CREDIT SCORING IN THE AGE OF DATA: A COMPARATIVE MODELLING APPROACH

Suleman Issa[1], Zakariyau Nurudeen Rufai[2] and Umar Muhammad Adamu*[3]

[1]Department of Statistics, University of Maiduguri, Maiduguri, Borno state, Nigeria.

[2]Department of Statistics, Federal Polytechnic, Oko, Anambra State

[*3]Department of Mathematical Sciences, Bayero University Kano, Nigeria

[*]Correspondence author Email: *umadamu.mth@buk.edu.ng

ABSTRACT

In the era of big data, credit scoring has become a crucial tool for financial institutions to evaluate creditworthiness and mitigate risk. This study investigates the trade-off between linear discriminant and logistic regression models for credit scoring and risk evaluation in the banking system. Using a dataset from FCMB, the performance of both models based on percentage correctly classified, sensitivity, specificity, and misclassification cost was compared. Results show that logistic regression outperforms linear discriminant analysis in terms of predictive accuracy and profit maximization, but exhibits limitations in specificity and type II error. Some covariates such as age, marital status, length of service, and amount requested were identified as significant predictors of credit risk. The findings have implications for financial institutions seeking to develop effective credit scoring models and early warning systems. This study contributes to the ongoing discussion on the role of statistical innovations in shaping the future of credit risk evaluation and management.

Keywords: Credit scoring, Model performance, Binary Logistic Regression, Linear Discriminant Analysis

1. INTRODUCTION

Credit scoring is a statistical technique used to estimate the likelihood that a loan applicant or an existing borrower will default or become delinquent on their financial obligations. Since its introduction in the 1950s, credit scoring has become a fundamental tool in consumer lending, particularly for credit cards, and is increasingly applied in mortgage lending and other credit domains. The growing interest in credit scoring stems from its ability to enhance cash flow, secure credit collections, and mitigate financial risk in the credit industry. According to Thomas *et al*. (2002) and Saporta (2006), credit scoring is the process of evaluating the probability that a specific applicant will fail to repay a loan. This evaluation typically classifies potential borrowers into two categories: "good" (low risk) and "bad" (high risk), as noted by Giudici (2003). To perform this classification, several statistical and machine learning techniques have been developed, including Linear Discriminant Analysis (LDA) and Logistic Regression (LR), among others.

Discriminant Analysis (DA) is a multivariate statistical method used to determine the linear combination of independent variables that best separates two or more predefined groups. Its primary goal is to assign new observations to one of these groups based on measured characteristics (Johnson & Wichern, 2007). Logistic Regression Analysis (LRA), on the other hand, models the relationship between multiple independent variables and a binary dependent variable, allowing for the estimation of probabilities of group membership without assuming multivariate normality (Sweet & Martin, 2003).

In the banking sector, these models are commonly referred to as credit scoring models, designed to support decision-making by identifying applicants likely to meet their repayment obligations. Predictive variables often include demographic and financial factors such as age, income, marital status, credit limit, and employment history. Alongside LDA and LR, other models such as Multivariate Adaptive Regression Splines (MARS), Classification and Regression Trees (CART), Case-Based Reasoning (CBR), and Artificial Neural Networks (ANNs) have also been employed for credit risk classification.

Among these, LDA is one of the earliest techniques used for credit scoring. However, its effectiveness has been questioned due to its underlying assumptions—namely, linear relationships between variables and multivariate normality—which are often violated in real-world financial data (West, 2000). Logistic Regression has gained popularity as an alternative because it does not rely on these assumptions and is specifically suited for binary classification problems. Nevertheless, both LDA and LR are inherently linear models, which may limit their accuracy in capturing complex patterns in credit data.

