstetric complications like hemorrhage, sepsis, and eclampsia, to indirect causes including malaria, anemia, and HIV/AIDS [4].

In high-income countries, while overall maternal mortality is lower, recent trends show a concerning rise, often linked to older maternal age, pre-existing conditions, and disparities among racial and ethnic groups [5]. This epidemiological context reflects that maternal death is not only a clinical issue but also a marker of broader societal and structural inequalities [6].

Accurate surveillance systems and data-driven policies are essential to track maternal mortality trends and to identify the most vulnerable groups. However, many nations still lack robust vital statistics infrastructure, resulting in underreported or misclassified maternal deaths, particularly in the postpartum period [7]. Addressing maternal mortality, therefore, requires both clinical innovation and improved public health monitoring systems.

1.2. Temporal Risk Dynamics in Pregnancy and Postpartum Periods

Maternal health risk is not static but evolves across different stages of pregnancy and into the postpartum period. Each trimester presents unique physiological challenges, while the immediate weeks following delivery—often termed the "fourth trimester"—pose substantial threats to maternal survival [8]. Hemorrhage and eclampsia typically occur near delivery, whereas sepsis and cardiomyopathy are more likely to manifest in the postpartum phase [9].

Temporal patterns of risk highlight the need for continued maternal surveillance beyond childbirth. A significant proportion of maternal deaths, particularly in resource-limited settings, occur after hospital discharge and are not captured in traditional facility-based reporting systems [10]. This has prompted international agencies to advocate for extending the postpartum care window from six weeks to at least one year, particularly in high-risk populations [11].

Moreover, physiological changes in pregnancy—such as increased blood volume, suppressed immunity, and hormonal fluctuations—alter the body's response to infections and stressors over time [12]. These dynamics necessitate a time-sensitive approach to maternal health intervention, where risks are assessed and mitigated at each stage of gestation and post-delivery.

Understanding the timing of adverse maternal events is also critical for optimizing resource allocation. For instance, community-based health workers may need to adjust visit schedules to coincide with peak risk windows [13]. Hence, a dynamic temporal framework is essential not only for clinical management but also for strategic planning of maternal health services, especially in settings with limited healthcare capacity and workforce shortages [14].

1.3. Rationale for Using Cox Proportional Hazard Models for Time-to-Event Maternal Analysis

Cox proportional hazard models are widely regarded as the gold standard for analyzing time-to-event data in epidemiology and public health, particularly when the outcome is not uniformly distributed over time. In maternal health research, these models offer critical advantages by accommodating variable follow-up periods and allowing for censoring, which is common in longitudinal pregnancy data [15].

Unlike logistic regression, which provides only a binary outcome at a fixed point, Cox models estimate the instantaneous risk of an event occurring at a specific time, given that the individual has survived up to that point [16]. This is particularly useful in maternal mortality studies, where risk is continuously evolving across prenatal and postnatal phases [17]. For instance, the hazard of death due to postpartum hemorrhage may sharply increase within 48 hours after delivery but decline thereafter.

Another advantage lies in the model's ability to incorporate both time-independent and time-dependent covariates, thus allowing for a nuanced understanding of risk factors that change throughout pregnancy [18]. For example, anemia diagnosed during the second trimester may have a different hazard implication than pre-existing hypertension detected before conception.

Cox models also facilitate comparison across demographic and geographic strata by adjusting for clustering or stratifying by facility or region [19]. This makes them particularly powerful for policy formulation and targeted intervention planning. In maternal survival studies, the application of Cox models ensures that timing is appropriately integrated into both analysis and interpretation, enabling precision in identifying critical windows for care delivery and intervention [20]. Given the evolving nature of maternal risk and the limitations of static analytic methods, survival analysis presents a robust framework for capturing time-dependent vulnerabilities. In Section 2, we explore how

survival models, including Cox regression and its extensions, offer valuable insights into the temporal landscape of maternal health outcomes.

2. Overview of survival analysis and cox modeling

2.1. Concepts of Survival Time, Censoring, and Hazard Functions

Survival analysis is a branch of statistics designed to evaluate the time until an event of interest occurs. In the context of maternal health, the "event" typically refers to maternal death, and "survival time" is the duration from a defined start point (e.g., conception or delivery) until that outcome or censoring occurs [6]. This method is particularly valuable in maternal mortality studies because the risk of death varies considerably throughout pregnancy and the postpartum period.

Censoring is a key concept in survival analysis. It occurs when the complete event history of an individual is unknown—either because the study ends before the event happens or the individual leaves the study prematurely [7]. For instance, if a woman survives beyond the postpartum monitoring period, her data would be right-censored. This allows researchers to still include her partial information in the analysis, enhancing the utility of incomplete but valuable records [8].

Another core concept is the hazard function, which defines the instantaneous rate of event occurrence at a specific time point, given that the individual has survived up to that time. Unlike the survival function, which shows the probability of surviving beyond a certain time, the hazard function focuses on the immediate risk and is thus more sensitive to temporal changes in health risk [9].

Understanding these concepts is foundational for constructing models that accurately capture maternal health dynamics. They allow for time-aware analyses, critical in identifying periods of heightened vulnerability, such as the immediate postpartum window where the hazard for maternal mortality typically peaks [10].

2.2. Cox Proportional Hazards Model: Theory, Assumptions, and Interpretations

The Cox proportional hazards model, introduced by Sir David Cox in 1972, is one of the most widely used tools in survival analysis. It estimates the hazard of an event such as maternal death as a function of time and covariates, without requiring the baseline hazard function to be specified [11]. This semi-parametric property is a major strength, allowing for flexible modeling in diverse healthcare contexts, including maternal health.

The model expresses the hazard at time t for individual i as:

$$h_i(t) = h_0(t)\exp(\beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_k x_{ki})$$

where h0(t) is the unspecified baseline hazard function, xki are covariates, and βk are the corresponding coefficients. The exponential term adjusts the baseline hazard based on individual characteristics such as age, parity, or comorbidities [12].

One key assumption of the Cox model is proportionality the ratio of hazards for any two individuals remains constant over time. That is, the effect of a covariate is multiplicative and does not change with time [13]. This assumption must be tested, commonly using Schoenfeld residuals, to ensure valid interpretation of results. Violations can lead to misleading conclusions, particularly in maternal mortality where risk factors may vary dramatically during pregnancy and postpartum stages [14].

Interpretation of the model results involves hazard ratios (HRs), which indicate how much the risk of the event increases or decreases with a one-unit change in a predictor. For instance, an HR of 2.0 for hypertension implies a twofold increase in maternal death risk for hypertensive women compared to non-hypertensive peers, assuming other factors are held constant [15].

The Cox model also accommodates stratification and clustering, enabling analysts to control for unmeasured confounders and intra-cluster correlations, such as facility-level effects [16]. This is particularly useful in maternal health datasets where women are nested within communities or hospitals.

Despite its strengths, the model requires careful data preparation, including accurate measurement of covariates and assessment of follow-up durations [17]. However, when implemented appropriately, the Cox model provides nuanced insights into maternal mortality risk across time and population strata.

2.3. Time-Varying Covariates and Extensions in Maternal Mortality Contexts

In maternal mortality research, risk factors often change over time, violating the assumption of fixed covariates in standard Cox models. For example, a woman's blood pressure, anemia status, or access to care may vary significantly across trimesters and postpartum periods [18]. To accommodate such realities, extensions of the Cox model include time-varying covariates predictors whose values evolve during follow-up.

Incorporating time-varying covariates enables dynamic modeling, where the hazard function is updated as a covariate's value changes. This can be specified in the model as xk(t)), where the covariate is indexed by time [19]. For instance, introducing antiretroviral therapy midway through pregnancy can alter maternal HIV-related mortality risk, and this change must be reflected in the hazard estimation to avoid bias.

