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Strategies for Improving Loan Restructuring Success Based on Business Analytics and Machine Learning in Rural Bank (Case Study: PT BPR Jabar Perseroda)

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Abstract
Credit restructuring remains essential to banking risk management because unsuccessful restructuring may lead to further deterioration in credit quality, particularly among rural banks with limited analytical capabilities. This study aimed to identify the factors associated with successful loan restructuring, develop a predictive model, and formulate data-driven strategies for PT BPR Jabar Perseroda. A quantitative business analytics approach was employed using the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework. Historical data consisting of 1,200 loan restructuring observations from January to December 2025 were analyzed through descriptive, predictive, and prescriptive analytics using RapidMiner. Three classification algorithms—Random Forest, Gradient Boosted Tree, and Decision Stump—were evaluated based on accuracy, precision, recall, and F1-score. The findings showed that Random Forest achieved the best predictive performance, with an accuracy of 96.67%, precision of 98.65%, and recall of 96.05%. Initial collectibility status was the factor most strongly associated with restructuring success, followed by collateral type and the number of arrears, whereas the debt-to-income ratio and economic sector showed relatively weaker relationships. These findings supported the implementation of risk-based debtor segmentation, appropriate restructuring schemes, intensive post-restructuring monitoring, and the development of an early warning system. The study concluded that the integration of business analytics and machine learning could improve loan restructuring decision-making; however, predictive results should complement rather than replace professional judgment and prudent banking governance practices.

INTRODUCTION

Nationally, credit restructuring remains an important component of bank credit risk management. The Financial Services Authority (Otoritas Jasa Keuangan [OJK]) noted that, in June 2025, outstanding banking restructuring loans reached IDR 499.87 trillion, although this figure decreased by 6.73% year-on-year. During the same period, Loan at Risk (LaR) remained at 9.73%, equivalent to approximately IDR 784 trillion. This condition indicated that although overall credit risk had begun to improve, the potential deterioration of credit quality following restructuring still required attention (Alamsyah et al., 2025).

This phenomenon became increasingly relevant in the context of Bank Perkreditan Rakyat (BPR) in West Java (Altman & Saunders, 1998). OJK data showed that the gross

Non-Performing Loan (NPL) ratio of BPR and Bank Perekonomian Rakyat Syariah (BPRS) in West Java increased from 11.85% in January 2025 to 13.63% in January 2026. At the same time, BPR and BPRS lending continued to grow by 5.99% year-on-year, reaching IDR 24.69 trillion. This condition demonstrated the challenge of maintaining asset quality amid the continued growth of BPR and BPRS financial intermediation in West Java (Ayari et al., 2026).

At the micro level, this phenomenon was reflected in the research dataset, which consisted of 1,200 credit restructuring observations. Of these, 756 observations (63.00%) were categorized as successful, while 444 observations (37.00%) were categorized as unsuccessful (Cahyani & Eriswanto, 2025; Chang, Sivakulasingam, et al., 2024; Chang, Xu, et al., 2024). The relatively high proportion of unsuccessful restructuring cases indicated that restructuring did not always result in improved credit quality. (Delen & Ram, 2018) Therefore, a data-driven approach was needed to identify debtor characteristics associated with restructuring success, develop a predictive model for restructuring outcomes, and formulate business strategies that BPRs could implement to improve restructuring effectiveness (H. Li & Wu, 2024).

The descriptive analysis of the dataset also revealed differences in success rates based on initial collectibility status. The success rate among debtors with collectibility levels of 3 or below (current) reached 92.31%, while debtors with collectibility level 4 (doubtful) achieved 54.55%, and those with collectibility level 5 (bad debt) achieved 52.05%. A similar pattern was observed based on the number of arrears, where debtors with 0–2 arrears had a success rate of 88.65%, decreasing to 55.00% among those with 3–5 arrears and to 51.30% among those with more than 5 arrears (Nallakaruppan et al., 2024). These findings indicated that pre-restructuring credit quality conditions and repayment behavior history were relevant characteristics for further analysis. Meanwhile, success rates also varied across economic sectors, reaching 62.75% in the agricultural sector, 82.35% in the investment sector, 68.22% in the trade sector, and 26.53% in the consumptive and other sectors. However, these differences should be interpreted cautiously because the number of observations across sectors was unequal. Therefore, descriptive differences in success rates could not independently determine which attributes had the strongest influence or relationship with restructuring success.

This phenomenon indicated that restructuring success had heterogeneous characteristics among debtors, requiring an analytical approach that not only described the distribution of successful and unsuccessful outcomes but also identified the relationships between debtor attributes and their predictive ability toward restructuring outcomes. Accordingly, this study employed a Business Analytics approach consisting of descriptive analytics to understand existing patterns, predictive analytics using classification algorithms to determine the best-performing model, and prescriptive analytics to translate analytical findings into business strategy recommendations for BPRs (Xia et al., 2017).

Previous research on credit restructuring has shown that restructuring success is influenced by various debtor characteristics and restructuring strategies. (Firdauza &

Rahadian, 2022), for instance, found that debtor criteria, restructuring cycles, combinations of interest rate adjustments, tenor extensions, payment deferrals, as well as guarantee, communication, and cooperation aspects were important components in successful restructuring at BRI. However, the study employed a qualitative case study approach, providing in-depth insights into success factors without developing a quantitative model to predict individual restructuring outcomes. Meanwhile, research on machine learning applications in credit risk management has expanded rapidly. (Suhadolnik et al., 2023) demonstrated that machine learning could improve credit risk assessment, while Chang et al. found that Gradient Boosting and Random Forest algorithms achieved strong performance in credit risk classification and could be supported by feature importance analysis to enhance model interpretability (Breiman, 2001). Other studies on Random Forest have also demonstrated its ability to identify important characteristics in credit risk analysis.

