# Early Warning Financial Distress Model for Listed Companies in Indonesia-Based Machine Learning Markov Chain Monte Carlo

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*Abstract:* - The purpose of this research is to predict the financial distress model with the Markov Chain Monte Carlo (MCMC) approach. Financial distress can have an impact on a country's macro economy. An early warning is needed to prevent financial distress by using machine learning. This research data comes from the Indonesian Stock Exchange (IDX) in 2021, with a total sample of 649 companies. To formulate machine learning, the research data is divided into two, namely, 70% for training and 30% for testing. The results of this study indicate that liquidity, sales growth, and profitability harm financial distress, and sales growth has a positive effect on financial distress. In addition, the accuracy level of determining companies experiencing financial distress in the Bayesian binary logistic model with MCMC is higher than the classic binary logistic for training data, which is 78.41% compared to 78.19%. While for testing data it is relatively the same, namely 78.35%. Since the data is unbalanced in the distress and no distress categories by less than 10%, as a result, the regression model with the MCMC procedure has the best accuracy.

*Key-Words:* - Early warning, Financial Distress, Liquidity, Sales Growth, Profitability, Corporate Size, Markov Chain Monte Carlo.

Received: January 4, 2025. Revised: May 19, 2025. Accepted: June 5, 2025. Published: June 20, 2025.

## 1 Introduction

One of the ongoing threats to Indonesia's many economic sectors is the COVID-19 outbreak, which affects the country's tourism, aviation, food and beverage, and retail industries. [1], states that the limited mobility of the community, both globally and domestically, is also one of the causes of the decline in people's purchasing power. Even, [2], states that most companies in Indonesia experienced a decline in sales, except for the information and communication sector. This condition has an impact on the decline in industry revenue. As a result, many companies in Indonesia experience financial distress. Financial distress is a condition of financial difficulty that causes the company to be unable to fulfill its obligations to creditors, bondholders, and others; this condition can cause bankruptcys, [3].

Financial distress can occur if a company cannot maintain the stability of the company's financial performance so that the company experiences losses or shows negative numbers in net income, operating profit, and book value of equity. Therefore, an early warning indicator of financial distress is needed in companies to prevent and anticipate early the occurrence of systematic risks that arise in the business world. The authorities can take preventive steps to reduce the systematic risk caused by the covid 19 outbreak. For this reason, Early Warning of financial distress must meet the requirements, such as statistical forecasting providing financial distress signals so that the authority has sufficient time to prepare the necessary policies, [4]. Hence, it is crucial to anticipate the company's financial hardship state in order to detect early indications of bankruptcy as a component of an early warning system for management. Early Therefore, predicting the company's financial distress condition is very important to get early signs of bankruptcy as part of an early warning system for management. Early warning of financial distress is even essential for stakeholders such as management, shareholders, vendors, companies, countries, investors, creditors, workers, and labor organizations. Several researchers have developed early warning financial distress models in various sectors; however, the accuracy of the methods still needs to be improved, [5].

In previous studies related to financial distress, most of them focus on variables that affect financial distress, [6]. This research focuses on what variables affect financial distress and has not been able to predict if there are changes in these variables on the financial distress condition of a company. Other study has analyzed and predicted financial distress, [7]. In the previous research, they analyzed and predicted financial distress using the binary logistic regression method. The binary logistic regression used in the study is a classic approach. There is a weakness of the classic binary logistic regression model, namely that if the sample size used is too small, the classic approach will tend to be biased. Several classic approaches sometimes become ineffective when the sample used is too large so that misleading conclusions are obtained, [8]. Therefore, it is necessary to formulate a new method that can overcome these shortcomings.

