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MODELING THE DURATION OF MATERNAL LABOR AT ANUTAPURA HAMMER HOSPITAL USING LIN-YING ADDITIVE HAZARD REGRESSION

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ABSTRACT

The Central Sulawesi government has a Sustainable Development Goals (SDGs) target for 2020-2024, which sets the maternal mortality rate below 70/100,000 KH. However, in 2018-2022, the maternal mortality rate fluctuated by 128/100,000 KH. One of the factors causing maternal mortality is the duration of the labor process. The factors that are thought to have an influence on the duration of labor are gestational age, maternal age, baby height, parity, and hemoglobin levels. Therefore, this study aims to see what modeling and factors affect the duration of birth using Lin-Ying additive hazard regression analysis. Data were obtained from the medical records of normal deliveries between January and December 2023 at Anutapura Palu Hospital. The results showed that the factors that affect the duration of birth are preterm gestational age, aterm gestational age, maternal age 20-35 years, primigravida mothers, multigravida mothers, and mothers who are not anemic. A limitation of this study is the relatively short data collection period of one year, which may not capture variations or trends in labor outcomes over time.

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1. INTRODUCTION

Normal delivery is a moment that is eagerly awaited by couples and families, so understanding the process and duration of birth is important, both medically to ensure the safety of the mother and baby, and socially to prepare emotional, logistical, and mental support from those closest to them. This process is characterized by the opening of the cervix for 13-14 hours in women who are pregnant for the first time, but shorter in mothers who have given birth before. Prolonged labor, which is more than 18-20 hours in primigravida and more than 12-24 hours in multigravida, can increase the risk of maternal and infant mortality. The duration of labor is influenced by the strength of contractions, the mother's age, history of labor, comorbidities, and the condition of the pelvis. If there is a narrowing or abnormality of the pelvis or the presence of an obstructing tumor, normal delivery is not possible, so a Cesarean section is required [1].

The Central Sulawesi government is targeting a maternal mortality rate below 70/100,000 live births by 2020-2024. However, in 2018-2022, this figure fluctuated to 128/100,000 live births. The number of maternal deaths is influenced by the number of live births, so the government continues to increase the capacity of medical personnel to reduce maternal and infant mortality [2].

Birth duration data contains censored data, i.e., data with an unknown exact time of occurrence. The incompleteness of observations makes linear regression inapplicable, so survival analysis is required. This analysis describes the time from a starting point to the occurrence of a particular event without relying on a parametric distribution. The risk factors in this data are interrelated between events, so it is categorized as a multivariate failure [3].

In biomedical science, multivariate failure encourages the use of alternative methods, one of which is the additive hazard model as a development of the Cox proportional hazard. Additive hazard models that have been developed include the Aalen additive hazard model and the Lin-Ying additive hazard model. The Aalen additive hazard model allows the regression coefficient to be a function that can change over time, while the Lin-Ying additive hazard model replaces the regression coefficient with a constant value so that it is easier to interpret [4].

Previous research, which is related to the Comparison of Cox Proportional Hazard and Lin & Ying Additive Methods in the Case of Myocardial Infarction Patients, with the results of the study that shows that there are 2 factors that affect acute myocardial infarction patients declared to improve [5]. Other related research has also been conducted, namely, Lin-Ying Additive Hazard Regression for Analysis of Improvement of Clinical Conditions of Breast Cancer Patients, with the results of the study showing that there are 2 factors that affect the clinical condition of breast cancer patients [6]. The same research has also been conducted, which is related to the Application of the Lin-Ying Additive Hazard Method as a Recurrence Predictor in Endometriosis Patients, with the results of the study showing that there is 1 influential factor that can increase the risk of relapse after surgical treatment [7]. The previous study used the Cox Proportional Hazard Regression method to model the waiting time for the birth of the first child in Lampung Province, with significant variables such as residence, education, pregnancy health knowledge, and marriage age. The difference in this study lies in the method, context, and variables used. While this study uses Lin-Ying Additive Hazard, which is more flexible because it does not assume a constant hazard. In terms of context, the previous study focused on the waiting time for the birth of the first child, while this study focused on the duration of normal labor at Anutapura Palu Hospital [8].

Based on the description above, the author plans to conduct research on the birth process at Anutapura Palu Hospital. The study will use the Lin-Ying additive hazard regression analysis method to model and analyze the data. This method is expected to help identify and interpret the factors that influence birth outcomes more effectively.

2. RESEARCH METHODS

2.1 Survival Analysis

Survival analysis is a form of statistical analysis that is widely used in medicine and public health. The event in survival analysis is usually death, hence the name survival analysis, but it can also be other outcomes. The analysis of data in the context of time, from a well-defined starting point to the occurrence of a specific event or endpoint, is referred to as survival analysis [9]. In survival analysis, there are three important terms.

First, survival time is the length of time the object survives during the observation period. Second, the event is the main event under study. Third, censorship refers to the condition when the survival time of the object is not known with certainty, although it is recorded during the observation [10]. The distribution of survival time is usually described or characterized by three functions: survival function, density function, and failure function. To determine the survival time T there are three elements that need to be considered [11]:

1. Time Origin or Starting Point is the time at which a research study begins.
2. Ending Event of interest is the event that is the main core of the research.
3. Measurement scale for the passage of time.

2.2 Survival Time

In research, if the end of recording is marked by the death of a patient, the resulting data is referred to as survival time. However, events in survival studies do not always end in death. The outcome can also be the patient's recovery from the disease, the reduction of symptoms experienced, or the recurrence of certain symptoms [12].

2.3 Survival Function

The survival function is a basic quantity used to describe the phenomenon of event timing. The survival function, denoted by $S(t)$, is the chance of an individual surviving beyond time t, or in other terms $S(t)$ is the probability that an event (e.g., death, machine failure, recurrence of a disease, or the end of a certain condition) occurs after time t [13].

$$\begin{aligned} S_t &= P(T \geq t) \\ &= \int_t^\infty f(x)\ dx \end{aligned} \tag{1}$$

Where:

$S(t)$: Survival function.
P : Probability.
T : Non-negative random variable.
t : Time.

