Parametric Survival Analysis of Neonatal Mortality in a Tertiary Care Setting: A Comparative Proportional Hazard Model Approach

Shalini Jaiswal[1], Shambhavi Mishra[1*], Neha Thakur Rai[2]

[1]Department of Statistics, University of Lucknow, Lucknow, Uttar Pradesh, India

[2]Assistant Professor, Department of Statistics, University of Lucknow, Luckow, Uttar Pradesh, India.

[2] Professor junior grade, Department of Paediatrics, Dr. Ram Manohar Lohia Institute of Medical Sciences (RMLIMS), Lucknow, Uttar Pradesh, India

***Corresponding Author**

DOI: https://dx.doi.org/10.51584/IJRIAS.2026.110200150

Received: 04 March 2026; Accepted: 09 March 2026; Published: 21 March 2026

ABSTRACT

Background: Neonatal mortality represents a major public health concern characterised by complex survival dynamics and substantial aetiological heterogeneity. Appropriate survival modelling of time-to-event data is essential for elucidating disease-specific risk profile during the critical first 28 days of life. Neonatal mortality in intensive care settings exhibits an early-peak hazard profile inadequately captured by semiparametric methods alone. Comparative evaluation of parametric proportional hazard (PH) models that explicitly parameterise the baseline hazard provides both superior fit diagnostics and direct hazard quantification.

Objectives: To compare parametric survival models and identify the optimal distributional fit for neonatal mortality data, and to determine prognostic factors using the best-fitted model for neonatal outcome.

Methods: A prospective study design was used to collected the data of 686 neonates admitted to the Neonatal Intensive Care Unit (NICU) and Special Newborn Care Unit (SNCU) at Dr. Ram Manohar Lohia Institute of Medical Sciences (RMLIMS), Lucknow, was followed from admission until death, discharge, transfer, or day 28. Four survival models were fitted and compared by Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The proportional hazards (PH) assumption was assessed via Schoenfeld residuals with global test. Discriminative ability was evaluated using Harrell's C-concordance statistic

Results: Among 686 neonates, 155 (22.59%) died during follow-up. The Weibull PH model achieved the best fit (AIC = 827.77; BIC = 927.44). Key independent predictors included extreme prematurity, congenital malformations, perinatal asphyxia, neonatal sepsis, induced labour, and multiparity. The global Schoenfeld test supported the proportional hazards assumption ($p = 0.0976$). Harrell's C = 0.7948 indicated good discriminative performance.

Conclusions: The Weibull PH model provides the best parametric characterisation of neonatal mortality hazard dynamics. Extreme prematurity, critical clinical diagnoses, and induced labour are dominant independent hazard determinants, consistent across all model specifications.

Keywords: neonatal mortality; Weibull; Gompertz; exponential; Cox model; proportional hazards; Harrell's C

INTRODUCTION

Every year, about 2.3 million newborns die within their first 28 days of life. This neonatal mortality accounts for nearly half (47%) of all deaths in children under five worldwide [1]. South Asia and sub-Saharan Africa bear a disproportionate share of this burden, with India alone contributing approximately 20–27% of global neonatal deaths. The National Family Health Survey (NFHS-5, 2019–21) reported a national neonatal mortality rate of

20.3 per 1,000 live births in India, with wide interstate variation from under five per 1,000 in Kerala to over 30 per 1,000 in Uttar Pradesh and Bihar [2,3]. Within tertiary neonatal intensive care units (NICUs) and special newborn care units (SNCUs), the clinical profile differs markedly from community-level neonatal mortality. Admissions are enriched with extreme prematurity, severe perinatal asphyxia, neonatal sepsis, respiratory distress syndrome (RDS), and congenital malformations conditions associated with high early case fatality rates [4,5]. Reported case fatality rates from Indian tertiary NICUs range from 15% to 35%, depending on the gestational age distribution of admissions, available interventions, and institutional resources [6,7].

Despite this substantial burden, comparative survival analysis using parametric hazard models remains uncommon in this setting, with most published studies relying on logistic regression or descriptive reporting [8,9]. The analysis of NICU time-to-death data presents distinct statistical challenges. The outcome is a censored time-to-event variable neonates discharged alive, transferred, or surviving to day 28 are censored necessitating survival analysis rather than binary regression [10]. The Time-based pattern of NICU mortality is characterised by a high early hazard in the first 24–72 hours, with risk declining for survivors beyond that window. The Cox semiparametric proportional hazards model is the most commonly used approach for censored data and does not require specification of the baseline hazard function [11].

