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BAYESIAN COX PROPORTIONAL HAZARDS SURVIVAL ANALYSIS FOR MODELING THE WAITING TIME OF BACHELOR'S DEGREE GRADUATES TO OBTAIN THEIR FIRST JOB (A CASE STUDY OF MATHEMATICS UNDERGRADUATE GRADUATES AT UDAYANA UNIVERSITY)

Juliani Tandi Tumbiri
Mathematics Study Program, Faculty of Mathematics and Natural Sciences, Udayana University
e-mail: julianitumbiri@gmail.com

Ni Luh Putu Suciptawati
Mathematics Study Program, Faculty of Mathematics and Natural Sciences, Udayana University
e-mail: suciptawati@unud.ac.id

Made Susilawati
Mathematics Study Program, Faculty of Mathematics and Natural Sciences, Udayana University
e-mail: mdsusilawati@unud.ac.id

Abstract: This study aims to modeling the duration of waiting time for graduates to get their first job, which is generally less than 12 months. The waiting time is influenced by internal and external factors. Internal factors include hardskill and softskill aspects. Hardskills in this study include Grade Point Average (GPA), graduation predicate, academic achievement, TOEFL score. Meanwhile, soft skills are measured through organizational experience. Then the factors outside of hard skills and soft skills are gender and sources of job vacancy information. The analysis was conducted using the Cox Proportional Hazard regression method using a Bayesian approach to understand the influence of each factor on the waiting time for graduates to get their first job. The results showed that gender, sources of information on job vacancies and hard skills did not have a significant effect on the waiting time for graduates to get their first job, while organizational experience had a significant effect in accelerating the waiting time for graduates to get their first job, showing the important role of soft skills in improving readiness and competitiveness in the world of work.
Keywords: Survival Analysis, Bayesian Approach, Regression Cox Proportional Hazard, Waiting Time of Undergraduate

INTRODUCTION

One of the initial efforts that can be undertaken to prepare individuals for entering the workforce is through education, as higher levels of education tend to enhance labor productivity. Therefore, pursuing higher education can increase opportunities to obtain better employment and higher income (Febianti et al., 2023). In an era of globalization and increasingly intense competition in the labor market, the success of graduates in securing employment has become one of the primary concerns of higher education institutions. Consequently, it is crucial for universities to ensure the quality and relevance of their graduates' competencies in meeting labor market demands (Lestari et al., 2021). However, during the transition from the education system to the world of work, graduates often face various challenges. One relevant indicator for assessing the success of this transition is the length of time graduates require to obtain their first job.

The waiting time for graduates refers to the duration required by a university graduate from the time of graduation until obtaining their first employment (Kurnia & Setyawan, 2021). Based on the Decree of the Minister of Education, Culture, Research, and Technology Number 210/M/2023 concerning the Key Performance Indicators of Higher Education Institutions and Higher Education Service Agencies, graduates' job readiness can be assessed based on whether they secure employment within 12 (twelve) months after graduation. If graduates fail to obtain employment within this 12-month period, it may be considered an indication of potential issues related to graduate preparedness. Various factors influence the length of time graduates need to obtain their first job.

Factors affecting waiting time can be classified into external and internal factors. External factors are beyond the control of graduates, such as the imbalance between the number of graduates and available job opportunities. In contrast, internal factors are those that can be controlled by graduates and consist of hard skills and soft skills. Hard skills refer to technical competencies that integrate knowledge and expertise acquired through formal and non-formal education, such as grade point average (GPA), graduation honors, academic achievements, and TOEFL scores (Putri et al., 2023). Meanwhile, soft skills, which are related to emotional intelligence (Emotional Quotient), include communication skills, leadership, time management, and teamwork, which can be developed through organizational experiences during university studies (Putri et al., 2023). Therefore, survival analysis is required to measure the duration of waiting time and the internal factors influencing it.

Survival analysis is a statistical method used to analyze data that focus on the time until the occurrence of a particular event of interest (Kleinbaum & Klein, 2012). One commonly used model in survival analysis is the Cox Proportional Hazards Regression, which examines the relationship between predictor variables and survival time as the response variable. This model is classified as semi-parametric because the distribution of survival time data is unknown, and thus the functional form of the baseline hazard function is unspecified; however, the parameters (β) of the model have identifiable distributions (Nur et al., 2024).