2.4 Hazard Function

The hazard function is also known as the hazard rate, which can be denoted by $h(t)$. The hazard function can be defined as the rate at which an individual experiences an event in the time interval from t to $t + \Delta t$ if it is known that the individual can still survive until time t [14]. Mathematically, it can be expressed as follows.

$$h(t) = \frac{ft}{S(t)}. \tag{2}$$

Where:

$h(t)$: Danger level.
$f(t)$: Density function.
$S(t)$: Survival function.

Specifically for a given value of t, the hazard function $h(t)$ has the following characteristics:

1. Always non-negative, i.e., equal to or greater than zero.
2. It has no upper limit.

The cumulative hazard function can be expressed as follows:

$$H(t) = \int_0^t h(x)dx. \tag{3}$$

Where:

$H(t)$: Cumulative hazard function,
$h(x)$: Hazard function.

This cumulative hazard function has a relationship with $S(t)$, namely:

$$H(t) = -\log S(t). \tag{4}$$

Where:

$H(t)$: Cumulative hazard function.
$S(t)$: Survival function.

2.5 Censored Data

Data is said to be censored if the length of life of a person that we want to know or observe only occurs in a predetermined time period (observation interval), while the info we want to know does not occur in that interval. Thus, we do not obtain any desired information during the observation interval. In survival analysis, there are 3 types of censoring, which are as follows [15].

1. Right censorship is censorship that occurs because the object of observation has not experienced an event until the end of the observation period. While the initial time of the observation object can be observed in full.
2. The left sensor is a sensor that occurs because the initial time of the observation subject cannot be observed at the beginning of the observation, while the failure can be observed in full before the end of the study.
3. An interval sensor is a sensor whose survival time is within a certain interval. This sensor occurs when it is only known that an event of interest occurs within a period of time.

2.6 Kaplan Meier

Kaplan-Meier analysis assumes that the risk of events in subjects who drop out of the study (censored) is the same as those who remain observed until the end of the observation period. To estimate the survival function $S(t)$, the Kaplan-Meier estimator, also known as the product-limit estimator, is used. This estimator calculates the probability of survival over time based on available data in a non-parametric manner [16].

$$S(t) = G\left(1 - \frac{d_i}{Y_i}\right) \tag{5}$$

Where:

d_i : Number of events.
Y_i : Number of individuals at risk (number at risk).

The Kaplan-Meier estimator is a non-parametric estimator that decreases in the presence of an event. This estimator is non-parametric in the sense that it does not assume an infinite number of parameters. The number of parameters or quantities to be estimated in Kaplan-Meier is as many as the points at which the event occurs. To perform inference about $S(t)$ using $\hat{S}(t)$ Kaplan-Meier, it is necessary to first calculate the standard error or variance of $S(t)$. The variance of the KM estimator $\hat{S}(t)$ is often referred to as Greenwood's formula:

$$var[S(t)] = S(t)^2 \sum \frac{d_i}{Y_i(Y_i - d_i)}\ . \tag{6}$$

Alternatively, the following formula can be used

$$var[S(t)] = S(t)^2 \frac{[1 - S(t)^2]}{Y(t)}. \tag{7}$$

Therefore, 95% confidence intervals can be constructed using the normal approach.

$$S(t) \pm 1.96 \times se[S(t)]. \tag{8}$$

Where:

d_i : Number of events.
Y_i : Number of individuals at risk (number at risk).
$S(t)$: Survival function.
$Y(t)$: Number of individuals at risk.

2.6 Log-Rank Test

The Log-Rank test is one of the statistical techniques used to compare differences between two or more survival curves or survival tables. This test is categorized as a chi-square test for large samples, with the hypothesis being to determine whether there is a significant difference between the groups being compared by comparing survival curves between two or more groups. The goal is to determine whether there is a statistically significant difference in the probability of survival between groups over the observation period. [17].

Hypothesis:

H_0 : There is no difference between groups on the survival curve.
H_1 : There is a difference between groups on the survival curve.

Test Statistics:

$$\chi^2 = \sum_{g=1}^{G} \frac{(O_i - E_i)^2}{E_i} \tag{9}$$

Where:

O_i : Individual observation value in the i-th group.
E_i : Individual expectation value in the i-th group.
G : Number of groups.

Rejection Criteria:

Reject H_0 if $\chi^2 > \chi^2_{(\alpha(G-1))}$

Using a 95% confidence level, it can be concluded that if the *p-value* $< \alpha$, there is a significant difference between groups.

2.7 Lin-Ying Additive Hazard Regression

In Lin & Ying's additive hazard regression, the technique used to estimate regression coefficients is similar to the partial likelihood estimation method for proportional hazard models. The regression coefficient estimate in this hazard model will be obtained through the equation obtained from the score equation. The regression coefficient in the Lin & Ying additive hazard model is constant [18].

The Lin-Ying additive hazard model for individual i with covariate vector $X_i(t)$ is as follows:

$$h[t|X_i(t)] = h_0(t) + \beta^t X_i(t) \tag{10}$$

Where:

$h[t|X_i(t)]$: Lin – Ying additive hazard model.
$X_i(t)$: Covariate vector for individual i.
$h_0(t)$: Baseline function.
β_t : $[\beta_1, \ldots, \beta_k]$ unknown parameters to be estimated.
t : Time.

2.8 Parameter Estimation of Lin-Ying Model

The estimation steps in the Lin & Ying hazard model are as follows [19].

