



Analysis Of Factors Influencing Credit Insurance Claims At Pt Asuransi Kredit Indonesia: A Logistic Regression Approach

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ABSTRACT

This study aims to analyze the factors influencing the occurrence of claims in credit insurance at PT Asuransi Kredit Indonesia (Askrindo) using a binary logistic regression approach. The analysis was conducted on 14,331 insurance policy records from the period 2021 to 2024, encompassing variables such as regional classification, insured value, premium, gender, age, credit type, insurance duration, and business source. The results reveal that region, debtor age, and credit type have a statistically significant effect on claim probability, with Region III and debtors aged above 55 exhibiting the highest likelihood of claim occurrence. In contrast, insured value and premium show no significant impact, indicating that the current underwriting process may not adequately reflect default risk. The logistic regression model successfully identified seven significant variables and passed all model fit and multicollinearity tests. These findings carry strategic implications for strengthening credit risk management, particularly in refining underwriting policies, improving debtor creditworthiness assessments, and ensuring financial sustainability amid increasing exposure to MSME guarantee programs.

INTRODUCTION

Credit insurance is an essential risk mitigation instrument in the financial system, particularly in developing countries such as Indonesia, which is actively promoting the growth of the MSME sector. Along with the expansion of credit markets and the diversity of borrower profiles, protection against default risk becomes increasingly important to maintain financial institution stability and the sustainability of lending. PT Askrindo, as one of the major players in Indonesia's credit insurance industry, faces growing challenges due to the rising claim ratio, especially during periods of economic uncertainty. Theoretically, this issue is closely related to

the concepts of risk pooling and adverse selection in insurance economics, where information asymmetry between the insurer and the insured may lead to a higher frequency of claims.

Although credit insurance plays a critical role in supporting financial inclusion and expanding access to credit, there is still limited empirical research that deeply investigates the main factors influencing default-based claims, particularly in developing countries. Previous studies tend to focus on macro-level dynamics, such as CDS spreads or the effects of regulation, or on other insurance products like health and life insurance. Their study showed that the presence of insurance could increase moral hazard and thus raise default risk. However, in volatile market conditions, insurance also plays a stabilizing role in the financial system. These findings provide a conceptual framework suggesting that risk protection schemes, such as credit insurance, can have dual effects on financial system stability. Gündüz, Ongena, Tümer-Alkan, and Yu (2025) examined the impact of CDS standardization on credit insurance costs and bank lending in Germany, using CDS trading data and the German Credit Register. Their results indicated that CDS standardization reduced the cost of credit protection and encouraged increased lending, especially by non-dealer banks. This study highlights the importance of efficient credit risk mitigation instruments in supporting financial intermediation. Widhoro Jati (2023) applied a survival analysis approach to study claim timing in life insurance in Indonesia. Using micro-level policy data from PT Asuransi Jiwa XYZ, the study showed that demographic factors such as age, gender, and marital status influenced the timing of claims. Although the context is life insurance, this research provides empirical evidence that the characteristics of insured individuals play an important role in shaping claim patterns. This study differs from the three aforementioned works by specifically focusing on credit insurance in Indonesia and applying logistic regression to actual policy data from PT Askrindo. While Liu et al. (2016) and Gündüz et al. (2025) emphasize macro-level dynamics and CDS instruments in international settings, and Widhoro Jati (2023) investigates time-to-claim in life insurance, this study fills the gap by examining claim determinants from a micro and regional perspective within the context of national credit insurance.

LITERATURE REVIEW

Insurance Theory

According to Law No. 40 of 2014 on Insurance in Indonesia, insurance is defined as a contract between two parties—namely, the insurance company and the policyholder—which serves as the legal foundation for the insurer to collect premiums in return for: Providing compensation to the insured or policyholder for losses, damages, incurred expenses, loss of income, or legal liability to third parties resulting from uncertain events; or Making payments based on the death or survival of the insured, where the benefit amount has been predetermined and/or is based on the outcome of fund management. Rejda and McNamara (2017) define insurance as “an economic protection mechanism against unexpected financial losses, in which individuals or businesses pay a premium to an insurance company in exchange for compensation in the event of covered risks.” Likewise, Vaughan and Vaughan (2013) describe insurance as “a contract that enables the insured to receive compensation for incurred losses by transferring the risk to an insurance company in exchange for a premium.”