In estimating parameters in survival analysis, two main approaches are commonly applied, namely the Bayesian approach and the classical approach. This study employs the Bayesian approach, in which parameter estimation does not rely solely on sample data but also incorporates prior distributions. These prior distributions are combined with sample data through the likelihood function to produce posterior distributions. In contrast, classical methods estimate parameters based solely on sample data, making the estimation results highly dependent on sample size. Therefore, parameter estimation using the Bayesian approach can be superior to the classical approach because it integrates additional information from both the prior and the likelihood, thereby potentially improving estimation accuracy (Congdon, 2006).

Based on the foregoing discussion, this study aims to develop a Cox Proportional Hazards regression model using a Bayesian approach and to identify factors that significantly influence the length of time graduates require to obtain their first job. This research focuses on undergraduate graduates of the Mathematics Study Program at Udayana University who graduated between the 146th graduation period in 2022 and the 164th graduation period in 2024.

METHOD

This study uses primary data collected through the distribution of online questionnaires via WhatsApp and Instagram applications. The sampling technique employed is quota sampling. The criteria for respondents in this study are undergraduate graduates of the Mathematics Study Program at Udayana University who graduated between the 146th graduation period in 2022 and the 164th graduation period in 2024. The sample size was set at 100 respondents, as determined by the researcher. The variables examined in this study are as follows:

Table 1. Research Variables

No.	Variable	Variable Name	Scale	Description
1	Y	Waiting Time	Ratio	Length of time required for a bachelor's degree graduate to obtain their first job (in days)
2	D	Status	Nominal	0 = Censored 1 = Observed
3	X_1	Gender	Nominal	0 = Male 1 = Female

No.	Variable	Variable Name	Scale	Description
4	X_2	Grade Point Average (GPA)	Ratio	Final GPA obtained at the time of graduation
5	X_3	Graduation Predicate	Ordinal	0 = With Honors (Cum Laude) 1 = Very Satisfactory 2 = Satisfactory 3 = Sufficient
6	X_4	Academic Achievement	Nominal	0 = No academic achievement 1 = Has academic achievement
7	X_5	Organizational Experience	Nominal	0 = No organizational experience 1 = Has organizational experience
8	X_6	TOEFL Score	Ratio	Score obtained from the TOEFL test
9	X_7	Source of Job Vacancy Information	Nominal	0 = Advertisement 1 = Internet 2 = Personal connections

The analytical technique in this study was conducted using the R and SAS software packages, with the following stages of analysis:

1. Data Collection

   Data were collected by distributing online questionnaires through the WhatsApp and Instagram applications.

2. Identification of Event Status

   The event status was identified by distinguishing between censored and observed data.

   a. $\delta = 0$ indicates censored data, where graduates obtained employment more than 365 days after graduation.

   b. $\delta = 1$ indicates observed data, where graduates obtained their first job within the observation period of 1 to 365 days after graduation.

3. Descriptive Analysis

   Descriptive analysis was conducted to examine the characteristics of undergraduate graduates of the Mathematics Study Program at Udayana University based on each variable included in the study.

4. Testing the Proportional Hazards Assumption

   The proportional hazards assumption was tested using the Goodness-of-Fit (GOF) test for predictor variables or suspected factors influencing the waiting time for graduates to obtain their first job. The hypotheses were tested at a significance level of $\alpha = 0.05$, as follows:

H_0: ρ = 0 (The proportional hazards assumption is satisfied)
H_1: ρ ≠ 0 (The proportional hazards assumption is not satisfied)

The test statistic is given by:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \qquad (1)$$

The null hypothesis is rejected if the p-value < α or if $\chi^2_{\text{calculated}} > \chi^2_{1,0.05}$.