1. Estimate the baseline cumulative hazard function first using the counting process theory. The counting process $N_i(t)$ is that each individual is 0 if $T_i > t$ and 1 if $T_i \leq t$, $Mi(t)$ is a martingale and $Y_i(t)$ is the i-th individual. The counting process, $N_i(t)$ is defined as follows.

$$N_i(t) = M_i(t) + \int_0^t i(t)[h_0(t) + \beta' x_i(t)]dt \tag{11}$$

2. Then the estimate of the baseline cumulative hazard function will be substituted into the score equation.

2.9 Parameter Model Testing

Parameter testing is done with the Wald test to check whether the independent variables have a real effect in the model, with the following hypothesis:

Hypothesis:

H_0 : Independent variables do not affect the model.
H_1 : Independent variables affect the model.

Test Statistics:

$$\chi^2 = \left(\frac{\beta_k}{SE(\beta_k)}\right)^2 \tag{12}$$

Rejection Criteria:

Reject H_0 if $p - value < \alpha$ or $\chi^2 \geq \chi^2_{\alpha;\, p}$

By using the 95% confidence level, t can be concluded that if the $p - value < \alpha$ it means that there is at least one variable that has a significant effect on the model [20].

2.10 Childbirth

Childbirth is a naturally occurring physiological process, characterized by a series of significant changes in the mother's body to allow the exit of the fetus through the birth canal. This process begins with regular uterine contractions and ends with the expulsion of the baby, placenta, and membranes, which generally lasts for 12 to 14 hours. Labor can also be defined as the process of expelling the result of conception that has reached an age sufficient to live outside the womb. Normal labor occurs in full-term pregnancies (37-42 weeks), takes place spontaneously with hind-head presentation, lasts less than 18 hours, and occurs without complications for both mother and fetus [21].

2.11 Gestational Age

The duration of pregnancy from ovulation to parturition is approximately 280 days (40 weeks) and not more than 300 days (43 weeks), 40 weeks of pregnancy is called a mature pregnancy (full term). A pregnancy more than 43 weeks is called a postmature pregnancy [22]. Pregnancies between 28 and 36 weeks are called preterm pregnancies. The latter pregnancy will affect the viability (survival) of the baby born because babies who are too young have a poor prognosis [23].

2.12 Mother's Age

Age is the length of a person's presence that can be estimated by units of time and viewed from a part of the sequence. One of the reasons for the maternal regenerative perspective is the age of the mother. The safe age for childbirth is at the age of 20 years to 30 years. Pregnancies at the age of less than 20 years and above 35 years fall into the category of high-risk pregnancies. At an age of under 20 years, the biological condition of the body is not optimal, emotions tend to be unstable, and mental maturity has not been achieved, making it vulnerable to psychological stress. This can have an impact on the lack of attention to the fulfillment of nutritional needs during pregnancy. Meanwhile, pregnancy over 35 years of age is risky due to a decrease in endurance and an increased likelihood of degenerative diseases. With age, there is progressive deterioration of the endometrial lining, so that to meet the nutritional needs of the fetus, more extensive placental growth is required [24].

2.13 Body Height

Body height or height is the maximum distance from the vertex to the sole of the foot. Height is defined as the maximum measurement of the length of the bones of the body that form the axis of the body, measured from the highest point of the head, called the vertex (top of the head), to the lowest point of the calcaneus bone, called the heel [25].

2.14 Parity

Maternal risk factors that affect the birth process include parity. Parity indicates the number of children born to a woman. Parity is an important factor in determining the fate of the mother and fetus both during pregnancy and during labor. In mothers with primiparas (women who give birth to live babies for the first time), because the experience of giving birth has never been experienced, the possibility of abnormalities and complications is quite large [26].

2.15 Hemoglobin Level

Hemoglobin level in the blood is one of the important parameters to determine the prevalence of anemia in pregnant women. A drop in hemoglobin levels from normal values indicates a blood deficiency known as anemia. Anemia is a condition in which hemoglobin (Hb) levels in the blood are below normal, which is generally caused by a lack of intake of nutrients necessary for hemoglobin formation. The World Health Organization (WHO) states that anemia in pregnancy is diagnosed when the hemoglobin (Hb) level is less than 11 g/dL. Meanwhile, the Centers for Disease Control and Prevention (CDC) defines anemia in pregnant women as a condition with Hb levels <11 g/dL in the first and third trimester, <10.5 g/dL in the second trimester, and <10 g/dL in the postpartum period [27].

2.16 Data Sources and Research Variables

This study took data from the Medical Record Room of Anutapura Palu Hospital and was conducted at the Applied Statistics Laboratory, Tadulako University. The population included all deliveries recorded at Anutapura Hospital Palu, with a sample of 82 cases of normal delivery of mothers and babies in January-December 2023.

2.17 Analysis Method

Data analysis in this study used Lin-Ying additive hazard regression analysis with the help of RStudio software. The stages of analysis carried out are as follows:

1. Data Collection.
2. Calculate descriptive statistics.
3. Survival analysis using Kaplan-Meier.
4. Log-rank testing.
5. Parameter estimation of Lin-Ying additive hazard model.
6. Lin-Ying additive hazard regression modeling.
7. Conclusions and suggestions.
8. Completed.

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

Descriptive analysis was used to analyze the data collected for each variable. The analysis was carried out using a pie chart. The descriptive analysis for each variable is as follows:

1. Patient Status

This chart shows the outcomes for mothers who gave birth at Anutapura Palu Hospital from January to December 2023. It reflects whether or not the mothers survived after giving birth

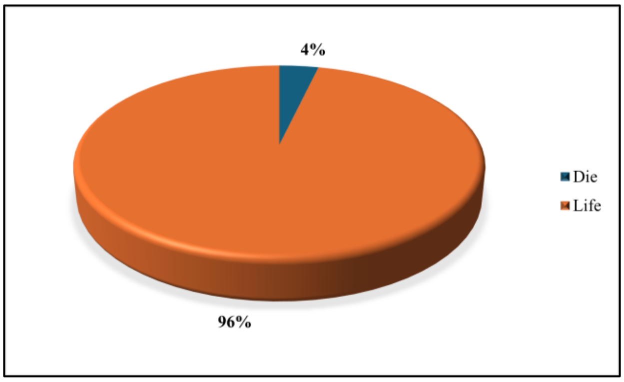

Figure 1. Pie Chart Patient Status
Source: RStudio

Based on Fig. 1, there were 82 normal deliveries from January to December 2023. A total of 3 mothers (4%) experienced death (censored), while 79 mothers (96%) did not experience death (uncensored).

