PREDICTING CREDIT DEFAULT AMONG MICROFINANCE CUSTOMERS AT ECLOF KENYA LIMITED

BY:

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DECLARATION

I Okarinon Jacktone Imayi hereby declare that this Research Project is my original work and has not been presented to any university or institution of learning for award of a degree.

Signature…… ..Date……23/11/2022………

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The Supervisor's Approval

This project has been submitted for examination with our approvals as the university supervisors

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Thank you all, and God bless.

DEDICATION

I dedicate this project to my spouse Christine and to my children Caleb, Keziah, Joshua and Deborah (The Okarinons) for their love, moral support and encouragements in my entire time of study.

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ABBREVIATIONS AND ACRONYMS

Ag:	Age
CBK:	Central Bank of Kenya
CRB:	Credit Reference Bureau
Dev:	Deviation.
EKL:	ECLOF Kenya Limited.
Gen:	Gender
Guar:	Guarantor
LoAm:	Loan Amount
LoPu:	Loan Purpose
LSF:	Loan Security Fund
LTW:	Loan Term in Weeks.
MaSt:	Marital Status
MFB:	Microfinance Banks
MFI:	Microfinance Institution
NLC:	Number of Loan Cycles
NSE:	Nairobi Securities Exchange
Std:	Standard Deviation
WLI:	Weekly Loan Installments

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ABSTRACT

Microfinance Institutions (MFIs) carry out a crucial role in the financial sector for economic development of many countries. The MFIs advance credit to the active poor who mostly lack formal collaterals to secure the loans. The advancement of loans can lead to the MFIs to suffer financial crisis/distress called credit default causing financial losses. Therefore, all MFIs are concerned whether the applicant of the loan will become a good or bad payer in order to minimize probability of loan repayment default. The Financial Reports from Central Bank of Kenya show that MFIs continue to incur losses emanating from Non-Performing loans due to loan defaults. The study sought to predict the credit default in MFIs customers. The research objectives entailed finding the factors that are important in establishing credit customers' default risk and to evaluate the relative degree of the importance of each of the factors that affect credit default in MFI customers using Altman Model. The study applied a descriptive research design. The population target was the 2000 EKL credit customers of Kisumu branch. Stratified Random sampling was used among the target population to get defaulted and non-defaulted loans for analysis. Secondary Data was obtained from loan applications advanced during the year 2018. The data extracted included the borrower and the loan factors such as Gender, Age, Marital Status, Guarantor, Loan Amount, Loan Term, Weekly Installments, LSF Contribution, Loan Purpose, and Loan Cycles. The sample size constituted 35 defaulted loans and 35 non-defaulted loans that were randomly selected from each category of defaulted and non-defaulted loans that formed 70 cases. The SPSS (IBM SPSS statistics 23) software and Discriminant Analysis were employed for data analysis. Loan Repayment status formed the dependent variable, while Loan and Borrower's characteristics were the independent variables. The findings of the research showed a statistical significant relationship between Borrower characteristics and Loan characteristics and Repayment status. The study indicated Loan Cycles, LSF Contribution, Weekly Installments and Loan Amount were more important in discriminating default and non-default categories hence determining the credit default of the borrower. The study also highlighted LSF Contribution, Number of Loan Cycles, Weekly Installments and Loan Amount as the highest predicting factors in the model. The study established that the Discriminant Analysis Model was able to predict default cases by 82.9% and non-default cases by 88.6% indicating that Altman MDA model is a strong model with a high prediction rate that can be used to predict the default status of credit clients. The study recommended that MFIs should consider

weekly LGF Contributions by all clients, do thorough loan appraisals to determine the client's potential to pay the loan. It is important for the MFIs to fund the right loan size that leads to good loan repayments while avoiding default. Again, the study recommended use of Altman Model-Discriminant Analysis by MFIs to discriminate good and bad borrowers in order to minimize the default risk in lending

CHAPTER ONE

INTRODUCTION

1.1.1 Background of the Study

The concept of Microfinance was first introduced by Prof Muhammad Yunus in Bangladesh. Many of the developing nations have adopted the concept of microfinance in alleviating poverty. The nations through their MFIs offer financial products and other related non-financial products and services to the active poor hence empowering credit clients economically (Qamruzzaman & Jianguo, 2016). In many countries that are developing, microfinance institutions (MFIs) do an important role in economic development. MFIs advance or extend credit to the poor who do not have tangible securities to secure such loan facilities in commercial banks. The loans from MFIs help the active poor to set up their income-generating activities with the aim of reducing poverty. However, the majority of the MFIs are faced with credit risk emanating from the default of the loans. Default is the state where the client fails to repay a loan in terms of the amount to be paid or the timing of the payment (Ofori et al., 2014).