5. Bayesian Cox Proportional Hazards Model Parameter Estimation

Parameter estimation for the Cox proportional hazards regression model was performed using a Bayesian approach, with the following steps:

Specification of Prior and Likelihood Distributions
The prior distribution for the regression parameters (β) was assumed to be identical for all individuals and to follow a normal distribution with a mean of zero. The probability density function of the normal distribution is defined as:

$$f(X;\mu,\sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} exp\left\{-\frac{1}{2}\left(\frac{X-\mu}{\sigma}\right)^2\right\} \qquad -\infty < x < \infty \qquad (2)$$

The partial likelihood function is expressed as follows (Collett, 1994):

$$L(\beta) = \prod_{j=1}^{r} \frac{exp\ (\beta' x_j)}{\sum_{l \in R(t_j)} exp\ (\beta' x_l)} \qquad (3)$$

Posterior Distribution Estimation

The posterior distribution was obtained using Markov Chain Monte Carlo (MCMC) simulation with the Gibbs Sampling algorithm. The posterior distribution can be written as:

$$f(\theta \mid x) \propto f(x \mid \theta) f(\theta) \qquad (4)$$

6. Analysis of Parameter Estimation Results

Convergence of the MCMC chains was assessed using trace plots, Monte Carlo (MC) error, and autocorrelation plots.

7. Model Interpretation Using Hazard Ratios

The Cox Proportional Hazards model is expressed as follows (Kleinbaum & Klein, 2012):

$$h(t,X) = h_0(t)exp\left(\sum_{j=1}^{p} \beta_j X_j\right) \quad (5)$$

where $h_0(t)$is the baseline hazard function, $X_j$represents the j-th predictor variable for $j = 1,2,\ldots,p$, and $\beta_j$denotes the corresponding regression coefficient.

The hazard ratio is defined as the ratio of the hazard function of one individual to that of another individual (Kleinbaum & Klein, 2012), expressed as:

$$\widehat{HR}(t) = \frac{\hat{h}(t,X^*)}{\hat{h}(t,X)} = exp\left[\sum_{i=1}^{p} \hat{\beta}_i\,(X_i^* - X_i)\right] \quad (6)$$

where:
$X^* = [X_1^*, X_2^*, \ldots, X_p^*]$represents an individual with a higher hazard, and
$X = [X_1, X_2, \ldots, X_p]$represents an individual with a lower hazard.

The hazard ratio provides important information for interpreting survival data and the fitted model. The interpretation of the hazard ratio is as follows:

a. HR < 1 indicates that variable Xacts as a protective factor against the occurrence of the event.
b. HR = 1 indicates no association between variable $X$and the occurrence of the event.
c. HR > 1 indicates that variable Xincreases the likelihood of the event occurring.

8. Conclusion

At this stage, conclusions were drawn based on the comprehensive results of the data analysis, including the identification of predictor variables that have a significant effect on the response variable.

RESULT AND DISCUSSION

The sample in this study consisted of 100 graduates, including 4 alumni who chose to prepare for or continue to a master's degree program, 6 alumni who had not yet obtained employment, 45 alumni who secured employment before graduation, and 45 alumni who obtained their first job after graduating with a bachelor's degree.

Table 2. Descriptive Analysis of Numerical Variables of Alumni Who Obtained Employment Before Graduation

Group	Variable	Min	Median	Mean	Max	Variance
Before Graduation	Y (days)	1	112	371	2898	345834
	GPA	2,90	3,72	3,66	3,91	0,04
	TOEFL	450	530	519	603	1534

Source: Processed data (2024)

Based on Table 2, variable Y describes alumni who were employed during their undergraduate studies or prior to graduation, with the waiting time calculated from the date the alumni began working until the graduation date. Some alumni obtained employment one day before graduation, while others began working up to 2,898 days prior to graduation. Furthermore, among alumni who obtained employment before graduation, the lowest GPA recorded was 2.90 and the highest was 3.91, with an average GPA of 3.66. In terms of TOEFL scores, the lowest score was 450 and the highest was 603, with an average TOEFL score of 519.