2. Gestational Age

This chart highlights the gestational age of mothers when they gave birth-whether it was preterm, full-term (aterm), or postterm.

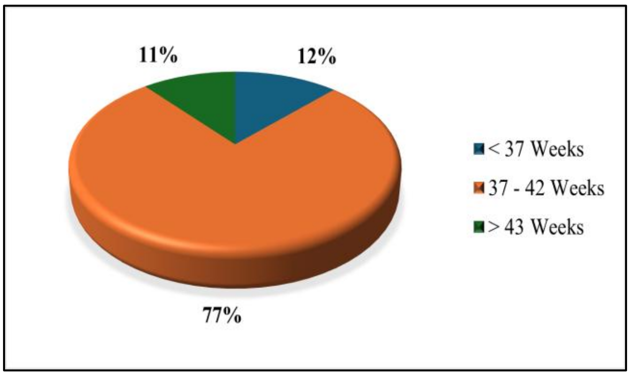

Figure 2. Pie Chart Gestational Age
Source: RStudio

Based on Fig. 2, it is known that in 2023, the majority of mothers who gave birth at Anutapura Palu Hospital had a aterm gestational age (full term) of 63 people (77%), while preterm 10 people (12%), and postterm 9 people (11%).

3. Mother's Age

The age range of mothers giving birth is shown in Fig. 3. The age range is divided into three groups: under 20, between 20–35, and over 35 years old.

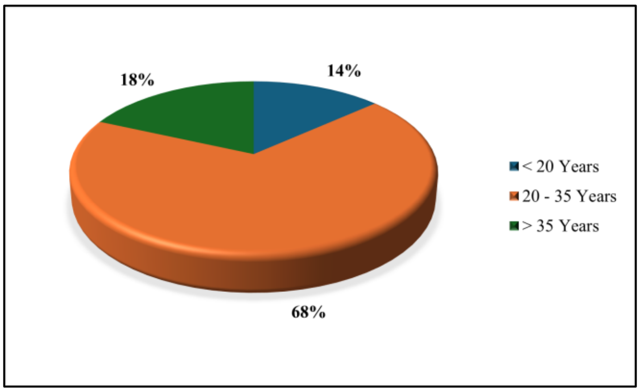

Figure 3. Pie Chart Mother's Age
Source: RStudio

Based on Fig. 3, it is known that mothers who gave birth in the age category <20 years were 11 mothers (14%), mothers who gave birth with the age of 20-35 years were 56 mothers (68%), and mothers who gave birth with the age >35 years were 15 mothers (18%). It can be concluded that more than 50% of mothers who gave birth at Anutapura Palu Hospital in 2023 were aged 20 - 35 years, which is a mature age for childbirth.

4. Baby's Height

This pie chart presents the height of newborns at birth, divided into two categories: below 48 cm and 48 cm or taller.

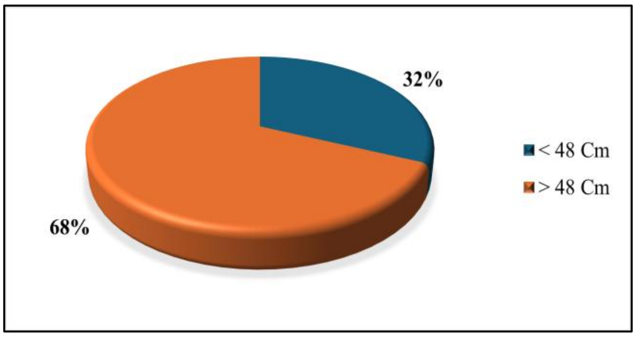

Figure 4. Pie Chart Baby's Height
Source: RStudio

Based on Fig. 4, it is known that 26 babies (32%) were born with a height of < 48 cm, and 56 babies (68%) were born with a height of ≥ 48 cm. This shows that most babies born at Anutapura Palu hospital in 2023 have normal height, so they are not at risk of stunting.

5. Parity

This chart illustrates whether mothers were giving birth for the first time or had done so before.

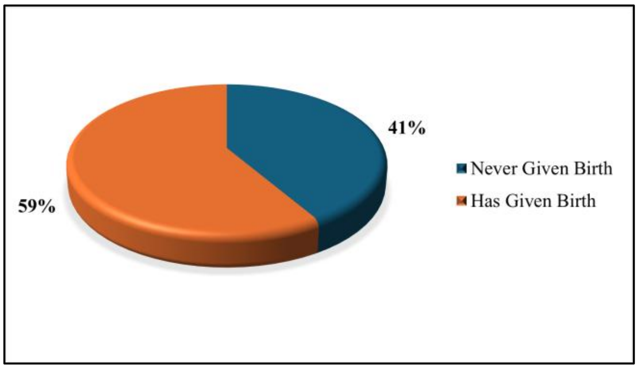

Figure 5. *Pie Chart* Paritas
Source: RStudio

Based on Fig. 5, it is known that mothers with the number of parities 0 or who have not previously given birth amounted to 34 mothers (41%), and mothers who had previously given birth amounted to 48 mothers (59%). It can be concluded that more than 50% of mothers who gave birth at Anutapura Palu Hospital in 2023 have had a childbirth experience.

6. Hemoglobin Level

The hemoglobin levels of mothers at the time of delivery, which indicate whether they had anemia or not, are shown in Fig. 6.