However, a theoretical gap remains between these two research streams. Credit restructuring studies have primarily focused on identifying factors and strategies associated with restructuring success, whereas machine learning studies have mainly concentrated on credit scoring, creditworthiness assessment, default prediction, and credit risk detection. Consequently, limited research has specifically positioned credit restructuring success as a predictive outcome using machine learning approaches, particularly within the BPR context. Furthermore, previous studies have generally addressed one of two primary questions: what factors influence risk or what outcomes may occur. From a Business Analytics perspective, however, the value of analytics extends beyond describing historical conditions and predicting future outcomes, as it also involves translating analytical results into actionable recommendations. Conceptually, descriptive, predictive, and prescriptive analytics represent three interconnected functions: descriptive analytics explains past events, predictive analytics estimates possible future outcomes, and prescriptive analytics provides recommendations for appropriate actions.

Therefore, the theoretical gap addressed by this study lies in the limited integration of these three analytical perspectives in research on credit restructuring success. This study not only identified debtor attributes associated with restructuring success but also developed a classification model to predict restructuring outcomes and translated the analytical results into practical business strategies that could be implemented by BPRs.

METHOD

This study employed a quantitative approach with a data science and business analytics design to analyze credit restructuring success at PT BPR Jabar Perseroda. Historical credit restructuring data were analyzed using statistical and computational methods to identify factors associated with restructuring success, develop predictive models, and formulate strategy recommendations. The study adopted the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, which guided the stages of business understanding, data understanding, data preparation, modeling, evaluation, and deployment. The Business Analytics approach incorporated descriptive analytics, predictive analytics, and prescriptive analytics to support the analysis and development of credit restructuring strategies. Data processing and model development were conducted using RapidMiner.

The research was conducted at PT BPR Jabar Perseroda using historical credit restructuring data from January to December 2025. The research implementation period was January–July 2026, covering problem identification, literature review, data collection and preparation, descriptive analysis, predictive modeling using RapidMiner, model evaluation, strategy formulation, and conclusion development.

Population and Sample

The research population is all data on debtors or loans that have undergone restructuring at PT BPR Jabar Perseroda during the January-December 2025 period. The data includes information on dti_ratio, jumlah_tunggakan, kolek_awal, jenis_agunan, sektor_ekonomi, and the status of the success of the restructuring. The research uses the purposive sampling technique, which is the selection of data based on criteria that are in accordance with the research objectives. The data used must be restructured credits, have complete information on predictor and target variables, can be identified consistently, and meet data quality requirements after the data preparation process. Based on these criteria, 1,200 observation data were obtained which were used for descriptive analysis and classification modeling.

The unit of research analysis is one data on credit or debtor restructuring. The predictor variables used consisted of dti_ratio, jumlah_tunggakan, kolek_awal, jenis_agunan, and sektor_ekonomi, while restruk_berhasil became the target variable with codes 1 for successful restructuring and 0 for failed restructuring.

Data Collection Techniques

The research uses secondary data in the form of historical credit restructuring data obtained from the Core Banking system of PT BPR Jabar Perseroda. The data is used to analyze credit characteristics, relationships between variables, and build a model for predicting the success of restructuring. In addition to the company's internal data, the research also uses secondary sources in the form of scientific journals, books, banking regulations, and literature related to credit restructuring, risk management, Business Analytics, Machine Learning, and the 5C principle as a theoretical basis and supporting the interpretation of research results. The data used has been adjusted to the needs of the research and does not reveal the personal identity of the debtor.

Data Analysis Techniques

Data analysis was carried out using the Business Analytics approach with the CRISP-DM framework. The analysis stages include understanding business problems, understanding data, preparing data, modeling, evaluation, and making recommendations. In the descriptive analytics stage, descriptive statistics and correlation matrix are carried out to determine the direction and strength of the relationship between dti_ratio, jumlah_tunggakan, kolek_awal, jenis_agunan, and sektor_ekonomi and restruk_berhasil. Correlation results are used to determine variables that have a relatively strong relationship with the success of restructuring without being interpreted as a cause-and-effect relationship.

In the predictive analytics stage, three classification algorithms are used, namely Random Forest, Gradient Boosted Tree, and Decision Stump. All three models are used to predict the success or failure of the restructuring based on the available predictive variables. The data first goes through the data preparation process, then it is divided into training data and test data. Model performance was evaluated using the Confusion Matrix, Accuracy, Precision, Recall, and F1-Score. The best model is determined based on the combination of performance indicators by considering the suitability of the model to BPR's business needs.

Furthermore, prescriptive analytics is used to translate the results of descriptive and predictive analysis into strategy recommendations. Factors related to the success of the restructuring are interpreted based on credit risk management and the 5C principles, namely Character, Capacity, Capital, Collateral (Berger & Udell, 1990), and Condition. The results are used to formulate strategies that can be applied by BPR in the process of analyzing debtors, determining restructuring schemes, monitoring post-structuring, and managing credit risk.