Machine learning is part of artificial intelligence. One of the mathematical models of machine learning that can be used to predict success or failure events is binary logistic regression, [9]. The parameter estimation in binary logistic regression models uses classical methods, [10]. Data characteristics that are often encountered in binary logistic regression are unbalanced response variables. Unbalance occurs when the number of cases of observations expressed in two groups, 'success' and 'failure', is unbalanced, [11]. These characteristics can affect the performance of the parameter estimation method used. To overcome the shortcomings of the classic method, there is a choice, namely Bayesian binary logistic regression, [12] concludes that Bayesian estimation is unbiased for unbalanced data. The results in their study of bayesian binary logistic regression are more suitable than classical binary logistic regression to model the case of unbalanced response variables. [13], shows the same results, the Bayesian binary logistic regression has better accuracy than classical binary logistic regression.

The parameter estimation process in Bayesian, it uses simulation because it will help calculate the process of integrating the joint posterior distribution. A well-known simulation method in the Bayesian method is the Markov Chain Monte Carlo (MCMC). Bayesian and MCMC methods are difficult to separate, [14]. In the MCMC process, there is a process of generating random sample data. If the integrating process in the model is easy to obtain, then we can solve it analytically. However, the model often encounters equations that are difficult to solve analytically and require a long time to solve. To facilitate and overcome the difficulties in the integralization process, the MCMC simulation is carried out.

To predict the financial distress condition of a company, variable inputs are needed which are called predictors. There are several predictors that can be used based on previous studies. The predictor variable are liquidity [15], sales growth [16], profitability [17], and company size [18]. The ratio is used because companies experiencing financial distress are reflected in a decrease in the ability to pay debts, a decrease in company profits, and no growth in the impact of the company not developing. The target variable, also known as the response variable, is a binary score of "0" or "1" that indicates whether a company is facing a financial crisis or not. When creating a machine learning model, the training data incorporates information from all companies listed on the Indonesia Stock Exchange (IDX). The ultimate machine learning model will unquestionably undergo evaluation for its precision in forecasting the financial crisis conditions of companies listed on the IDX using testing data. The objective of this study is to develop a financial distress model for companies listed on the IDX using Bayesian binary logistic regression with MCMC simulation.

# 2 Literature Review and Hypotheses

## 2.1 Agency Theory

Agency theory examines issues related to employment contracts between agents and principals. Goal misalignment is one of the agency problems that arise when the goals of the two actors are not perfectly aligned. Theoretically, when the goals of the principal and the agent are aligned, there is a high probability that the agent will work for the benefit of the principal. In practice, however, the goals of principals and agents are rarely fully aligned, [19]. While the proprietor of the company is operating in the capacity of principal, the company manager will be given the ability to function as an agent in order to supervise the company and make the best possible decisions. The encompassing viewpoint maintains that the agent is fully responsible for all of the operations that the principal organization carries out. When information is unequally distributed, it frequently leads to principal-agent conflicts, as [20] have called them. These difficulties entail a conflict of interest between the two parties involved. There is a theoretical alignment between the objectives of management (agent) and those of the principal, who is the owner of the organization.

On the other hand, because the two sides have different points of view, disagreements with each other commonly occur. Comparatively speaking, the owner of the company has a different frame of mind than the agency that frequently performs inside a particular industry. However, because the principal entrusts the agent with the responsibility of making decisions and achieving the goal, the agent may, at times, prioritize financial conditions that are different from the rules that have been set, which can result in financial issues. In order to evaluate the current health of the company's finances, it is required to conduct a financial analysis. This study should focus on analyzing various financial metrics, including profitability, liquidity, sales growth, and firm size.

## 2.2 Liquidity and Financial Distress

This indicator illustrates the extent to which the company is able to fulfill both short-term and long-term commitments using readily available assets. When the liquidity level of the company is larger, the likelihood of the company experiencing a crisis is lower. As a stand-in for the liquidity ratio, the current ratio is being used in this investigation. In this particular investigation, the Current Ratio variable was selected for the purpose of determining the extent to which the availability of current assets to satisfy current liabilities is a factor in determining the likelihood of experiencing financial difficulty, [21], [22], [23]. The current ratio has a negative impact on financial distress due to the fact that if the company's state is liquid, the company is able to fund its short-term obligations, which allows the company to avoid experiencing financial distress.

