Design and Development of Credit Scoring Model for the Commercial banks of Pakistan: Forecasting Creditworthiness of Individual Borrowers

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Abstract

This research study summarizes the loan evaluation method known as credit scoring.Credit scoring is a technique that helps banks decides whether to grant credit to applicants who apply to them or not.The main objective of the research was to evaluate credit risk in commercial banks of Pakistan using credit scoring models.The requirement of credit scoring models by commercial banks of Pakistan to assess the creditworthiness of individuals was described. A credit scoring modelwas developed called as Credit Scoring Model for Individuals (CSMI), which can be used by commercial banks to determine the creditworthiness of individual borrowers requesting for personal loans. The CSMI was explained along with a detailed look at different credit scoring models. The results of the developed credit scoring model were compared with the other statistical credit scoring techniques known as logistics regression and discriminant analysis. Type I and type II errors had been calculated for all the credit scoring models used. The results shows that the proposed model "CSMI"has more accuracy rate with no errors as compared to LR and DA.Also, several suggestions for further research were presented.

Keywords: Credit Scoring;Credit Risk; Personal Loans; Creditworthiness; Discriminant Analysis; Commercial Banks

1. Introduction

The motivation for this research is to explore insights into the level of loan delinquency and creditworthiness among the individualborrowers and the lending practice of banks to ultimately reduce the number of non-performing loans of commercial banks of Pakistan.

This study is mainly done to build a model for commercial banks with various exhaustive list parameters among different degrees of importance. The proposed credit scoring models will facilitate the banks to check the creditworthiness of the individuals. The proposed credit scoring model will decide among the good and bad loan applications. Credit scoring models assess the risk of a borrower by using the generated credit score that will be made by extracting data from loan applications, socio-demographic variables and credit bureau reports.

Dimitriu, Avramescu and Caracota (2010) defined that lending money is risky, but at the same time profitable. Interest and fees on loans are source of profits for the banks. Banks do not want to grant credit to those borrowers who are not able to repay the loan. Over time, some of the loans can become bad even if the banks do not want to have bad loans.

Historically, credit risk caused heavy losses to commercial banks functioning in Pakistan. The senior management of banks required to design policies, methods, and procedures to measure, monitor and control credit risk. (Kanwar, 2005).

During 2008, the growth rate of non-performing loans (NPL) in Pakistan had risen at a shocking rate of 65%, but the growth rate reduced to 20% in 2009. Consumers are the common defaulters. (Aazim, 2010)

By analyzing the written off loans of commercial banks in Pakistan, this will assist in taking effectual measures to enhance the quality of credit approval process and ultimately reduce the losses of banks from bad debts. Many written off loans have been caused by the improper management of the loan applications starting from disregarding the accepted rules of loaning. This want to be observed cautiously and banks should take effective measures to minimize bad debts or written off loans in the future.

The commercial banks of Pakistan have to find a remedy to reduce their non-performing loans, since the slowdown in the economy; one mostly implemented system for solving this problem is "Credit Scoring."

1.1 Objectives

The objectives of this study are as follows:

- To design a credit scoring model for individuals to assess their creditworthiness
- The validity of the proposed credit scoring model would be compared with the preexisting statistical credit scoring models.

1.2 Rationale of Study

Before offering credit to individuals, their financial position should be examined as offering loan is very risky. On the basis of the financial position of their applicants requesting credit, banks assign credit scoring and on the basis of credit scores the bank decides whether to offer the credit to these applicants and also decides the credit limits. Our research aimed to evaluate the creditworthiness of individuals by calculating the credit scores via credit scoring models.

2. *Research Questions*

The questions of the research study are as follows:

- What is the creditworthiness of individual borrowers requesting banks for loan?
- What is the risk category of individual borrowers?

3. *Review of Literature*

Thomas, Edelman and Crook (2002) described "Credit Scoring is the set of decision models and their underlying techniques that aid lenders in the granting of consumer credit. These techniques decide who will get credit, how much credit they should get, and what operational strategies will enhance the profitability of the borrower to the lenders."

A creditor can make revenues when they successfully predict the creditworthiness and default risk of applicants depending on the default predictor factors. Credit scoring is a proper technique that connects these factors to the probability of default. (Lieli & White, 2010)

While the concept of credit is 5000 years old, the credit scoring is only 50 years old. Credit scoring is basically an approach to classify distinctive groups when the lender cannot consider all the characteristics that describes the groups but just describes those that are closely related. Fisher (1936) as cited in (Thomas, Edelman, & Crook, 2002) initiated to solve this problem of identifying distinctive classes in a total population. Further, it was concluded that good and bad creditors could be classified by using the single method, as described by Durand (1941).