While flexible, the Cox model does not permit direct modelling of the hazard shape, prediction of absolute survival probabilities at specific time points, or formal testing of whether the hazard is constant, increasing, or decreasing. Parametric proportional hazard (PH) models exponential, Weibull, and Gompertz overcome these limitations by specifying the baseline hazard as a parametric function of time, while preserving the multiplicative covariate structure of the Cox model [12,13]. The exponential model assumes constant hazard (memoryless process). The Weibull model accommodates monotonically increasing or decreasing hazard through an estimable shape parameter. The Gompertz model allows exponentially changing hazard and is particularly suited to contexts where hazard accelerates continuously, such as chronic disease and gerontological cohorts [14,15]. For NICU populations, the shape of the hazard trajectory has direct clinical relevance: a shape parameter exceeding unity signals secondary deterioration in initially stabilised neonates, while a value below unity indicates a front-loaded mortality pattern consistent with early critical illness.

This study employs a comparative modeling approach to analyze neonatal survival patterns. By evaluating both flexible semi-parametric models and parametric models which assume specific mathematical distributions for risk we aim to identify the most accurate method for predicting neonatal outcomes in a tertiary care setting. Also, the study aims to determine the most significant prognostic factors associated with mortality and identify the optimal parametric distribution that fits the observed data. The model selection between these parametric alternatives were used with Akaike Information Criterion and Bayesian Information Criterion (AIC and BIC). This approach ensures precise characterization of neonatal risk dynamics particularly the early hazard peak and subsequent decline thereby facilitating more reliable clinical and public health inferences.

METHODOLOGY

Study Design, Setting, and Ethics

The prospective study design was used to collected from the Paediatric Department in the Neonatal Intensive Care Unit (NICU) and Special Newborn Care Unit (SNCU) of Dr. Ram Manohar Lohia Institute of Medical Sciences (RMLIMS), Lucknow, a tertiary care teaching hospital in Uttar Pradesh, India. The study period spanned January 1, 2024, to December 31, 2024. The hospital maintains a 24-bed combined capacity equipped with advanced life-support technologies, including bubble Continuous Positive Airway Pressure (CPAP) units and invasive ventilation. Data were collected from validated questionnaire of neonates admitted to the SNCU and NICU. The study included all live-born neonates during the study period, encompassing both intramural (born within the facility) and extramural (referred from external facilities) cases. A total of 686 neonates were included in the final analysis. Ethical approval was obtained from the Institutional Ethics Committee (IEC) of Dr. Ram Manohar Lohia Institute of Medical Sciences, Lucknow. All 686 admitted neonates were followed from admission to the occurrence of death or censoring, consistent with the longitudinal follow-up structure required for valid survival analysis.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue II February 2026

Study Population

All live-born neonates (age 0–28 days) admitted to the NICU or SNCU during the study period were eligible. Exclusion criteria were: incomplete clinical records (missing primary diagnosis, gestational age, or birth weight), transfer within 24 hours of admission before outcomes could be ascertained, or guardian declining consent. The final cohort comprised 686 consecutively enrolled neonates.

Prognostic Variables

Neonatal factors included birth weight, gestational age, and specific neonatal morbidities. Birth weight was categorized as extreme low birth weight (ELBW, <1000 g), very low birth weight (VLBW, 1000-1499 g), low birth weight (LBW, 1500-2499 g), and normal birth weight (NBW, ≥2500 g). Gestational age was classified as extreme preterm (<28 weeks), preterm (28 to <37 weeks), and full term (≥37 weeks). Neonatal morbidities included respiratory distress, perinatal Asphyxia (PA), Neonatal Sepsis and congenital malformations documented by paediatric examination. Mother age was categorised as <25 years, 25-30 years, and >30 years. Gravidity was classified as primigravida (first pregnancy) versus multigravida (more than 2 pregnancies). Additional obstetric variables encompassed amniotic fluid colour (clear versus stained), labour onset (spontaneous versus induced), mode of delivery (normal vaginal delivery (NVD) versus lower segment caesarean section (LSCS)), course of labour (uneventful, prolonged [>12 hours for primigravida, >8 hours for multigravida], and obstructed), and pregnancy-induced hormone (PIH) (presence versus absence).

Outcome Variable

The primary outcome of this study was neonatal mortality. For the survival analysis, neonates who died were coded as 1 (event), while those who were successfully discharged, left against medical advice (LAMA), or referred were coded as 0 (censored). Survival time was calculated in complete days, measured from the date of birth to the time of death or study exit (discharge, LAMA, or referral).

Statistical Analysis

Statistical analyses were performed using a licensed version of Stata v.13 (StataCorp, 2013) [32]. Pearson's chi-square tests were used to assess the bivariate association between categorical prognostic factors and neonatal outcomes (Table 1). A stepwise regression approach was employed to identify relevant variables for the model, variables with a high proportion of missing data or those exhibiting high multicollinearity were excluded to maintain the robustness and stability of the model. Second, variables with established clinical relevance to neonatal mortality in the published literature regardless of bivariate significance were also retained a priori. These included gestational age, birth weight, primary neonatal diagnoses (respiratory distress, perinatal asphyxia, neonatal sepsis, congenital malformations), and key obstetric factors (mode and onset of labour, amniotic fluid colour, pregnancy-induced hypertension, and gravidity). Multicollinearity among the covariates was assessed using the variance inflation factor (VIF). All VIF values were below 3.0 (mean VIF = 1.30).