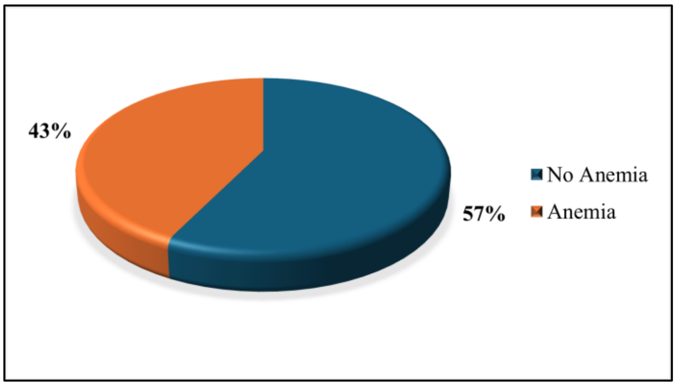

Figure 6. Pie Chart Hemoglobin Level
Source: RStudio

Based on Fig. 6, it is known that the number of maternity mothers in Anutapura Palu Hospital who experienced anemia was 35 mothers (43%), meaning they had hemoglobin levels < 11g/dL, while the number of those who did not experience anemia was 47 mothers (57%), meaning they had hemoglobin levels > 11g/dL.

7. Birth Duration

This chart breaks down how long mothers were in labor, with durations ranging from 9 to 13 hours.

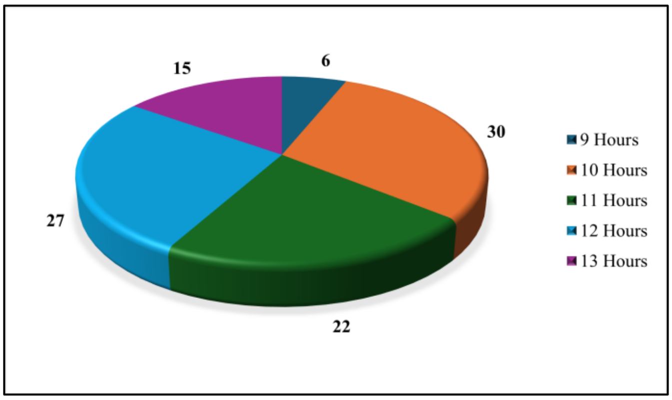

Figure 7. Pie Chart Birth Duration
Source: RStudio

Based on Fig. 7, It is known that labor with a duration of 9 hours amounted to 5 mothers (6%), labor with a duration of 10 hours amounted to 25 mothers (30%), labor with a duration of 11 hours amounted to 18 mothers (22%), labor with a duration of 12 hours amounted to 22 mothers (27%), and the longest labor with a duration of 13 hours as many as 12 mothers (15%). Thus, it can be concluded that the fastest delivery in Anutapura Palu Hospital in 2023 was 9 hours, and the longest duration of labor was 13 hours.

3.2 Survival Analysis

Survival analysis is a data analysis with the variable that is the focus is the time until an event occurs, for example, labor, neonatal death, or pregnancy complications. In the context of obstetrics and neonatology, maternal age and gestational age are two important variables that can affect the time and risk of these events, such as a higher risk of premature labor, risk of preeclampsia, gestational diabetes, and neonatal or perinatal death. The time referred to in the analysis is from the start of contractions to the start of labor. The following is a survival analysis.

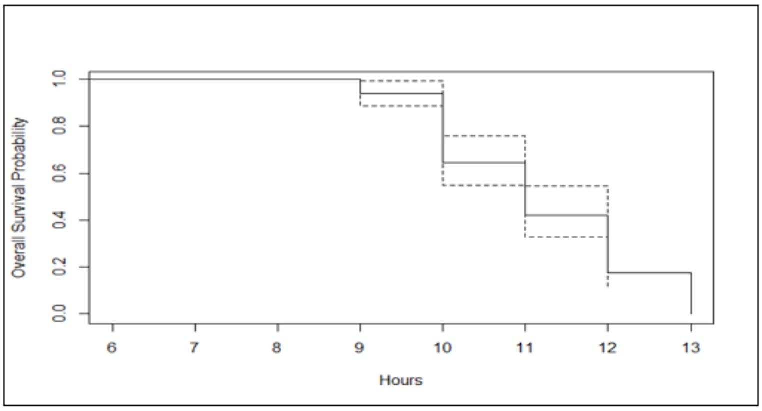

Figure 8. Survival Analysis Curve
Source: RStudio

The survival curve shows that at a birth duration of 9 hours, the chances of survival are high (close to 1). The short duration reduces the risk of complications for both mother and baby, so the chances of failure or death are small. On the contrary, the longer the birth process, the greater the risk of complications, which have an impact on decreasing the chances of survival, as shown by the curve.

Table 1. Survival Analysis

Time	N. Risk	N. Event	Survival	Std. Error	Lower 95% CI	Upper 95% CI
9	82	5	0.939	0.0264	0.889	0.992
10	77	24	0.646	0.0528	0.551	0.759
11	52	18	0.423	0.0549	0.328	0.545
12	34	20	0.174	0.0422	0.108	0.280
13	12	12	0.000	NaN	NA	NA

Based on the survival analysis in Table 1, it is known that the longer the duration of Labor, the less the chance of survival. At a duration of 9 hours, out of 82 mothers at risk, there were 5 deliveries with a 93.9% chance of survival. At 10 hours, out of 77 mothers, there were 24 deliveries with a 64.6% chance. At 11 hours, out of 52 mothers, there were 18 deliveries with a 42.3% chance. At 12 hours, out of 34 mothers, there were 20 deliveries with a 17.4% chance. At 13 hours, all 12 mothers gave birth, with a 0% chance of survival. This suggests that the longer the duration of Labor, the higher the risk of death of the mother and baby. The survival function is as follows.

$$S_t(t) = \sum_{t_i \leq t} (1 - \frac{d_i}{ni})$$

$$S_t(9) = 1 \times (1 - \frac{5}{82})$$

$$S_t(9) = \ 0.9390$$

From the example of manual calculation of the survival function above, it is known that at a duration of 9 hours, the number of objects at risk is known to be 82, and there are 5 births or events, while the chances of survival at this time are 93.9%.