Default is one form of financial distress because financial distress is normally seen in terms of default, failure, distressed restructuring, and bankruptcy depending on the objectives and methodology of the research (Haregewayin 2017). Default is a result of credit risk. Therefore, credit risk can be viewed as the likelihood of the pledged future cash flows on financial claims held by a financial institution not being paid as agreed. Lack of information is the originator of credit risk, that is; if lenders have perfect information they will not extend credit to potential defaulters. Information asymmetry theory suggests that on a loan transaction, borrowers have more information than lenders (CFI, 2021). When lenders act purely on the information given by the borrowers, there is a probability to advance credit to borrowers who do not deserve resulting in the adverse selection problem and the result is market failure. In addition, borrowers might borrow on account of low-risk projects but later shift the money to high-risk projects causing the moral hazard problem (Orgler, 1970). On the other hand, the Credit Risk Theory is based on the terms and conditions where product offerings are provided to an entity or a person for the payments on the later agreed dates. When borrowers fail to honor payments of their dues in time agreed, then the lenders will be subjected to credit risk leading to loan default (Chen 2021).

Lending institutions classify their customer as either bad or good, in which case it is usefully separating potential bad customers from potential good customers to avoid extending credit to potential defaulters. This requires developing a model that discriminates between bad and good borrowers (Haregewayin 2017). The borrower's characteristics used by the models are usually refined into smaller groups called predictive variables. The predictive variables are believed to indicate if the applicant will fall into the good or bad repayment category (FDIC 2007). In this study, the following variables were used: Gender, Age, Marital Status, Guarantor, LSF Contribution, Loan Amount, Loan Term, Weekly Loan Installments, Loan Purpose, and Number of Loan Cycles. According to the study done by Kitonyi et al., (2019), nonperforming loans affect MFIs' financial performance negatively and there should be in place a management system to curb default. The study also showed an increase of losses amounting to $3.54 million between the years 2016 and 2017 from microfinance institutions as quoted from the Central Bank of Kenya (CBK) Report of 2017. ECLOF Kenya Limited (EKL) is among the microfinance institutions that do credit lending in Kenya and it has its presence country-wide with established offices in Nyanza including Kisumu Branch. The study will focus on the clients of the EKL Kisumu Branch. Sutra Tanjung, (2020) indicated in the study the need for financial institutions to analyze their credit customers and develop ability to predict default rate among the credit customers. Altman Model-Discriminant Analysis was used in this study to predict credit default among microfinance customers at ECLOF Kenya limited.

1.1.1 Altman Model-Multiple Discriminant Analysis

Altman Model, as it was developed by Altman (1968) is widely used by corporates to predict credit risk and financial distress, and it is basically a discriminant analysis (credit classification model) from the family of linear discriminant models. The Altman model remains the standard against which many other prediction models of default and bankruptcy are measured, and, most academic scholars and financial market practitioners use the model for various purposes (Altman, 2018).

The management of financial institutions is always concerned whether the applicant of the loan will end up being a good payer or a bad payer. To enable the management make prudent decisions of lending, Credit Score models are useful in determining the probability of the borrower's default and to group credit clients into risk classes. The credit models hence capture characteristics of the borrower that will generate scores to enable the lender gauge the borrower's risk at any particular moment. The lenders then use the results of the credit models to either lend or not lend to the potential borrowers as a way to manage the risk of default and loss of funds (Orgler, 1970).