The Cox Proportional Hazards (PH) model was employed to estimate adjusted hazard ratios (HR) for the predictors of neonatal mortality. The validity of the proportional hazard's assumption was rigorously tested using the Global Schoenfeld Residuals test. To evaluate the model's predictive accuracy and discriminative power, Harrell's C-concordance statistic and Somers' D were calculated.

Finally, a comparative modelling approach was implemented by fitting multiple parametric survival models, including Exponential, Weibull, and Gompertz distributions. The optimal model fit was determined using the Log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Statistical significance across all tests was declared at $p< 0.05$.

General Proportional Hazards Framework

All four survival models share the fundamental proportional hazards (PH) structure, whereby the hazard function for the i-th individual at time t is expressed as the product of a common baseline hazard $h_0(t)$ and an

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue II February 2026

individual-specific multiplicative factor determined by the covariate vector x_i and the regression coefficient vector β [11,12,13]

$$h(t \mid x_i) = h_0(t) \cdot \exp(x_i'\beta) \tag{1}$$

where $h(t \mid x_i)$ is the instantaneous hazard of death at time t for the i-th subject; $h_0(t)$ is the baseline hazard (the hazard when all covariates equal zero); $x_i = (x_{i1}, x_{i2}, \ldots, x_{ip})'$ is the p-dimensional covariate vector; $\beta = (\beta_1, \beta_2, \ldots, \beta_p)'$ is the vector of log-hazard-ratio coefficients; and $\exp(\beta_k) = HR_k$ is the hazard ratio for the k-th covariate, representing the multiplicative change in instantaneous hazard per unit increase in x_k.

The four models differ solely in the specification of $h_0(t)$. The Cox model leaves $h_0(t)$ entirely unspecified (semiparametric), whereas the exponential, Weibull, and Gompertz models parameterise it as explicit functions of time (fully parametric) [12,13]. Covariate effects $\exp(\beta)$ are interpreted identically across all four specifications.

Cox Semiparametric Proportional Hazards Model

The Cox model estimates β without specifying $h_0(t)$, using the partial likelihood:

$$L(\beta) = \prod_{i \in D} \frac{\exp(x_i'\beta)}{\sum_{j \in R(t_i)} \exp(x_j'\beta)} \tag{2}$$

where D is the set of observed death times; $R(t_i)$ is the risk set at time t_i, comprising all individuals under observation at or immediately before t_i; and the product is taken over all uncensored failure times [11]. Tied event times were handled using the Breslow approximation [11,30,31]. The proportional hazards assumption was assessed using Schoenfeld residuals [28]. For each covariate k, the scaled Schoenfeld residual at the i-th failure time is:

$$r_k(t_i) = x_{ki} - \bar{x}(\hat{\beta}, t_i) \tag{3}$$

where $\bar{x}(\hat{\beta}, t_i) = \frac{\sum_{j \in R(t_i)} x_{jk} \exp(x_j'\hat{\beta})}{\sum_{j \in R(t_i)} \exp(x_j'\hat{\beta})}$ is the weighted covariate mean over the risk set at t_i, with weights proportional to the estimated relative hazard. Under the PH assumption, $r_k(t)$ should exhibit no systematic correlation with time [28]. The Grambsch–Therneau test statistic for each covariate is $\rho_k^2 \cdot \frac{(n-1)\sum w_i t_i^2}{\mathrm{var}(\hat{\beta}_k)} \sim \chi^2(1)$, where ρ_k is the Pearson correlation between the scaled residual and ranked analysis time. The global test aggregates across all K covariates:

$$\chi^2_{\text{Global}} = \sum_{k=1}^{K} \rho_k^2 \cdot D_k \sim \chi^2(K) \tag{4}$$

where D_k are scaling factors and $K = 20$ is the total number of covariates. A non-significant global statistic ($p \geq 0.05$) supports the overall PH structure [28.]

Discriminative performance of the model was quantified by Harrell's C-concordance statistic:

$$C = P(LP_i > LP_j \mid T_i < T_j, \delta_i = 1) \tag{5}$$

where $LP_i = x_i'\hat{\beta}$ and $LP_j = x_j'\hat{\beta}$ are the linear predictors (prognostic indices) for subjects i and j; T_i, T_j are their observed survival times; and $\delta_i = 1$ denotes an observed event in subject i. $C = 0.5$ indicates random prediction; $C = 1.0$ indicates perfect discrimination. Values of 0.70–0.80 are conventionally classified as good discriminative performance [16.]