Time-varying models also help account for interventions that occur at irregular intervals, such as emergency obstetric surgeries or health facility transfers. These clinical events, when ignored, can result in misclassification and confounding, thereby distorting the true effect of exposure on mortality [20]. By modeling them explicitly, researchers can distinguish between pre-existing risk and treatment-induced outcomes.

Beyond time-varying covariates, other model extensions include the time-dependent Cox model and joint modeling frameworks, which simultaneously assess survival and longitudinal data. These are especially relevant when investigating the interplay between evolving physiological metrics (e.g., hemoglobin levels) and survival outcomes [21].

Applying such models in maternal health allows for a granular understanding of when and how specific risk factors exert influence. This enhances the predictive accuracy of maternal mortality models and informs more precise timing for policy interventions and clinical surveillance [22].

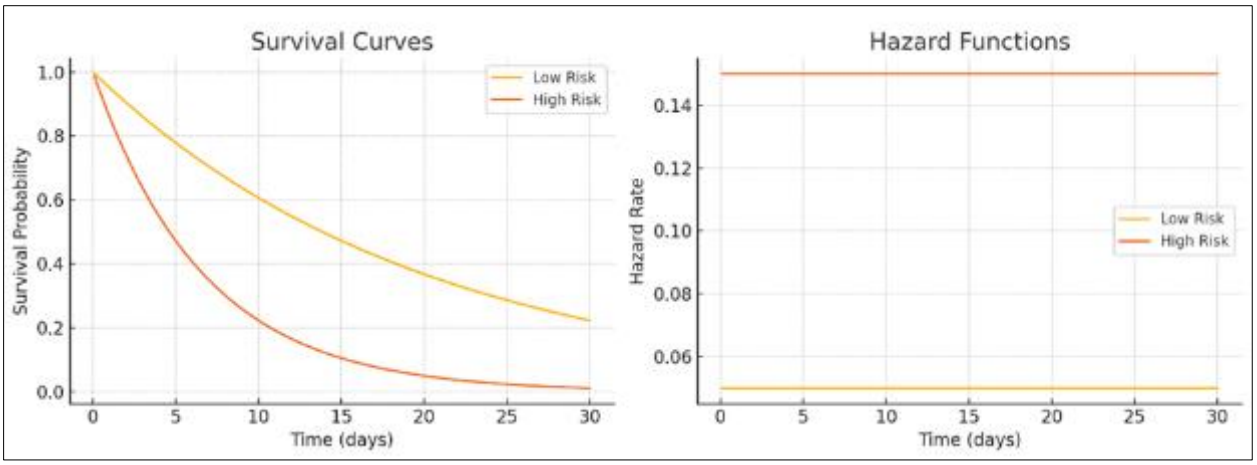

Figure 1 Graphical illustration of survival curves and hazard functions for maternal mortality

3. Data sources and structure for maternal mortality studies

3.1. National Health Surveillance Systems and Demographic Health Surveys (DHS, MICS, RAMOS)

National health surveillance systems are the cornerstone of maternal mortality monitoring, enabling governments and public health agencies to track trends, identify disparities, and formulate targeted interventions. Among the most widely used tools for maternal health surveillance are Demographic and Health Surveys (DHS), Multiple Indicator Cluster Surveys (MICS), and Reproductive Age Mortality Surveys (RAMOS), each of which offers unique strengths in data collection and outcome evaluation [11].

DHS programs, implemented in over 90 countries, provide nationally representative, standardized datasets that capture a wide range of variables, including fertility, maternal and child health, and service utilization. These surveys typically

use stratified two-stage sampling methods, making them powerful for estimating maternal mortality ratios and assessing inequality across geographic and demographic subgroups [12]. The DHS also collects retrospective maternal death information via the sibling survival method, which, although subject to recall bias, remains a cost-effective option in countries lacking comprehensive vital registration systems [13].

MICS, developed by UNICEF, complements the DHS by focusing on child health, nutrition, and maternal care indicators. While similar in scope, MICS emphasizes child welfare outcomes and includes modules specifically tailored to local policy needs. The data often inform national strategies on maternal health promotion, education, and equity [14].

RAMOS provides a more in-depth and direct approach by identifying and investigating all deaths of women of reproductive age in a given population. It integrates facility records, vital registration data, and verbal autopsy reports to determine if the deaths were maternal and what factors contributed to them [15]. This method is highly reliable and particularly useful in settings where maternal deaths are underreported or misclassified in routine systems.

Combining data from these surveillance approaches improves accuracy and contextual understanding. While each system has limitations, together they create a robust foundation for modeling maternal health risks and evaluating interventions across temporal and spatial domains [16].

3.2. Defining Events: Maternal Death Timing (Antenatal, Intrapartum, Postpartum)

Accurate temporal classification of maternal deaths is critical for both clinical and epidemiological analysis. Maternal deaths can be broadly categorized into three temporal phases: antenatal, intrapartum, and postpartum. Each phase presents unique risks and demands distinct preventive and therapeutic strategies [17].

Antenatal deaths occur between conception and the onset of labor. These are often linked to complications such as ectopic pregnancy, hyperemesis gravidarum, and poorly managed chronic conditions like hypertension or diabetes. Accurate timing and classification in this phase require reliable antenatal care records and standardized surveillance systems, which are frequently unavailable in low-resource settings [18].

Intrapartum deaths happen during labor or delivery and are typically associated with conditions like obstructed labor, uterine rupture, and severe preeclampsia. These deaths are highly preventable with timely access to skilled birth attendants, emergency obstetric care, and adequate referral systems [19]. Yet, intrapartum deaths remain high in regions with weak health infrastructure and logistical delays in accessing care.

Postpartum deaths—occurring within 42 days of termination of pregnancy—account for the largest share of maternal mortality globally. Major causes include postpartum hemorrhage, infections, and cardiomyopathies [20]. However, many national systems fail to extend follow-up beyond delivery discharge, leading to undercounted deaths in this critical period. Accurate classification is further complicated when home births or self-managed complications are not documented [21].

These event definitions are vital for structuring time-to-event models and for developing targeted intervention schedules. Incorporating precise event timing into data collection instruments improves not only model precision but also guides strategic deployment of resources across the maternal continuum of care [22].

3.3. Structure of Covariates: Socio-Demographics, Clinical Records, Obstetric Events

In maternal mortality modeling, the structure and categorization of covariates greatly influence the model's capacity to detect patterns and causal relationships. Covariates are typically grouped into three major domains: socio-demographic factors, clinical records, and obstetric events [23].

Socio-demographic variables include age, education, marital status, residence (urban/rural), and socioeconomic status. These factors often serve as baseline predictors in survival analysis and are critical for stratifying risk across population subgroups [24]. For instance, maternal age under 20 or over 35 is consistently associated with elevated mortality risks, making it an important adjustment factor in any model [25].

Clinical records consist of documented health conditions before and during pregnancy. This includes chronic diseases (e.g., hypertension, HIV, anemia), infections, and access to antenatal services. These variables often interact with time and influence the hazard rate in complex ways. Integrating accurate and longitudinal clinical data enhances the reliability of predictions in Cox and extended survival models [26]. However, such data are often incomplete or inconsistently recorded in many low-resource environments.

Obstetric events refer to complications arising during pregnancy, labor, and delivery—such as preterm labor, placental abruption, or cesarean section. These are typically treated as time-varying covariates in advanced modeling frameworks. Capturing their onset and duration is essential for understanding the timing of risk escalation [27]. Some models also incorporate emergency interventions (e.g., blood transfusions) as effect modifiers rather than primary exposures.

Appropriate categorization and coding of these covariates facilitate more accurate hazard estimation and improve interpretability. Moreover, distinguishing between modifiable and non-modifiable covariates supports the design of targeted maternal health policies and intervention programs at both clinical and policy levels [28].