There are several financial models that have been developed to predict financial crisis. The models are Altman Z-Score and Zmijewski model. Also there is Springate model and Ohlson model. These models are used to predict financial distress and credit default (Sutra Tanjung, 2020). This study was predicting the credit default status of microfinance customers and the Altman Model (Discriminant Analysis) was used.

1.1.2 Discriminant Analysis Model.

Altman (1968) used the term Discriminant analysis in the article 'Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy' as a statistical tool used to sort observations into one or more groupings that are dependent upon observable characteristics of an individual. The Discriminant Analysis Model is also called the Altman Model and is used to predict a company's financial failure such as credit default. This method is useful to explore the relationship that might exist between a group of discriminators (independent variables) with one output (dependent variable) simplified as zero (0) or one (1)

Based on the number of variations found in qualitative variables, Discriminant Analysis Model could be for two or more groups. The Discriminant Analysis Model is applied in many fields such as in financial institutions. The MFIs can use this model to evaluate and predict credit default risk based on the borrower's characteristics for prudent management decisions before advancing credit to the borrowers (Manousaridis 2017).

1.1.2.1 When to Use Discriminant Analysis Model.

Discriminant Analysis is used to show that one variable which is dependent is as a result of a linear combination of variables that are independent. The dependent variable is usually categorical while independent variables are continuous and are assumed to have a normal distribution. Therefore, the Model differentiates groups using some predictor variables. It helps to identify the factors that are more important in discriminating the group classes in a given phenomenon. The relative coefficients and significance of each predictor factor are given in the results of Standardized Canonical Discriminant Function Coefficients. It then helps in theory validation to know whether the cases were rightly classified as predicted.

1.1.2.2 Assumptions of Discriminant Analysis Model.

The following are assumptions for the Discriminant Analysis: For each group of the dependent variable, the independent variables are assumed to be normally distributed. Across all levels of independent variables, the group variances are assumed to be equal and it is tested with Box's M. An increase in correlation between independent variables will decrease the predictive power of the discriminant model. And, on independence, sampling is done randomly to get the sample cases to be analyzed (Katam 2018).

1.1.2.3 Discriminant Analysis Function

According to Leech, Barrett, and Morgan (2015), Discriminant Analysis Function is a linear combination of the independent variable for a given class of dependent variables. The function helps in discriminating a class of groups by using a set of predictor variables to explain an event observed. Discriminant scores are used in the function to find the capability of the function in predicting group classes.

The Linear discriminant analysis model presents a linear combination of the variables as shown below:

$Z = a + \beta 1\ X1 + \beta 2\ X2 + \beta 3\ X3 + \ldots\ldots.. + \beta N\ XN.$

Given:

Z = Dependent Variable,

a = the Constant, and $\beta1$, $\beta2$, $\beta3$…......are discriminant coefficients.

X1, X2, X3…… are Independent Variables.

X1= Gender of the borrower, X2=Age of the borrower, X3= Marital Status of the borrower, X4= Guarantor of the borrower, X5= Loan Amount to be borrowed, X6= Loan Term in weeks, X7= Weekly Loan Installment, X8= LSF Contribution made by the borrower, X9= Loan Purpose, X10= Number of Loan Cycles.

1.1.2.4 Discriminant Coefficients

Discriminant Coefficient is the weight for every predictor in the Discriminant Analysis Model. This weight is a unique contribution by each predictor when group classes have to be predicted. The results are gotten using discriminant coefficients to achieve the purpose of classifying the group membership that determines the dependant variable in the research.

The standard canonical discriminant function coefficients indicated the importance of each independent variable and the direction of their relationships. Variables with high coefficients values are the strongest predictors of credit default (Leech, Barrett, and Morgan, 2015).

1.1.2.5 Eigenvalue

From the Discriminant Analysis Model, the eigenvalue is a measure of explained variance.

It is useful to get the ratio between the explained and unexplained variables in the analysis hence the bigger the value (greater than 1.0) the better the discrimination. The Eigenvalue is used to know how groups are well differentiated in the function. When the eigenvalue is greater than 1.0 it indicates that the function differentiates the groups in a better way (Leech, Barrett, and Morgan, 2015).