Table 3. Descriptive Analysis of Alumni Variables for Graduates Who Obtained Employment After Graduation

<table>
<tr><th>Group</th><th>Variable</th><th>Min</th><th>Median</th><th>Mean</th><th>Max</th><th>Variance</th></tr>
<tr><td rowspan="3">After Graduation (Observed)</td><td>Y (hari)</td><td>2</td><td>59</td><td>85</td><td>324</td><td>7380,51</td></tr>
<tr><td>IPK</td><td>2,92</td><td>3,71</td><td>3,64</td><td>3,89</td><td>0,04</td></tr>
<tr><td>TOEFL</td><td>450</td><td>530</td><td>524</td><td>630</td><td>2087,40</td></tr>
<tr><td rowspan="3">>365 Days (Censored)</td><td>Y</td><td>438</td><td>529</td><td>518</td><td>578</td><td>4013,66</td></tr>
<tr><td>IPK</td><td>3,23</td><td>3,41</td><td>3,41</td><td>3,61</td><td>0,02</td></tr>
<tr><td>TOEFL</td><td>455</td><td>478</td><td>487</td><td>540</td><td>1653,58</td></tr>
</table>

Source: Processed data (2024)

Based on Table 3, variable Y represents alumni who obtained their first job after graduating with a bachelor's degree, with time calculated from the graduation date until employment was secured. The fastest time to obtain a first job was 2 days after graduation, while the longest time was 578 days after graduation. The average waiting time to obtain the first job was 85 days after graduation.

For alumni who obtained employment after graduation, the lowest GPA recorded was 2.92 and the highest was 3.89, with an average GPA of 3.64. Meanwhile, alumni who obtained employment more than 365 days after graduation had a minimum GPA of 3.23 and a maximum GPA of 3.61, with an average GPA of 3.41. In terms of TOEFL scores, alumni who obtained employment after graduation had an average score of 524, with scores ranging from 450 to 630. In contrast, alumni who obtained employment more than 365 days after graduation had an average TOEFL score of 487, with scores ranging from 455 to 540.

Based on Table 4, out of 90 alumni, 25 were male and 65 were female. In terms of graduation predicate, 10 alumni graduated With Honors, 66 obtained the Very Satisfactory predicate, 12 obtained the Satisfactory predicate, and 2 obtained the Sufficient predicate. Regarding academic achievement (such as winning mathematics olympiads, scientific debates, or scientific writing competitions), 79 alumni had no academic achievements, while 11 alumni had academic achievements. With respect to organizational experience, 21 alumni were not actively involved in organizations, whereas 69 alumni were actively involved. Based on the source of job vacancy information, 1 alumnus obtained job information through advertisements (newspapers, posters, banners), 51 through the internet (job search websites, social media, company websites), and 38 through personal connections (friends, family, lecturers).

Table 4. Descriptive Analysis of Categorical Variables

Variable	Category	Before Graduation	After Graduation (Observed)	>365 Days (Censored)	Total
Gender	Male	11 (24,44%)	13 (31,71%)	1 (25%)	25
	Female	34 (75,56%)	28 (68,29%)	3 (75%)	65
Graduation Predicate	With Honors	6 (13,33%)	4 (9,76%)	0 (0%)	10
	Very Satisfactory	33 (73,33%)	31 (75,61%)	2 (50%)	66
	Satisfactory	6 (13,33%)	5 (12,20%)	1 (25%)	12
	Sufficient	0 (0%)	1 (2,44%)	1 (25%)	2
Academic Achievement	No Achievement	38 (84,44%)	38 (92,68%)	3 (75%)	79
	Has Achievement	7 (15,56%)	3 (7,32%)	1 (25%)	11

Variable	Category	Before Graduation	After Graduation (Observed)	>365 Days (Censored)	Total
Organizational Experience	Not Active	10 (22,22%)	9 (21,95%)	2 (50%)	21
	Active	35 (77,78%)	32 (78,05%)	2 (50%)	69
Source of Job Vacancy Information	Advertisement	1 (2,38%)	0 (0%)	0 (0%)	1
	Internet	18 (40%)	31 (75,61%)	2 (50%)	51
	Personal Connections	26 (57,78%)	10 (24,39%)	2 (50%)	38

Source: Processed data (2024)

Table 5. Proportional Hazards Assumption Test for Predictor Variables

Variable	Chi-square Value	p-value	Decision
Gender (X_1)	0,0246	0.87	Fail to reject H_0
Grade Point Average (GPA) (X_2)	3,2310	0,07	Fail to reject H_0
Graduation Predicate (X_3)	2,0838	0,14	Fail to reject H_0
Academic Achievement (X_4)	1,1829	0,27	Fail to reject H_0
Organizational Experience (X_5)	0,2560	0,61	Fail to reject H_0
TOEFL Score (X_6)	1,3443	0,24	Fail to reject H_0
Source of Job Vacancy Information (X_7)	1,1880	0,27	Fail to reject H_0