**$H_1$: Liquidity has a negative effect on financial distress**

## 2.3 Sales Growth and Financial Distress

The growth of sales is a measurement that demonstrates the level of achievement of income for the current year in comparison to the income achieved in the preceding year. When a firm's sales growth demonstrates growth, it is an indication that the company has the appropriate plan to preserve its operational continuity. One hypothesis that investors use to express that they expect that if the growth ratio of the company is higher, then the sales will also be higher. Furthermore, when the firm exhibits increasing sales growth, it is an indication that the company's financial state is good, which allows the company to avoid experiencing financial difficulties whenever possible. It is due to the fact that businesses that experience elevated sales growth have the potential to earn bigger profits, which in turn allows these businesses to avoid experiencing financial difficulties. According to the findings of a number of researchers, an increase in sales has a detrimental impact on financial distributions, [24], [25].

**$H_2$: Sales Growth has a negative effect on financial distress**

## 2.4 Profitability and Financial Distress

By calculating profitability ratios, a company can determine whether or not it is successful in terms of its ability to create profits from each sale it makes. Investors are able to readily evaluate the success of the company's management and make accurate projections regarding the company's capacity to be profitable in the future by utilizing this profitability ratio. Return on Assets (ROA) is used as a stand-in for the profitability ratio in this investigation. ROA is determined by determining the extent to which a firm is able to create net income from the total assets that it possesses. With the profits that are created, the company will be able to meet its short-term obligations as well as its operational requirements. As a result, when the profitability ratio is larger, the likelihood of the company experiencing financial trouble is reduced. The Return on Asset (ROA) is the indicator of profitability that is being used in this study. If the return on assets (ROA) of the firm is increasing, it indicates that the company is becoming more efficient; hence, the company will be able to maintain its operations. On the other hand, if the ROA is decreasing to the point where it is detrimental, the company is likely to encounter financial trouble, [26].

**$H_3$: Profitability has a negative effect on financial distress**

## 2.5 Firm Size and Financial Distress

One way to determine the size of a firm is to count the number of assets that it possesses. The size of a firm is proportional to the amount of physical assets that it possesses. When it comes to the assets that are possessed, the capital and sales that are generated as a result will also be higher for businesses that have larger assets. When the corporation has access to capital, the assets that it possesses are able to fulfill its short-term obligations. Because of a lack of resources or cash within the organization, it is typically simpler for a corporation to satisfy its short-term obligations if the assets that the company owns are relatively small.

Furthermore, large-scale businesses tend to enhance negotiating strength in the market where they operate. The company's bargaining strength will contribute to a rise in investor trust in the business. Therefore, the possibility of experiencing financial trouble can be prevented by having a larger size. Companies that have considerable total assets send a favorable signal to creditors since the company is able to diversify its operations and pay off its commitments in the future, preventing the company from experiencing financial distress. Such a company is able to avoid financial distress. It is common practice for businesses to use the size of their company as a reference when determining the likelihood of filing for bankruptcy. Companies that have greater company sizes are more likely to encounter a crisis in their financial operations. [27], state that the size of the firm has a negative effect on financial distress.

**$H_4$: Firm size has a negative effect on financial distress**

## 2.6 Early Warning Financial Distress

It is the company's financial situation that determines whether or not it will continue to exist. As a consequence of this, the process of financial management includes an essential component that comprises early warning of financial difficulty. The pioneering research in the field of financial early warning that uses quantitative data analysis for firm risk early warning is for the purpose of selecting non-failed enterprises. [28] used the single ratio paired sample approach. This method is characterized by the following phrase: "For each failed firm in the sample, a non-failed firm in the same industry and asset size is selected." The purpose of this strategy is to adjust for the influence of factors (asset size and industry) on financial ratios and failures. It is the motive behind this method. The comparison that Beaver made between the average financial ratios of failed firms and those of non-failed firms reveals that the financial ratios of failed firms are significantly worse and exhibit a deterioration in contrast to non-failed firms as the year of failure draws closer.