1.1.2.6 Wilks's Lambda

According to Leech, Barrett, and Morgan (2015), the validity of the Discriminant Analysis Function is confirmed by Wilk's Lambda. The value for Wilk's Lambda normally ranges from 0 to 1 and it helps in testing the Discriminant Function's significance; that is, the discriminatory power of the model is strong when the value of Wilk's Lambda is smaller.

1.1.1.7 Classification of Results

The Classification of Results in Discriminant Analysis shows the correct prediction percentage of the model in predicting the group membership. It indicates how well is the dependent variable being predicted by the combination of independent variables. This then helped the researcher to know the prediction power of the Discriminant Function in predicting the default and non-default status of the credit customers (Leech, Barrett, and Morgan, 2015).

1.1.3 ECLOF Kenya Limited

ECLOF Kenya Limited (EKL) is a microfinance institution offering financial and non-financial related products to customers in Kenya. The customers are either micro, small or medium business people engaged in income-generating ventures. EKL registered in 1994 as a credit – only company which is limited by guarantee. EKL then restructured to a company limited by shares in the year 2019. ECLOF Kenya Limited uses its credit facilities as tools of empowerment among the youths, women and men to strategically unlock their God-given potential as entrepreneurs. ECLOF Kenya Limited covers 40 counties in Kenya and it is involved in Microcredit lending. Therefore, EKL is a classical representation of microfinance institutions in Kenya (www.ECLOF-kenya.org, 2021).

1.1 Research Problem

The exposure to credit default is experienced by MFIs all over the world making it necessary for the MFIs to design mechanisms that are viable to deal with credit default. Loans are the main income-generating assets for MFIs. However, non-performing loans in various arrearage categories affect the financial performance of MFIs significantly. There is a need to have better loan management systems, and, also a need to rely on the information about customer creditworthiness and diligent business assessment so as to make prudent decisions on credit lending (Kitonyi et al., 2019).

Haregewayin (2017) noted the importance of MFIs in developing countries. Haregewayin showed that the MFIs provide financial services to the people who cannot get such services from commercial banks. The study then recommended that the portfolio at risk (PAR) over 30 days need to be closely watched and taken care of because it negatively affects the financial health of

MFIs. Musango (2018) indicated that in credit lending the future is always uncertain and loans advanced to customers carry a credit risk leading to financial distress. Credit customers can default voluntarily or involuntarily causing additional costs of recovery and refinancing to the lender.

Several scholars have not agreed on the factors that cause credit default in MFI customers. Ofori et al., (2014), highlighted Marital Status, Age, Gender, Residential Status, Loan Amount, Income Level, Number of Defendants, and Tenure as significant in determining default. While Aslam et al., (2019) noted that Age, Education levels, monthly revenue, extra income, number of dependents, and type of business were seen as indifferent in predicting default status.

Qamruzzaman & Jianguo, (2016) used four financial distress prediction models; AltmanZscore, Grover G-score, Springate S-score, & Zmijewski X-score were used. The study revealed mixed predictions of financial distress. Ofori et al., (2014) and Sayuti & Ibrahim, (2018) used Logistic Regression to find the determinants of credit default. Makini, P.A. (2015) showed that the Altman Z-Score model was still appropriate in determining the probability of financial distress of firms. Hence, methodological gap exists because several models have been used to predict financial distress and each model gives different results. This research used Discriminant Analysis Model to predict default in microfinance clients.

Based on the above research gaps, this study aimed at predicting credit default among microfinance credit customers and to answer the question; can the MFI credit customers be discriminated into good or bad borrowers before lending?

1.3 Research Objective

The objectives of this study are:

- To find the factors that are important in establishing credit customers' default risk.
- To evaluate the relative degree of the importance of each of the factors that affect credit default in MFI customers.

1.4 Value of the Study

The research work is important to various stakeholders. To the Academicians and scholars, the research will be useful to carry out further studies in predicting financial distress of microfinance credit customers.

The research will provide a model that is needed in predicting whether or not a credit customer will default, and as a result, to enable the management of microfinance institutions to make informed decisions in credit lending. Lending institutions can classify their customer as either bad or good, in which case it is usefully separating potential bad customers from potential good customers to avoid extending credit to potential defaulters.

The policymakers will use the research findings to establish guidelines in the microfinance sector.