Source: Processed data (2024)

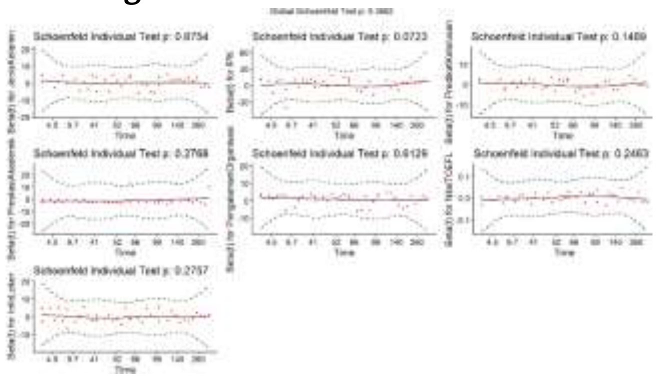
The proportional hazards assumption test for the predictor variables was conducted using the R software. Table 5 presents the results of the proportional hazards assumption test using a Goodness-of-Fit (GOF) approach based on the Chi-square test at a significance level of α = 0.05. The hypotheses tested are as follows:

H_0: ρ = 0 (The proportional hazards assumption is satisfied)

H_1: ρ ≠ 0 (The proportional hazards assumption is not satisfied)

The test results indicate that all predictor variables have p-values greater than 0.05. Therefore, the decision is to fail to reject H_0 for all variables. This finding suggests that the proportional hazards assumption is satisfied for all predictor variables included in the model.

Figure 1. Schoenfeld Residual Plot



Source: Processed data (2024)

Based on Figure 1, the residual plots display the residual patterns for each predictor variable. The dashed line represents the mean residual, while the red points indicate individual residuals. For each predictor variable, no systematic pattern over time is observed in the residual plots, supporting the assumption that the relationship between each predictor variable and the hazard remains constant over time. These residual patterns are consistent with the p-value results obtained from the proportional hazards assumption test, indicating that the proportional hazards assumption is not violated. Therefore, all predictor variables are suitable for inclusion in subsequent analyses.

In parameter estimation, both classical and Bayesian approaches can be applied. This study adopts the Bayesian approach, as it is considered superior to the classical approach due to its ability to incorporate additional information from both prior distributions and likelihood functions, which can improve estimation accuracy (Congdon, 2006).

In this study, alumni who obtained employment within the observation period were those who secured their first job starting from the time of graduation up to 365 days after graduation. Alumni who obtained employment more than 365 days after graduation were treated as censored observations. According to Allison (2010), individuals who experience the event of interest before the start of the observation period should be excluded from the dataset. Therefore, alumni who obtained employment before graduation were excluded from the Bayesian Cox proportional hazards analysis, as they had already experienced the event prior to the commencement of the study.

a. Determination of the Likelihood Function

The likelihood function used in Cox regression is the partial likelihood, which is formulated as follows (Collett, 1994):

$$L(\beta) = \prod_{j=1}^{r} \frac{exp\left(\beta' x_j\right)}{\prod_{k=1}^{\mathrm{d}_j}\left[\Sigma_{l\in R(t_{(j)})} exp(\beta' x_l) - (k-1)\,\mathrm{d}_j^{-1}\sum_{l\in D(t_{(j)})} exp((\beta' x_l)\right]}$$

where $s_j$denotes the vector sum of independent variables for individuals experiencing the event at time $t_{(j)}$. $R(t_{(j)})$represents the risk set consisting of individuals who have not yet experienced the event up to time $t_{(j)}$. $\boldsymbol{x}_l$denotes the independent variables of individuals who have not yet experienced the event and are members of $R(t_{(j)})$. $D(t_{(j)})$represents the set of individuals experiencing the event, and $d_j$denotes the number of events occurring at time $t_{(j)}$.