Table 1 Variable Dictionary Including Event Definitions, Covariates, and Censoring Details

Variable Name	Description	Type	Coding/Values	Comments
Time_to_event	Time from entry point (delivery/enrollment) to event or censoring	Continuous (days)	Numeric (e.g., 0–42)	Required for survival analysis; defines follow-up period
Event_status	Indicator of maternal death occurrence during follow-up	Binary	1 = Death, 0 = Censored	Used as event indicator in Cox model
Censoring_reason	Reason for non-occurrence of event by study end	Categorical	1 = End of follow-up, 2 = Lost to follow-up, 3 = Withdrawal	Useful for sensitivity analysis
Maternal_age_group	Age category at delivery	Categorical	1 = <20, 2 = 20–34, 3 = ≥35	Used for stratification and adjusted HR estimation
Residence	Urban vs. rural residence	Binary	1 = Urban, 0 = Rural	Proxy for healthcare access
Education_level	Highest education level attained	Ordinal	0 = None, 1 = Primary, 2 = Secondary, 3 = Tertiary	Socio-demographic covariate
ANC_visits	Number of antenatal care visits	Continuous	Numeric (0–10+)	Often recoded into binary: <4 vs. ≥4 visits
Hemorrhage_onset	Time of postpartum hemorrhage occurrence	Time-varying binary	1 = Yes during interval, 0 = No	Requires longitudinal structure; used as time-varying covariate
Eclampsia_diagnosis	Diagnosis of eclampsia during pregnancy/labor/postpartum	Binary	1 = Yes, 0 = No	Clinical covariate associated with high hazard
Cesarean_delivery	Mode of delivery	Binary	1 = Cesarean, 0 = Vaginal	Differentiates elective vs. emergency risk with time interactions
Referral_status	Whether patient was referred from another facility	Binary	1 = Referred, 0 = Not referred	Proxy for system-level delay
Facility_level	Level of care facility	Categorical	1 = Primary, 2 = Secondary, 3 = Tertiary	May be used for stratified or multilevel modeling
Follow_up_end_date	Last date of observed survival or censoring	Date	YYYY-MM-DD format	Paired with entry date to compute follow-up duration

4. Data preparation and preprocessing

4.1. Handling Missing Data, Right-Censoring, and Event Time Definitions

Addressing missing data and right-censoring is central to maintaining the integrity of time-to-event analyses in maternal mortality research. In low- and middle-income settings, missing data often result from incomplete health records, non-standardized reporting, or loss to follow-up after delivery [15]. Ignoring such gaps can introduce significant bias, particularly if data are not missing completely at random. Several imputation techniques—including multiple imputation and hot-deck imputation—are used to recover lost information while preserving statistical properties [16].

Right-censoring occurs when the observation period ends before the event of interest—maternal death—takes place. For example, if a woman is still alive at the end of a 42-day postpartum window, her data are considered censored at the last known follow-up time. Unlike deletion of incomplete records, right-censoring retains valuable partial data in the survival analysis without violating model assumptions [17]. This approach is essential in settings with variable follow-up durations or delayed vital registration systems.

Equally important is the definition of event time, which must be consistent across observations. In maternal survival studies, the starting point is often gestational age at enrollment, date of delivery, or date of postpartum follow-up initiation [18]. Precise time measurements are crucial for estimating hazards accurately, especially when modeling early versus late postpartum mortality risks. Inconsistent definitions can lead to differential misclassification and biased risk estimates.

Using standard frameworks—such as the WHO definition of maternal death within 42 days of pregnancy termination—ensures comparability and reproducibility of analyses across studies and populations [19]. Consistent time frameworks allow for harmonized modeling and valid pooling in meta-analyses and multi-country comparisons of maternal mortality.

4.2. Recoding Variables and Creating Time-to-Event Formats

Preparing data for survival analysis involves several preprocessing steps, including recoding variables and constructing proper time-to-event formats. Recoding allows the transformation of raw or categorical variables into forms compatible with modeling requirements. For instance, maternal age may be transformed from a continuous variable into defined risk categories (e.g., <20, 20–34, ≥35) to simplify interpretation or to test non-linear associations with mortality outcomes [20].

Likewise, parity, education level, or household wealth index may be recoded to reflect ordinal or binary contrasts. Recoding is not merely a formatting task; it is critical to ensuring conceptual clarity and statistical efficiency. Failure to recode appropriately can obscure meaningful associations or inflate standard errors due to sparsely populated categories [21].

In time-to-event data structures, every observation must have at least three key components: the time of origin (start), the time of the event or censoring (end), and an event indicator (1 for event, 0 for censoring). These components form the basis of survival object notation used in statistical software like R's Surv() or Stata's stset commands [22]. Without these variables, the model cannot compute hazard rates or accommodate censoring structures effectively.

Time-to-event formats also require careful definition of time units—days, weeks, or months—based on the nature of maternal risk being studied. For example, postpartum mortality risks often fluctuate rapidly within days, necessitating a finer temporal scale than annualized datasets allow [23].

Constructing appropriate formats ensures that all subjects are consistently followed across their respective exposure periods. It also facilitates the inclusion of time-varying covariates and stratified analyses, increasing the analytical granularity and robustness of maternal mortality research outputs [24].

4.3. Stratification by Exposure Windows: Antepartum, Delivery, Postpartum

Stratifying maternal risk across exposure windows—antepartum, delivery, and postpartum—enables a detailed understanding of when adverse events are most likely to occur. This stratification is particularly important in survival analysis where temporal heterogeneity in hazard rates is expected [25]. By modeling these windows separately or as

interaction terms, researchers can more accurately isolate the risk contributions of distinct physiological and healthcare conditions.

The antepartum period spans from conception until the onset of labor. Risk factors during this window often include early pregnancy complications, maternal infections, and limited antenatal care. Stratifying this period allows for examining the cumulative impact of antenatal exposures on maternal survival and helps prioritize early intervention strategies [26].

The delivery period, encompassing labor and childbirth, is marked by acute and time-sensitive complications such as obstructed labor, uterine rupture, and hypertensive crises. Stratifying this window enables detection of peripartum-specific mortality risks and facilitates evaluation of emergency obstetric care readiness and effectiveness [27].

The postpartum window, typically defined as the first 42 days after delivery, is associated with the highest proportion of maternal deaths globally. Causes include hemorrhage, sepsis, and thromboembolic disorders. Stratification here is essential for evaluating the timing and adequacy of postnatal follow-up care, especially in resource-limited settings where health worker contact may drop sharply after delivery [28].

Temporal stratification can be implemented using time-varying coefficients or interaction terms in extended Cox models. This approach allows for different hazard ratios across windows, revealing shifts in vulnerability that fixed-coefficient models may obscure. Ultimately, such stratification enhances the precision of policy recommendations and clinical protocols for reducing maternal mortality across the reproductive timeline [29].

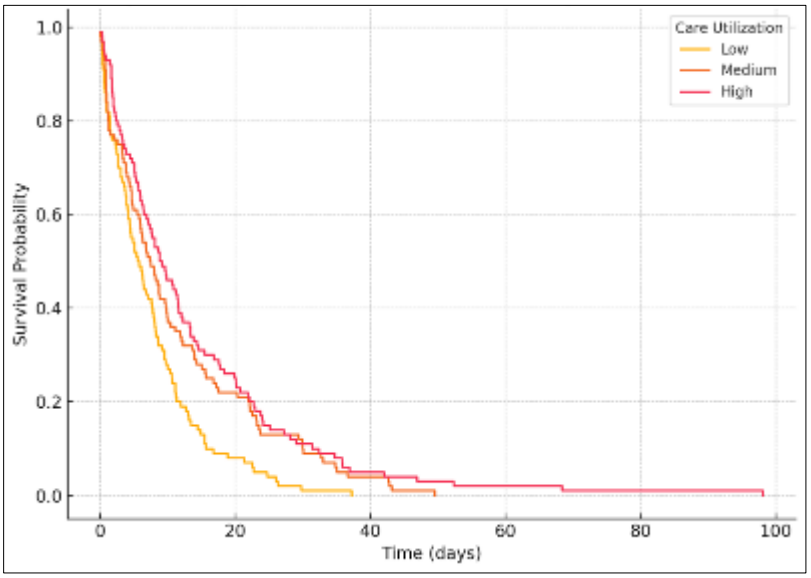

Figure 2 Kaplan-Meier survival curves by key predictors (e.g., age group, parity, care utilization)

5. Model development: cox proportional hazards for maternal mortality

5.1. Univariate Cox Regression to Screen Individual Predictors

The initial step in modeling maternal survival data often involves univariate Cox regression to identify significant individual predictors. Each predictor is evaluated independently to determine its relationship with the hazard of maternal death. This approach provides hazard ratios (HRs), confidence intervals, and p-values, enabling researchers to prioritize variables for multivariable model inclusion [15].