Effective credit decision-making is vital for financial institutions, as loan defaults can result in significant financial losses. While some banks rely on manual judgment, others adopt automated credit scoring systems, especially for smaller loans such as agricultural credit or credit cards. These systems use historical data to identify patterns in borrower behavior and guide approval decisions. Despite the widespread use of scoring models, there is limited comparative analysis of commonly applied statistical techniques—specifically Binary Logistic Regression and Linear Discriminant Analysis. This study addresses the need to evaluate these models' effectiveness in credit scoring, focusing on their predictive accuracy and practical implications for risk management.

The aim of this study is to compare the predictive performance of the Binary Logistic Regression model and the Linear Discriminant Analysis model in credit scoring. With a view to developing a Binary Logistic Regression model for predicting applicants' credit status; developing a Linear Discriminant Analysis model for the same predictive task; comparing the predictive accuracy and classification performance of both models in assessing credit risk.

2. LITERATURE REVIEW

In the context of credit scoring, numerous studies have applied and compared models such as Logistic Regression Analysis (LRA) and Discriminant Analysis (DA) to evaluate their effectiveness.

Pohar *et al*. (2004) conducted a comparative study on the robustness of DA and LRA under conditions involving categorization and non-normality of explanatory variables. Their findings suggest that both models yield similar results when the assumptions of normality are not severely violated. Similarly, Panagiotakos (2006) compared LRA and DA in predicting categorical health outcomes and concluded that both methods often lead to the same model structure and performance.

Charlo (2010) carried out an empirical study on risk analysis using DA, LRA, and Artificial Intelligence Techniques (AIT). The study showed that intelligent systems, particularly AIT, significantly reduced prediction error rates, offering strong support for decision-making in banking risk assessment. Amin *et al*. (2011) used both DA and Binary Logistic Regression (BLR) to identify determinants of consumer preference for genetically modified palm oil, highlighting the importance of credible information dissemination by regulatory authorities.

In recent years, more advanced comparative studies have emerged. Alabi *et al*. (2013) evaluated Neural Networks (NN) against DA in credit scoring, finding that NNs exhibited superior predictive performance and lower misclassification costs. Similarly, Suleiman *et al*. (2014) used Principal Component Analysis (PCA) alongside DA and LRA to predict credit status. Their findings showed that logistic regression models based on PCA outperformed DA in predictive accuracy.

Suleiman *et al*. (2017) further explored credit scoring using PCA-based BLR, demonstrating that using principal components as input variables improved model accuracy by reducing complexity and mitigating multicollinearity among predictors. Oyeyemi & Issa (2018) compared parametric models (such as LRA and DA) with non-parametric or pattern recognition models (including Neural Networks, Classification and Regression Trees [CART], and k-Nearest Neighbors [k-NN]). Their results indicated that LRA outperformed DA among the parametric models, while Neural Networks delivered the highest predictive accuracy among the non-parametric approaches.

Collectively, these studies underlined the relevance of both logistic regression and discriminant analysis in credit risk modeling, while also highlighting the growing interest in alternative and more flexible methods such as neural networks. Notably, various researchers have proposed hybrid models and dimensionality reduction techniques (e.g., PCA) to improve classification performance and address data limitations such as multicollinearity.

This present study contributes to the literature by comparing the predictive accuracy and risk evaluation capabilities of Binary Logistic Regression and Linear Discriminant Analysis within the banking sector. The focus is to determine which model provides better decision support for credit risk assessment using real-world data.

3. METHODOLOGY

This study utilizes a real-life credit dataset to ensure the practical relevance and validity of the findings. The dataset comprises information from 300 randomly selected loan applicants who applied for financial assistance from a Fidelity Bank branch. Among these, 230 applicants were classified as "creditworthy", while 70 were considered "non-creditworthy", based on their loan repayment history or credit evaluation. The dataset was structured for analysis using BLR and LDA. It includes a total of nine variables, of which three are categorical (nominal) and six are numerical (scale/ratio). There are eight predictor variables (independent variables) and one response variable (credit status), which serves as the dependent variable. The variables can be categorized into the following groups:

Personal information: Age, Marital status, Sex

Employment history: Length of service

Loan and financial details: Loan amount requested**,** Repayment period**,** Salary**,** Existing credit amount

This dataset provides a solid foundation for evaluating and comparing the predictive performance of the two statistical models in identifying creditworthy applicants.