According to new Basel II Capital Accord, default is defined as 90 days delinquent this is defined by Siddiqui (2006). Kanwar (2005) defined credit risk as risk arises when the borrower either is unwilling to repay the loan or he is not able to repay the loan granted which results in economic loss to the bank.

Credit scoring has used the data on consumer behavior for the first time so it can be declared as the grandfather of data mining. Firstly, a lender should take two decisions in the credit approval process; one is whether to give loan to a fresh borrower; the technique that used to make this judgment is credit scoring and, other, whether to increase the credit limits of the existing debtors; the techniques that assist the second decision are called behavioral scoring. (Thomas, Edelman, & Crook, 2002) Lenders in developed countries analyze the creditworthiness of borrowers based on their credit histories taken from credit bureau and also check borrower's salary and experience before loan approval. (Schreiner, 2000)

According to Thomas, Edelman and Crook (2002) lending institutions started adopting the credit scoring models in evaluating personal loans, after few years for the evaluation of mortgage and small business loans in 1980, after analyzing the effectiveness and accuracy of credit scoring models in the evaluation of credit cards.

Classification models in credit scoring analyze the characteristics of applicants such as age, income, marital status, payment history are used to classify new candidates into good or bad (Chen and Huang, 2003). Many banks use only two groups as "good" or "bad" applicants and many use three groups "good", "bad" or "refused". The credit managers analyze the refused applications once again. (Abdou, Masry, & Pointon, 2007)

According to Chijoriga (2011), Credit scoring models can be qualitative as well as quantitative in nature. Qualitative technique is judgmental and subjective; the disadvantage of qualitative method is that there is no objective base for deciding the default risk of an applicant. While, quantitative technique is a systematic method to categorize into performing or non- performing loans and it has removed the shortcomings of qualitative technique and proved to be more reliable & accurate model.

Both the lenders and the borrowers could bear the costs of loan delinquencies. The creditor will not get the interest payments and also the loan given. The debtor will come in the list of defaulters so his character will be affected as well as he cannot further take loans from the same creditor and also could not invest that loan taken. (Baku & Smith, 1998)

Lieli and White (2010) analyzed that credit is granted to applicants after assessing their creditworthiness, when an applicant meeting the cut off score the he/she will be a accepted and considered as good applicant and increase their credit limits while all those applicants having credit score with total scores lower than cut off score is rejected.

Sullivan (1981) defined that the credit scoring technique work on the addition or subtraction of credit score based on number of factors such as time on a current job, education level of an individual applicant. On the basis of this statistically derived cut off score compared to generated credit score of an applicant, the loan application is accepted or rejected.

Sullivan (1981) pointed out that the credit scoring models have biasedness as it discriminates the females with males in granting loans. Despite the criticism, credit scoring models can be considered as very effective tools in the area of Finance and Business. It is prohibited to include variable of race and religion in the default prediction factors but that does not stop some authors.(Thomas L. C., 2000)

Steenackers&Goovaerts (1989) describes the most fundamental application of credit scoring models is the evaluation of new individual loans. According to Orgler (1971), there are many research studies done on granting loans to current individual but less literature is present on loans given to fresh individual.

According to Basel II rules, banks should have a sound internal rating system to assess the credit risk of debtors through which bank loan officers can effectively and accurately quantify risk and define credit limits accordingly(Hasan & Zazzara, 2006). Lopez and Saidenberg (2000) defined that according to Basel Capital Accord; banks must keep 8% capital against the risk-weighted assets.

Barefoot (1996) described several key benefits of credit scoring: credit scoring lowers the cost of lending as it has reduced the part of human in evaluating a loan application. Credit scoring models has increased the accuracy of predicting the actual credit risk of debtor. According toPonicki (1996), for banks credit scoring provided a standard technique of loan evaluation across the entire bank, efficient way of executing the transactions and also enhances the collection of loan. Credit scoring models provide benefits to customers by offering simple application process, results of credit approval in a timely manner, access to credit when they need it.