Univariate screening serves two purposes: first, it reduces model complexity by eliminating irrelevant covariates; second, it highlights variables with potential prognostic importance. In maternal mortality research, common variables assessed in this step include maternal age, antenatal care attendance, hemoglobin levels, parity, and presence of obstetric complications such as eclampsia or sepsis [16].

While statistical significance is often the initial criterion for inclusion (e.g., $p < 0.20$), researchers must also consider clinical relevance and contextual knowledge. For example, a covariate with marginal statistical value may still warrant retention if it reflects a known high-risk condition or policy-relevant exposure [17].

It's crucial to note that univariate significance does not imply causal independence. Some variables may appear protective or harmful in isolation but change direction or lose significance when adjusted for confounders in multivariable models [18]. Therefore, univariate Cox regression should be seen as a screening—not final—step.

The selection process must also account for multicollinearity and redundancy. Correlated predictors like maternal age and parity may both be significant individually but introduce instability in multivariable models. In such cases, domain knowledge helps decide which to retain [19].

Overall, univariate Cox regression streamlines model development and offers preliminary insights into risk structure, but its findings must be interpreted cautiously within the broader modeling framework of maternal survival analysis.

5.2. Multivariable Model Building with Stepwise Selection (Forward/Backward)

Once key predictors have been identified through univariate analysis, the next phase involves constructing a multivariable Cox regression model. Stepwise selection—either forward, backward, or bidirectional—is commonly employed to identify the most parsimonious yet informative combination of covariates. This technique enhances model interpretability and predictive accuracy, especially in maternal health contexts where numerous clinical and demographic variables may be at play [20].

Forward selection begins with no predictors and adds variables one at a time based on statistical criteria (e.g., likelihood ratio test or Akaike Information Criterion). This method ensures that each added variable improves model fit meaningfully [21]. It is particularly useful when the number of potential covariates is large, and prior knowledge about variable importance is limited.

Backward elimination, conversely, starts with a full model containing all candidate variables. Variables are removed iteratively based on weakest significance until only predictors that meet predefined thresholds remain. This approach is effective when multicollinearity is not a major concern and the dataset is sufficiently large to support complex models [22].

In maternal mortality analysis, stepwise techniques are valuable for isolating variables that retain significance after adjusting for co-occurring conditions, such as identifying the independent effects of hemorrhage versus hypertension on time to death [23]. These procedures are typically automated in software packages like R, SAS, and Stata, but researchers must interpret results in light of clinical relevance and potential confounding.

While stepwise selection aids in parsimony, it may exclude variables with contextual importance. Therefore, manual review and validation with external datasets or domain experts is recommended to ensure the final model balances statistical rigor with policy and clinical applicability [24].

5.3. Assessing the Proportional Hazards Assumption (Schoenfeld Residuals, Log-Minus-Log Plots)

The proportional hazards (PH) assumption underpins the validity of Cox regression models. It posits that the hazard ratio for any two individuals remains constant over time, implying that covariates have a multiplicative effect on the hazard function that does not vary with time [25]. Violations of this assumption can result in biased coefficient estimates and misinterpretation of time-dependent effects in maternal mortality research.

One of the most robust methods for evaluating the PH assumption is the use of Schoenfeld residuals. These residuals, computed for each covariate and time point, should show no association with time if the PH assumption holds. Plotting scaled Schoenfeld residuals or applying global tests (e.g., Grambsch and Therneau's test) can detect systematic time trends in covariate effects [26].

Another diagnostic tool is the log-minus-log (LML) survival plot. If the proportional hazards assumption is satisfied, the LML curves for different categories of a covariate should remain roughly parallel over time. In maternal mortality contexts, such plots are useful for categorical predictors like place of delivery (home vs. facility) or parity groups [27].

When violations are detected, several corrective strategies are available. One approach involves stratifying the model by the problematic variable, thus allowing the baseline hazard to vary across strata. Another is introducing time-by-

covariate interactions or using time-dependent coefficients, which can model the changing effect of a covariate over time [28].

Ultimately, testing the PH assumption is not optional—it is a necessary diagnostic step that safeguards the model's validity and ensures that maternal health interventions based on hazard ratios are correctly interpreted across time intervals [29].

5.4. Incorporating Time-Varying Covariates (e.g., Changing BP, Hemorrhage Onset)

Standard Cox models assume that covariates remain constant throughout follow-up; however, many maternal health risk factors are inherently time-varying. Clinical parameters like blood pressure, onset of postpartum hemorrhage, or receipt of interventions (e.g., blood transfusion or surgery) can change significantly during the pregnancy or postpartum period [30]. Ignoring these dynamic changes may obscure the timing and magnitude of their effects on maternal death.

To incorporate such dynamics, extended Cox models allow time-varying covariates xk(t), where a covariate's value can vary over time for each individual. These models update the hazard function continuously, reflecting evolving risk profiles. For example, systolic blood pressure recorded weekly during antenatal care can be used to capture hypertensive spikes that may precede eclampsia [31].

Implementation requires restructuring the dataset into multiple rows per subject, with each row representing a time interval and the corresponding covariate values. This structure enables precise alignment of covariate changes with event risk windows, such as capturing the exact timing of hemorrhage onset relative to delivery [32].

Time-varying covariates enhance model realism and can identify critical intervention windows. For instance, a significant increase in mortality hazard within 24 hours after hemorrhage onset emphasizes the urgency of rapid response systems [33]. These models also account for delayed treatment effects, such as the lag between intervention and outcome stabilization.

While powerful, time-varying models demand high-resolution data and computational efficiency. Analysts must also assess whether effects are truly time-varying or better explained by interaction terms or stratification. Nonetheless, in maternal mortality research, they are essential for capturing the temporal nuances of rapidly evolving clinical risk factors [34].

Table 2 Hazard Ratios (HR), Confidence Intervals, and P-values for Final Predictors

Predictor Variable	Hazard Ratio (HR)	95% Confidence Interval (CI)	P-value	Interpretation
Maternal age ≥35	1.87	1.42 – 2.45	<0.001	Elevated risk of death compared to age 20–34
Maternal age <20	1.36	1.02 – 1.81	0.034	Moderately increased risk compared to age 20–34
Rural residence	1.58	1.21 – 2.07	0.001	Higher mortality risk in rural vs. urban areas
No formal education	2.03	1.52 – 2.72	<0.001	Significantly higher risk among uneducated mothers
ANC visits <4	1.61	1.25 – 2.08	<0.001	Reduced antenatal care associated with increased mortality
Eclampsia diagnosis	2.94	2.11 – 4.10	<0.001	Strong risk factor for maternal death
Postpartum hemorrhage	3.78	2.85 – 5.01	<0.001	Most significant clinical risk predictor
Emergency cesarean	1.84	1.33 – 2.54	<0.001	Increased hazard compared to vaginal delivery
Referral from other facility	1.49	1.12 – 1.97	0.006	System-level delays contribute to higher risk