Again, the business advisors and financial investors will have the knowledge of customer factors that discriminate the good and bad loan payers, and the prediction model that can predict customers' credit default for guided investment decisions.

CHAPTER TWO

LITERATURE REVIEW

2.1 Theoretical Review of Literature

From early studies of Beaver (1966) and Altman (1968), a wide variety of financial ratios have been used to assess the economic health of companies through accounting literature. However, the literature predicting credit default and financial distress has evolved over time without an explicit theory that really indicates what financial ratios or how many ratios, or what weighting approach will best be used to work on the assessment of default probability (Sievers et al., 2017). This section covers the theoretical Framework regarding credit default that is relevant to the study.

2.1.1 Credit Risk Theory

Credit is the offering of services or goods to an entity or person based on the agreed conditions and terms for the payments to be made later. The payments can be with or without interest within the contract period. Credit Risk then happens when a debtor does not make the payments of what is due as and when they fall due. Therefore, when the debtor fails to pay the dues on agreed time, the lender will be exposed to credit risk which then leads to default.

Credit Risk is then stated as the investor's risk of loss, financial or otherwise emanating from the borrower's failure to honor the payment of their dues as agreed in the terms of the contract (Haregewayin 2017).

2.1.2 Information Asymmetry Theory

The information Asymmetry Theory was started by Akerlof in 1970. The theory describes a state where one party in a given relationship has better information than another.

This theory is based on the notion that the lender may not get all the necessary information about the intended purpose of the loan the credit client wants to borrow. The lack of full information from the borrower that will enable the lender to make informed decisions can lead to moral hazard and adverse selection. The information gaps then cause financial distress as the credit customer defaults (Musango 2018).

2.1.4 Credit Scoring Models

Credit Scoring Models also called Scorecards in the financial industry are majorly used by the management to get predictive information that will enable them to make decisions on loan processing and risk pricing.

Investopedia (2021) defined credit scoring as a statistical analysis done by financial institutions to ascertain the probability of delinquency or default of a potential credit client. The credit scores generated by the model are then used to determine the borrower's ability to be loaned. The popular score models are FICO (Fair Isaac Corporation) and Vantage Score. The FICO score is mostly used and it gives a score number of between 300 and 850 with the highest score reflecting a lower credit risk.

In Kenya, FICO scores used by financial institutions include TransUnion and Metropol and EKL uses Metropol to determine the credit scores of its clients.

2.1.5 Description of the Variables.

This study has two variables; Dependent and Independent Variables.

The Dependent Variable is the default prediction status of the credit client. From the data used, if the position of the borrower is default, it is denoted by one (1) and if the position is non-default, the client is denoted by zero (0).

The Independent Variables in this research relate to the loan characteristics and borrower's characteristics. The independent variables included Gender, Age, Marital Status, Guarantor, LSF Contribution, Loan Amount, Loan Term, Weekly Loan Installments, Loan Purpose, and Number of Loan Cycles. These are some predictor characteristics that affect the likelihood of default of a credit customer in microfinance institutions. This study aimed at establishing which factors are important in establishing credit default risk and to evaluate the relative degree of the importance of each of the factors in credit default prediction.

2.1.7 Borrowers' Characteristics

In this category, characteristics such as the borrower's Gender, Age, Marital Status, Guarantor, LSF Contribution were used. The age was measured in terms of years. The age of the borrowing client could influence the level of risks a client may want to take which in turn showed the probability of default. The Gender showed a client was either a male or a female. Gender could indicate the cultural influence and responsibilities of the borrowers in loan repayments. Responsible customers would not want to default loans as opposed to those who were less responsible. The guarantor was someone with the ability to repay the loan in case the borrower had financial challenges to service loans so as to allow or prevent default. In the study, the guarantor was either the spouse or another person other than the spouse who gave consent to guarantee the loan. Marital status showed whether the borrower was staying with a spouse (married) or living without a spouse in such a case as being single or not applicable (unmarried, separated or widowed). LSF Contribution was a mandatory weekly savings a client made before and during the entire loan period as cash collateral. These mandatory savings showed the commitment of the borrower which in turn gave the probability of loan default (Aslam et al., 2019).