Lending institutions adopt seventy percent of credit scoring models to evaluate microcredit and 97% to assess the credit card requests.(Mester, 1997)

Credit scoring models rely on the credit history of those debtors who are accepted by the banks. Overlooking the rejected applicants affects forecast accuracy of credit scores and has some effect on their discriminatory power(Barakova, Glennon, & Palvia, 2011).

There are numerous commercially available decision support systems for credit scoring of any type of corporation but they suggested that there should be minimum one standard system of credit scoring that can be used by commercial banks worldwide.(Emel, Oral, Reisman, & Yolalan, 2003)

According to Schreiner (2002), statistical scoring cannot replace the loan officers because ultimately it is the duty of the credit analysts to make the credit decision and these scoring techniques can act as a help guide. Statistical scoring reminds the credit manager the elements of risks that they have ignored.

4. Theoretical Framework

4.1 Dependent Variable

In this research study the '*Credit Score'* is the independent variable.Credit score is a number that denotes the creditworthiness of applicants. The higher the credit score, the higher the creditworthiness of an applicant, while the lower the credit score, the lower the creditworthiness of an applicant.

4.2 Independent Variables of CSMI

There were total sixteen independent variables for the credit scoring model for individuals. Most of these factors are socio- demographic variables.

1	Gender	9	Occupation
2	Client's locative situation	10	Working period with the last employer
3	Education level	11	Working period with the current employer
4	Proximity towards bank X branches	12	Loan period
5	Marital status	13	Banking references at Bank X
6	Age	14	Monthly net income of the applicant
7	Number of dependents	15	Credit History
8	Loan tenure	16	Loan from other banks

5. Research Methodology

The primary data was collected by personal interviews with the credit managers and by administering a questionnaire. Personal interview method is used for the analysis of credit approval process by the banks. Here, personal interviews will be conducted with the credit managers of different commercial banks. A questionnaire was distributed to the credit departments of commercial banks to collect data about customer's personal loans.

The sensitivity of the topic turned out to be a bigger constraint, restricting the research sample to be 250. These 250 customers are those who have applied for the grant of credit and were accepted by the bank. The individuals data was collected from the well reputed commercial banks of Pakistan namely, Standard Chartered Bank and Askari Bank from different branches of Lahore and Islamabad.

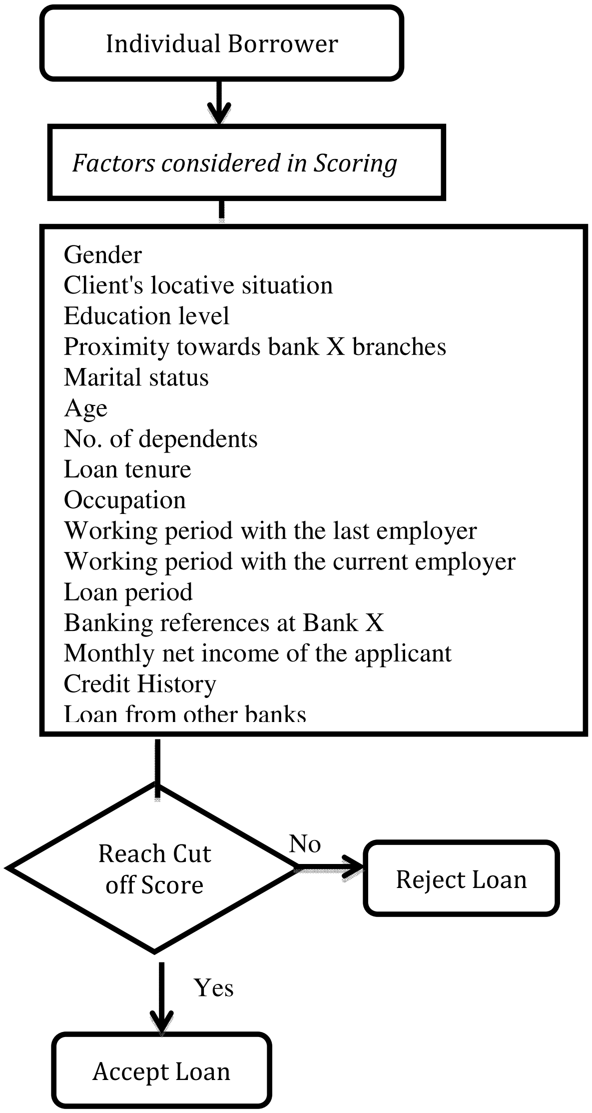
5.1 Data Analysis Tools

Financial tools that were used to calculate the creditworthiness of individuals which includes Descriptive Statistics (Frequency Distribution &Cross Tabulation), the Discriminant Analysis (DA), Logistic Regression analysis on SPSS 17.0.