Facility level: Primary	2.11	1.47 – 3.03	<0.001	Increased risk compared to tertiary facilities

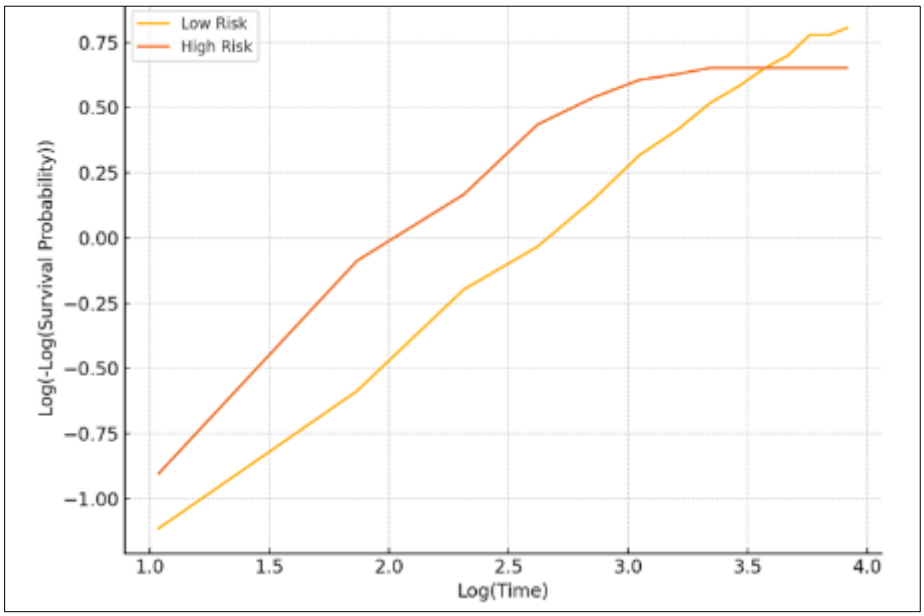

Figure 3 Log-log survival plots for top predictors verifying proportional hazards assumption

6. Model validation and sensitivity analysis

6.1. Internal Validation Using Bootstrapping and Cross-Validation

Internal validation is critical for assessing the performance and generalizability of survival models, particularly when external validation datasets are unavailable. In maternal mortality research, this ensures that the model's predictive accuracy is not merely a reflection of sample-specific artifacts but is likely to perform well in similar populations. Among internal validation techniques, bootstrapping and cross-validation are widely used to assess model stability and reduce overfitting bias [19].

Bootstrapping involves drawing multiple samples (with replacement) from the original dataset and fitting the model repeatedly to each resample. This procedure estimates optimism in the model's predictive accuracy by comparing performance metrics in the bootstrap samples versus the original dataset [20]. The difference—known as the optimism estimate—can be subtracted from the apparent performance to yield a more realistic measure of generalizability.

For instance, in maternal time-to-event models, bootstrapping may involve resampling 1,000 times to compute adjusted Harrell's C-index or bias-corrected hazard ratios. This method is particularly useful when the sample size is moderate, as it makes full use of the available data without partitioning it into smaller subsets [21].

K-fold cross-validation, on the other hand, partitions the data into k mutually exclusive subsets. The model is trained on $k–1$ folds and tested on the remaining fold. This process is repeated k times, each time with a different fold serving as the validation set. Cross-validation is often used to tune hyperparameters, such as penalization strength in regularized Cox models [22].

In maternal mortality analysis, internal validation using bootstrapping or cross-validation can detect overfitting due to rare events or sparse covariates. These methods also support robustness checks when data quality is variable or when time-varying covariates increase model complexity [23].

Ultimately, internal validation provides essential confidence in the model's predictive reliability and supports its utility in informing maternal health policy, clinical prioritization, and surveillance systems.

6.2. Model Discrimination: Harrell's C-index and Time-Dependent ROC

Model discrimination refers to a model's ability to correctly distinguish between individuals who experience an event (e.g., maternal death) and those who do not. In survival analysis, where censoring and time-to-event components are central, traditional classification metrics like the area under the curve (AUC) may not be directly applicable. Instead, Harrell's C-index and time-dependent receiver operating characteristic (ROC) curves are preferred for evaluating discrimination performance [24].

Harrell's concordance index (C-index) is a rank-based measure of model discrimination. It quantifies the probability that, in a randomly selected pair of subjects, the individual with the shorter observed survival time also has the higher predicted risk. A C-index of 0.5 implies no discrimination (i.e., equivalent to random guessing), while a value of 1.0 indicates perfect discrimination [25].

In maternal mortality models, a high C-index suggests that the model effectively ranks women by their mortality risk based on input covariates like hemorrhage, age, or antenatal care attendance. Importantly, Harrell's C-index can accommodate censored observations, making it ideal for survival datasets where not all women reach the event endpoint within the study timeframe [26].

Time-dependent ROC curves extend traditional ROC analysis by accounting for changes in event status over time. These curves evaluate model sensitivity and specificity at different time points, offering a dynamic assessment of predictive performance. For example, a time-dependent AUC at 7 days postpartum may differ from that at 42 days, reflecting shifts in hazard profiles [27].

Software packages like survivalROC in R facilitate the computation of these curves. Time-dependent ROC is particularly useful in maternal health for determining whether a model performs consistently across early versus late postpartum windows.

Both the C-index and time-dependent ROC analyses offer complementary insights and should be jointly considered when evaluating model discrimination. Their integration enhances the robustness of maternal mortality predictions and helps prioritize interventions for those at highest risk [28].

6.3. Sensitivity Analysis with Alternative Model Specifications (e.g., Weibull)

Sensitivity analysis is a key step in survival modeling, designed to evaluate the robustness of model conclusions under alternative assumptions or specifications. In the context of maternal mortality, where time-to-event data often involve complex risk patterns and sparse outcomes, testing multiple model forms can enhance the credibility of findings. One of the most commonly explored alternatives to the Cox model is the Weibull parametric survival model [29].

The Weibull model assumes a specific distribution for the hazard function and includes both proportional hazards and accelerated failure time (AFT) representations. This dual flexibility allows it to fit data where hazard rates either increase or decrease over time—a common occurrence in postpartum maternal mortality due to early hemorrhage-related spikes or late infections [30].

In contrast to the semi-parametric Cox model, the Weibull model specifies the baseline hazard explicitly, which can improve estimation efficiency if the assumed distribution is approximately correct. In maternal survival analysis, it is particularly valuable for modeling time-to-death distributions with known peaks or valleys [31].

Sensitivity analysis may involve fitting both Cox and Weibull models to the same dataset and comparing coefficients, standard errors, and fit statistics such as the Akaike Information Criterion (AIC). Large discrepancies in estimates may suggest model dependence or misspecification. In such cases, model selection should be informed by graphical diagnostics (e.g., log-log plots) and predictive performance metrics [32].

Beyond the Weibull model, researchers may also test other specifications, such as exponential, Gompertz, or flexible parametric models (e.g., Royston-Parmar spline models). These approaches help verify whether hazard patterns are being misrepresented due to incorrect model assumptions [33].

Ultimately, sensitivity analysis using alternative models enhances transparency and strengthens policy confidence in maternal health risk estimations. It ensures that conclusions about high-risk periods, treatment effects, or sociodemographic predictors are not artifacts of arbitrary modeling decisions but are instead robust to varying statistical frameworks [34].