This foundational concept illustrates that insurance is essentially a financial arrangement designed to manage risk, promote economic stability, and distribute losses across a pool of policyholders. In the context of credit insurance, this mechanism plays a crucial role in absorbing credit risk, especially for lenders operating in environments with high borrower uncertainty.

Credit Risk

Credit risk is one of the main factors that can affect the financial stability of credit insurance companies such as PT Askrindo. According to Servigny & Renault (2004), credit risk can

be defined as the possibility that a counterparty fails to fulfill its obligations, which can cause a negative impact on the financial condition of financial institutions and insurance companies. In credit insurance, an increase in claims that is not balanced with adequate premiums can threaten the company's solvency, leading to a rise in the claim ratio which directly affects the company's profitability and liquidity. This highlights the importance of analyzing credit risk, which is one of the crucial aspects in the financial industry, with the objective of identifying, measuring, monitoring, and controlling the risk of default that can impact the stability of financial institutions (Löeffler & Posch, 2011).

Default

Default is a condition in which a debtor or a party with financial obligations fails to fulfill its payment obligations in a timely manner as agreed in the contract (Basel Committee on Banking Supervision, 2023). In the context of credit risk, default is often associated with the borrower's inability to repay loans, either in principal or interest, thereby potentially causing losses to financial institutions, including banks and credit insurance companies.

According to Löeffler & Posch (2011), default occurs when a party is unable to meet its financial commitments, which may result from internal factors such as liquidity difficulties or external factors such as changes in economic conditions and monetary policy. In credit insurance, default has broader consequences because it triggers claims from creditors who have obtained insurance protection on the loans disbursed.

Logistic Regression

Logistic regression is a statistical method used to analyze the relationship between one or more independent variables and a dependent variable that is binary or dichotomous in nature (e.g., 0 and 1). According to Hosmer and Lemeshow (2013), logistic regression is applied when the dependent variable consists of two categories, such as claim occurred (1) or did not occur (0). The general form of the binary logistic regression equation is as follows:

$$P(Y = 1) = \frac{e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}}{1 + e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}}$$

Alternatively, it can be written in the form of a logit function as follows:

$$\log\left(\frac{P(Y = 1)}{1 - P(Y = 1)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$$

Logistic regression uses the Maximum Likelihood Estimation (MLE) method to estimate the model parameters and determine which independent variables have a significant influence on the probability. This model is built on several key assumptions, namely:

- a. The dependent variable is binary (e.g., claim occurs or does not occur).
- b. There is no direct linear relationship between the independent variables and the dependent variable, as the model uses a logit (log-odds) function.
- c. There is no high multicollinearity among the independent variables.
- d. A sufficiently large sample size is required to obtain stable estimates.

METHODS

A quantitative method is employed in this study. According to Sujarweni (2014), quantitative research is a type of research that produces findings through the application of statistical procedures or other forms of quantitative measurement. In this research, the focus is on analyzing the factors that influence the probability of claim occurrence at PT Askrindo. The

analysis combines a descriptive approach to understand the characteristics of the claim data with logistic regression to identify variables that contribute to the likelihood of a claim.

The object of this study is the credit insurance claims at PT Askrindo, particularly the factors that affect the probability of a claim. The subjects of this research are claim reports and policy data over the past four years, which include information on region, sum insured, premium, gender, age, credit type, contract duration, and business source. The population consists of all insurance policy records issued by PT Askrindo during the four-year period from 2021 to 2024. A total of 14,331 insurance policies were selected as the sample using a systematic random sampling technique.

Logistic Regression Analysis Technique

The analytical technique used in this study is binary logistic regression, which aims to identify the factors that influence the probability of claim occurrence at PT Askrindo. Logistic regression is employed because the dependent variable in this study is binary in nature (0 = no claim, 1 = claim). The equation and variables used in this research are as follows:

$$\log\left(\frac{P(Y = 1)}{1 - P(Y = 1)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9$$

- Y** = Dependent variable indicating claim status (0 = no claim, 1 = claim)
X₁ = Dummy variable for Region I (Sumatra and surrounding areas)
X₂ = Dummy variable for Region II (Banten, DKI Jakarta, and West Java)
X₃ = Independent variable for Sum Insured
X₄ = Independent variable for Premium
X₅ = Dummy variable for Gender (0 = Female, 1 = Male)
X₆ = Independent variable for Debtor's Age
X₇ = Dummy variable for Credit Type (0 = Productive Credit, 1 = Consumptive Credit)
X₈ = Independent variable for Contract Duration (in months)
X₉ = Dummy variable for Business Source (0 = Direct, 1 = Non-Direct)

Model Fit Testing

To evaluate whether the logistic regression model used in this study provides a good explanation of the relationship between the independent and dependent variables, several model fit tests were conducted:

- Hosmer and Lemeshow Test, to assess the goodness-of-fit between the model and the observed data.
- Pseudo R-Square (Nagelkerke R²), to indicate how well the independent variables explain the variation in the dependent variable.
- Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), to compare the current logistic regression model with alternative model specifications.