In addition, [29] developed the Z-value model, which is now commonly referred to as the Altman model, and applied it to the field of financial early warning. A company's financial situation, whether it is bankruptcy or not, can be determined by selecting certain parameters as discriminative variables, which results in the generation of the Z-score. The univariate Beaver model is less accurate than the Altman model, which is more accurate. Following years, [30], developed the ZETA model after doing research for nearly six years, during which they collected and analyzed financial data from more than fifty companies that were in the process of going bankrupt at the time. Then, in order to get around the fundamental flaws that are present in the linear discriminant model, [31], introduced a novel use of logistic modeling in his research on predicting bank failures. [32], addressed the subject of predicting firm failure, which utilized a logistic regression approach to solve the problem. The requirement of identical variance-covariance matrices for both groups (failed and non-failed) and the requirement of normally distributed predictors were two of the stringent restrictions of multiple discriminant analysis. In accordance with the logistic model that Martin had built, a more intricate Probit model was established.

## 2.7 Classical logistics and Bayesian logistics MCMC

Over the years, many scholars have performed logistic analysis using the Bayesian model to correct parametric estimation errors and establish a more realistic model than classical logistics. Bayesian unbiased estimation for unbalanced data. Bayesian binary logistic regression is more suitable than classical binary logistic regression for modeling cases of unbalanced response variables. Due to these shortcomings, this study adopted the Bayesian probit model in conjunction with the MCMC for this study to overcome the constraints above. After utilizing simulation to redistribute the parameters, we compared the posterior probability to the prior probability via the Bayesian probit model to create a realistic scenario. This model is also more effective and stable than others for determining early signs of financial distress. [33] obtained the same results, where Bayesian binary logistic regression has better accuracy than classical binary logistic regression.

**$H_5$: Bayesian MCMC logistics is more rigorous in predicting financial distress than classical logistics**

# 3 Methodology

This study makes use of secondary data that was gathered from the Indonesian Stock Exchange (IDX). According to the financial statements of 649 firms that were listed on the IDX in 2021, the data that was used was obtained from those companies. In this particular investigation, there are two types of variables: response variables and predictor variables. Distress in one's financial situation serves as the response variable in this study. When a company's financial performance continues to deteriorate over a specific period, this is an indication that the organization is experiencing financial hardship. The measuring scale for this variable is nominal, with a value of 0 indicating that the company is not suffering financial difficulty and a value of 1 indicating that the company is experiencing financial distress. In the context of this study, the variables that serve as predictors are liquidity, sales growth, profitability, and the size of the organization. For the sake of this investigation, the current ratio serves as a stand-in for the liquidity variable, the sales growth variable is represented by sales growth itself, the profitability variable is represented by return on assets, and the quantity of total assets represents the firm size variable.

The first step of this study is conducting a descriptive analysis of research data and continuing the modeling stage. For the modeling stage, the division of training data and testing data is carried out. The training data used in this study is 70%, and the testing data is 30%. The next stage is to perform Bayesian binary logistic regression modeling using the MCMC procedure with the Gibbs Sampler algorithm. Based on the full conditional distribution for each parameter, the MCMC procedure with the Gibbs Sampler algorithm is as follows [34]:

i. Determine the number of Z iterations
ii. Determine the initial value $\beta_0^{(0)},\beta_1^{(0)},\beta_2^{(0)},\cdots,\beta_m^{(0)}$
iii. For z = 0, 1, 2,..., Z i.e. generate:

$$\beta_0^{(z+1)} \sim p\left(\beta_0 \mid \beta_1^{(z)},\beta_2^{(z)},...,\beta_m^{(z)},\boldsymbol{Y},\boldsymbol{X}\right)$$

$$\beta_1^{(z+1)} \sim p\left(\beta_1 \mid \beta_0^{(z)},\beta_1^{(z)},...,\beta_m^{(z)},\boldsymbol{Y},\boldsymbol{X}\right)$$

$$\beta_m^{(z+1)} \sim p\left(\beta_m \mid \beta_0^{(z)},\beta_1^{(z)},...,\beta_{m-1}^{(z)},\boldsymbol{Y},\boldsymbol{X}\right)$$