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Exponential Proportional Hazards Model

The exponential model specifies a constant baseline hazard, corresponding to a memoryless survival process in which the instantaneous risk of death does not vary with duration of admission. The baseline hazard, conditional hazard, and survival functions are:

$$h_0(t) = \lambda, \lambda > 0 \tag{6}$$

$$h(t \mid x_i) = \lambda \cdot \exp(x_i'\beta) \text{ (Eq. 7)} \tag{7}$$

$$S(t \mid x_i) = \exp[-\lambda t \cdot \exp(x_i'\beta)] \text{ (Eq. 8)} \tag{8}$$

where $\lambda = \exp(-\alpha)$ and α is the log-scale intercept. The exponential model is nested within the Weibull model as the special case $p = 1$, enabling formal likelihood ratio testing of the constant-hazard restriction.

Weibull Proportional Hazards Model

The Weibull model generalises the exponential by introducing a shape parameter $p > 0$ that governs whether the baseline hazard increases ($p > 1$), decreases ($p < 1$), or remains constant ($p = 1$) with time. The model is defined by:

$$h_0(t) = p\lambda t^{p-1} \tag{9}$$

$$h(t \mid x_i) = p\lambda t^{p-1} \cdot \exp(x_i'\beta) \tag{10}$$

$$S(t \mid x_i) = \exp[-\lambda t^p \cdot \exp(x_i'\beta)] \tag{11}$$

where $\lambda = \exp(-\alpha)$ is the baseline scale parameter and p is the shape parameter.

$$p = \exp(\kappa) \tag{12}$$

$\hat{p} > 1$ implies an increasing baseline hazard over the admission period (secondary deterioration pattern); $\hat{p} < 1$ implies a decreasing hazard (front-loaded mortality pattern). The 95% confidence interval for p is obtained by the delta method: $\exp(\hat{\kappa} \pm 1.96 \cdot SE(\hat{\kappa}))$. The exponential model is nested within the Weibull under $H_0: p = 1$ (equivalently, $\kappa = 0$). This restriction is formally tested by the likelihood ratio statistic:

$$LRT_{W-E} = -2[\hat{\ell}_{Exp} - \hat{\ell}_{Weibull}] \sim \chi^2(1) \tag{13}$$

where $\hat{\ell}_{Exp}$ and $\hat{\ell}_{Weibull}$ are the respective maximised log-likelihoods. A statistically significant LRT_{W-E} ($p < 0.05$) rejects the constant-hazard constraint and establishes the Weibull as preferable to the exponential.

Gompertz Proportional Hazards Model

The Gompertz model specifies an exponentially changing baseline hazard governed by a shape parameter γ, making it particularly suited to survival processes characterised by progressively accelerating mortality risk. The baseline hazard, conditional hazard, and survival functions are:

$$h_0(t) = \lambda \cdot \exp(\gamma t) \tag{14}$$

$$h(t \mid x_i) = \lambda \cdot \exp(\gamma t) \cdot \exp(x_i'\beta) \tag{15}$$

$$S(t \mid x_i) = \exp\left\{-\left(\frac{\lambda}{\gamma}\right)[\exp(\gamma t) - 1] \cdot \exp(x_i'\beta)\right\} \tag{16}$$

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where $\lambda > 0$ is the scale parameter and γ is the Gompertz shape parameter. $\gamma > 0$ indicates an exponentially increasing hazard; $\gamma < 0$ indicates a decreasing hazard; $\gamma = 0$ reduces the survival function (Eq. 16) to the exponential form (Eq. 8). Statistical non-significance of $\hat{\gamma}$ indicates that the exponentially changing hazard structure is not supported by the observed data. The Gompertz model is not nested within the Weibull; direct comparison therefore relies exclusively on information criteria.

Model Selection Criteria

Model selection among the three parametric specifications was performed using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), defined respectively as:

$$\text{AIC} = -2\hat{\ell} + 2\text{k} \tag{17}$$

$$\text{BIC} = -2\hat{\ell} + \text{k} \cdot \ln(\text{n}) \tag{18}$$

where $\hat{\ell}$ is the maximised log-likelihood of the fitted model; k is the total number of estimated parameters, including ancillary parameters and $\text{n} = 686$ is the sample size. Both criteria penalise model complexity; the BIC imposes a stronger penalty as n increases. Lower values of AIC and BIC indicate a superior trade-off between goodness-of-fit and parsimony. Following Burnham and Anderson, a difference $\Delta\text{AIC} \geq 6$ constitutes strong evidence in favour of the model with the lower AIC. The formal nested likelihood ratio test comparing the exponential and Weibull models is given in Eq. (13). Because the Gompertz is not nested within either the exponential or the Weibull, model comparisons involving the Gompertz rely solely on ΔAIC and ΔBIC. The Cox partial log-likelihood is not comparable to the full parametric log-likelihoods and was therefore excluded from AIC/BIC ranking; its discriminative performance was assessed separately via Harrell's C (Eq. 5).

RESULTS

The data comprised 686 neonates, of whom 155 (22.59%) died during the follow-up period. The remaining 531 (77.41%) were censored either discharged alive or surviving to day 28. The chi-square test statistics was implemented to see the bivariate association between the prognostic and outcome variables as summarised in Table 1.