Multicollinearity Testing

Multicollinearity is tested by examining the Variance Inflation Factor (VIF). If the VIF value is excessively high (typically greater than 10), it indicates a high degree of correlation among independent variables, which may distort the reliability of the model estimates.

Model Validation

Model validation is carried out using the classification accuracy of the logistic regression to evaluate how well the model distinguishes between claim and non-claim cases. Confusion matrix and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) are utilized to assess the predictive performance of the model.

Interpretation of Regression Coefficients

- a. The exponentiated coefficients (Odds Ratios) are used to interpret the impact of each independent variable on the likelihood of a claim occurring.
- b. The significance values (p-values) are compared to the confidence level (e.g., 5%) to determine which variables have a statistically significant effect.

Hypotesis Testing

The Effect of Region on Claim Probability

H₀₁: There is no significant effect of Region I (Sumatra and surrounding areas) on claim probability.

H₁₁: Region I (Sumatra and surrounding areas) has a significant effect on claim probability.

H₀₂: There is no significant effect of Region II (Banten, DKI Jakarta, and West Java) on claim probability.

H₁₂: Region II (Banten, DKI Jakarta, and West Java) has a significant effect on claim probability.

The Effect of Sum Insured on Claim Probability

H₀₃: Sum insured does not have a significant effect on claim probability.

H₁₃: Sum insured has a significant effect on claim probability.

The Effect of Premium on Claim Probability

H₀₄: Premium does not have a significant effect on claim probability.

H₁₄: Premium has a significant effect on claim probability.

The Effect of Gender on Claim Probability

H₀₅: Gender (male/female) does not have a significant effect on claim probability.

H₁₅: Gender has a significant effect on claim probability.

The Effect of Debtor's Age on Claim Probability

H₀₆: Debtor's age does not have a significant effect on claim probability.

H₁₆: Debtor's age has a significant effect on claim probability.

The Effect of Credit Type on Claim Probability

H₀₇: Credit type (productive/consumptive) does not have a significant effect on claim probability.

H₁₇: Credit type has a significant effect on claim probability.

The Effect of Contract Duration on Claim Probability

H₀₈: Contract duration does not have a significant effect on claim probability.

H₁₈: Contract duration has a significant effect on claim probability.

RESULTS

This study uses a descriptive analysis was conducted on claim data based on several key factors, namely region, gender, credit type, debtor's age, and business source. This analysis aims to understand claim patterns and to identify the factors that contribute to high or low claim rates.

Table 1. Claim Distribution by Regional Classification

Region	No Claim	Claim	Total	Claim Rate
Region I (Sumatera dan Sekitarnya)	1,096	463	1,559	29.70%
Region II (Banten, DKI Jakarta, dan Jawa Barat)	2,466	1,971	4,437	44.42%
Region III (Selain Wilayah I dan II)	3,911	4,424	8,335	53.08%
Total	7,473	6,858	14,331	47.85%

Regarding the distribution of claims based on regional classification, and in accordance with the regional division established by the Indonesian Financial Services Authority (OJK), Indonesia is categorized into three main regions as shown in Table 1. The analysis results indicate that region has a notably significant impact on claim levels. Region III recorded the highest claim rate at 53.1%, followed by Region II at 44.4%, while Region I had the lowest claim rate at 29.7%. This finding suggests that Region III poses a higher risk compared to the other regions, whereas Region I appears to be relatively safer in terms of claim submissions. Environmental factors, economic conditions, and the types of businesses supported by credit in each region are likely to contribute to these differences in claim rates.

Table 2. Distribution of Claims by Gender

Gender	No Claim	Claim	Total	Claim Rate
Female	2,889	2,531	5,420	46.70%
Male	4,584	4,327	8,911	48.56%
Total	7,473	6,858	14,331	47.85%

The analysis of gender reveals no significant difference between male and female debtors in terms of claim occurrence. The claim rate among male debtors stands at 48.6%, which is slightly higher than the 46.7% observed among female debtors. This relatively minor difference suggests that gender is not a primary factor influencing the likelihood of a claim. Therefore, underwriting policies may be more effectively directed toward other variables with greater influence, such as region or borrower age.