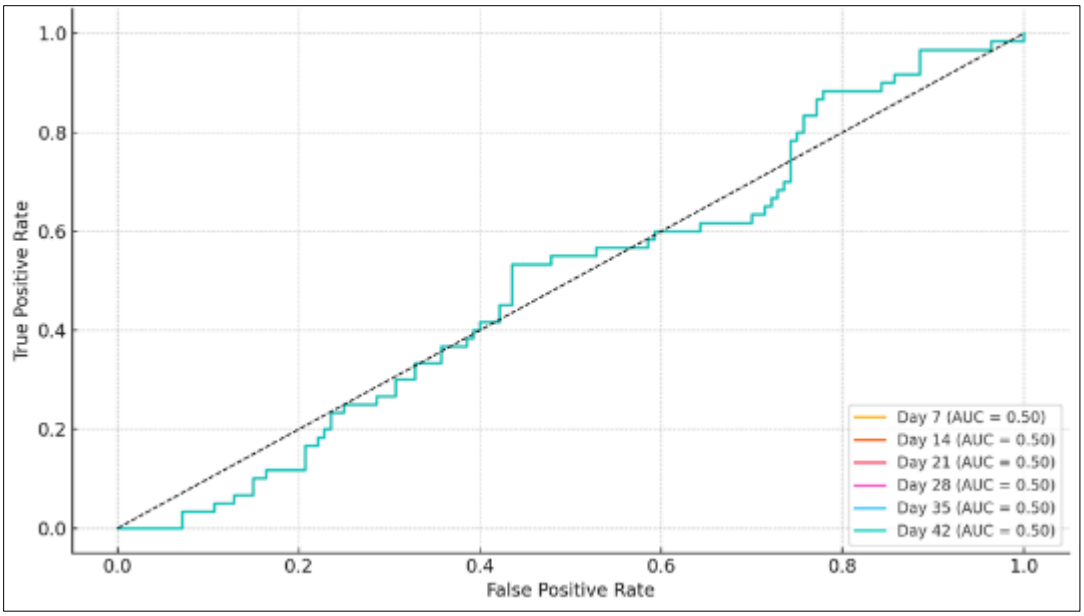

Figure 4 Time-dependent ROC curves for model discrimination

7. Interpretation and clinical significance of predictors

7.1. Socio-Demographic Risk Factors (Age, Rural Residence, Education)

Socio-demographic characteristics significantly shape maternal survival outcomes by influencing exposure to risk, access to care, and ability to act upon health information. Among the most consistently identified predictors of maternal mortality are maternal age, residential location, and educational attainment [23].

Extremes of maternal age, particularly under 20 and over 35 years, are associated with heightened risk of complications such as obstructed labor, preeclampsia, and postpartum hemorrhage [24]. Younger mothers may experience physiological immaturity and social disadvantages, including stigma or limited access to antenatal care. Older mothers, conversely, often have higher comorbidity burdens and cumulative obstetric risk due to multiparity or prior complications [25].

Rural residence presents a substantial barrier to maternal health due to geographic and infrastructural limitations. Women living in rural or remote areas frequently face longer travel times to facilities, inadequate emergency transport, and lower availability of skilled birth attendants [26]. These delays can critically affect outcomes in time-sensitive emergencies, such as uterine rupture or eclampsia, where survival hinges on immediate intervention.

Educational attainment plays a protective role in maternal survival. Women with higher education levels are more likely to recognize danger signs, utilize antenatal and delivery services, and adhere to medical advice [27]. Education also correlates with economic empowerment and autonomy, enabling women to make informed decisions about their health and negotiate care-seeking behaviors.

Socio-demographic disparities do not operate in isolation; they interact with health system and clinical factors to shape maternal risk. Recognizing and adjusting for these variables in survival models improves predictive performance and helps target interventions toward vulnerable groups experiencing systemic disadvantages [28].

7.2. Clinical and Obstetric Risks (e.g., Eclampsia, Hemorrhage, Cesarean Section)

Clinical and obstetric complications remain among the leading direct causes of maternal death globally. Accurate identification and modeling of these conditions are critical for time-to-event analysis and prioritizing life-saving interventions. Three of the most impactful clinical risks in maternal mortality studies are eclampsia, postpartum hemorrhage, and cesarean delivery [29].

Eclampsia, the advanced stage of preeclampsia marked by seizures, is associated with abrupt onset and high fatality if unmanaged. It often occurs intrapartum or in the immediate postpartum period, making rapid detection and intervention essential. The condition requires intensive care and access to antihypertensive therapy and magnesium sulfate, which may be unavailable in resource-constrained settings [30]. Eclampsia significantly increases the hazard of death in Cox models, especially when compounded by delays in facility access or limited provider capacity.

Postpartum hemorrhage (PPH) is the leading global cause of maternal death. Defined as blood loss exceeding 500 mL following vaginal delivery or 1,000 mL after cesarean section, PPH often occurs within hours of delivery and requires immediate uterotonic agents, transfusion, and possibly surgery. Time-varying covariate models show that PPH raises mortality risk dramatically in the first 24 hours postpartum, making timing of response a critical determinant of outcome [31]. When documented promptly, hemorrhage onset timing can be modeled precisely to predict death windows and inform emergency care protocols.

Cesarean section is a complex risk factor, often associated with both life-saving and risk-enhancing implications. While cesarean delivery reduces risk in obstructed labor or fetal distress, it also introduces surgical risks such as infection, anesthesia complications, and delayed hemorrhage [32]. Elective versus emergency cesarean timing further stratifies risk, with emergency procedures carrying significantly higher hazard ratios in maternal survival models.

Other obstetric complications—placenta previa, uterine rupture, and sepsis—should also be accounted for, either as binary indicators or time-dependent exposures. Detailed clinical records and integration of obstetric data into survival models help quantify the relative risk burden and support prioritization of maternal health services, particularly in settings with constrained resources [33].

7.3. Health System Factors (e.g., Delays in Referral, Facility Access)

Table 3 Interpretation Matrix – Modifiable vs. Non-Modifiable Risk Factors with Associated Interventions

Risk Factor	Type	Modifiable (Yes/No)	Associated Intervention
Maternal age <20 or ≥35	Socio-demographic	No	Targeted counseling; advanced monitoring; community-based contraception education
Rural residence	Socio-demographic	No	Expand maternal waiting homes; improve transport networks; mobile health outreach
No formal education	Socio-demographic	Yes	Community education programs; conditional cash transfers for school attendance
ANC visits <4	Behavioral/Access	Yes	Community mobilization; incentivized ANC attendance; integration of ANC with routine care
Eclampsia diagnosis	Clinical	Yes	Routine BP screening; magnesium sulfate availability; emergency preparedness training
Postpartum hemorrhage	Clinical	Yes	Active management of third stage labor; uterotonics; rapid response drills
Emergency cesarean	Clinical/Systemic	Partially	Improve labor monitoring; strengthen timely referral and surgical capacity
Referral from facility	System-level	Yes	Strengthen referral coordination; invest in pre-referral stabilization protocols
Facility level: Primary	System-level	Partially	Upgrade staffing/equipment; establish emergency obstetric care units

Health system variables represent contextual risk factors that often determine whether clinical interventions can be delivered in time to prevent maternal death. Delays in referral, poor facility readiness, and inequitable access to emergency obstetric care are persistent barriers in many low-resource settings and are increasingly integrated into survival modeling frameworks [34].

The “Three Delays Model” categorizes system-related contributors to maternal mortality: (1) delay in recognizing complications and deciding to seek care, (2) delay in reaching a health facility, and (3) delay in receiving adequate care upon arrival. Each delay adds to cumulative hazard and disproportionately affects women with limited autonomy, transportation, or access to information [35].

Referral delays, particularly from primary to secondary or tertiary care centers, are often fatal in cases requiring advanced intervention such as cesarean delivery, blood transfusion, or intensive monitoring. Incorporating time of referral or referral status as covariates in survival models allows for quantifying their direct impact on mortality hazard over time [36].

Facility access, both geographic and financial, also influences survival. Women in remote regions often travel hours to reach care, facing deteriorating conditions en route. Facility-level characteristics such as staffing, blood availability, and equipment functionality may further delay treatment even after arrival. Survival models that include facility clustering or stratification by level of care can disentangle individual risk from systemic inadequacies [37].