Table 1. These are the variables (characteristics of applicant) used to build the Credit scoring models.

Attributes of applicant	Type	Scale	Details of characteristics of applicant
Age	Input variable	Scale	Age of applicant in year
Sex	Input variable	Nominal	0=Male, 1=Female
Marital status	Input variable	Nominal	0=Single, 1=Married
Length of service	Input variable	Scale	Client must be in service not less than 30 or 35
Amount request	Input variable	Scale	Amount Request
Repayment period	Input variable	Scale	Client have to pay back at stipulated month
Credit amount	Input variable	Scale	Credit Amount
Salary	Input variable	Scale	Salary
Credit status	Output variable	Nominal	0=Creditworthy,1=Non-creditworthy

3.1 Logistic Regression Analysis (LRA)

Logistic Regression Analysis (LRA) is a statistical modeling technique used when the dependent variable is binary or ordinal in nature (Anthony, 2011) as well as multinomial. Unlike linear regression, which predicts continuous outcomes, LRA estimates the probability of a binary outcome occurring. Significance of the predictors in LRA is commonly evaluated using the Wald Chi-square statistic (Hosmer & Lemeshow, 2000).

3.1.2 Logistic Regression Model Specification

The logistic regression model estimates the probability that a particular event (e.g. loan default) occurs, based on a set of explanatory variables. When there is a single binary outcome variable Y (e.g., creditworthy= 1, non-creditworthy= 0) and a single predictor X, the logistic model is defined as follows:

$$logit(p) = \beta_0 + \beta_1 X \quad (1)$$

The model can be extended to include multiple predictors:

$$logit(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \quad (2)$$

where p is the probability that $Y = 1$ (e.g., applicant is creditworthy), $\frac{p}{1-p}$ represents the odds of the success, ln denotes the natural logarithm, β_0 is the intercept, β_1 is the coefficient for predictor, X_i may be continuous or categorical. Here, $X_1, X_2, \ldots, X_k$ are predictor variables, and the parameters $\beta_0, \beta_1, \ldots, \beta_k$ are typically estimated using the Maximum Likelihood Estimation (MLE) method (Peng & So, 2002; Hosmer & Lemeshow, 2000).

3.2 Discriminant Analysis (DA)

Discriminant Analysis (DA) is a multivariate statistical technique applied across various disciplines. It involves creating a discriminant function—a linear combination of two or more predictor variables—that best separates objects into predefined groups (Joseph *et al*., 2010).

3.2.1 Linear Discriminant Function Model

The linear discriminant function can be expressed as:

$$D_i = a + w_1 x_{i1} + w_2 x_{i2} + \cdots + w_k x_{ik} \quad (3)$$

where D_i is the object discriminant score, a is the constant (intercept), w_j are the discriminant weights, x_{ij} are the predictor variables for object i (Joseph *et al*., 2010).

The probability that an object with a score D_i belongs to group j is estimated as:

$$P(G_j \mid D_i) = \frac{\pi_j f_j(D_i)}{\sum_{g=1}^{G} \pi_g f_g(D_i)} \quad (4)$$

where π_j is the prior probability, $f_j(D_i)$ is the probability density function for group, Classification is made by comparing the discriminant score to a cutoff value (Memic, 2015).

3.2.2 Wilks' Lambda Test for Canonical Correlation

Canonical correlation measures the strength of the linear relationship between two sets of variables, ranging from -1 to $+1$. A value close to ±1 indicates a strong relationship and, consequently, a more effective discriminant function.

The significance of this relationship is evaluated using Wilks' Lambda, defined as:

$$\Lambda = \frac{Within-group\ variance}{Total\ variance} = \frac{|E|}{|E+H|} \quad (5)$$

Lower values of Λ suggest better discriminatory power. The test statistic for significance is given by:

$$\chi^2 = -\left(N - 1 - \frac{p+g}{2}\right) ln(\Lambda) \quad (6)$$

where N is the sample size, p is the number of predictors, g is the number of groups.