RESULTS AND DISCUSSION

Predictive Model Implementation

Based on the results *of descriptive, predictive*, and *prescriptive analytics*, this study not only produces a classification model to predict the success of credit restructuring, but also a strategy implementation plan that can be implemented by PT BPR Jabar Perseroda. The goal is to translate the results of data analysis into policies and operational actions that increase the effectiveness of restructuring programs, increase credit settlement opportunities, and reduce the potential for repeat restructuring (Friedman, 2001).

The results of the study confirm that the success of restructuring is not solely determined by the decision to carry out the restructuring itself, but also by the characteristics of the debtor, the ability to pay after the restructuring, the credit condition before the restructuring, and the quality of monitoring afterwards. Therefore, the results of the model need to be translated into a decision-making mechanism that links the debtor's risk profile, form of restructuring, monitoring intensity, and remedial actions.

It should be emphasized that these four elements the debtor's risk profile, the form of restructuring, the intensity of monitoring, and remedial measures cannot be viewed in isolation from each other, but rather as a series of decisions that affect each other. The debtor's risk profile resulting from the predictive model is the basis for determining the appropriate form of restructuring, the form of restructuring chosen then determines how intensive monitoring needs to be carried out, and the monitoring results ultimately become input for remedial action decisions if the initial scheme proves to be inadequate (Montevechi, 2024). This integrated set of decisions is a concrete manifestation of the paradigm shift in credit restructuring management, from mere approval administration to sustainable credit risk management throughout the life cycle of the restructured credit facility.

The first priority is the early identification of debtors with a low probability of success. The classification model can be used by the Credit Division and the Risk Management Division to segment debtors before the restructuring decision is made, so that the decision is no longer uniform but is adjusted to the characteristics and recovery capabilities of each debtor. The predicted results are then translated into *risk-based restructuring treatment*: high-probability debtors obtain a scheme as needed with standard monitoring, medium-probability debtors require more intensive monitoring, while low-probability debtors require a solvency analysis, cash flow evaluation, adjustment of installment schemes, and alternative credit settlement if the recovery prospects are inadequate.

The next strategy is to strengthen post-structuring monitoring. Restructuring is not the end point of resolving non-performing loans, but the beginning of a recovery period that must be monitored by Account Officers and Collection Officers for compliance with new schedules, changes in business conditions, and early indicators of failure. In *the Capacity* aspect, the evaluation of the ability to pay needs to be updated periodically using actual post-structuring cash flow data, not just pre-restructuring conditions. BPR also needs to strengthen *the Post-Restructuring Early Warning System* (EWS) which warns when symptoms of late payment or decreased business ability appear, so that follow-up can be carried out faster.

As a complement to the monitoring priorities, the results of the model can also be used to develop a mechanism for evaluating and adjusting the restructuring scheme in a sustainable manner. Debtors who show a discrepancy between the restructured installment scheme and their actual repayment ability need to obtain a separate *review mechanism*, involving the Credit Division, Credit Committee, and Risk Management Division, so that the restructuring scheme becomes more adaptive to the development of the debtor's condition after the restructuring, rather than rigid and final from the beginning of the agreement.

At an advanced stage, a predictive model can be developed into *a decision support system* (DSS) for credit restructuring. This system does not replace the authority of credit analysts or Credit Committees, but provides data-driven information on the probability of success, making decisions more objective, consistent, and documented. This implementation needs to be accompanied by periodic evaluation of the model's performance through *monitoring*, validation, and *retraining* models because debtor characteristics, economic conditions, and payment behavior can change over time.

Overall, this implementation plan illustrates a shift from a reactive to a proactive approach: data is used to determine who is worthy of restructuring, what schemes are appropriate, how intensive monitoring is needed, and when corrective action should be taken. The implementation structure still maintains the principle that the results of the analysis must be translated into programs, persons in charge (PIC), implementation periods, performance indicators (KPIs), and *outcomes* that can be measured concretely, so that recommendations do not stop as academic discourse but become operational work references that can be monitored for realization by BPR management.

It is important to underline that the overall implementation strategy is prepared while respecting the limits of the authority of the relevant units in the BPR organizational structure. Predictive models and data analysis results serve as *inputs* to support decisions, while the final decision on restructuring remains with credit analysts, Credit Committees, and authorized officials in accordance with internal policies, prudential principles, and applicable banking regulatory regulations. This approach is in line with sound *risk governance* practices, where technology and data analytics reinforce, rather than replace, human decision-making processes that consider qualitative and contextual aspects that are not always captured by historical data.

Table 4.1 Summary of Strategy Implementation Priorities

Priorities	Strategy	Main PIC	Term	Outcome
1	Debtor segmentation based on the probability of success of the model	Credit Division, Risk Management	0–3 months	Restructuring decisions are more objective and data-driven
2	*Risk-based restructuring treatment*	Credit Division, Credit Committee	3–6 months	Restructuring scheme according to the debtor's risk profile
3	Post-structuring payability analysis	Credit Analyst, Account Officer	0–3 months	The risk of failure due to non-conforming payment capacity decreases
4	Construction *of the Early Warning System* after restructuring	Risk Management, IT Division	3–6 months	Early detection of potential restructuring failures
5	Increased intensity of monitoring of high-risk debtors	Account Officer, Collection Officer	3–6 months	Mitigation is done before the failure occurs
6	Evaluation and adjustment of the restructuring scheme	Credit Division, Credit Committee	6 months+	The scheme is more adaptive to the debtor's actual condition
7	Integration of models into the restructuring DSS	IT Division, Risk Management	6–12 months	Faster, consistent, *data-driven decision processes*
8	Validation and development of periodic models	Risk Management, IT Division, SKAI	Every 6–12 months	The model remains relevant to portfolio changes

Source: Processed by researcher (2026).