After obtaining a sample of Z iterations, the parameters with the Bayesian method for vectors can be found using the following formulation:

$$\mu_{\boldsymbol{\beta}|\boldsymbol{Y},\boldsymbol{X}} = \frac{1}{Z}\sum_{z=1}^{Z}\boldsymbol{\beta}^{(z)}.$$

The modeling results of classical binary logistic regression are also displayed to find out the advantages of the Bayesian binary logistic regression model. The prediction results of the two models are compared for accuracy.

# 4 Results and Discussion

## 4.1 Results

Descriptive analysis is carried out to find out the description of the research data. Based on Figure 1, in 2021 on the IDX, 244 companies were experiencing financial distress, and 405 companies were not experiencing financial distress. This condition shows that in 2021 many companies on the IDX have healthy finances even though, at that time, COVID-19 was still a pandemic in Indonesia.

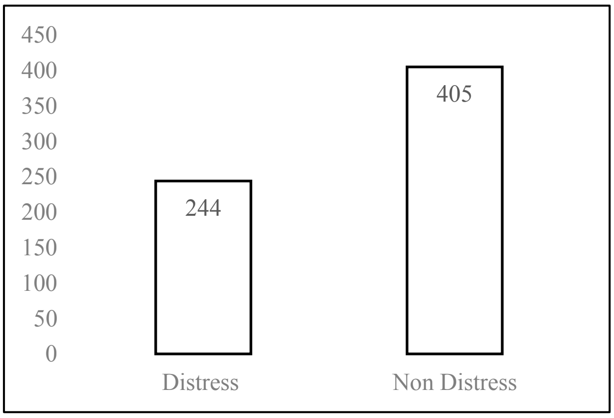


Fig. 1: Descriptive Analysis of Research Variables

When viewed from the data characteristics of the response variable, the extremely unbalanced category does not occur in companies experiencing financial distress 38%, and the remaining 62% of companies that are not experiencing financial distress. Although the condition shows an unbalanced response, the condition is still not categorized as highly unbalanced. Extreme unbalanced conditions occur if one response category is less than 10%.

The descriptive results of the predictor variables are presented in Table 1. Table 1 shows that the minimum value of the current ratio is 0.00, and the maximum value is 1026.01. This figure is the company's value from PT Leyland International Tbk and PT Maharaksa Biru Energi Tbk. The average current ratio is 8.99; based on this figure, it is found that 45 companies have a current ratio value above 8.99. The standard deviation value shows the deviation of the data from the average, where the standard deviation value of the current ratio is 59.61. The minimum value of sales growth is -19.88, and the maximum value of sales growth is 236.96. This value is the sales growth value of the company PT Panca Global Kapital Tbk and PT Dosni Roha Indonesia Tbk. The average sales growth is 0.88; based on this figure, it is found that 73 companies have a sales growth value above 0.88.

The standard deviation value of sales growth is 9.92. The minimum value of ROA is -1396.86, and the maximum value of ROA is 2.07. This value is the ROA value of the company PT Leyland International Tbk and PT Express Transindo Utama Tbk. The average ROA is -2.14; based on this figure, it is obtained that there are 646 having an ROA value above -2.14. The standard deviation value of ROA is 54.83. The minimum size value is -18.17, and the maximum size is 40.56. This value is the size value of the company PT Leyland International Tbk. and PT Perma Plasindo Tbk. The average size is 28.24; based on this figure, it is found that there are 316 having a size value above 28.24. The standard deviation value of size is 2.02.