5.2 Developing Credit Scoring Model

The main objective of the research is the design & development of a new and potentially more effective credit scoring model defined as the Credit Scoring Model for Individuals ("CSMI"). The 1st step in developing the credit scoring models was finding the different components affecting the creditworthiness of applicants. For identifying these factors many articles and websites related to consumer loans were studied.

5.2.1 Credit Scoring Process



5.2.2 Credit Scoring Model for Individuals

FACTORS	Score
Gender	
○ Male	1
○ Female	0
Client's locative situation	
○ Own house	3
○ Personal apartment	2
○ Parents apartment	1
○ Rent	0
Education level	
○ PhD.	4
○ Master / M-Phil	3
○ Graduate	2
○ Inter / Matriculation	1
○ < Matriculation	0
Proximity towards bank X branches	
○ Bank X branch exists in the residence place of the applicant	2
○ Bank X branch does not exist in the residence place of the applicant	0

Marital status	
○ Married	3
○ Single / Widow / Divorced	1
Age	
○ Between 20 and 30 years	4
○ Between 30 and 40 years	3
○ Between 40 and 50 years	2
○ Between 50 and 60 years	1
○ Above 60	0
No. of dependents	
○ 0 person	3
○ 1 person	2
○ 2 persons	1
○ 3 or more persons	0
Loan tenure	
○ 1 year	4
○ 2 Years	3
○ 3 Years	2
○ 4 Years	1
○ 5 years	0
Occupation	
○ Salaried employee	3
○ Businessman	2
○ Student	1
○ Unemployed	0
Working period with the last employer	
○ Greater than 5 years	4
○ Between 2 and 5 years	3
○ Between 1 and 2 years	2
○ Retired	1
○ NA	0
Working period with the current employer	
○ Greater than 5 years	4
○ Between 2 and 5 years	3
○ Between 1 and 2 years	2
○ Retired	1
○ NA	0
Loan period	
○ Shorter than the remaining period till pension	2
○ Higher than the remaining period till pension	0
Banking references at Bank X	
○ Deposit and loan	3
○ Loan / credit card	2
○ Deposit / credit card	1
○ None	0
Monthly net income of the applicant	
○ Above 100,000	4
○ Between 55,000 and 100,000	3
○ Between 40,000 and 55,000	2
○ Between 25,000 and 40,000	1
○ Between 10,000 and 25,000	0
Credit History	
○ 90 days default	1
○ 60 days default	2
○ 30 days default	3
○ None	4
Loan from other banks	
○ Yes	0
○ No	1

The socio-demographic factors were used to measure creditworthiness of individual applicants. Each of factors used in SCMI has several attributes with certain scores. There are total 16 variables included in the construction of the credit scoring for individuals.

The range of credit scores is from 2-49. The maximum credit score that an individual can have is 49 and lowest credit score is 2. Individuals with lower credit scores have more default risk & lower creditworthiness as compared to individuals with high credit score, who have low risk & they are considered to be more creditworthy.

Credit Score %	**Credit Score Range**	**Quality**	**Risk Class**
91% -100%	44 - 49	Highest	**A**
76%- 90%	37 – 43	Good	**B**
50% – 75%	25 - 36	Average	**C**
Below 50 %	< 25	Below Average	**D**

When an applicant's credit score lies in the range of 44-49, it means he/she will lie in the risk class A that is showing lowest possible risk and bank considered the applicant of highest quality. We have taken 90 to 100 % (top 10%) of the maximum score of 49. The second risk class is B having good quality of loan applications; the credit score of this category is between 37 to 43. All applicants having credit score greater than & equal to 25 but less than & equal to 36 will lie the risk class C, having an average quality of loan application.

The cut off score of this model is 25, which is 50% of the total credit score of 49. Applicants having total credit score less than 25 will not be qualified for loan, hence rejected.

The lowest possible credit score an individual can have is the cut off score..Any applicant having credit score below 25, will be rejected and any applicant having credit score above 25 will be accepted and loan granted to that applicant. Below cut off score the risk is very high to accept an applicant's loan application and above cut off score there is relatively low depending upon their risk class.Risk class 'A' shows no default risk due to highest credit score. Risk class 'B' shows lowest default risk because of high credit score. Risk class 'C' represents medium level of default/ credit risk as having average level of credit score. Risk class 'D' indicates the high level of risk and also having below average credit score.