The eight programs, when examined, form two major groups based on their nature: preventive programs (priorities 1, 2, 3, and 6), which focus on improving the quality of decisions before and at the time of the restructuring; and *detective-corrective* programs (priorities 4, 5, 7, and 8), which focus on early detection and follow-up of potential failures after the restructuring is underway. This division is important for BPR management in allocating resources, given that the two program groups require slightly different work unit competencies and involvement—the preventive group involves more credit analysts and the Credit Committee in the early stages of the business process, while the detective-corrective group involves more Account Officer, Collection Officer, and Information Technology Division in the post-approval stage.

The strategic affirmation of the eight programs is summarized in three main principles: *(1) Predict Before Restructure* the probability of success of the debtor needs to be known before the scheme is determined; *(2) Monitoring After Restructure* success is measured by payment consistency, not just the implementation of contracts; *(3) Learn and Improve* the data from the restructuring continues to be re-entered into the system so that the model is updated, forming a cycle of Restructuring Data → Prediction → Treatment → Monitoring → Outcome → New Data → Model Improvement. This cycle is what makes this research move from just a prediction model to *a Business Analytics* that produces operational decisions.

1. Phased Implementation Roadmap

The implementation of the strategy is arranged in four stages so that the research results can be translated applicatively into BPR business processes.

Stage I – Quick Wins. Short-term implementation leverages the processes already in place: the creation of a risk-based restructuring checklist that emphasizes the variables contributing to the restruk_berhasil, as well as the initial segmentation of debtors based on success tendencies. This is achieved through the improvement of SOPs, analysis forms, and *approval mechanisms* — without waiting for the construction of a new IT system.

Phase II – Business Process Improvement. The results of the model were used to strengthen risk-based post-structuring monitoring, developed into a restructuring EWS that warns of a decline in repayment. The approach shifts from reactive to proactive, requiring the coordination of the Credit Division, Credit Analyst, Account Officer, Collection/Remedial, and Risk Management.

Phase III – Digital Transformation. The best model (Random Forest) is integrated into the DSS that provides *risk scores*, probability categories, and monitoring level recommendations — as a tool, not a substitute for credit officers' authority. The main responsibility lies with the IT Division, Credit Division, Risk Management, and management/board of directors.

Stage IV – Continuous Improvement. Continuous evaluation through re-measurement *of Accuracy*, *Precision*, *Recall*, *back-testing* of actual realization, as well as business indicators such as re-default rate and *recovery rate*. When performance decreases significantly, the model is recalibrated or retrained.

Table 4.2 Strategy Implementation Roadmap

Stages	Focus	Main Programs	Person in Charge
I – Quick Wins	Utilization of research results in the running process	Risk-based checklist; Initial segmentation of debtors	Credit Division, Credit Analyst, Credit Committee
II – Business Process Improvement	Restructuring business process improvement	Improvement of SOPs; EWS restructuring	Credit Division, Risk Management, AO, Collection

Stages	Focus	Main Programs	Person in Charge
III – Digital Transformation	Integration of models into information systems	DSS development; *risk score automation*	IT Division, Credit Division, Risk Management, Board of Directors
IV – Continuous Improvement	Continuous evaluation and improvement	*Model validation, back-testing, retraining*	Risk Management, IT Division, SKAI, Board of Directors

Source: Processed by researcher (2026).

When compared to Table 4.1, this four-stage roadmap is essentially a regrouping of the eight priority programs into a clearer time frame and level of complexity of transformation. Programs in Phase I generally intersect with priorities 1 and 3 (debtor segmentation and payability analysis) that can be implemented immediately without investment in new technology; Phase II intersects with priorities 4, 5, and 6 (EWS, intensification of monitoring, and evaluation of the scheme) which requires the refinement of cross-unit processes; while Phases III and IV intersect with priorities 7 and 8 (DSS integration and periodic model validation) which require a medium-long term information technology investment commitment. The alignment between these two frameworks shows internal consistency between business priority-based strategy recommendations and recommendations based on organizational transformation stages, so that BPR management can use one or a combination of both according to planning needs. Table 4.1 is more suitable for the preparation of annual work plans per unit, while Table 4.2 is more suitable for the preparation of a medium-term digital transformation roadmap at the board of directors.

This roadmap emphasizes that the results of the research do not stop at the prediction model, but are directed to produce a more systematic, measurable, and data-based restructuring management mechanism to improve the quality of decisions, reduce the risk of re-default, and maintain the quality of the credit portfolio in an ongoing manner.

The four stages of the roadmap also reflect the awareness that data-based transformation in financial institutions such as BPR cannot be carried out simultaneously (*big-bang*), considering the limitations of information technology resources, budgets, and human resource readiness which are generally more limited than commercial banks. A phased approach starting from the use of existing processes (*Quick Wins*) before moving on to more complex system investments (*Digital Transformation*) allows BPRs to benefit from research results more quickly while gradually building organizational capacity to support the management of analytics models in the future.