Table 2. Median Survival Analysis

N	Events	Median	0.95 LCL	0.95 UCL
82	79	11	11	12

Based on Table 2 above, it is known that the number of data on the duration of birth is as many as 82 births, with the number of events as many as 79. The average of these data distributions is 11. There is also a 95% confidence interval for the median given by the Lower Confidence Limit (LCL) and Upper Confidence Limit (UCL). This means that 95% of the median is actually between 11 and 12.

3.3 Kaplan Meier

Kaplan-Meier is a method for visually analyzing survival odds based on an individual's survival time. This method calculates the chance of survival in order to understand the characteristics of the survival curve of maternity mothers based on factors that are thought to affect the duration of birth.

1. Gestational Age

Gestational Age is the measurement of pregnancy duration based on a specific method used to determine the time elapsed from conception to delivery. The following is a Kaplan-Meier curve generated using R software.

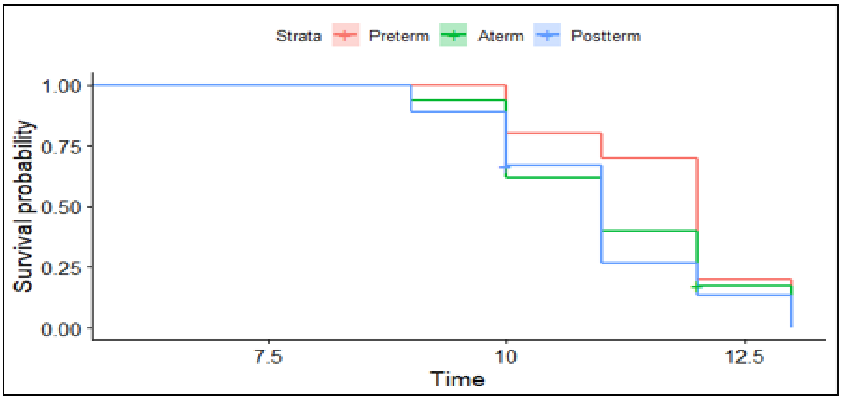

Figure 9. Kaplan Meier Curve Gestational Age
Source: RStudio

Gestational age is divided into three groups: preterm (<37 weeks), aterm (37-42 weeks), and postterm (>42 weeks). In preterm pregnancy, no patient is censored or dies, but the chances of survival decrease. Aterm pregnancy has a decreased chance of survival over time. Similarly, in postterm pregnancy, the chances of survival continue to decrease as the gestational age increases.

2. Mother's Age

Mother's Age refers to the age of a woman at the time of giving birth to her child. The following is a Kaplan-Meier curve generated using R software.

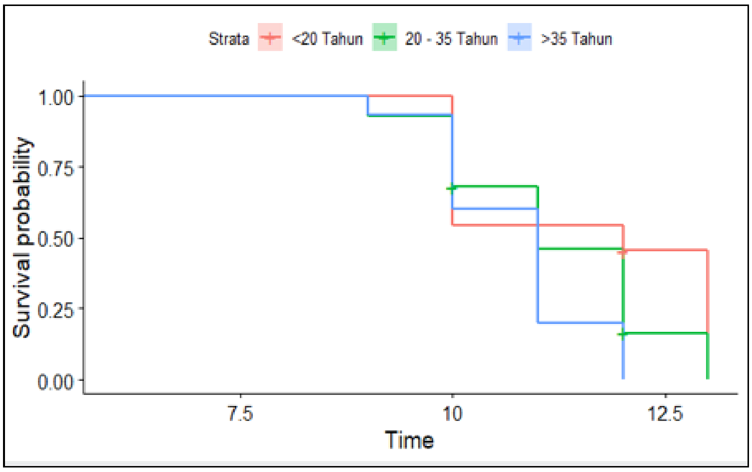

Figure 10. Kaplan Meier Curve Mother's Age
Source: RStudio

Maternal age groups exhibit varying survival probabilities. The age group under 20 years shows a Kaplan-Meier curve that remains high until the end of the observation period, indicating a higher survival probability. However, the duration of labor in this group tends to be longer compared to the 20-35 years age group. The 20-35 years age group shows a steeper decline in the survival curve, suggesting a lower survival probability. Meanwhile, the age group over 35 years experiences the most rapid decline in the curve, reflecting the lowest survival probability; however, the duration of labor in this group tends to be shorter.

3. Baby's Height

Baby's Height refers to the measurement of a newborn's length or height taken after birth. The following is a Kaplan-Meier curve generated using R software.

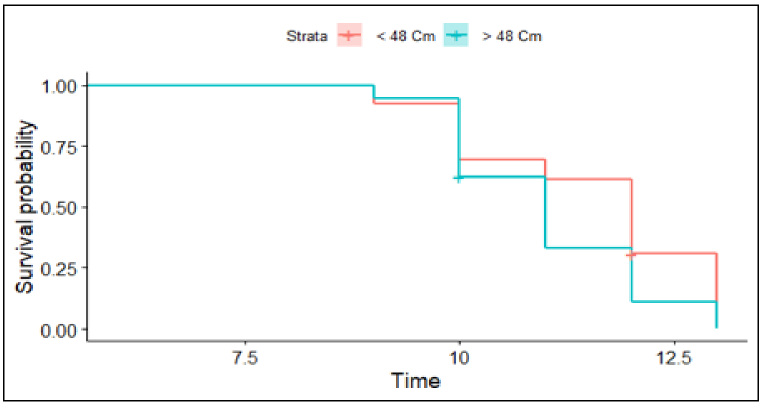

Figure 11. Kaplan Meier Curve Baby's Height
Source: RStudio

Infants who are more than 48 cm tall had a higher probability of survival, indicated by a higher curve until the end of the observation. Babies who are less than 48 cm tall, meanwhile, declined more slowly, indicating fewer events and a greater chance of survival.

4. Parity

Parity refers to the number of times a woman has given birth. The following is a Kaplan-Meier curve generated using R software.