b. Determination of the Prior Distribution

The prior distribution for the regression parameter $\boldsymbol{\beta}$is assumed to be identical for all individuals and follows a normal distribution with mean μ, as expressed below (Işık et al., 2023; Omurlu et al., 2009):

$$f(\beta) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left\{-\frac{1}{2}\left(\frac{\beta-\mu}{\sigma}\right)^2\right\} \qquad -\infty < \beta < \infty$$

c. Construction of the Posterior Distribution

Using a Bayesian approach, the posterior distribution can be constructed as follows:

$$P(\beta|D) \propto \left(\prod_{j=1}^{r} \frac{exp\left(\beta' x_j\right)}{\prod_{k=1}^{\mathrm{d}_j}\left[\Sigma_{l\in R(t_{(j)})} exp(\beta' x_l) - (k-1)\,\mathrm{d}_j^{-1}\sum_{l\in D(t_{(j)})} exp((\beta' x_l)\right]}\right) \times \left(\frac{1}{\sqrt{2\pi\sigma^2}} exp\left\{-\frac{1}{2}\left(\frac{\beta-\mu}{\sigma}\right)^2\right\}\right) \quad -\infty < \beta < \infty$$

Due to the complexity of the model and the difficulty in obtaining an analytical solution, the Markov Chain Monte Carlo (MCMC) simulation method with the Gibbs sampling algorithm is employed

d. Analysis of Estimation Results

In the survival data analysis of alumni, with $n = 45$as the total number of individuals observed and $T = 41$indicating individuals who experienced the event, a burn-in period of 1,000 iterations was applied with an MCMC sample size of 50,000.

The Bayesian Cox Proportional Hazards regression was conducted using SAS software.

Based on the results, the graduation predicate variable exhibited high autocorrelation. When predictor variables in a model show high autocorrelation, the MCMC chain samples tend to display repetitive patterns and similarities across consecutive iterations. This leads to high autocorrelation, which slows convergence and reduces efficiency in generating independent and representative samples. Therefore, this variable was excluded from the model (Gelman et al., 2013).

Table 6. Parameter Estimates Using the Bayesian Approach

Parameter	Mean	HPD Interval		Significance
		Lower	Upper	
Gender	0,3628	-0,4498	1,1867	Not significant
Grade Point Average (GPA)	2,6517	-0,4392	3,8661	Not significant
Academic Achievement	-1,2236	-2,5846	0,0177	Not significant
Organizational Experience	**0,8539**	**0,0138**	**1,7091**	Significant
TOEFL Score	0,00132	-0,00557	0,00866	Not significant
Job Vacancy Information Source	0,0272	-0,8169	0,8797	Not significant

Source: Processed data (2024)

The 95% Highest Posterior Density (HPD) interval serves as a confidence interval ranging from the lower to the upper bound. A parameter is considered significant if the interval does not include zero. Based on Table 6, only one variable organizational experience does not include zero within its interval; therefore, this variable significantly affects the waiting time to obtain the first job.

e. Convergence Diagnostics

In Bayesian analysis, the Markov Chain Monte Carlo (MCMC) method is commonly used to estimate the posterior distribution of model parameters. To ensure that the estimation results are accurate, it is essential to verify that the MCMC chain has reached convergence, that is, when the chain adequately represents the target distribution.

Several visual diagnostic methods can be employed to assess convergence. These include trace plots, which depict the relationship between the number of iterations and the generated samples; autocorrelation plots, which are used to identify the strength of correlation among the sampled values; and density plots, which illustrate the distribution of samples produced by the MCMC chain (Ntzoufras, 2009).

Based on the analysis, the resulting trace plots, autocorrelation plots, and density plots are presented as follows.