Evaluation of Predictive Models and Their Relation to Previous Research

This study has different characteristics from most previous studies in that it not only discusses restructuring as a risk mitigation policy, but builds a predictive model to classify the success of individual credit restructuring with restruk_berhasil target variables. The focus of the research thus shifts from the question of "whether restructuring policies affect credit risk in the aggregate" to the operational question: what kind of debtor is likely to succeed or fail.

Testing of three classification algorithms showed Random Forest as the model with the best performance (*Accuracy* 96.67%, *Precision* 98.65%, *Recall* 96.05%), followed by Gradient Boosted Tree (*Accuracy* 95.00%, *Precision* 97.30%, *Recall* 94.74%), while Decision Stump was far behind (*Accuracy* 63.33%, *Precision* 63.33%, A perfect 100.00% *recall* but low *precision* indicates this model tends to classify almost all cases as "successful").

These results show that *ensemble learning* algorithms have much better predictive capabilities than a simple single decision tree model in identifying the success of restructuring an *outcome* that is influenced by many debtor and credit characteristics simultaneously, so that a model that is able to capture a combination of relationships between variables is more suitable than a simple decision structure.

Methodologically, the advantage of Random Forest over Gradient Boosted Tree despite the relatively thin difference in performance (less than 2 percentage points on all three evaluation metrics) can be explained by the characteristics of each algorithm. Random Forest builds many decision trees independently through *bagging* techniques and combines the results through voting, so that it tends to be more resistant to *overfitting* and more stable when dealing with data that has variations or *noise*, as is commonly found in BPR credit restructuring data which covers various characteristics of debtors and types of businesses. Gradient Boosted Tree, on the other hand, builds trees gradually with each new tree attempting to correct the previous tree's mistakes, which has the potential to provide higher accuracy in cleaner data but is also more prone to *overfitting* if parameters are not optimally set. The not-so-small difference in performance between the two models essentially sends a positive signal to BPR: both Random Forest and Gradient Boosted Tree are worthy of consideration as production model candidates, with Random Forest slightly favored due to its combination of optimal performance and relatively easier interpretation than *boosting models*.

Thethematically, this research is related to (Ananda & Budianto, 2026), (Akbar, 2026), (Cahyani & Eriswanto, 2025)), (Khosyati & Rahima, 2024)), and Firdauza and (Firdauza & Rahadian, 2022) who both discuss restructuring as part of bank credit risk management. The difference is that these studies are generally descriptive, qualitative, or policy analysis at the aggregate level, while this study develops a predictive quantitative approach based on *machine learning* at the individual debtor level complementing the literature with patterns of debtor and credit characteristics related to the likelihood of success in a more systematic manner.

The relationship is stronger with machine learning-based research: (Primasatria & Setiyono, 2025) built a model to predict the success of restructuring using XGBoost in the corporate/commercial segment of Bank BCA, while this study applied a similar approach in the context of BPR by comparing three different algorithms. Random Forest's superior results are in line with (Y. Li et al., 2024) who show Random Forest's stability in predicting credit risk, and (Bitetto et al., 2024) who prove that *machine learning* remains effective despite limited credit data. These findings reinforce the argument that *tree-based ensemble models*, especially Random Forest, could potentially be used to identify credit risk patterns in financial institutions with different portfolio characteristics such as BPRs.

This research is also related to Bosker, Gürtler, and (Bosker et al., 2025) and (Fernández Lafuerza & Galán, 2025) who emphasize the importance of the selection of debtor variables and characteristics in risk modeling. In line with that, the results *of the Correlation Matrix* showed that kolek_awal, jenis_agunan, and jumlah_tunggakan had a relatively stronger relationship with restructuring success than other variables. The difference is that this study does not focus on the prediction of *default* or *Loss Given Default* in the early stages of lending, but rather on the success of debtors who have entered the restructuring process suggesting that the prediction model needs to be adjusted to the characteristics of the portfolio, debtor segment, and credit cycle of the institution being analyzed.

In general, the study of credit restructuring can be mapped to three approaches: econometrics (restructuring policy vs aggregate NPLs, e.g. Ananda & Budianto), qualitative (mechanism, affordability, 5C principle, e.g. Akbar; Cahyani & Eriswanto; Khosyati & Rahima; Firdauza & Rahadian), and *machine learning* (risk/*default*/success prediction, e.g. Primitive and Scientologist; Li & Wu; Bitetto et al.). This research is on the development of a third approach with a specific focus on predicting the success of individual-level restructuring in the context of Indonesian BPR the strongest similarity with (Primasatria & Setiyono, 2025), but differing in the context of institutions, units of analysis, algorithms, and analytical outputs.

The main contribution of this research is not just the use of Random Forest, but the incorporation *of descriptive*, *predictive*, and *prescriptive analytics* within the framework of CRISP-DM: the descriptive stage identifies restructuring patterns, the predictive stage builds and compares models, and the prescriptive stage translates the prediction results into risk-based strategy recommendations. With this approach, the research results can be directly used for debtor segmentation, monitoring priorities, EWS strengthening, post-structuring evaluation, and DSS development in BPRs.

The fairly wide performance differences between *the ensemble* models (Random Forest, Gradient Boosted Tree) and Decision Stump also provide important methodological lessons for credit analytics practices in similar financial institutions. Decision Stump, as a decision tree model with one level of branching, basically only considers one dominant predictor variable in making classification decisions. When applied to an inherently multidimensional problem such as the success of a restructuring which is simultaneously influenced by a combination of credit conditions, collateral characteristics, repayment capabilities, and other factors such a simple model loses the ability to capture interactions between variables, reflected in the much lower accuracy of the recall is perfect. For BPRs considering the development of similar analytical systems, these findings serve as a warning not to be tempted to choose a model because of the simplicity of its interpretation, without considering the trade-offs to the accuracy of the predictions produced.