Table 1. Descriptive analysis predictor variable

| Variable | Minimum | Maximum | Mean | StDev |
|---|---|---|---|---|
| Current Ratio (%) | 0,00 | 1026,01 | 8,99 | 59,61 |
| Sales Growth (%) | -19,88 | 236,96 | 0,88 | 9,92 |
| ROA (%) | -1396,86 | 2,07 | -2,14 | 54,83 |
| Ln total assets | 18,17 | 40,56 | 28,24 | 2,02 |

For Bayesian binary logistic regression modeling using 5,000 000 iterations with a thin of 50. The results of the iteration process for the posterior distribution with 5,000 iterations and a thin of 50 reached equilibrium conditions. The trace plot obtained has shown a random plot and is stable in a domain of values, and there are no strong tendency patterns and periodic patterns. In addition, the Autocorrelation Function (ACF) obtained is so tiny that it is close to zero, so it can be stated that the parameter sample obtained has fulfilled the strongly ergodic MCMC properties or equilibrium conditions that have been achieved. The parameter estimation results of the Bayesian binary logistic regression model for hypotheses testing are presented in Table 2.

Table 2. Hypotheses testing
Bayesian binary logistic regression parameter estimation result

| Variable | Mean | C.I. 2,50% | C.I. 97,50% |
|---|---|---|---|
| Constanta | -4,07 | -7,45 | -0,75 |
| Current Ratio (%) | -0,52 | -0,72 | -0,35 |
| Sales Growth (%) | -0,18 | -0,46 | 0,00 |
| ROA (%) | -6,33 | -9,04 | -3,74 |
| Ln total assets | 0,17 | 0,06 | -0,29 |

Table 2 shows that all the average coefficients of the predictor variables are located between C.I. 2.50% and C.I. 97.50%, indicating that the predictor variables influence financial distress. The logit financial distress model formed based on the parameter estimation results in Table 2 is as follows:

$$\pi(X) = -4{,}07 - 0{,}52\text{Current Ratio} - 0{,}18\text{Sales Growth} - 6{,}33\text{ROA} + 0{,}17\text{Size}$$

Then the probability function of the logit model formed for financial distress is as follows:

$$\pi(X) = \frac{\exp(-4{,}07 - 0{,}52\text{Current Ratio} - 0{,}18\text{Sales Growth} - 6{,}33\text{ROA} + 0{,}17\text{Size})}{1 + \exp(-4{,}07 - 0{,}52\text{Current Ratio} - 0{,}18\text{Sales Growth} - 6{,}33\text{ROA} + 0{,}17\text{Size})}.$$

Based on Table 2 shows that the average value of current ratio coefficients of -0.52 is located between the value of C.I. -7.45 to -0.75, thus the hypothesis that liquidity has a negative effect on financial distress is accepted, meaning that the higher the current ratio value, the lower the company will experience financial distress. The average value of sales growth coefficients of -0.18 is located between the C.I values of -0.46 and 0.00, it can be concluded that the hypothesis stating that sales growth has a negative effect on financial distress is supported, meaning that the higher the level of sales growth, the lower the company will experience financial distress. The average value of coefficients of -6.33 which is located between the C.I. values of -This shows that the hypothesis that profitability has a negative effect on financial distress can be supported, meaning that the higher the profitability proxied by ROA will reduce the company experiencing financial distress or the healthier the company. The average value of coefficients ln total assets is 0.17 which is located between the C.I. values of 0.06 to 0.29. Thus, it can be concluded that the hypothesis that firm size has a negative effect on financial distress can be unsupported. This means that the higher the firm size proxied by ln total assets can increase the company experiencing financial distress.

Based on the Bayesian binary logistic regression model with MCMC procedure and the classical binary logistic regression model, prediction results are obtained for training and testing data. Based on the prediction data, the accuracy of each model can be measured. The accuracy of the training data for both models is presented in Table 3 and Table 4.