Table 3. Claim Distribution by Age Group

Age	No Claim	Claim	Total	Claim Rate
15-25	624	298	922	32.32%
25-35	2,099	1,533	3,632	42.21%
35-45	2,494	2,250	4,744	47.43%
45-55	1,643	1,821	3,464	52.57%
>55	613	956	1,569	60.93%
Total	7,473	6,858	14,331	47.85%

The age group of 15–25 years recorded the lowest claim rate at 32.3%. Debtors in this group are generally just entering the workforce or starting a business, and therefore tend to

have fewer financial responsibilities compared to older age groups. In addition, the loans granted to this segment are likely to be smaller and more controlled, resulting in a relatively lower default risk. In the 25–35 year age group, the claim rate increases to 42.2%, indicating that debtors in this range begin to face greater financial obligations, such as mortgage payments, vehicle installments, or business expansion. As age increases, the claim rate continues to rise, with the 35–45 year group recording a claim rate of 47.4%. At this stage, debtors typically carry more financial burdens and larger loan amounts, which may elevate the likelihood of default. Furthermore, the 45–55 year group shows a claim rate of 52.6%, suggesting that claim risk continues to rise with age. At this point, health-related factors also become increasingly relevant, particularly for self-employed individuals or those working in sectors that are more vulnerable to economic fluctuations. The age group above 55 years reports the highest claim rate at 60.9%, which may be attributed to declining productive capacity, rising living expenses, and increased reliance on credit-based financing.

Table 4. Claim Distribution by Credit Type

Credit Type	No Claim	Claim	Total	Claim Rate
Productive	3,871	3,596	7,467	48.16%
Consumptive	3,602	3,262	6,864	47.52%
Total	7,473	6,858	14,331	47.85%

There are two main categories of credit type: productive credit and consumptive credit. Productive credit exhibits a claim rate of 48.2%, while consumptive credit shows a slightly lower rate of 47.5%. Although the difference is relatively small, it still indicates that productive credit carries a marginally higher claim risk compared to consumptive credit. One of the primary reasons for the higher claim rate in productive credit lies in its dependence on economic and market conditions. Productive loans are typically used to finance business capital or investment activities, making them more vulnerable to business failure, which in turn may hinder the debtor's ability to meet repayment obligations. Conversely, although consumptive credit shows a lower claim rate, this does not imply that it is entirely free from risk. Consumptive credit is generally used for purchasing goods or fulfilling personal needs that do not generate additional income. As such, if the debtor encounters financial disruptions—such as job loss or unexpected expenses—they may struggle to meet repayment commitments. However, consumptive credit often features more structured repayment mechanisms, including automatic salary deductions or fixed income-based payment plans, which help to contain the associated claim risk more effectively than in the case of productive credit. Overall, the data indicate that productive credit tends to be slightly riskier than consumptive credit in terms of claim occurrence, although the gap is not substantially large.

Table 5. Claim Distribution by Business Source

Business Source	No Claim	Claim	Total	Claim Rate
Direct	6,266	5,720	11,986	47.72%
Non-Direct	1,207	1,138	2,345	48.53%
Total	7,473	6,858	14,331	47.85%

In terms of business source, the analysis shows that the claim rate for policies acquired through the Direct channel is 47.7%, while that from the Non Direct channel is 48.5%. This very small difference indicates that the method of policy marketing or distribution does not have a significant impact on claim probability. Consequently, customer acquisition strategies may continue to be implemented through both channels without a substantial difference in claim risk.

DISCUSSION

Interpretation of Regression Coefficients

The resulting logistic regression model can be expressed as follows:

$$\log\left(\frac{P(\text{Claim} = 1)}{1 - P(\text{Claim} = 1)}\right) \\ = -0,862 - 0,931X_1 - 0,510X_2 + 0,000X_3 + 0,000X_4 + 0,030X_6 \\ + 0,705X_7 - 0,092X_8$$

Based on the estimation results, several variables were found to have a statistically significant effect on the probability of a claim:

Region Code 1 (Sumatra and Surrounding Areas)

The regression coefficient for Region Code 1 is $B = -0.931$, with an $\text{Exp}(B)$ value of 0.394. This indicates that the Sumatra region and surrounding areas have a lower likelihood of claim occurrence compared to the reference region. The calculated reduction in claim probability is 60.6%, derived from the following computation:

$$(1 - 0.394) \times 100\% = 60.6\%$$

Accordingly, Sumatra and its neighboring regions exhibit a significantly lower claim risk relative to other geographic areas, reinforcing the importance of regional risk segmentation in underwriting decisions.