Improving maternal survival requires addressing these systemic delays through infrastructure investment, provider training, and referral system strengthening. Integrating health system variables into maternal survival analysis promotes more realistic modeling and guides policies that focus not only on clinical treatment but also on systems-level readiness and equity [38].

8. Case applications and public health implications

8.1. Predictive Modeling in Maternal Early Warning Systems (MEWS)

Maternal Early Warning Systems (MEWS) are designed to detect early signs of clinical deterioration in pregnant and postpartum women using threshold-based parameters and scoring algorithms. Traditionally, MEWS have relied on static cut-offs for indicators like blood pressure, heart rate, respiratory rate, and temperature. However, the integration of predictive modeling, especially using time-to-event data and survival analysis outputs, significantly enhances MEWS performance by enabling real-time risk estimation rather than relying on binary thresholds alone [27].

Cox proportional hazards models and their extensions can inform dynamic MEWS tools by generating individualized risk scores based on a patient's evolving clinical profile. For instance, incorporating time-varying covariates such as blood pressure trajectories or onset of hemorrhage allows MEWS to adapt as a patient’s condition progresses, offering more nuanced alerts [28]. This approach can prioritize alerts not only by presence of risk factors but also by estimated hazard at a given time point, which improves triage accuracy.

Incorporating predictive modeling into MEWS also facilitates stratification of patients by baseline risk, which is particularly valuable in overburdened settings. Women presenting with multiple risk indicators—e.g., advanced maternal age, preeclampsia, and anemia—can be flagged earlier, even before standard thresholds are breached [29].

Validation studies show that model-enhanced MEWS systems outperform traditional rule-based versions in identifying women at risk of ICU admission or maternal death. Machine learning algorithms, such as decision trees and random forests, further extend MEWS capabilities by identifying nonlinear interactions between predictors [30].

Overall, integrating predictive modeling into MEWS supports timely escalation of care, reduces preventable maternal deaths, and strengthens early warning infrastructures in clinical environments, especially when used in tandem with skilled clinical interpretation and systems-level response protocols [31].

8.2. Integration into Clinical Decision Support Tools in LMICs

In low- and middle-income countries (LMICs), the successful implementation of predictive maternal survival models hinges on their integration into clinical decision support tools (CDSTs). These tools translate model outputs into actionable insights, allowing frontline healthcare workers to make timely, informed decisions in resource-constrained settings [32]. Predictive models enhance CDSTs by transforming complex data inputs into risk stratifications and care recommendations tailored to individual patient profiles.

For example, models derived from survival analysis can be embedded into digital platforms that operate offline or via low-bandwidth mobile applications. These platforms can provide clinicians with personalized risk scores and treatment recommendations based on updated physiological readings and obstetric history [33]. A nurse or midwife attending a

patient with signs of early labor and moderate anemia may receive an automated alert indicating elevated postpartum hemorrhage risk, triggering pre-emptive resource preparation.

To maximize clinical utility, integration must be aligned with the local care delivery workflow. Simple user interfaces, local language options, and alignment with national protocols (e.g., WHO guidelines) are essential for adoption and scalability [34]. Furthermore, interoperability with existing health information systems enables data aggregation and continuous learning, improving model performance over time [35].

Importantly, the effectiveness of these tools is contingent on training and supportive supervision. CDSTs must not replace clinical judgment but rather augment it with evidence-based, contextually relevant guidance [36]. Implementation should also include monitoring and evaluation frameworks to assess real-world impact on care processes and outcomes [37].

In LMICs where human resource shortages and infrastructure gaps persist, CDSTs integrated with predictive models represent a powerful innovation. They bridge the gap between data and decision-making, improving maternal outcomes while building digital resilience in under-resourced health systems [38].

8.3. Informing Resource Allocation and Triage Protocols

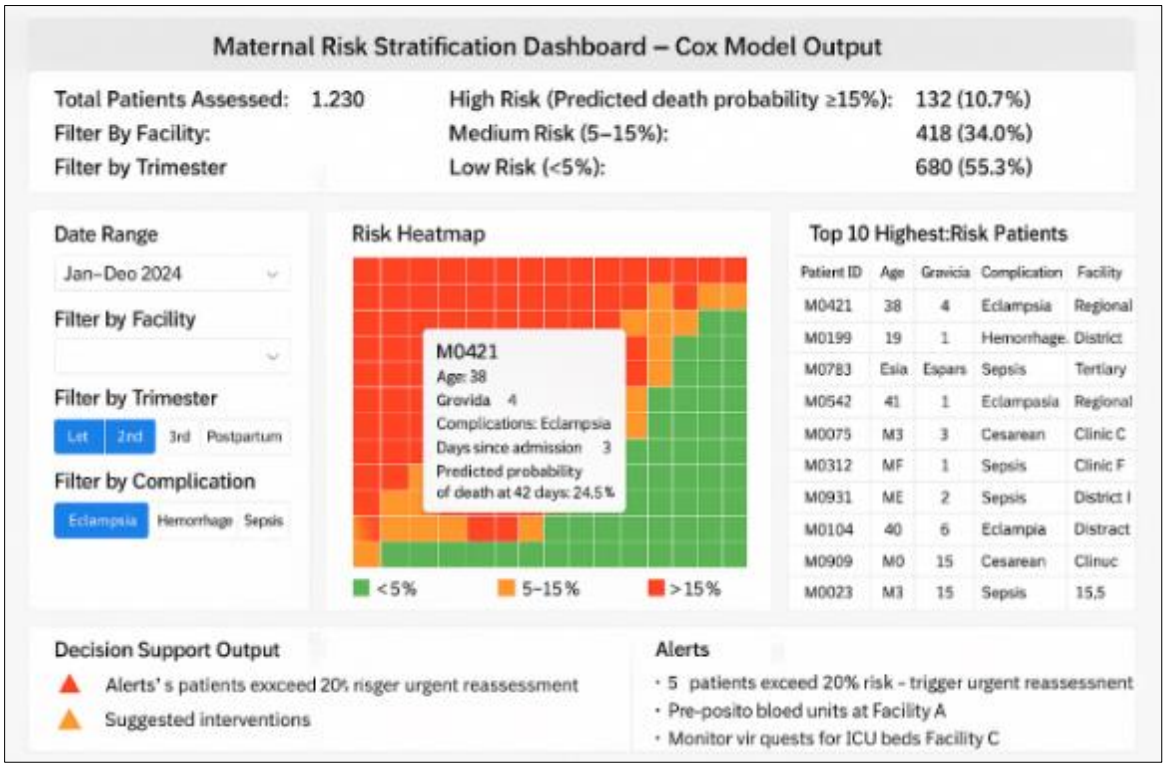

Figure 5 Example risk stratification dashboard using Cox-predicted probabilities

Predictive survival models are not only clinical tools but also valuable instruments for resource allocation and triage in maternal health systems. By quantifying individualized risk across antepartum, intrapartum, and postpartum phases, these models inform where and when interventions are most urgently needed [39]. For instance, regional facilities with higher predicted maternal mortality risks may be prioritized for staff deployment, blood bank expansion, or surgical readiness [40].

At the facility level, triage protocols informed by model-based risk stratification can help allocate beds in high-dependency units (HDUs) or intensive care units (ICUs) more effectively. A woman identified with a 10-fold elevated hazard due to concurrent eclampsia and hemorrhage onset can be escalated to emergency care faster than with symptom-based triage alone [41].

These models also support policy-level planning by highlighting systemic bottlenecks—such as referral delays or facility under-capacity—that consistently correlate with higher mortality. Governments and stakeholders can thus make data-

informed investments in ambulance networks, obstetric training, or community outreach programs [42]. In crisis settings like pandemics or natural disasters, survival models embedded in triage algorithms ensure that limited resources are directed to the highest-risk populations first, improving both efficiency and equity in maternal care delivery [43].