Correlation Matrix and Comparison with Previous Research

The *results of the Correlation Matrix* showed that the variable with the strongest relationship to restruk_berhasil was kolek_awal (-0.367), followed by jenis_agunan (-0.338), jumlah_tunggakan (-0.190), dti_ratio (0.112), and sektor_ekonomi (-0.060). This pattern suggests that credit conditions at the time of restructuring particularly initial collectibility and collateral characteristics have a stronger relationship with restructuring success than with the ratio of repayment ability and economic sectors.

Kolek_awal as the variable with the strongest relationship indicates (assuming the collectibility code increases as credit quality deteriorates) that the worse the debtor's collectibility condition when the restructuring begins, the lower the likelihood of success business-logical because the recovery room becomes more limited as credit conditions deteriorate. This finding is in line with Firdauza and Rahadian (2022) who find the criteria for debtors and the restructuring cycle as critical factors for success, and consistent with Khosyati and Rahima (2024) who emphasize that restructuring needs to be given to debtors who still have positive business prospects based on the 5C principle. The implication is that BPRs should not wait for credit deterioration to deepen before restructuring the earlier debtors with recovery prospects are identified, the greater the chance of success.

Jenis_agunan, as the second strongest variable, needs to be interpreted carefully because it is a categorical variable that is numerically encoded, so the direction of correlation cannot be directly interpreted literally without knowing the coding scheme. Substantively, collateral functions more as a mitigation of losses when a default occurs, rather than a direct determinant of the debtor's ability to repay. This finding is comparable to (Firdauza & Rahadian, 2022) who included *loan guarantees* as one of the components supporting success, but emphasized that success is influenced by a combination of many factors. Therefore, collateral should be placed as a single component in the feasibility analysis, rather than a single basis.

Jumlah_tunggakan show a negative but relatively weak relationship: the larger the arrears before the restructuring, the lower the success rate, reflecting payment pressures and the potential for heavier cash flow problems. This finding is related to (Cahyani & Eriswanto, 2025) on the restructuring of Bank BTN mortgages which shows that the effectiveness of restructuring is influenced by economic conditions, layoffs, and collection team capacity even after restructuring, credit quality can still deteriorate if debtor problems are not resolved effectively. This reinforces the importance of delinquency analysis the amount, cause, and actual ability to pay before restructuring is established.

Dti_ratio have a positive relationship but are very weak, which is interesting because conceptually DTI is an indicator of affordability rather than income. The possible explanation is that the success of restructuring is not only determined by the ability to pay at one point in time, but also the initial credit condition, the amount of arrears, the characteristics of collateral, and the quality of post-structuring monitoring. Compared to (Fernández Lafuerza & Galán, 2025) who found that the origination financial condition indicator (*debt-to-assets*, *interest coverage ratio*) is related to the risk of future *default* but the strength varies according to the sector, size, and financial cycle of the company the difference in context (not *default* at *origination*, but the success of restructuring on non-performing loans) explains why DTI in this study is not dominant. DTI remains relevant as a supporting indicator of *Capacity*, but it is not enough to stand alone.

Sektor_ekonomi has the weakest relationship (-0.060), it needs to be interpreted carefully as the limitation of the interpretation of linear correlations on categorical variables, not evidence that the economic sector has no effect at all. This is relevant to Fernández Lafuerza and Galán (2025) who show that credit risk relationships can differ by sector—for follow-up research, the influence of sectors should be tested with categorical approaches such as *cross-tabulation*, *Chi-Square*, or *Cramer's V*.

The strength of the relationship patterns of these five variables also provides an important picture of the restructuring risk structure in BPR in general. The three variables with relatively strong relationships — kolek_awal, jenis_agunan, and jumlah_tunggakan both represent credit conditions at the time of the restructuring, rather than the characteristics of the debtor outside the credit context (such as the business sector) or static financial ratios (such as DTI). This indicates that in the context of BPRs, the success of the restructuring is determined more by "how deeply" the credit problem has developed before rescue action is taken, rather than by the debtor profile in general. Implicitly, the speed and timeliness of BPRs in responding to early signs of credit quality deterioration before collectibility deteriorates and arrears accumulate become factors that are at least as important as the design of the restructuring scheme itself.

Table 4.3 Synthesis of Correlation Matrix with Previous Research

Variable	**Correlation**	**Brief Interpretation**	**Literature Suitability**
kolek_awal	-0,367	Initial credit conditions deteriorate → chances of success decrease	Seline Firdauza & Rahadian (2022)
jenis_agunan	-0,338	Direction depends on the *coding scheme*; collateral as mitigation, not the primary determinant	Seline Firdauza & Rahadian (2022)
jumlah_tunggakan	-0,190	Large arrears → heavier payment pressures	Seline Cahyani & Eriswanto (2025)
dti_ratio	0,112	Ability to pay is not the single dominant factor	Different powers of Fernández Lafuerza & Galán (2025)
sektor_ekonomi	-0,060	Needs to be categorically retested	Fernández Lafuerza & Galán (2025)

Source: Results of research data processing and synthesis of previous research. The interpretation kolek_awal assume the collectibility code increases as credit quality deteriorates.