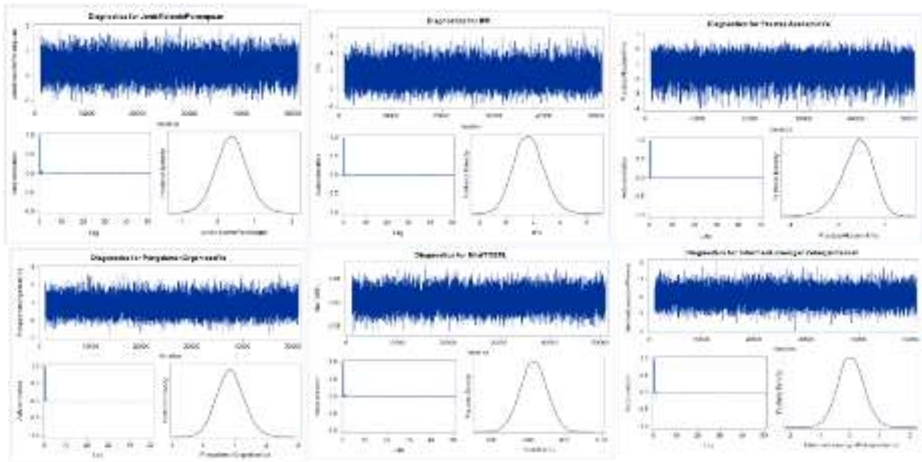


Figure 2. Trace Plots, Autocorrelation Plots, and Density Plots of Predictor Variables

Based on Figure 2, the trace plots for each predictor variable appear dense, are not consistently positive, and do not form any discernible pattern. This indicates that the model has converged for all variables (Ntzoufras, 2009).

As shown in Figure 2, the autocorrelation plots indicate that at lag 0 the autocorrelation value equals 1, and at subsequent lags the values gradually approach 0. This pattern suggests that the model has achieved convergence for all variables (Ntzoufras, 2009).

From the density plots in Figure 2, the estimated densities of the six variables closely approximate a normal distribution. When the posterior distribution follows the expected (normal) shape, it provides additional evidence that the MCMC algorithm has performed well and generated representative samples (Gelman et al., 2013).

In addition to visual diagnostic methods, convergence can also be assessed by examining the Monte Carlo (MC) error values. The MC error values for each predictor variable are presented as follows:

Table 7. Monte Carlo Error Values for Each Predictor Variable

Parameter	SD_MCE	SE_MCE	SE_MCE / SD_MCE
Gender	0,4134	0,00284	0,00688
Grade Point Average (GPA)	1,1059	0,00712	0,00644

Parameter	SD_MCE	SE_MCE	SE_MCE / SD_MCE
Academic Achievement	0,6711	0,00424	0,00632
Organizational Experience	0,4330	0,00283	0,00654
TOEFL Score	0,00363	0,000025	0,00683
Job Vacancy Information Source	0,4312	0,00282	0,00653

Source: Processed data (2024)

Table 7 shows that the Monte Carlo standard error (SE_MCE) is smaller than the Monte Carlo standard deviation (SD_MCE) for each variable. The relatively small SE_MCE values indicate that the parameter estimates are more precise.

The efficiency of the MCMC method can be evaluated using the ratio of the Monte Carlo standard error (SE_MCE) to the Monte Carlo standard deviation (SD_MCE). This ratio reflects the variability of the parameter estimates obtained from the MCMC simulation. A ratio of 1% or lower indicates that the MCMC method has achieved a good level of efficiency in producing stable estimates (Teklezgi, 2023). Based on Table 7, the SE_MCE/SD_MCE ratios for all variables are below 1%, indicating low variability in the estimation results.

Referring to the mean values in Table 6 as the regression coefficients of variables that significantly affect survival time, the Bayesian Cox Proportional Hazards model for alumni waiting time to obtain their first job is expressed as follows:

$$h(t, X) = h_0(t)e^{(0{,}8539X_5)}$$

Based on this model, the hazard ratio for the organizational experience variable is calculated as the ratio between one hazard level and another.

The hazard ratio for organizational experience is calculated as follows:

$$HR = \exp\left[\sum_i^p \hat{\beta}_i(X_i^* - X_i)\right] = \exp(\hat{\beta}_5(1-0)) = \exp 0{,}8539 = 2{,}34$$

Interpretation:

A hazard ratio of 2.34 for the organizational experience variable (HR > 1) indicates that having organizational experience increases the likelihood that alumni obtain employment more quickly. In other words, alumni with organizational experience have a 2.34 times higher chance of obtaining their first job sooner compared to alumni without organizational experience.

4. CONCLUSIONS

Based on the results of the analysis, the conclusions of this study can be summarized as follows:

1. The model constructed using the Bayesian Cox Proportional Hazards approach is expressed as follows:

$$h(t, X) = h_0(t)e^{(0{,}8539X_5)}$$

This result indicates that alumni with organizational experience have a 2.34 times higher chance of obtaining their first job more quickly compared to alumni without organizational experience.