Table 3. Prediction accuracy of Bayesian binary logistic for training data

| Correctness of classification | | Prediction: Non-Distress | Prediction: Distress | True Percentage |
|---|---|---|---|---|
| Observation | Non-Distress | 231 | 42 | 84,62% |
| | Distress | 56 | 125 | 69,06% |
| Total Percentage | | | | 78,41% |

Table 4. Prediction accuracy of classical binary logistic regression for training data

| Correctness of Classification | | Prediction: Non-Distress | Prediction: Distress | True Percentage |
|---|---|---|---|---|
| Observation | Non-Distress | 231 | 42 | 84,62% |
| | Distress | 57 | 124 | 68,51% |
| Total Percentage | | | | 78,19% |

Based on Table 3 and Table 4, there are differences in the prediction accuracy results of the two models. The prediction results of the Bayesian binary logistic regression model with MCMC procedures have higher accuracy than the classical logistic regression model, which amounted to 78,41% compared to 78,19%. This means that the hypothesis that Bayesian binary logistics using MCMC is better at predicting financial distress than classical binary logistics is supported.

The accuracy of the Bayesian binary logistic model with MCMC procedures and the classic binary logistic regression model for testing data are presented in Table 5 and Table 6. The prediction accuracy results for testing data show that both models have the same accuracy, which can predict correctly by 78.35%.

Table 5. Bayesian binary logistic regression accuracy for testing data

| Correctness of Classification | | Prediction: Non-Distress | Prediction: Distress | True Percentage |
|---|---|---|---|---|
| Observation | Non-Distress | 111 | 21 | 84,09% |
| | Distress | 21 | 41 | 66,13% |
| Total Percentage | | | | 78,35% |

Table 6. Prediction accuracy of classical binary logistic regression for testing data

| Correctness of Classification | | Prediction: Non-Distress | Prediction: Distress | True Percentage |
|---|---|---|---|---|
| Observation | Non-Distress | 111 | 21 | 84,09% |
| | Distress | 21 | 41 | 66,13% |
| Total Percentage | | | | 78,35% |

## 4.2 Discussion of Research Findings

The first finding indicates that liquidity has a detrimental impact on the amount of financial distress experienced. If a firm's current assets are more than its current liabilities, it is considered to be in a liquid position. Consequently, this indicates that the company can pay its existing liabilities with its present assets, thereby preventing the company from encountering financial distress. This finding is in line with previous research, [35]. The findings of this study align with agency theory, which posits that the agent, as the authorized party, is responsible for effectively managing the company. This is evidenced by the significantly high average liquidity level of 8.99, indicating the company's ability to meet short-term debt obligations and mitigate financial distress. According to economic theory, there is a negative relationship between a company's liquidity and its likelihood of experiencing financial hardship. This means that as a company's liquidity increases, it is more likely to escape financial difficulties.

Secondly, the findings indicated that an increase in sales hurts financial distress. This implies that the company can prevent financial difficulties when sales growth increases. This finding is supported by previous researchers, [25], [36], [37]. Sales growth is a quantitative measure that indicates the company's capacity to augment its revenues over different time intervals. Profits earned increase proportionally with the more significant sales growth of the company. The company's high profits will safeguard it against financial difficulty since it possesses a stable financial situation and can sustain its business operations without interruption. Conversely, if the company has a low growth value, it will result in poor profits and financial distress.