3.2.3 Box's M Test for Equality of Covariance Matrices

One of the key assumptions of LDA is the equality of group covariance matrices. Box's M test is used to verify this assumption. A significant result suggests a violation, which could undermine the validity of DA.

Test Statistic:

$$M = (n - 1) \cdot \ln\left(\frac{|Pooled|}{|Group1|^{n_1}.|Group2|^{n_2}}\right) \quad (7)$$

where $|.|$ represents the determinant of the covariance matrices, n_1 and n_2 are sample sizes for each group.

3.3 Confusion Matrix and Classification Performance

A confusion matrix summarizes the actual versus predicted classification results. For binary classification (e.g., Creditworthy vs. Non-Creditworthy), it appears as follows:

Actual/Predicted	Creditworthy	Non-Creditworthy	Row Total
Creditworthy	True CW (TCW)	False NW (FNW)	$\boldsymbol{TCW + FNW}$
Non-Creditworthy	False CW (FCW)	True NW (TNW)	$\boldsymbol{FCW + TNW}$
Column Total	$\boldsymbol{TCW + FCW}$	$\boldsymbol{FNW + TNW}$	$\boldsymbol{TCW + TNW + FCW + FNW}$

3.3.1 Sensitivity

$$Sensitivity = \frac{True\ Creditworthy\ (TCW)}{True\ Creditworthy\ (TCW) + False\ Non-Creditworthy\ (FNW)} \quad (8)$$

3.3.2 Specificity

$$Specificity = \frac{True\ Non-Creditworthy\ (TNW)}{True\ Non-Creditworthy\ (TNW) + False\ Creditworthy\ (FCW)} \quad (9)$$

3.3.3 Misclassification Costs (Type I and Type II Errors)

To evaluate the effectiveness of a credit scoring model, misclassification costs must be considered alongside sensitivity, specificity, and accuracy. The total expected misclassification cost (EMC) is given by:

$$EMC = C_{10} \cdot P_{10} \cdot \pi_0 + C_{01} \cdot P_{01} \cdot \pi_1 \quad (10)$$

where $C_{10} =$ cost of classifying a Non-Creditworthy applicant as Creditworthy (Type I error), $C_{01} =$ cost of classifying a Creditworthy applicant as Non-Creditworthy (Type II error), $P_{10}, P_{01} =$ probabilities of Type I and Type II errors, respectively, π_0, π_1 prior probabilities of each group (West, 2000).

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics and Distribution of Variables

Table 2 presents the descriptive statistics for the predictor variables used in estimating the logistic regression model, including their distribution across creditworthy and non-creditworthy bank applicants. The table includes mean values, standard deviations, and results from two-sample t-tests that compare group means. The analysis reveals that there are no statistically significant differences between the two groups for certain variables.

Table 2. Descriptive Profile: Means, Standard Deviations, and Group Differences

Predictors variables	Applicant status				Group difference			
	Creditworthy		Non-creditworthy					
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Error	t-value	p-value
Age	43.326	9.465	47.589	10.075	-4.26	1.836	-2.32	0.021
Amount request	320965.2	186568.8	378514.3	244856.2	-57549	42628.89	-1.35	0.122
Credit amount	320115.9	211678.9	303827.1	189340.0	16289	40722.5	0.40	0.687
Length of service	18.000	8.288	25.571	9.817	-7.57	1.624	-4.66	0.000
Repayment period	25.435	6.191	23.229	5.300	2.21	1.176	1.88	0.062
Salary	43154.35	29689.74	45350.00	27288.76	-2196	5630.769	0.39	0.699

It is important to note that this descriptive analysis is not predictive in nature but serves to illustrate the general characteristics of creditworthy versus non-creditworthy banks. As shown in the table, significant differences in mean values were observed in variables such as age of the applicant, length of service, and repayment period. However, differences in amount requested, credit amount, and salary were not statistically significant.