Region Code 2 (Banten, DKI Jakarta, dan Jawa Barat)

The regression coefficient for Region Code 2 is $B = -0.510$, with an $\text{Exp}(B)$ value of 0.601. This indicates that the region of Banten, DKI Jakarta, and West Java also has a lower probability of claim occurrence compared to the reference region, although it is higher than that of Region 1. The calculation shows that the claim probability in this region is 39.9% lower than the reference region, as calculated below:

$$(1 - 0.601) \times 100\% = 39.9\%$$

Sum Insured

The regression coefficient for sum insured is $B = 0.000$, with an $\text{Exp}(B)$ value of 1.000. This indicates that changes in the sum insured do not have a significant impact on the probability of a claim. Although this variable is statistically significant, the $\text{Exp}(B) = 1.000$ suggests that an increase in the insured amount does not substantially alter claim probability.

Premium

The regression coefficient for premium is $B = 0.000$, with an $\text{Exp}(B)$ value of 1.000, indicating that the premium paid also has no considerable influence on the likelihood of a claim.

Debtor's Age

The regression coefficient for debtor's age is $B = 0.030$, with $\text{Exp}(B) = 1.031$. This means that each additional year of debtor age increases the probability of a claim by 3.1%, calculated as:

$$(\text{Exp}(B) - 1) \times 100\% = (1.031 - 1) \times 100\% = 3.1\%$$

Therefore, the older the debtor, the higher the likelihood of a claim occurring.

Credit Category

The regression coefficient for credit category is $B = 0.705$, with an $\text{Exp}(B)$ value of 2.024. This result indicates that consumptive credit is associated with a 2.024 times higher likelihood of a claim compared to productive credit. Thus, debtors holding consumptive credit have a greater risk of claim occurrence relative to those holding productive credit.

Contract Duration

The regression coefficient for contract duration is $B = -0.092$, with an $\text{Exp}(B)$ value of 0.912. This indicates that the longer the coverage period, the lower the probability of a claim occurring. Each additional year of coverage reduces the likelihood of a claim by 8.8%, as calculated below:

$$(1 - \text{Exp}(B)) \times 100\% = (1 - 0.912) \times 100\% = 8.8\%$$

In other words, insurance policies with longer durations are associated with lower claim risk compared to those with shorter coverage terms.

Constant

The regression constant has a coefficient of $B = -0.862$, with an $\text{Exp}(B)$ value of 0.422, indicating that when all independent variables are held at zero, the probability of a claim remains below 50%. This suggests that, overall, the variables included in the model contribute positively to explaining the increase in claim probability.

Implications of Findings for Claim Risk Management Strategy

One of the key implications of this study is the importance of developing a risk profile based on debtor portfolio characteristics. Variables such as region, age, credit type, and contract duration have been shown to significantly influence the probability of claims. Accordingly, each of these variables can be positioned as risk drivers—factors that directly affect the level of risk exposure within the company's portfolio. The corresponding risk matrix and claim mitigation strategies are presented in Table 6.

Table 6. Risk Matrix and Claim Mitigation Strategies

No.	Risk Factor	Likelihood Level	Risk Impact	Risk Mitigation Strategy
1	High-Claim Region (Region III)	High	High	Risk-based pricing & strict underwriting
2	Debtor Age > 55 Years	High	High	Limit coverage period and set maximum age thresholds
3	Consumptive Credit	Medium	Medium	Income verification & differentiated premium pricing
4	Short-Term Policy (<1 year)	Medium	Medium	Expand long-term policies with incentive schemes
5	Medium-Claim Region (Region II)	Medium	Medium	Enhanced monitoring and review
6	Debtor Age between 45 and 55 Years	Medium	Medium	Additional risk scoring
7	Productive Credit	Low	Low	Portfolio diversification & regular monitoring
8	Long-Term Policy (>2 years)	Low	Low	Promotion of stable long-term insurance products

From a regional perspective, the significant differences in claim rates highlight the relevance of applying geographical risk segmentation. Regions with high claim rates, such as Region III, should be treated as areas with elevated risk exposure, warranting the implementation of targeted risk mitigation strategies. These may include risk-adjusted pricing, limits on the sum insured, or the imposition of additional conditions such as stronger collateral requirements to better manage the risk associated with policies issued in high-risk areas.