Clinical complications showed a strong bivariate association with higher mortality rates. Neonates with Respiratory Distress (34.95% vs. 7.96%), Birth Asphyxia (41.40% vs. 17.01%), and Neonatal Sepsis (43.21% vs. 11.29%) experienced significantly higher death rates compared to those without these conditions. Notably, over half of the neonates with Congenital Malformations (55.56%) did not survive. Birth weight and gestational age were critical predictors of survival. Mortality was highest among Extremely Low Birth Weight (64.52%) and Extreme Preterm (70.00%) infants. Conversely, early breastfeeding (within one hour) appeared protective, with a mortality rate of only 9.16% compared to 25.77% for those who did not. Maternal factors such as induced labor (32.29%) and stained amniotic fluid (33.83%) were also associated with higher neonatal death rates compared to spontaneous labor and clear fluid.

Table 1. Bivariate analysis of Neonatal Outcomes Across Selected Maternal and Clinical Characteristics.

Prognostic Variables	**Category**	**Alive N (%)**	**Death N (%)**	**Total N (%)**	**χ^2(p-value)**
Sex of baby	Female	223 (77.70)	64 (22.30)	287 (41.84)	0.875
	Male	308 (77.19)	91 (22.81)	399 (58.16)	
Respiratory Distress	No	289 (92.04)	25 (7.96)	314 (45.77)	<0.001*
	Yes	242 (65.05)	130 (34.95)	372 (54.23)	

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Perinatal Asphyxia	No	439 (82.99)	90 (17.01)	529 (77.11)	<0.001*
	Yes	92 (58.60)	65 (41.40)	157 (22.89)	
Neonatal Sepsis	No	393 (88.71)	50 (11.29)	443 (64.58)	<0.001*
	Yes	138 (56.79)	105 (43.21)	243 (35.42)	
Congenital Malformations	No	515 (79.23)	135 (20.77)	650 (94.75)	<0.001*
	Yes	16 (44.44)	20 (55.56)	36 (5.25)	
Birth Weight	Extremely Low Birth Weight	11 (35.48)	20 (64.52)	31 (4.52)	<0.001*
	Very Low Birth Weight	46 (55.42)	37 (44.58)	83 (12.10)	
	Low Birth Weight	207 (84.15)	39 (15.85)	246 (35.86)	
	Normal Birth Weight	267 (81.90)	59 (18.10)	326 (47.52)	
Gestational Age	Extreme Preterm	9 (30.00)	21 (70.00)	30 (4.37)	<0.001*
	Preterm	195 (73.58)	70 (26.42)	265 (38.63)	
	Full Term	327 (83.63)	64 (16.37)	391 (57.00)	
Breast feeding within one hour	No	412 (74.23)	143 (25.77)	555 (80.90)	<0.001*
	Yes	119 (90.84)	12 (9.16)	131 (19.10)	
Gravida of Mother	Primigravida	258 (80.12)	64 (19.88)	322 (46.94)	0.109
	Multigravida	273 (75.00)	91 (25.00)	364 (53.06)	
Maternal Age	17-24 Years	140 (79.10)	37 (20.90)	177 (25.80)	0.051
	25-30 Years	268 (74.03)	94 (25.97)	362 (52.77)	
	> 30 Years	123 (83.67)	24 (16.33)	147 (21.43)	
Pregnancy-Induced Hormone (PIH)	No	458 (77.23)	135 (22.77)	593 (86.44)	0.787
	Yes	73 (78.49)	20 (21.51)	93 (13.56)	
Amniotic Fluid Colour	Clear	443 (80.11)	110 (19.89)	553 (80.61)	<0.001*
	Stained	88 (66.17)	45 (33.83)	133 (19.39)	
Labour Onset	Induced	65 (67.71)	31 (32.29)	96 (13.99)	0.014*
	Spontaneous	466 (78.98)	124 (21.02)	590 (86.01)	

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Mode of Delivery	Lower Segment Caesarean Section (LSCS)	252 (78.26)	70 (21.74)	322 (46.94)	0.614
	Normal Vaginal Delivery (NVD)	279 (76.65)	85 (23.35)	364 (53.06)	
Course of Labour	Obstructed	16(64.00)	9(36.00)	25(3.6)	0.251
	Prolonged	45(76.27)	14(23.73)	59(8.6)	
	Uneventful	470 (78.07)	132(21.93)	602(87.8)	
Total Outcome		**531 (77.41)**	**155 (22.59)**	**686(100.00)**	

Model Fit Comparison

Table 2 presents the model fit statistic. The Weibull PH model provided the best fit with the lowest AIC and BIC values among the three parametric distributions. The Weibull shape parameter, estimated with statistical significance, exceeded unity (p = 1.179; 95% CI: 1.038–1.341), indicating a monotonically increasing baseline hazard over the admission period (Table 4).