Table 3. Chi-squared test of independence.

Sex of applicant versus applicant status		Applicant status				
		Creditworthy	Non-creditworthy	Total	Chi-square test	p-value
Sex	Male	134	48	182	2.391	0.122
	Female	96	22	118		
	Total	**230**	**70**	**300**		
Marital status versus applicant status		**Applicant status**				
		Creditworthy	**Non-creditworthy**	**Total**	**Chi-square test**	**p-value**
Marital status	Single	66	32	98	9.527	0.023
	Married	145	37	182		
	Widow	14	1	15		
	Divorce	5	0	5		
	Total	**230**	**70**	**300**		

Table 3 reports results from Chi-square tests assessing associations between applicant status and categorical variables. For sex of applicant, the Chi-square statistic is 2.391 with a p-value of 0.122, which is greater than the 0.05 significance level. This indicates that applicant status is not dependent on sex. In contrast, the relationship between marital status and applicant status yields a Chi-square value of 9.527 with a p-value of 0.023, indicating a significant association. This suggests that marital status has a significant effect on creditworthiness classification.

4.2 Estimation of Models

4.2.1 Discriminant Analysis

Discriminant analysis is used to classify applicants into either creditworthy or non-creditworthy groups based on selected characteristics (Plewa & Friedlob, 1995). Assumptions for this model include normality, linearity, homoscedasticity, absence of multicollinearity, and no significant outliers (Meyers *et al*., 2005).

4.2.2 Statistical Significance of the Discriminant Function

Table 4 summarizes the canonical discriminant function. A high canonical correlation (0.745) and a low Wilks' Lambda (0.750) indicate that the discriminant function significantly separates the two groups. The Chi-square test value of 84.412 ($p = 0.000$) supports the statistical significance of the model, allowing us to reject the null hypothesis that all discriminant coefficients are zero.

Table 4. Canonical Discriminant Function Summary

Function	Canonical Correlation	Wilks' Lambda	Chi-square	Sig.
1	0.745	0.750	84.412	0.000

4.2.3 Importance of Independent Variables

From the structure matrix in Table 5, only variables with loadings ≥ 0.40 are included. Age of applicant and length of service are the strongest contributors to the discriminant function.

Table 5. Structure Matrix (Key Variables Only)

Variable	Function Loading
Age of Applicant	0.409
Length of Service	0.661

4.2.4 Unstandardized Discriminant Function

The unstandardized discriminant function, based on raw scores, is derived using the coefficients in Table 6. The function is expressed as:

$$Discriminant\ Score = .028 \times (Age\ of\ Applicant) + 0.085 \times (Length\ of\ Service) - .89 \quad (11)$$

Table 6. Unstandardized Classification Function Coefficients

Variable	Function 1
Age of Applicant	0.028
Length of Service	0.085
Constant	-0.899

4.2.5 Group Centroids and Classification

Table 7 shows group centroids for creditworthy and non-creditworthy applicants**.**

Table 7. Centroids for Discriminant Function

Applicant Status	Function 1
Creditworthy	-0.317
Non-creditworthy	1.042

Classification rule:

$$\hat{M} = \frac{1}{2}\left(\hat{I}_1 + \hat{I}_2\right) = \frac{1}{2}(1.042 - 0.317) = 0.363 \quad (12)$$

Classify as Creditworthy if Discriminant Score < 0.3625

Classify as Non-Creditworthy if ≥ 0.3625

4.2.6 Model Predictive Ability

As shown in Table 8, the model correctly classified 75.0% of the original cases and 74.0% in cross-validation.