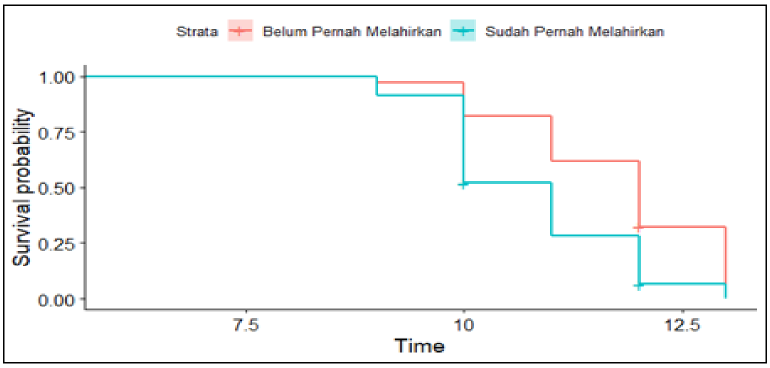

Figure 12. Kaplan Meier Curve Parity
Source: RStudio

Mothers with a history of parity experienced an earlier decrease in the curve due to censored data, which caused the chances of survival to decrease over time. In contrast, mothers without a history of parity have a slower decline curve because there is no censored data, so their chances of survival are greater

5. Hemoglobin Level

Hemoglobin level refers to the concentration of hemoglobin in the mother's blood at the time of delivery. The following is a Kaplan-Meier curve generated using R software.

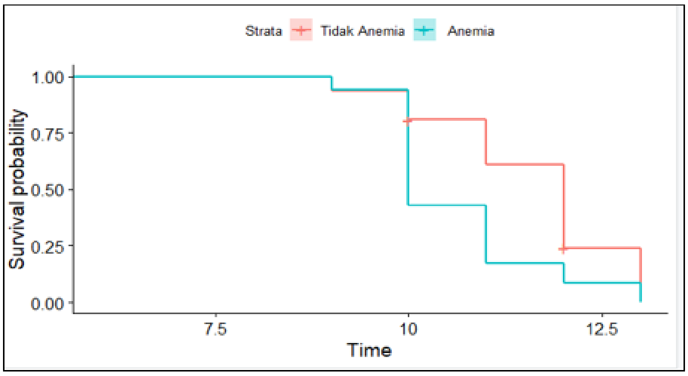

Figure 13. Kaplan Meier Curve Hemoglobin Level
Source: RStudio

The curve shows that mothers without anemia (red line) decreased more slowly than mothers with anemia (Green Line). As a result, the chances of survival of mothers without anemia are higher than mothers with anemia.

3.4 Log-Rank Testing

The log-rank test is a statistical method for comparing survival curves between groups. This test is used in survival analysis to measure significant differences in survival chances between different groups.

Hypothesis:

H_0: There is no difference between groups on the survival curve.
H_1: There are differences between groups on the survival curve.

By using the help of RStudio software, obtained log – rank test scores on the duration of birth data can be seen in Table 3 below.

Table 3. Log-Rank Test for Each Variable

Variables	*Log – Rank*	D_f	$P - value$
Gestational Age (X_1)	1.4	2	0.5
Mother's Age (X_2)	7.3	27	0.03
Baby's Age (X_3)	4.8	1	0.03
Parity (X_4)	12.7	1	4×10^{-4}
Hemoglobin Level (X_5)	15	1	3×10^{-4}

Based on Table 3, it is known that the variables that have $p - value$ (< 0.05), namely, the baby's height, mother's age, parity, and hemoglobin levels have significant differences between the groups.

3.5 Baseline Hazard

This baseline hazard function is the initial or basic function of the hazard function. The baseline hazard function is a hazard function that involves time but does not involve covariates. By using the help of RStudio software obtained baseline values of cumulative hazard in the duration of birth data can be seen in Table 4 below.

Table 4. Baseline Hazard Cumulative

Time	*Baseline Hazard Cumulative*
9	0.06251954
10	0.43310820
11	0.85294216
12	1.71958983
13	4.82280051

Based on Table 4, the value of the hazard value at a duration of 9 hours was recorded at 0.0625, which indicates a relatively low level of risk of death. At a duration of 10 hours, however, the hazard value increases sharply to 0.4331, posing an additional risk. This increase continued temporarily at a duration of 11 hours with a hazard value of 0.8529, and reached 1.7196 at a duration of 12 hours. It aims to raise awareness of the increasingly significant health risks over time. The peak occurred at a duration of 13 hours, where the hazard value reached a drastic value of 4.8228. This figure indicates a very high level of health risk and deserves special attention. Overall, these trends suggest that health risks increase progressively over time, so they can serve as an important basis in risk management and planning more effective control strategies.

3.6 Estimation of Lin-Ying Additive Hazard Model Parameters

In the Lin-Ying model to estimate the equation is not yet known, we will also use the method of partial probability score equation. By using the help of RStudio software, the regression coefficient estimation is done for each error in the error duration data, which can be seen in Table 5.

Table 5. Baseline Hazard Cumulative

Variables	Estimate (β)	Standard Error	Z	$Pr(>\|z\|)$
Preterm Gestational Age ($X_{1,1}$)	-0.12246	0.05571	-2.198	0.02794*
Gestational Age At Term ($X_{1,2}$)	-0.10726	0.04848	-2.212	0.02694*
Postterm Gestational Age ($X_{1,3}$)	-0.08862	0.04573	-1.938	0.05263
Mother's Age < 20 Years ($X_{2,1}$)	0.06232	0.04427	1.408	0.15916
Mother Age 20 – 35 Years ($X_{2,2}$)	0.09077	0.04128	2.199	0.02787*
Maternal Age > 35 Years ($X_{2,3}$)	0.06654	0.04735	1.405	0.15995
Baby Height <48 Cm ($X_{3,1}$)	0.02205	0.06544	0.337	0.73613
Baby Height >48 Cm ($X_{3,2}$)	0.03923	0.06380	0.615	0.53867
Has No Parity History ($X_{4,1}$)	0.14666	0.05612	2.613	0.00897**
Have A History Of Parity ($X_{4,2}$)	0.18373	0.05681	3.234	0.00122**
Anemia ($X_{5,1}$)	-0.06435	0.04663	-1.380	0.16755
Not Anemic ($X_{5,2}$)	-0.12463	0.04736	-2.632	0.00849**