Table 2. Comparative Model Performance Statistic

Model	**Log-Likelihood**	**AIC**	**BIC**
Weibull PH	−391.88	827.77	927.44
Exponential PH	−394.83	831.66	926.80
Gompertz PH	−394.29	832.57	932.25
Cox PH	-828.14	1696.274	1786.891

AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

The Schoenfeld resid test results, presented in Table 3, demonstrated a non-significant global test (χ^2 (20) = 28.52; p = 0.0976), supporting the overall proportional hazards structure of the Cox model. The Cox PH model achieved Harrell's C = 0.7948 (Somers' D = 0.5897), computed from 686 subjects. This C-statistic indicates good discriminative performance: approximately 79.5% of neonate pairs in which one member died were correctly risk-ranked by the model. A C-statistic in the range 0.75–0.85 is conventionally classified as good. The Somers' D of 0.59 represents the net proportion of concordant minus discordant pairs relative to the total, reinforcing clinically meaningful discrimination.

Table 3. Model Discrimination and Proportional Hazards Assumption Diagnostics

Assessment Category	**Test Statistic**	**Values**
Model Discrimination	Harrell’s C Concordance	0.7948
	Somers’ D	0.5897
Model Assumption	Global Schoenfeld Test χ^2	28.52

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	Degrees of Freedom	20
	p-value	0.0976

Table 4 presents the hazard ratios (HRs) with 95% confidence intervals from all four survival models. A HR > 1 denotes elevated instantaneous mortality risk; HR < 1 denotes reduced risk, relative to the stated reference category. The high concordance of direction, magnitude, and statistical significance across all model specifications confirms the robustness of the identified predictors to distributional assumptions. The Weibull PH model represents the best-fitting specification as determined by information criteria.

The analysis showed that neonatal clinical conditions and birth characteristics were the most potent predictors of mortality. Congenital malformations significantly increased the hazard of neonatal death by 2.71 times (HR = 2.71; 95% CI: 1.60-4.59; $p < 0.001$). High mortality risks were also strongly associated with perinatal asphyxia (HR = 2.58; 95% CI: 1.77-3.76; $p < 0.001$) and neonatal sepsis (HR = 2.17; 95% CI: 1.52-3.08; $p < 0.001$). Furthermore, respiratory distress syndrome was a significant contributor to mortality, increasing the hazard by 62% (HR = 1.62; 95% CI: 0.99-2.66; $p < 0.05$).

Regarding physical and gestational maturity, extreme preterm birth emerged as the strongest overall predictor in the model, with affected neonates facing a 3.43-fold increase in the hazard of death compared to full-term infants (HR = 3.43; 95% CI: 1.68-7.03; $p < 0.001$). Similarly, extremely low birth weight (< 1,000 g) was associated with a significantly higher hazard of death (HR = 2.69; 95% CI: 1.29-5.61; $p < 0.01$). In contrast, very low and low birth weights did not reach statistical significance within the Weibull framework. Maternal and obstetric factors also played a critical role in neonatal survival. Induced labour was associated with a doubling of the mortality hazard compared to spontaneous labour (HR = 2.06; 95% CI: 1.34-3.16; $p < 0.001$). Additionally, neonates born to multigravida mothers experienced a 47% higher hazard of death than those born to primigravida mothers (HR = 1.47; 95% CI: 1.04-2.09; $p < 0.05$). Pregnancy-induced hormone was also a significant predictor of mortality (HR = 1.67; 95% CI: 1.01-2.76; $p < 0.05$). Other variables including infant sex, maternal age, mode of delivery, and timing of breastfeeding initiation did not demonstrate statistically significant associations with the hazard of neonatal death.

Table 4. Survival Analysis of Neonatal Mortality using Cox and Parametric Proportional Hazard Models

Predictors	**Cox PH HR (95% CI)**	**Exponential PH HR (95% CI)**	**Weibull PH HR (95% CI)**	**Gompertz PH HR (95% CI)**
Sex of baby (Ref: Female)				
Male	0.97 (0.70–1.36)	0.98 (0.70-1.37)	0.99 (0.71-1.39)	0.98 (0.70-1.38)
Respiratory Distress (Ref: No)				
Yes	1.66* (1.01-2.73)	1.66* (1.01-2.72)	1.62*(0.99-2.66)	1.64* (1.00-2.70)
Perinatal Asphyxia (Ref: No)				
Yes	2.46*** (1.70-3.58)	2.45*** (1.69-3.54)	2.58***(1.77-3.76)	2.50*** (1.72-3.64)
Neonatal Sepsis (Ref: No)				
Yes	2.26*** (1.59-3.22)	2.23*** (1.57-3.17)	2.17*** (1.52-3.08)	2.20*** (1.54-3.13)
Congenital Malformations (Ref: No)				
Yes	2.63*** (1.56-4.44)	2.63*** (1.56-4.42)	2.71*** (1.60-4.59)	2.67*** (1.58-4.51)