Table 8. Confusion Matrix for Discriminant Model

		Predicted Group Membership		
Partition	**Applicant Status**	**Creditworthy**	**Non-creditworthy**	**Total**
Original	Creditworthy	170	60	230
	Non-creditworthy	15	55	70
Cross-validated	Creditworthy	168	62	230
	Non-creditworthy	16	54	70

[a]75.0% of selected original grouped cases are correctly classified. [b]74.0% of cross-validated grouped cases are correctly

4.2.5 Discriminant model performance assessment

In order to judge the performance of the model, the percentage correctly classified (PCC) was used: misclassification cost (MC) (Type I error and Type II error), sensitivity (SE), specificity (SP). In this study, equal misclassification cost was assumed (that is, the costs of both type I error and type II errors are the same) and so, a 0.5 cutoff probability was used under the percentage correctly classified (PCC). Table 9 provides the performance results. It is evident that the model recorded a PCC of 75.0% that is the model was able to accurately classify 75.0% of the creditworthy and non-creditworthy. It is well recognized that, in order to evaluate the overall credit scoring capability of a design model, it is important to factor in the misclassification costs (type I error and Type II errors). The type I error associated with model means that, there is a 0.261 (26.1%) probability of classifying high risk borrowers into a low risk group.

Table 9. Discriminant model performance.

			Misclassification	
Sensitivity	**Specificity**	**Percentage Corrected Classified**	**Type I**	**Type II**
73.9%	78.6%	75.0%	26.1%	21.4%

Predictions are based on 0.5 cutoff probability for the percentage correctly classified (PCC).

(1) $Misclassification\ cost = \begin{cases} Type\ I\ error = \frac{60}{230} = 26.1\% \\ Type\ II\ error = \frac{15}{70} = 21.4\% \end{cases}$

(2) $sensitivity = \frac{170}{230} = 0.739 = 73.9\%$

(3) $specificity = \frac{55}{70} = 0.786 = 78.6\%$

(4) $Percentage\ correctly\ classified = 75.0\%$

4.3 Logistic Regression Analysis

Logistic regression is increasingly favored over discriminant analysis due to fewer assumptions (Greenacre & Blasius, 2006; Jentzsch, 2007).

4.3.1 Model Fit and Significance

As shown in Table 10, the model is statistically significant. The Omnibus Test of Model Coefficients yields a Chi-square of 80.803 ($p < 0.000$), while the Hosmer and Lemeshow test confirms good model fit ($p = 0.808$).

Table 10. Model Fit Tests (Omnibus test and Hosmer and Lemeshow test).

	Omnibus test of model coefficient			Hosmer and Lemeshow Test		
Parameter	Chi-square	Df	Sig	Chi-square	df	Sig.
Model fit test	80.803	10	0.000	4.517	8	0.808

4.3.2 Logistic Regression Results

Significant predictors are marital status, length of service, and amount requested. Odds ratios reveal: Married applicants are 447M times more likely to default than divorced ones. Length of service increases creditworthiness likelihood by 1.129. Amount requested has a neutral (1.000) effect.

Table 11. Parameter estimates

Variables	Estimates	Std. Error	Wald	df	Sig.	$\exp(\boldsymbol{\beta})$
Age of applicant	0.022	0.021	1.109	1	0.292	1.022
Female	0.127	0.416	0.416	1	0.759	1.136
Marital status			9.772	3	0.021	
Married	21.520	22027.481	0.000	1	0.999	2218143597.117
Widow	20.246	22027.481	0.000	1	0.999	620679330.949
Divorce	19.919	22027.481	0.000	1	0.999	447241050.862
Length of service	0.122	0.026	22.147	1	0.000	1.129
Amount request	0.000	0.000	8.549	1	0.003	1.000
Repayment period	-0.088	0.074	1.408	1	0.235	0.915
Credit amount	0.000	0.000	0.000	1	0.991	1.000
Salary	0.000	0.000	0.500	1	0.480	1.000
Constant	-24.292	22027.481	0.000	1	0.999	0.000