2.1.8 Loan Characteristics

These factors were related to the loans borrowed by the credit customers. They included Loan Amount, Loan Term, Weekly Loan Installments, Loan Purpose, and Number of Loan Cycles. Loan Amount was the principal amount borrowed by the credit client at the time of loan application. The client would pay the principal loan plus the loan interest as per the loan contract and this had significance in default determination. The Loan Term was the period of the loan contract which was either short-term or long-term. This loan period then demonstrated that the borrower had a longer or shorter commitment in paying the loan which contributed to the probability of the loan being defaulted. Weekly Loan Installments was the amount the borrower repaid in equal repayment amounts. When loan installments were not favorable to the borrower, it could lead to loan default. Loan Purpose meant the category of the client's business where the borrower made use of the loan. The purpose of the loan was either Agricultural/Business or Otherwise, which indicated the cash flow cycles that determined the success of loan repayments. The Number of Loan Cycles meant the loan graduations which showed the number of loans the client had previously taken and completely paid. The loan cycle measured the customer's willingness to continue borrowing affecting the status of their repayments (Aslam et al., 2019).

2.2 Empirical Review

Ofori et al., (2014) carried out a study that sought to find the determinants of credit default in MFIs in Ghana. 2631 loan applications were considered in the study and used Binary Logistic Regression Model in predicting the probability of default. Many of the microfinance institutions studied were faced with default problems even though they played a major role in economic development. The study found such factors as Marital Status, Age, Gender, Residential Status, Loan Amount, Income Level, Number of Defendants, and Tenure significant in determining default. The study also found that among the young generation and the males, there was more default; however, loan purpose was not significant in credit default determination. The study recommended the understanding of the factors that cause loan borrowers to default so that MFIs can develop countermeasures to prevent and reduce the probability of default occurrence. Sayuti & Ibrahim, (2018) conducted a study in the Niger state of Nigeria to identify the social and economic factors that affect the likelihood of the occurrence of default rate in MFB loans. The study used 300 borrowers selected through multistage random sampling and the data was analyzed using Logit Model. The study found out that the credit client's age, family size, sex, interest rate of loan, income, and loan term were significant in determining the probability of loan default. On the other hand, the study showed borrowers' experience and education levels were not significant in loan default prediction.