6. Data Analysis

In the questionnaire of credit scoring model for individuals, a data set of 250 applicants was collected; out of which there were 158 males comprises of 63.2% of the total population and only 92 females which made 36.8% of the total population.

It is concluded that there were 17.2 % defaulter female borrowers as compared to 21.2% of defaulter male borrowers, so females have less probability of default as compared to males. There were 19.6% of non-defaulter female borrowers as compared to 42% of non-defaulters male borrowers, so it is concluded that males were more creditworthy, have less probability of default because they were more financially strong in Pakistan as compared to female borrowers.

Results shows that all those individuals who have their own house have high creditworthiness and less probability of default. All the sampled applicants have education level less than matriculation were forecasted to be defaulters or bad applicants.Among the good applicants or non-defaulters there were 0% applicants who have education level less than intermediate and 16 applicants consists of 84.2% of the total population of PhD's within education level. So it is concluded that as the education level increases the creditworthiness also increases and probability of default decreases and vice versa.

6.1.1 Credit Scoring Models

For the purpose of determining creditworthiness of individuals we have used several credit scoring techniques such as credit scoring model for individuals, logistic regression (LR) and discriminant analysis (DA). We have used the LR and DA to compare the accuracy of the developed credit scoring model. We have discussed the results of each credit scoring model and also compared their results.

6.1.1.1 Credit Scoring Model for Individuals (SCMI)

We have developed a new credit scoring model named as "Credit Scoring Model For Individuals (CSMI)" which has considered all the important factors such as socio demographic variables, credit history, loan tenure, age, occupation etc.

Classification results using Credit Scoring Model for Individuals (CSMI) [a]

		Predicted group		
		Credit Score		
Observed group		0 Bad	1 Good	Percentage
Credit Score	0 Bad	96	0	100.0
	1 Good	0	154	100.0
Overall Percentage				100.0

a. Cut-off point 0.50

After adding the credit score of all sixteen predictors on a 3, 2 & 1 basis we developed a total credit score. This total credit score of an individual was compared with a cut off score which is 50%. The resulting decision was accept and grant loan when the credit score was above the cut off score and rejected when falls below loan. All the applicants who lied at the cut off score exactly are accepted but designated for further analysis by credit analysis.

The classification results using Credit scoring model for Individuals are that out of 250 applicants, there are 96 applicants comprising of 38.4% of the total population who are predicted to be bad or defaulters and these defaulter applicants have credit score below the cut off score.

There are 154 applicants consists of 61.6% of the total population, who have credit score above the cut off score, so they are predicted to be good customers showing good creditworthiness and less probability of default. The overall accuracy of this model is 100%. There are 0 applicants considered bad as a good and there are also 0 applicants considered good as a bad. So there is no misclassification cost as there is no Type I and Type errors.

6.1.1.2 Logistic Regression

As we can see from Table 59 and Table 65, all the variables are significant except the credit history of 30 days and loan from other banks at 0.01. According to commercial banks in Pakistan 30 days default is not considered as a default, hence applicant is acceptable at 30 days default, so that is why it is not significant at 0.01. The overall model is significant as the p-value is 0.000 ,which is less than 0.01 as shown in Table 60. The classification results generated by using logistic regression credit scoring model (LR) using the sixteen factors are as follows:

Classification Results of LR [a]

			Predicted		
			Credit_Score		
	Observed		Bad	Good	Percentage Correct
Step 0	Credit_Score	Bad	95	1	99.0
		Good	2	152	98.7
	Total Percentage				98.8

a. The cut value is .500

The results from the classification of LR shows that there are 95 applicants predicted to be bad or defaulters, comprising of 38% of the total population and there are 152 applicants (60.8%) out of 250 applicants who are above the cut point 0.5 and acceptable for the grant of loan, hence they are good applicants.

The correct classification rate was 98.8% of LR having cut value equal to 0.5, as the P-value of LR shown to be lower than 0.01 so it resulted that default predictors are significantly related at the 95% confidence level.

There are two types of error which must be mentioned are Type I and Type II error. Type I error is predicting a bad credit application as a good credit application while Type II error is predicting a good credit application as a bad credit application. According to our results, there is 1.3% Type I error and the Type II error is 1.04%.