From Table 11, the fitted logistic regression equation is,

$$\hat{\pi}(AS = 1|x) = \frac{e^{-24.292+21.520M+20.246W+19.91D+.122LS+.000AR-.088RP+.000CR\ldots+.000S}}{1+e^{-24.292+21.520M+20.246W+19.91D+.122LS+.000AR-.088RP+.000CR\ldots+.000S}} \qquad (13)$$

and the logit model

$$\hat{\pi}(AS = 1|x) = -24.292 + 21.520M + 20.246W + 19.91D + .122LS + .000AR - .088RP + .000CR \ldots + .000S \qquad (14)$$

where AS is applicant status, M is married, W is Widow, D is Divorce, LS is length of service, AR is Amount request, RP is Repayment period, CA is Credit Amount and S is Salary.

Table 12. Confusion matrix for the logistic model of sample.

Partition	Observed	Predicted: Applicant Status: Creditworthy	Predicted: Applicant Status: Non-creditworthy	Percentage correct
Training samples	Creditworthy	216	14	93.9
	Non-creditworthy	44	26	37.1
Overall Percentage				80.7

4.3.3 Logistic model performance assessment

In order to judge the performance of the model, we used the percentage correctly classified (PCC), misclassification cost (MC) (Type I error and Type II error), Sensitivity (SE), Specificity (SP). In this study, we assumed equal misclassification cost (that is, the costs of both type I error and type II errors are the same) and so, a 0.5 cutoff probability was used under the percentage correctly classified (PCC). Table 12 provides the performance results. It is evident that the model recorded a PCC of 80.7%, that is, the model was able to accurately classify 80.7% of the creditworthy and non-creditworthy. It is well recognized that, in order to evaluate the overall credit scoring capability of a design model, it is important to factor in the misclassification costs (type I error and Type II errors). The type I error associated with model means that, there is a 0.061 (6.1%) probability of classifying high risk borrowers into a low risk group (Table 13).

Table 13. Logistic regression for model performance.

Sensitivity	Specificity	Percentage Corrected Classified	Misclassification: Type I	Misclassification: Type II
93.9%	37.1%	80.7%	6.1%	62.9%

Predictions are based on 0.5 cutoff probability for the percentage correctly classified (PCC).

$$(1) Misclassification\ cost = \begin{cases} Type\ I\ error = \frac{14}{230} = 0.061 = 6.1\% \\ Type\ II\ error = \frac{15}{70} = 0.629 = 62.9\% \end{cases}$$

$$(2)\ sensitivity = \frac{216}{230} = 0.939 = 93.9\%$$

$$(3)\ specificity = \frac{26}{70} = 0.371 = 37.1\%$$

$$(4)\ Percentage\ correctly\ classified = 80.7\%$$

Table 14. Summary Comparison of Model Performance

Metric (Model Assessment)	Logistic regression	Discriminant Analysis	Better model
Sensitivity (%)	**93.9**	73.9	**Logistic Reg.**
Specificity (%)	37.1	**78.6**	**Discriminant**
Corrected Classified (%)	**80.7**	75.0	**Logistic Reg.**
Misclassification ***Type I*** (%)	**6.1**	26.1	**Logistic Reg.**
Misclassification ***Type II*** (%)	62.9	**21.4**	**Discriminant**

5. CONCLUSION

Table 14 presents a comparative analysis of the credit scoring results from the discriminant model and the logistic regression model using key performance indicators: Misclassification Cost (MC), Sensitivity (SE), Specificity (SP), and Percentage Correctly Classified (PCC).

The findings indicate that the logistic regression model outperforms the discriminant model in several critical aspects. It achieves a lower Type I error rate (6.1%) and demonstrates higher sensitivity (93.9%) and overall classification accuracy (80.7%). This suggests that the logistic model is more effective at correctly identifying non-creditworthy applicants, thereby reducing the risk of false approvals.

Conversely, the discriminant model performs better in terms of specificity (78.6%) and has a lower Type II error rate (21.4%), indicating it is more accurate in identifying creditworthy applicants, which helps reduce false rejections.

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