Third, the findings of this study reveal that profitability proxied by ROA has a negative impact on financial distress. Implying that the higher the quantity of profit obtained by the company, the smaller the corporation will endure financial distress. The results of this study are matched by several previous studies, [27], [38]. While, [39] state that an inverse correlation exists between profitability and financial hardship, suggesting that decreased profitability will result in elevated financial distress levels, increasing the probability of bankruptcy. Agency theory suggests that profitability can reduce conflict by offering external parties valuable information to evaluate the company's condition. By assessing the company's state, we can determine the profit made and the efficiency with which the company's assets are managed. Greater profitability indicates more effective asset management in generating profits, resulting in less danger of financial trouble. The company's chance of incurring financial difficulties decreases as it lowers. The company's ability to create substantial profits suggests it possesses the finances to meet its responsibilities and fulfill its financial liabilities. Conversely, a decrease in profitability corresponds to an increase in the likelihood of financial trouble, as the company lacks adequate finances to meet its financial obligations.

Fourth, the data reveals a positive correlation between the size of a corporation, as measured by its total assets, and the occurrence of the financial crisis. Consequently, as the size of a company increases, it is more likely to have financial difficulties; conversely, as the size decreases, the likelihood of financial trouble diminishes. The same results come from [40] where it states that firm size has a positive effect on financial distress. It is feasible because corporations with substantial assets typically incur significant operating expenses, particularly when confronted with the COVID-19 pandemic. The average corporate profitability can be observed by the negative level of -2.14. Unfortunately, the findings of the study do not support the theory and previous research such as, [15], [27] and [38].

Fifth, it is evident that Bayesian logit regression with MCMC utilizing training data is more effective in predicting financial distress than classical logistic regression. The accuracy of the Bayesian logit regression model is 78.41%, whereas the accuracy of the traditional logistic regression model is 78.19%. When using testing data, both Bayesian logit regression and classical logistic regression yield identical prediction results, which amount to 78.35%. This outcome is feasible due to the failure to fulfill the criteria for extreme data companies classified as distressed and non-distressed. Bayesian binary logistic regression is better suited than conventional binary logistic regression for modeling imbalanced response variables, [12], [13].

# 5 Conclusion

This study focuses on developing a financial distress early warning model using MCMC machine learning. The predictor variables used in the model are liquidity ratio, sales growth ratio, profitability ratio, and company size. The analysis indicates that the liquidity ratio hurts financial hardship. This means that higher levels of liquidity decrease the likelihood of a company experiencing financial distress. Furthermore, the sales growth ratio exerts a detrimental impact on financial distress. Thus, a more significant company sales growth will prevent financial trouble, whereas a lower sales growth will lead to financial distress.

Furthermore, financial distress is adversely impacted by profitability. This implies that a greater degree of profitability will prevent financial distress. Additionally, the size of a corporation has a favorable impact on the occurrence of financial distress. Consequently, as the organization's size increases, the company's likelihood of encountering financial distress also increases. Furthermore, empirical evidence suggests that the Bayesian binary logistic regression model using the Markov Chain Monte Carlo (MCMC) process exhibits superior accuracy compared to the conventional binary logistic regression model. The Bayesian binary logistic regression model with the MCMC process achieves an accuracy level of 78.41% for training data and 78.35% for testing data. The similarity in the accuracy level of the two models in this investigation can be attributed to the absence of very imbalanced data situations.

The research is limited by the inappropriate data acquired, resulting from the research sample consisting of 130 industrial sub-sectors listed on the Indonesian Stock Exchange, each with various features. In addition, the requirements for Bayesian MCMC data must be two categories of distress and no distress which are not balanced in extremely below 10%, while in this study 38% of distress category companies were found and 62% non-distress companies were categorized in the study.

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**Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)**

- Anang Subardjo has carried out the results and discussion.
- Muktar Redy Susila has conducted the proposal and data processing (statistics).
- Juwita Sari has done the proofreading.
- George Nikolov was responsible for the Statistics.

**Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself**

This research is funded by the Directorate of Research, Technology, and Community Service (DRTPM); Directorate General of Higher Education, Research, and Technology (DIKTI); Ministry of Education, Culture, Research, and Technology (KEMDIKBUDRISTEK) with Contract Number DRPTM - LLDIKTI VII: 183/E5/PG.02.00.PL/2023.

**Conflict of Interest**

The authors have no conflicts of interest to declare.