2. Using the Bayesian Cox Proportional Hazards model, only one variable is found to have a significant effect on the survival time of alumni in obtaining their first job, namely organizational experience (X_5). Meanwhile, gender (X_1), grade point average (GPA) (X_2), academic achievement (X_4), TOEFL score (X_6), and job vacancy information sources (X_7) do not have a significant effect on the survival time of alumni in obtaining their first job.

RECOMMENDATIONS

This study only analyzes several internal factors affecting the waiting time for university graduates to obtain their first job. Therefore, future studies are expected to incorporate additional internal factors that may influence the waiting time to first employment. Furthermore, future research is encouraged to examine external factors, such as labor market conditions, economic factors, and institutional characteristics, that may also affect the duration of job search among university graduates.

REFERENCES

Allison, P. D. (2010). Survival Analysis Using SAS: A Practical Guide (2nd ed.). SAS Institute Inc.

Collet, D. (1994). Modelling Survival Data In Medical Research. Chapman & Hall.

Congdon, P. (2006). Bayesian Statistical Modelling (2nd ed.). John Wiley & Sons Ltd.

Febianti, A., Shulthoni, M., Masrur, M., & Safi'i, M. A. (2023). Pengaruh Tingkat Pendidikan, umur, jenis kelamin, dan Pengalaman Kerja Terhadap Produktivitas Kerja di Indonesia. Jurnal Sahmiyya, 2(1), 198–204.

Gelman, A., Carlin, J. B., Stern, H. S., Bunson, D. B., Vehtari, A., & Rubin, D. B. (2013). Bayeisan Data Analysis (3rd ed.). Chapman and Hall/CRC.

Işık, H., Karasoy, D., & Karabey, U. (2023). A new adjusted Bayesian method in Cox regression model with covariate subject to measurement error. Hacettepe Journal of Mathematics and Statistics, 52(5), 1367–1378. https://doi.org/10.15672/hujms.1120196

Kleinbaum, D. G., & Klein, M. (2012). Survival Analysis: A Self-Learning Text, Third Edition. Springer New York, NY.

Kurnia, F. Y., & Setyawan, Y. (2021). Metode Regresi Cox Proportional Hazard untuk Analisis Data Waktu Tunggu Mendapatkan Pekerjaan Program Sarjana S1 (Studi Kasus : Mahasiswa Fakultas Sains Terapan Angkatan 2015 Institut Sains & Teknologi AKPRIND Yogyakarta). Jurnal Statistika Industri Dan Komputasi, 6(2), 141–158.

Lestari, K. E., Utami, M. R., & Yudhanegara, M. R. (2021). Evaluasi Penyelenggaraan Pendidikan Di Perguruan Tinggi: Relevansi Bidang Pekerjaan dengan Program Studi. JURNAL PENDIDIKAN UNSIKA, 9(2), 149–162. http://journal.unsika.ac.id/index.php/judika

Ntzoufras, I. (2009). Bayesian Modeling Using WinBUGS. John Wiley & Sons, Inc.

Nur, St. H., Hikmah, H., & Rahmawati, R. (2024). Model Regresi Cox Proportional Hazard dengan Penaksiran Parameter Efron Partial Likelihood. Journal of Mathematics: Theory and Applications, 6(2), 192–203. https://doi.org/10.31605/jomta.v6i2.3907

Omurlu, I. K., Ozdamar, K., & Ture, M. (2009). Comparison of Bayesian survival analysis and Cox regression analysis in simulated and breast cancer data sets. Expert Systems with Applications, 36(8), 11341–11346. https://doi.org/10.1016/j.eswa.2009.03.058

Putri, I. I., Sinring, B., Arfah, A., Alwany, T., & Taufan, R. R. (2023). Pengaruh Hard Skill dan Soft Skill Terhadap Kinerja Karyawan. Center of Economic Students Journal, 6(2), 223–238. https://doi.org/10.56750/csej.v6i2.588

Teklezgi, M. G. (2023). Bayesian Ananlysis of Mammalian Animals. https://doi.org/10.21203/rs.3.rs-3363107/v1