Overall, *the results of the Correlation Matrix are* relatively consistent with the literature on the importance of debtor conditions, initial credit quality, delinquencies, and characteristics of credit facilities although there are differences in the strength of the relationship between dti_ratio and sektor_ekonomi suggesting that the success factors of restructuring are strongly influenced by the characteristics of the population, object, and context of the research institution. These findings also reinforce the rationale for using *machine learning*: correlations only describe initial relationships individually, whereas predictive models are able to capture nonlinear combinations and patterns between variables that are not always visible from correlation matrices alone. Thus, research can move from the descriptive question "what happened?" to the predictive "how well can success be predicted?", and then the prescriptive "what strategy should BPR implement?"

Research Findings

First, the success of the restructuring can be predicted with *machine learning*. Random Forest excelled (*Accuracy* 96.67%, *Precision* 98.65%, *Recall* 96.05%) over Gradient Boosted Tree and far exceeded Decision Stump, suggesting *that the ensemble learning* approach had much better classification capabilities than a simple *single-tree* model. These findings reinforce the *literature on credit risk predictions* such as Li and Wu (2024) and Bitetto et al. (2024), albeit with a different *focus on outcomes* — not just *defaults*, but restructuring successes.

Second, credit characteristic factors have varying degrees of relationship to success. Kolek_awal (-0.367) was the strongest, followed by jenis_agunan (-0.338) and jumlah_tunggakan (-0.190), while dti_ratio (0.112) and sektor_ekonomi (-0.060) were very weak underscoring the importance of early credit conditions and facility characteristics rather than a single indicator of affordability. Keep in mind, correlations show relationships in datasets, not cause-and-effect relationships.

Third, the initial condition of credit is important information for debtor segmentation. The highest kolek_awal correlation value has practical implications in the form *of a risk-based restructuring* approach: early-stage debtors are better off obtaining schemes with standard monitoring, while worse-performing debtors require more in-depth solvency analysis and more intensive monitoring. This finding is relevant to Primasatria and Setiyono (2025), although they differ in algorithms (XGBoost vs comparison of three algorithms) and objects (corporate/commercial BCA vs BPR).

Fourth, *machine learning* provides a more operational approach than just descriptive analysis. *The Correlation Matrix* describes the relationships between variables individually, while the predictive model captures a combination of variables simultaneously showing the connectivity flows *of Descriptive Analytics* (identifying patterns) → *Predictive Analytics* (predicting success) → *Prescriptive Analytics* (translating into strategy recommendations).

Fifth, Random Forest has the most potential to support restructuring decision-making. With a balanced performance between *Accuracy*, *Precision*, and *Recall*, this model can be developed into a DSS that aids in the evaluation of debtors as a data-driven tool, not a substitute for the decisions of credit analysts or decision-makers. These findings expand the application of *machine learning* to credit risk because they are outcome-oriented after restructuring actions, rather than just default predictions.

The five findings are interrelated and form a unity of argument. The first and fifth findings confirm the technical-methodological side of the research, namely that the problem of restructuring success can be modeled quantitatively with a high degree of accuracy using ensemble algorithms, especially Random Forest. The second and third findings affirm the substantive-business side, i.e. what are the most relevant variables to consider and how the initial credit conditions can be used as the basis for segmentation. The fourth finding bridges the two, showing that the real strength of the *Business Analytics* approach lies not in one stage of analysis, but in the integration of the three stages descriptive, predictive, and prescriptive sequentially and complementarily. Without a descriptive stage, the selection of predictive variables does not have an adequate basis for business understanding; Without a predictive stage, the descriptively identified intervariable relationship patterns cannot be translated into actionable probability estimates; and without a prescriptive stage, the prediction results will only stop as statistical numbers without providing concrete action guidance for BPRs.

It should also be noted that the high performance obtained by Random Forest in this study (*Accuracy* above 96%) should be interpreted proportionally and cannot be separated from the characteristics of the data used. Excellent model performance on historical data does not automatically guarantee the same performance when applied to new data in the future, given that macroeconomic conditions, financial services authority policies, and debtor behavior may change over time. Therefore, as mentioned in the implementation plan, periodic evaluation of model performance and *retraining* mechanisms are an integral part of the use of this model in BPR operational practice, not just optional additional recommendations.

The novelty of this study is not only in the use of Random Forest, but in a combination of six aspects: (1) the shift of prediction targets to the restruk_berhasil level of individual BPR debtors different from Ananda and Budianto (2026) who focus on aggregate risk and Primasatria and Setiyono (2025) who research the corporate/commercial segment of commercial banks; (2) emphasis on the specific context of BPRs with typical debtor characteristics and credit scales; (3) the comparative evaluation of three algorithms with Random Forest proved to be the best; (4) methodological integration of three levels of *Business Analytics* (*Descriptive–Predictive–Prescriptive*); (5) translating statistical results into concrete business strategy recommendations; and (6) preparing a gradual implementation roadmap from *Quick Wins* to *Continuous Improvement* that bridges the predictive model with BPR operational decisions.

These six aspects of novelty reinforce each other so that they form a more comprehensive contribution than previous studies that tend to focus on only one aspect — be it aspects of aggregate policy, qualitative mechanisms, or predictive modeling separately. By bringing the three together in one coherent research framework and applied to the context of BPR which has not been studied much from the perspective of *machine learning*, this research is expected to be an initial reference for the development of similar research in other micro and medium financial institutions in Indonesia, especially in an effort to encourage the adoption of *Business Analytics* As part of the digital transformation of credit risk management in the banking sector which has not been fully touched by advances in data analytics technology compared to commercial banks.