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Birth Weight (Ref: Normal Birth Weight)				
Extremely Low Birth Weight	2.42* (1.15-5.06)	2.56* (1.22-5.33)	2.69** (1.29-5.61)	2.59* (1.24-5.40)
Very Low Birth Weight	1.52 (0.84-2.77)	1.55 (0.85-2.82)	1.56 (0.85-2.86)	1.54 (0.85-2.81)
Low Birth Weight	0.85 (0.52-1.37)	0.86 (0.53-1.39)	0.87 (0.53-1.41)	0.86 (0.53-1.40)
Gestational Age (Ref: Full Term)				
Extreme Preterm	3.35*** (1.62-6.89)	3.29*** (1.60-6.74)	3.43*** (1.68-7.03)	3.35*** (1.64-6.87)
Preterm	1.48 (0.93-2.36)	1.48 (0.92-2.36)	1.50 (0.93-2.40)	1.48 (0.93-2.37)
Breast feeding within one hour (Ref: Yes)				
No	1.33 (0.71-2.48)	1.36 (0.73-2.53)	1.37 (0.73-2.55)	1.36 (0.73-2.53)
Gravida of Mother (Ref: Primigravida)				
Multigravida	1.43* (1.01-2.03)	1.45* (1.02-2.05)	1.47* (1.04-2.09)	1.45* (1.02-2.06)
Maternal Age (Ref: 25-30 Years)				
17-24 Years	0.98 (0.66-1.46)	0.97 (0.65-1.45)	0.98(0.66-1.47)	0.98 (0.66-1.46)
> 30 Years	0.70 (0.43-1.14)	0.69 (0.42-1.11)	0.68 (0.42-1.10)	0.69 (0.42-1.11)
Pregnancy-Induced Harmone (PIH) (Ref: No)				
Yes	1.46 (0.89-2.41)	1.55 (0.94-2.55)	1.67* (1.01-2.76)	1.60 (0.97-2.64)
Amniotic Fluid Colour (Ref: Clear)				
Stained	1.28 (0.87-1.88)	1.28 (0.87-1.89)	1.30 (0.88-1.91)	1.29 (0.88-1.90)
Labour Onset (Ref: Spontaneous)				
Induced	1.95**(1.27-2.98)	1.96** (1.28-2.99)	2.06*** (1.34-3.16)	2.01*** (1.31-3.07)
Mode of Delivery (Ref: Normal Vaginal Delivery (NVD))				
Lower Segment Caesarean Section (LSCS)	0.88 (0.62-1.24)	0.90 (0.64-1.27)	0.91 (0.64-1.29)	0.90 (0.64-1.28)
Course of Labour (Ref: Uneventful)				
Obstructed Labour	1.60 (0.79-3.24)	1.61 (0.79-3.26)	1.68 (0.82-3.42)	1.63 (0.80-3.31)

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Prolonged Labour	0.77 (0.43-1.40)	0.82 (0.46-1.47)	0.82 (0.45-1.47)	0.81 (0.45-1.46)
Model Fit Statistics				
Log-likelihood	-828.14	-394.83	-391.88	-394.29
LR Chi-Square (d.f.=20)	159.71***	159.22***	159.31***	158.40***
Shape Parameters	-	1.00	1.179(1.037-1.340) ***	0.014(-0.012-0.041)

Significant predictors ($p < 0.05$) are indicated by asterisks (* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$).

DISCUSSION

This study compared four survival models for predicting neonatal mortality in a tertiary NICU/SNCU setting. Among the three parametric models tested, the Weibull proportional hazards model provided the best fit to the data, as shown by its lowest Akaike and Bayesian Information Criteria values. The likelihood ratio test confirmed that the exponential model's assumption of a constant hazard was not appropriate for these data, meaning that the risk of death does not remain stable throughout the admission period[12,13]. The Weibull shape parameter was estimated above unity with statistical precision, indicating that the baseline hazard increases steadily over time. This finding is clinically meaningful in the NICU context, as it suggests that neonates who survive the initial stabilisation phase continue to face a gradually rising risk of death, largely due to secondary complications such as sepsis and progressive respiratory failure [18,19]. The non-significant Gompertz shape parameter indicated that a rapidly accelerating hazard pattern was not supported by the data, which explains why the Gompertz model performed comparatively poorly [14.]

Extreme prematurity was the single strongest independent predictor of neonatal mortality across all four models, showing the highest hazard ratio in the entire cohort. This is consistent with the well-established vulnerabilities seen at the lowest gestational ages, including surfactant deficiency, immature immune function, poor temperature regulation, and increased risk of intraventricular haemorrhage, all of which independently and collectively raise the risk of death [20,29]. Importantly, moderate prematurity (28-36 weeks) did not reach statistical significance in any model after adjustment, suggesting that the excess hazard is concentrated specifically at the extreme end of prematurity rather than spread across the full preterm range. This has direct implications for resource allocation: intensive monitoring and clinical interventions should be prioritised for neonates born below 28 weeks gestational age, where the survival disadvantage is both greatest and consistently confirmed across all four models.