Based on the estimation results in Table 5, it is known that the variables that have a significant effect are gestational age (X_1), Parity (X_4), and hemoglobin level (X_5). The Lin-Ying additive hazard regression model is obtained as follows:

$$h[t|xi(t)] = h_0(t) - 0.12246X_{1,1} - 0.10726X_{1,2} + 0.09077X_{2,2} + 0.14666X_{4,1} + 0.18373X_{4,2} - 0.12463X_{5,2}$$

3.7 Interpretation of Lin-Ying Additive Hazard Regression Model

From the results of Lin-Ying's additive hazard regression analysis, the following models were obtained:

$$h[t|xi(t)] = h_0(t) - 0.12246X_{1,1} - 0.10726X_{1,2} + 0.09077X_{2,2} + 0.14666X_{4,1} + 0.18373X_{4,2} - 0.12463X_{5,2}$$

Variable gestational age $(X_{1,1})$ has a regression coefficient of -0.12246. A negative value indicates that if the mother has a preterm gestational age (<37 weeks) who wants to give birth is lower, the duration of Labor is faster. The value of 0.12246 indicates the difference in risk or risk difference between mothers who have preterm age (<37 weeks) with mothers who have other gestational ages. In other words, mothers with preterm age (<37 weeks) have a 0.12246 less chance of giving birth quickly than mothers with other ages.

Variable gestational age $(X_{1,2})$ has a regression coefficient of -0.10726. A negative value indicates that if the mother has a term gestational age (37 – 42 weeks) and wants to give birth, the lower the duration of Labor, the faster. A value of 0.10726 indicates a difference in risk or risk difference between mothers who have a term pregnancy age (37-42 weeks) with mothers who have other ages. In other words, mothers with gestational age at term (37-42 weeks) have a 0.10726 less chance of giving birth faster than mothers with other ages.

Variable mother's age $(X_{2,2})$ has a regression coefficient of 0.09077. Positive values indicate that the mother's age of 20 - 35 years has a rapid duration in the process of childbirth. The value of 0.09077 indicates the difference in risk or risk difference between mothers who are aged 20-35 years with mothers who are of other ages. In other words, mothers aged 20-35 years have a 0.09077 greater chance of giving birth faster than mothers of other ages.

Variable parity $(X_{4,1})$ has a regression coefficient of 0.14666. A positive value indicates that mothers who have not had a history of parity are faster in the process of giving birth. A value of 0.14666 indicates a risk difference between multigravid mothers (women who are pregnant more than once) and primigravid mothers (women who are pregnant for the first time). In other words, primigravid mothers have a 0.14666 greater chance of giving birth faster than multigravid mothers.

Variable parity $\left(X_{4,2}\right)$ has a regression coefficient of 0.18373. A positive value indicates that mothers who have not had a history of parity are faster in the process of giving birth. A value of 0.18373 indicates a risk difference between multigravid mothers (women who are pregnant more than once) and primigravid mothers (women who are pregnant for the first time). In other words, although primigravidian mothers also have a chance to give birth faster by 0.14666 but not as much as the chances of multigravid mothers who have a chance to give birth faster by 0.18373.

Variable gestational age $\left(X_{5,2}\right)$ has a regression coefficient of -0.12463. A negative value indicates that if the mother has no anemia and wants to give birth, the lower the duration of Labor, the faster. The value of 0.12463 indicates the difference in risk or risk difference between mothers who do not have anemia and mothers who have anemia. In other words, mothers who do not have anemia have a 0.12463 less chance of giving birth faster than mothers who have anemia.

Previous studies have used the Cox Proportional Hazard Regression method, which assumes that the hazard is proportional and constant over time. This means that the influence of independent variables, such as place of residence, education level, health knowledge, and age at marriage, is considered unchanged during the observation period. In contrast to that, this study uses the Lin-Ying Additive Hazard Regression method, which does not require risk proportionality. This method is more flexible because the influence of independent variables, such as gestational age, maternal age, parity, and anemia, can change over time, making it more suitable for modeling the dynamic duration of labor.

4. CONCLUSION

Based on the results and discussion, this study concluded that the factors influencing the duration of childbirth include the gestational age preterm $(X_{1,1})$, gestational age aterm $(X_{1,2})$, mother's age 20 – 35 years $(X_{2,2})$, have no history of parity $(X_{4,1})$, have a history of parity $(X_{4,2})$, and do not have anemia $(X_{5,2})$. Using the Lin-Ying additive hazard regression analysis on birth duration data from Anutapura Palu Hospital, the following models were developed:

$$h[t|xi(t)] = h_0(t) - 0.12246X_{1,1} - 0.10726X_{1,2} + 0.09077X_{2,2} + 0.14666X_{4,1} + 0.18373X_{4,2} - 0.12463X_{5,2}$$

The resulting Lin-Ying additive hazard regression model is able to represent the effect of risk, especially in the context of changes in risk during labor. With this research, government agencies are expected to pay more attention to community services, such as hospitals, to improve the quality of service delivery, such as identifying high-risk groups, optimizing medical intervention scheduling, increasing facility readiness, establishing evidence-based clinical protocols, and improving risk communication to patients.

Author Contributions

Fadjryani: Conceptualization, Methodology, Formal Analysis, Writing-Original Draft, Writing Review and Editing. Iman Setiawan: Writing-Review and Editing. Hartayuni Sain: Formal Analysis. Mohammad Fajri: Visualization. Nurul Fiskia Gamayanti: Validation. Aryani Radi: Data Curation, Investigation, Validation, Writing-Review. Cici Aisya: Editing and Software. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no competing interests.

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