The following three aspects of the implications system, managerial, and subsequent research are arranged in stages from the most technical-operational to the most conceptual-academic, reflecting that the results of this study have a range of benefits that are not limited to one stakeholder alone, but are relevant for information system developers, BPR internal policy makers, and academics who are interested in continuing research on similar topics.

System implications. This research opens up opportunities for the development of data-based credit restructuring DSS within BPR. The Random Forest model can be used by credit analysts to predict potential success based on the debtor's historical characteristics, developed gradually from an analytical dashboard to integration with credit information systems and EWS. Variables kolek_awal, jenis_agunan, and jumlah_tunggakan can be used as risk indicators for early warning. However, the use of the model should still be placed as a decision supporter not a substitute for the role of credit analysts, Credit Committees, internal policies, regulatory provisions, and professional considerations.

Managerial implications. The results of the study confirm the importance of *a risk-based restructuring approach*. Management can segment debtors based on initial collectibility, collateral characteristics, amount of arrears, and model prediction results to determine the form of restructuring and the appropriate level of monitoring. Debtors with a lower probability of success are prioritized for intensive supervision field visits, verification of business conditions, evaluation of payability. The characteristics of collateral need to be evaluated not only from their existence, but also from their legality, economic value, liquidation value, and ease of execution. This research also encourages the development of restructuring KPIs that are not only oriented towards the number of restructured loans, but also the post-restructuring success rate, the quality of payments, the re-default rate, and its contribution to the quality of the credit portfolio.

Implications of further research. This study opens up development opportunities in terms of data, variables, and methods: addition of variables such as length of operation, changes in income, restructuring tenors, changes in installments, frequency of post-restructuring payments, age of debtors, ratio of loans to collateral value, and history of previous payments; use of longitudinal data/panels so that the development of debtors' conditions can be observed before, during, and after restructuring; comparison of Random Forest with other algorithms (XGBoost, LightGBM, SVM, Logistic Regression, Neural Network); the application *of Explainable AI* such as SHAP to improve interpretability; as well as external validation using other BPR data, different regions, or periods to test model generalizations. Thus, further research can evolve from simply predicting restructuring success to a prescriptive analysis that recommends the most appropriate restructuring scheme for each debtor profile.

As a concluding note, the results and discussion in this chapter confirm that the application *of Business Analytics* to the problem of BPR credit restructuring is not just a technical exercise in building a model with high accuracy, but an effort to bridge the results of data analysis with the operational reality of micro-medium financial institutions that have limited resources compared to commercial banks. The strength of this research lies in the consistency between statistical findings (dominance of kolek_awal, jenis_agunan, and jumlah_tunggakan as strong predictors, as well as the advantage of Random Forest over comparative algorithms) and recommendations for applicable and gradual strategies, so that the results of the study have a contribution value both academically and practically to the credit risk management of PT BPR Jabar Perseroda and other BPRs with similar portfolio characteristics.

In summary, Chapter IV shows that the success of credit restructuring at PT BPR Jabar Perseroda can be reliably predicted using Random Forest, with kolek_awal, jenis_agunan, and jumlah_tunggakan as the most influential factors, and that these results have been translated into a phased implementation plan and roadmap that is applicable to BPR management in managing credit restructuring risks more proactively and data-driven.

CONCLUSION

This study concluded that the integration of descriptive, predictive, and prescriptive business analytics provided an effective framework for evaluating loan restructuring outcomes at PT BPR Jabar Perseroda. Based on 1,200 restructuring observations, the Random Forest algorithm achieved the best predictive performance, with 96.67% accuracy, 98.65% precision, and 96.05% recall, outperforming the Gradient Boosted Tree and Decision Stump algorithms. Initial collectibility (kolektibilitas awal) demonstrated the strongest association with restructuring success ($r = -0.367$), followed by collateral type (jenis agunan; $r = -0.338$) and the number of arrears (jumlah tunggakan; $r = -0.190$), whereas the debt-to-income ratio and economic sector showed relatively weak relationships. These findings indicated that machine learning could support risk-based debtor segmentation, the selection of appropriate restructuring schemes, and more intensive post-restructuring monitoring. Nevertheless, the model should function as a decision-support tool rather than a replacement for the professional judgment of credit analysts, credit committees, or authorized decision-makers.

Future research should validate the model using data from other rural banks, regions, and observation periods to evaluate its generalizability and stability under changing economic and regulatory conditions. Longitudinal or panel data approaches should also be considered to capture changes in debtor conditions before, during, and after restructuring. Additional predictors, including income changes, business duration, restructuring tenor, installment adjustments, payment history, loan-to-value ratio, and post-restructuring payment frequency, may improve predictive performance. Future studies may compare the Random Forest algorithm with other machine learning methods, such as XGBoost, LightGBM, Support Vector Machines, Logistic Regression, and Neural

Networks, while applying explainable artificial intelligence techniques, such as SHAP (Shapley Additive Explanations), to improve model transparency. Further research should progress beyond predicting restructuring success by developing recommendations for the most appropriate restructuring schemes based on debtor profiles and evaluating their real-world impacts on repayment quality, re-default rates, and overall credit portfolio performance.

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