CONCLUSION

The findings of this study indicate that default risk in credit insurance at PT Askrindo poses a substantial threat to the company's financial stability, as evidenced by claim ratios that significantly exceed premium growth. Through the analysis of 14,331 policy records from 2021 to 2024 using binary logistic regression, several key insights were identified:

- 1. High Claim Ratios Reflect Systemic Risk in the Credit Insurance Portfolio**
The claim ratio for Askrindo's small credit insurance reached an alarming 821.8% in 2022, indicating that the volume of claims significantly exceeded the company's premium income. This situation imposes considerable pressure on profitability and threatens the company's solvency and long-term business sustainability.
- 2. Regional Factor Has a Significant Impact on Claim Probability**
The regression analysis reveals that the debtor's geographical location is a key determinant of claim probability. Region III (outside of Sumatra, DKI Jakarta, and West Java) exhibits the highest claim risk, which can be attributed to weaker local economies, limited infrastructure, and more vulnerable borrower capacities. In contrast, Region I demonstrates a 60.6% lower claim probability compared to Region III.
- 3. Debtor Age Positively Correlates with Claim Probability**
There is a consistent pattern indicating that younger debtors are associated with a lower likelihood of claim occurrence, while older debtors face higher claim probabilities. Debtors aged above 55 exhibit the highest claim rate (60.9%). Each additional year of age increases the claim probability by approximately 3.1%, suggesting that age serves as a critical risk indicator in underwriting.
- 4. Credit Type and Insurance Tenure Influence Claim Risk**
Productive credit guarantees are marginally more prone to claims than consumptive ones, highlighting that UMKM-related credit—while essential—also involves considerable risk if not supported by proper assessments. Conversely, longer insurance durations are associated with reduced claim probabilities, possibly due to greater business maturity and operational stability over time.
- 5. Financial Variables Have No Substantial Predictive Power**
Although both insured value and premium are statistically significant, their odds ratios are close to 1 ($\text{Exp}(B) \approx 1.000$), indicating a negligible practical impact on claim probability. Thus, monetary amounts of coverage and premiums are not reliable predictors of claims, which are more strongly influenced by structural and behavioral factors.
- 6. Gender and Business Source Are Statistically Insignificant**
These two variables were eliminated during model selection due to lack of statistical significance. This suggests that gender-based segmentation and distribution channels (direct vs. non-direct) do not provide meaningful differentiation in claim risk and should not be used as the basis for risk mitigation policy.

SUGGESTIONS

Based on the findings and conclusions of this study, PT Askrindo should undertake several strategic and operational initiatives to strengthen its credit risk management framework. The following recommended steps are proposed:

1. Formulation of Risk-Based Underwriting Strategies
 - Implement a risk-based underwriting framework that integrates key risk variables such as debtor age, business location, and credit type into the decision-making process.
 - Utilize an integrated risk scoring system that captures historical claim patterns based on combinations of demographic and geographic factors.
 - Reevaluate underwriting standards for high-risk profiles, particularly debtors from Region III or aged above 55, through selective acceptance criteria or risk-adjusted premium pricing.
2. Claims Monitoring and Early Warning System (EWS)
 - Develop a machine learning-based Early Warning System (EWS) to detect abnormal claim submission patterns and potential fraud.
 - Leverage digital technologies for real-time monitoring of MSME portfolios, including integration with transactional data and monthly reporting from partner banks or financial institutions.
3. Optimization of Reinsurance Policies and Risk Diversification
 - Increase the proportion of proportional reinsurance for regions or sectors with historically high claim ratios to offload concentrated risk exposures.
 - Diversify the guarantee portfolio by expanding coverage to sectors and regions with lower risk profiles to maintain solvency and reduce claim volatility.
4. Collaboration with Government and Regulatory Bodies
 - Partner with the Financial Services Authority (OJK) and the Ministry of Cooperatives and SMEs to redesign government-backed guarantee programs, such as KUR, to incorporate more risk-sensitive mechanisms.
5. Further Research and Model Enhancement
 - Enrich the current logistic regression model by incorporating additional variables such as business sector, financing history, borrower income, and collateral status.
 - Explore alternative predictive models (e.g., random forest, XGBoost) to improve classification accuracy and adapt better to Indonesia's diverse geographic and economic landscape.

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