According to Table 64 at Step 9, the coefficients of the logistic equation are given and on that basis the logistic regression is as follows:

Z =-30.304 + 3.257 Client's_locative_situation + 5.233 Education_level + 4.462 Proximity_towards_BankX_Branches + 3.059 Marital_Status - 48.2 Occupation + 2.301 Working_period_with_the_last_employer + 4.370 Loan_period +4.496 Banking_references_at_BankX - 23.721 Credit_History (1)

6.1.1.3 Discriminant Analysis

Discriminant analysis was used as a credit scoring model to calculate the credit score that is the dependent variable based on sixteen independent variables.

Classification Results of DA[b,c,d]

			Predicted Group Membership		
		Credit_Score	Bad	Good	Total
Original	Count	Bad	93	3	96
		Good	4	150	154
	%	Bad	96.9	3.1	100
		Good	2.6	97.4	100
Cross-validated[a]	Count	Bad	91	5	96
		Good	7	147	154
	%	Bad	94.8	5.2	100
		Good	4.5	95.5	100

a. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b. 97.2% of original grouped cases correctly classified.

c. 95.2% of cross-validated grouped cases correctly classified.

d. Cut off value is .500

The result from the classification of DA shows that there are originally 93 applicants (96.9%) predicted to be bad and 150 applicants (97.4%) as good applicants. It can be observed that Type I error rate is 2.6% and Type II error is 3.1%. So Type II error is greater than Type I error, which does not cause any trouble because good applicant is considered as bad and this cannot be so costly. There is 97.2% of accuracy that the original group cases correctly classified.

After cross validating the results of DA, there are 91 applicants (94.8%) predicted to be bad and 147 applicants (95.5%) as good applicants. It can be observed from the cross-validated classification results that Type I error rate is 4.5% and Type II error is 5.2%.

The correct classification rate was 95.2% of DA after cross-validated having cut value equal to 0.500, as the P-value of DA shown to be lower than 0.01, so it resulted that default predictors are significantly related at the 95% confidence level. The overall model is also significant as the p-value is less than 0.01.

Eq. (2) represents the resulting standardized canonical discriminant function as seen from Table 71:

Z=0.081Gender + 0.305Client's_locative_situation + 0.089Education_level + 0.214 Proximity_towards_BankX_Branches + 0.271Marital_Status - 0.017Age +0.422No._of_dependents +0.040Loan_tenure+0.466Occupation+0.218Working_period_with_the_last_employer+0.261Working_period_with_the_current_employer+0.224Loan_period+0.260Banking_references_at_BankX+ .173Monthly_Net_Income_of_the_applicant +0 .671Credit_History +0 .024Loan_from_other_banks (2)

6.1.1.4 Comparing Credit Scoring Models For Individuals

The accuracy rate is vital in comparing the classification accuracy of all the credit scoring models used in this research study. We have compared the accuracy rates of all the models so that these models like LR and DA would support the proposed credit scoring model for individuals. The credit scoring results along with the accuracy rates of SCMI, LR and DA are as follows:

Credit Scoring Model	Credit Scoring results		
	Bad-Bad (0-0)	Good-Good (1-1)	Accuracy rate*
SCMI	100% (96/96)	100% (154/154)	100%
LR	99% (95/96)	98.7% (152/154)	98.8%
DA	94.8% (91/96)	95.5% (147/154)	95.2%

* cut off point is 0.5

The accuracy rate of SCMI is 100%, accurately classified the bad and good customers and logistic regression (LR) has the accuracy rate of 98.8%, with 99% accurately classified the bad applicants and 98.7% accurately predicted the good customers. The discriminant analysis credit scoring model has the accuracy rate of 95.2%, with 94.8% accurately classified the bad applicants and 95.5% accurately predicted the good applicants.

Hence it is concluded from the credit scoring results that the proposed CSMI have the highest accuracy rate and also the most effective model as compared to other two credit scoring model of logistic regression (LR) and discriminant analysis (DA). The accuracy rate of CSMI > LR > DA.

Comparing Errors

Credit Scoring Model	Error results	
	Type I	Type II
SCMI	0% (0/154)	0% (0/96)
LR	1.3% (2/154)	1.04% (1/96)
DA	4.5% (7/154)	5.2% (5/96)

Discriminant analysis has the highest Type I as well as Type II error as compared to SCMI and LR. As there is no Type I & Type II errors in SCMI so there will be no misclassification cost. The Misclassification cost of DA would be higher as compared to other two credit scoring models.