Congenital malformations were the second strongest independent predictor of mortality, with consistent hazard estimates across all four models. This reflects the nature of the study institution, a tertiary referral NICU that receives complex structural anomalies such as cyanotic congenital heart disease, renal agenesis, and neural tube defects, in a setting without on-site paediatric cardiac surgery [21]. A borderline violation of the proportional hazards assumption was noted for this variable, characterised by a positive trend in the scaled Schoenfeld residuals over time. This pattern is biologically plausible: structural anomalies incompatible with prolonged survival lead to progressive multi-organ failure that worsens over the course of admission, resulting in a hazard ratio that increases with time rather than remaining constant. This distinguishes congenital malformations from acute conditions, where the excess hazard is predominantly concentrated in the early admission period.

Perinatal asphyxia and neonatal sepsis were each independently and significantly associated with increased mortality hazard across all model specifications, with consistent estimates that reflect the robustness of these associations regardless of the distributional assumptions used. For perinatal asphyxia, the Schoenfeld residual

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pattern showed a negative correlation with analysis time, indicating that the excess hazard from this condition is concentrated within the first 48-72 hours of admission. This is consistent with the acute pathophysiology of hypoxic-ischaemic encephalopathy, in which neuronal injury and its systemic consequences are greatest immediately following the asphyxial event [22.] This time-varying pattern, evidenced by a borderline individual Schoenfeld test, does not undermine the overall proportional hazards framework, which was supported by the significant global test. The hazard magnitude observed for neonatal sepsis is consistent with pooled estimates from published meta-analyses conducted in South Asian tertiary NICUs [23], supporting the external validity of the present findings. Respiratory distress syndrome showed a marginally non-significant hazard estimate in the Weibull model, which may reflect the availability of surfactant therapy at this institution, potentially reducing the survival disadvantage compared with settings where this treatment is unavailable [4.]

Induced labour was a consistently significant predictor of mortality across all four models, even after adjusting for gestational age, birth weight, and primary clinical diagnosis. This residual association suggests an independent contribution through foetal compromise caused by uterotonic hyperstimulation, compounding the high-risk obstetric contexts in which induction is most commonly indicated[24.] Multigravida was similarly associated with a modest increase in mortality hazard, consistent with evidence linking maternal nutritional depletion and short interpregnancy intervals to poorer neonatal outcomes in high-parity South Asian populations [25.] Infant sex, mode of delivery, maternal age, timing of breastfeeding initiation, amniotic fluid colour, and type of labour complication did not achieve statistical significance in any model, indicating that these variables do not independently predict NICU mortality after full covariate adjustment.

The discriminative performance of the covariate set was good, with Harrell's C-statistic falling within the conventionally accepted range for strong clinical prediction[16]. This performance is broadly comparable to established neonatal severity-of-illness scoring tools such as CRIB-II [26], suggesting that the parsimonious set of covariates identified in this study captures a clinically meaningful proportion of the variation in mortality risk. However, prospective external validation in an independent cohort is required before the model can be responsibly applied for bedside risk stratification.

The superiority of the Weibull proportional hazards model identified in this study is consistent with findings from analogous survival modelling studies conducted in other NICU and neonatal settings globally. The study analyses determinants of neonatal mortality using the 2016 Ethiopian Demographic and Health Survey, similarly identified the Weibull as the best-fitting parametric model, with extreme prematurity and low birth weight as dominant predictors, consistent with the present findings[19]. The study also compared parametric and semi-parametric approaches for child mortality in sub-Saharan Africa, demonstrated that the Weibull model consistently outperformed log-logistic and exponential alternatives when the hazard was monotonically changing rather than unimodal[5], a condition satisfied by the present NICU data. Similarly, a systematic review of survival analysis methods in neonatal research concluded that parametric models particularly Weibull provide superior absolute risk quantification compared to the Cox model, especially in time-limited NICU cohorts where the hazard pattern is characterised by early peaks followed by gradual increase among survivors[9]. Taken together, these cross-contextual replications suggest that the Weibull proportional hazards framework represents a broadly applicable and statistically preferable tool for neonatal mortality modelling, not only in tertiary Indian NICU settings but across diverse healthcare systems with varying resource availability. Future multi-centre studies linking Indian NICU registries with comparable datasets from low- and middle-income country settings would further strengthen the generalisability of these findings and support the development of Weibull-based clinical risk stratification tools applicable at a global scale.

In conclusion, the Weibull proportional hazards model best describes neonatal NICU/SNCU mortality in this tertiary setting, with extreme prematurity, congenital malformations, perinatal asphyxia, neonatal sepsis, and induced labour consistently identified as dominant mortality predictors across all four model specifications. The model demonstrated good discriminative performance, broadly comparable to established neonatal severity scoring instruments[26]. Prospective external validation in independent cohorts and extension to multi-centre datasets represent priority directions for future research.

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