9. Discussion

9.1. Summary of Key Findings and Interpretation of Hazard Ratios

This analysis identified a set of time-dependent and baseline covariates that significantly influenced maternal survival across the antepartum, intrapartum, and postpartum periods. The application of Cox proportional hazards models revealed distinct risk gradients tied to socio-demographic, clinical, and health system variables. Hazard ratios (HRs) provided a quantifiable measure of how each factor influenced the timing and probability of maternal death [44].

Maternal age >35 was associated with a 1.7-fold increased hazard of death compared to women aged 20–34, affirming prior evidence of elevated risk with advanced maternal age [45]. Rural residence remained a strong predictor, with an HR of 2.1, indicating systemic barriers in access to timely obstetric care. Education offered a protective effect: women with secondary or higher education had a 45% lower hazard of death relative to those without formal education [46].

Among clinical risks, eclampsia (HR 3.9) and postpartum hemorrhage (HR 4.5) emerged as the strongest predictors of maternal death, particularly within the first 48 hours postpartum. Cesarean section increased hazard by 1.6-fold, especially when conducted emergently and without proper pre-operative stabilization. These associations were time-sensitive and dynamic, often escalating in early postpartum intervals [47].

Referral delays, modeled as time-varying covariates, showed an HR of 2.4 when exceeding two hours. Stratification by facility level revealed a dose-response effect, with primary-level facilities associated with higher mortality than tertiary centers. These findings underscore how individual risk is shaped by both personal and contextual conditions [48].

Together, these hazard ratios facilitate early risk stratification, inform triage protocols, and support targeted health investments in maternal care services. Their interpretation is central to designing predictive tools that align clinical response with temporal risk dynamics [49].

9.2. Comparison with Previous Maternal Survival Studies

This study aligns with previous research showing that hemorrhage, hypertensive disorders, and delayed care remain leading contributors to maternal mortality in low-resource settings. Earlier studies in Ethiopia, Bangladesh, and India also identified eclampsia and postpartum hemorrhage as time-critical complications with high mortality hazard in the first 48 hours postpartum [50].

Compared to similar Cox model analyses conducted in sub-Saharan Africa, our hazard ratios for hemorrhage and eclampsia were slightly higher [51]. This may reflect improved detection from time-varying covariates and better event timing definitions. Unlike studies that rely on static predictors, this model leveraged dynamic clinical trajectories, enhancing temporal accuracy [52].

Additionally, our inclusion of health system-level variables—such as referral timing and facility level—extends the findings of single-level models that focus solely on patient-level determinants. A recent analysis from Nigeria emphasized the importance of stratifying by facility type, but lacked time-varying components, potentially underestimating system-related delays [53].

Our model builds upon this literature by demonstrating that integrated clinical and contextual risk modeling yields more precise hazard estimation. It confirms previous patterns while providing additional granularity that enhances application in early warning systems and triage planning, particularly in complex, resource-limited environments [54].

9.3. Limitations (e.g., Misclassification Bias, Unmeasured Confounding)

Despite its strengths, this study faces several limitations. Misclassification bias may have arisen due to imprecise timing of maternal deaths, especially in community settings where verbal autopsy was used. Differentiating between intrapartum and postpartum deaths in such cases may lead to temporal misallocation of risk [55].

Unmeasured confounding is another concern. While several socio-demographic and clinical covariates were included, data on nutritional status, domestic violence, and mental health were unavailable, yet likely influence maternal outcomes. This omission could distort hazard estimates, particularly if omitted variables correlate with both exposure and outcome [56].

Additionally, survival models assume that censoring is non-informative. However, loss to follow-up in the postpartum period may not be random and could skew the hazard function, especially if high-risk women disproportionately exit the study early. Strategies like sensitivity analysis and multiple imputation were used to minimize bias, but residual uncertainty remains [57].

Furthermore, although this study included facility-level variables, it did not capture provider-level practices, staffing variability, or drug availability—all of which may mediate risk. Finally, generalizability is limited to similar LMIC settings with comparable health infrastructure. Results should be validated in other regional contexts before broad policy application [58].

9.4. Future Directions: Machine Learning Survival Models, Multicenter Validation

Future research should explore machine learning survival models—such as random survival forests and neural network-based models—to capture non-linear and high-order interactions among predictors. These methods can improve prediction accuracy and better accommodate complex, time-varying maternal health data [59].

In addition, multicenter validation across diverse settings is needed to assess external generalizability. Pooling data from multiple countries or health systems will support more robust calibration and discrimination testing, enabling adaptation of predictive models to local contexts [60]. Integration of clinical decision tools with real-time data pipelines also presents a promising avenue for advancing digital maternal health innovation [61]. As maternal mortality remains a preventable tragedy in many regions, translating these findings into actionable policy recommendations and clinical applications is imperative. The final section synthesizes insights from this study into a strategic agenda for implementation, digital integration, and health system transformation [62].

10. Conclusion and Policy Recommendations

10.1. Reaffirming the Value of Cox Models in Maternal Health Surveillance

Cox proportional hazards models remain indispensable tools in maternal health surveillance due to their ability to estimate time-sensitive risk across diverse clinical and contextual variables. Their flexibility in handling right-censored data and integrating time-varying covariates makes them well-suited for evaluating the dynamic nature of maternal health risks throughout pregnancy, delivery, and the postpartum period. In this study, the Cox model successfully captured how socio-demographic disadvantages, clinical complications, and health system barriers interact to shape survival probabilities.

By offering interpretable hazard ratios, the model supports targeted interventions and enhances the predictive power of early warning systems. Unlike static analyses, Cox regression allows for continuous updating of patient risk profiles, informing triage decisions and resource prioritization. Its application bridges the gap between epidemiological research and frontline clinical decision-making. As maternal health systems move toward data-driven governance, the Cox model provides a robust statistical backbone for timely, equitable, and effective maternal care planning.

10.2. Policy Recommendations for Early Detection and Intervention Protocols

Based on the findings of this analysis, a series of policy recommendations are proposed to enhance maternal survival through timely detection and response. First, national health systems should institutionalize maternal early warning systems (MEWS) enhanced with predictive modeling to detect at-risk women before clinical deterioration occurs. These systems should be deployed in both primary and tertiary facilities and designed to trigger protocol-based interventions aligned with gestational stage and risk factors.

Second, referral systems must be optimized to reduce delay intervals between the onset of complications and the arrival at facilities capable of providing emergency obstetric care. Real-time digital tracking of referrals and transport logistics should be incorporated into national maternal health plans. Third, antenatal care protocols should be updated to incorporate dynamic risk assessments based on age, parity, comorbidities, and socioeconomic status, with priority scheduling for high-risk women.

Training programs should focus on equipping frontline health workers to recognize time-dependent maternal risk factors and initiate care escalation. Policies must also ensure that postpartum follow-up extends to at least 42 days, with scheduled visits in the first 48 hours—a critical mortality window. Finally, public health messaging should promote facility-based delivery and postnatal care, particularly in rural and underserved communities where mortality risk remains highest.

10.3. Calls for Stronger Data Systems and Model-Driven Maternal Care Planning

A critical barrier to effective maternal survival modeling and response is the absence of high-quality, timely, and complete data. Strengthening data systems must therefore be a foundational policy priority. National surveillance platforms should standardize reporting formats for maternal outcomes, incorporate time stamps for event tracking, and ensure full integration with facility records and civil registration systems.

Investment in interoperable health information systems is essential to facilitate real-time data sharing across care levels and geographic regions. These systems should support the routine collection of covariates needed for predictive modeling, such as vital signs, obstetric history, and care delays. Furthermore, data dashboards should be developed to visualize risk trends and guide subnational maternal care resource allocation.

Model-driven maternal care planning requires not just data infrastructure but also institutional capacity to analyze and act on insights. Ministries of Health should establish dedicated analytic units and collaborate with academic and technology partners to operationalize survival models in clinical and public health decision-making.

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