7. Discussion

The proposed model of credit scoring was developed keeping in view the increasing trend of NPLs as can be seen in Figure 82 and this models was created only for individual borrowers as they are contributing to a large extent in non-performing loans of the banks presented in Figure 81.

The accuracy rate of Credit Scoring Model for Individuals was 100%, more than the other models used. Among the individual applicants the accuracy rate of LR (98.8%) is more as compared to DA, which is 95.2%.

There is no Type I error as well as Type II error in CSMI. The Type I error of CSMI is 0% and mostly banks require that assessment tool which give less misclassification cost. Type I as compare to Type II error costs more to banks as in Type I error bad applicants are considered as good which is highly risky. In Type II error the banks just loose the potential applicants hence reduce their revenues. The credit scoring model which has the highest accuracy rate and lowest error rates are considered to be the most effective, accurate, efficient and useful model.

Classification models in credit scoring analyze the characteristics of applicants such as age, income, marital status, payment history are used to classify new candidates into good or bad (Chen and Huang, 2003)

The results from credit scoring model for individuals proved that the marital status is a strong predictor of credit risk. We can estimate that married applicants are considered by banks to be less risky and more creditworthy because they have responsibility of their spouses and families as compared to single applicants. Another factor which may makes the married applicants more creditworthy is dual income.

Education is an essential factor in assessing creditworthiness, according to CSMI it is concluded that all those applicants who have higher level of education can default less and usually repay the loan taken on time. Because when applicants have a higher education he/she would easily get a better job. Applicants who have lower level of education would become difficult for them to find a better job, hence not showing a strong financial health.

Kocenda and Vojtek (2009) considered education as a fundamental component of credit scoring. He said that debtors having high level of education are can default less as compared to debtors with low level of education.

It is proved from results that as the age increases the creditworthiness decreases because younger applicants have less responsibilities and less number of dependents as compared to all those applicants who are elder. Hence, lower age groups are more creditworthy as compare to high age groups. Loan tenure was also an essential factor and shows considerable results, as the tenure of loan increase the credit risk increases. So, short term loans are less risky and long term loans are more risky.

Occupation was also an essential factor is determining the creditworthiness of individuals. Hence, it is concluded that salaried employees have less credit risk and more creditworthiness as compared to businessmen and students. All the unemployed applicants are not considered to be creditworthy as they are not financially strong, having no source of income to repay the loan.

The most important factor that must be considered is the credit history of the applicants. It can see from our results as well as from past literature that those borrowers who have defaulted previously can be predicted to default in the future.

8. Conclusion

This research study shows an evaluation of creditworthiness of individuals having personal loans to improve the credit approval process and to decrease the non-performing loans in the commercial banks of Pakistan.In this research study we have taken a sample set of 250 individual borrowers who have taken personal loans from the various commercial banks of Pakistan, out of which 144 applicants who have clear history having no default ever, there were 51 applicants who have default up to 30 days, 37 applicants have 90 days default.

The results using Credit scoring model for Individuals (SCMI) are that out of 250 applicants, there are 96 applicants who are predicted to be bad or defaulters. All these defaulter applicants have credit score below the cut off score. There are 154 applicants are predicted to be good customers. The Credit Scoring Model for Individuals (CSMI) assessed the creditworthiness of individual borrowers with 100% accuracy rate and distinguished the high risk loan applications to low risk prior to default.

We have used logistic regression and discriminant to support the results of developed credit scoring model. The accuracy rate of Credit Scoring Model for Individuals was 100%, logistic regression (LR) has the accuracy rate of 98.8% and the discriminant analysis credit scoring model for individuals has the accuracy rate of 95.2%. It shows that proposed CSMI have the highest accuracy rate and also the most effective model as compared to other two credit scoring model of logistic regression and discriminant analysis.

9. Recommendations

It is highly recommended that commercial banks should use this proposed credit scoring model as a part of their evaluation process. By adopting this model banks can reduce their non performing loans. CSMI have included all the factors that banks consider but in a systematic way.

It is recommended that future research studies should use the advanced credit scoring techniques like genetic algorithms, fuzzy discriminant analysis and neural networks.For the generalization and accuracy of the results generated by the credit scoring models, it is recommended to have a large data of individual borrowers. New variables can also search which will help predicting the probability of default of individuals and corporations.In our current research study we have used the accepted applicants in our sample; it is highly advisable to collect the data of rejected applicants by banks, so that more versatile results could be obtained.

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