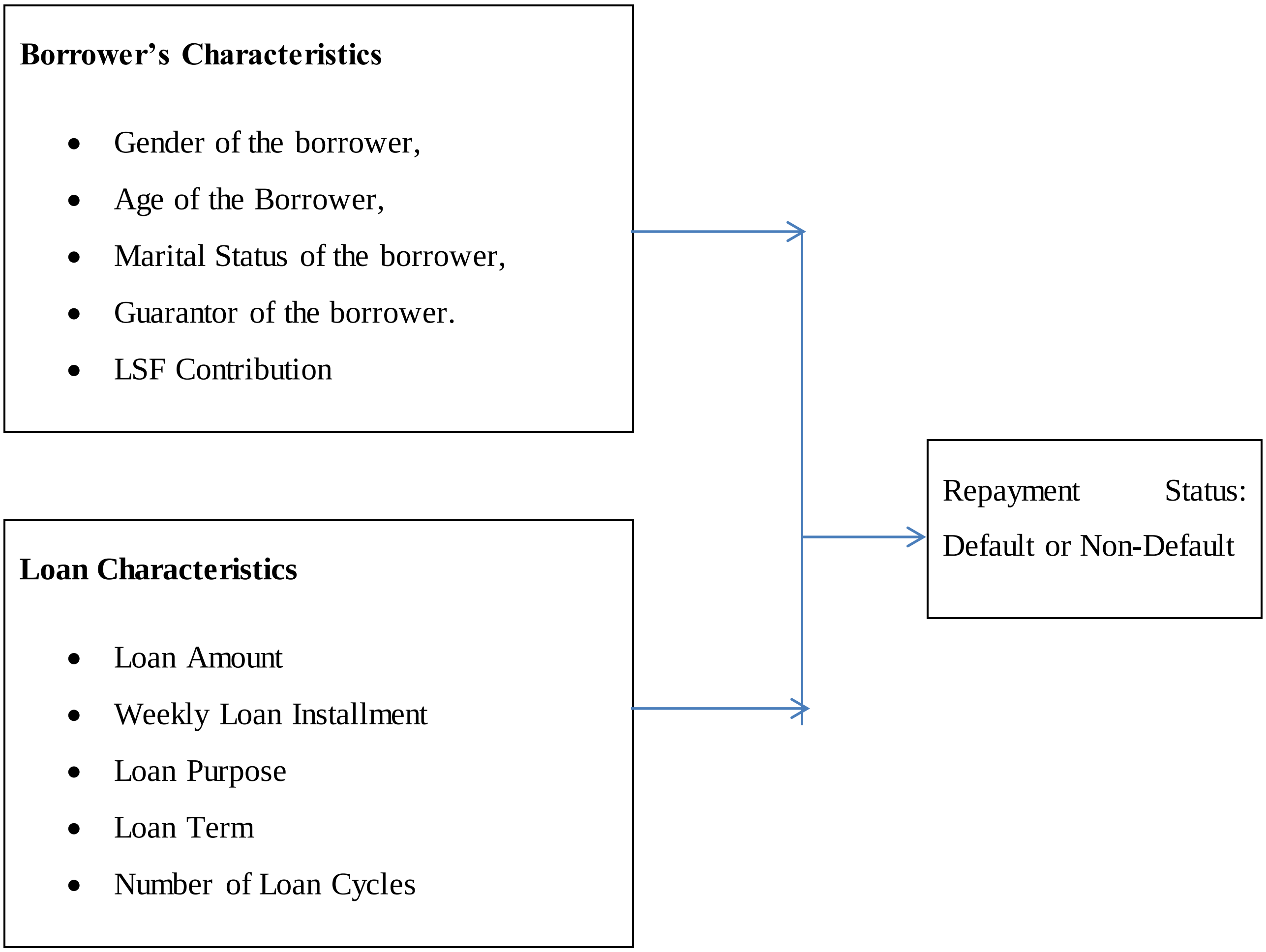
Aslam et al., (2019) empirically carried out a study on predicting the probability for loan default among bank borrowers. The study focused on the factors contributing to the default among Grameen Bank (GB). Through the use binomial logistic regression, the study noted that the living status of the borrower and the type of loan product contributed highly to the prediction of default. Other factors like Age, Education levels, monthly revenue, extra income, number of dependents, and type of business were seen as indifferent in default prediction, while age did not account in the prediction of loan default.

Musango (2018) investigated the determinants of loan repayments defaults in Microfinance Banks in Kenya (MFB). The descriptive research design was applied and from the 13 licensed MFB, 2 credit officers and two borrowers were randomly sampled from each MFB. Primary data used was gotten through administered questionnaires and data was analyzed using SPSS and Regression Model. The study established borrowers' characteristics such as income levels, loan amounts, and loan terms had a positive significance to determine default rates. However, the borrowers' age, loan purpose, and duration of stay in the institution did not influence the default rate. Again, the findings showed that Institutional factors like credit appraisal, loan monitoring and credit officers' training influenced status of loan repayment. On the other hand, credit policies and procedures did not determine the loan repayment default.

Manousaridis (2017) stated that one of the limiting factors for economic growth is corporate bankruptcy. Banks play a crucial role nationally and internationally and their impact is significant in the economies. The study highlighted the need of all the stakeholders to get reliable prediction models to measure and assess the financial health of banks. The study aimed at knowing whether Altman's Z-score model could be used in the emerging markets to measure the financial health of the banking organizations. Through multivariate discriminant analysis, two groups of the testing sample were used. From the period 2006-2016, "Failed" groups of banks that had problems of the economy and the 'Non-failed' group that were still active were used. The findings showed that Z-Score Model could predict financial distress particularly two years before the known time of 'failure' with effectiveness. However, there were limitations to predicting the financial distress and credit risk of bank institutions for the emerging economies. The research suggested the improvement of the Z-Score model to take into account the financial institutions operating with high leverage.

Makini, P.A. (2015) noted that both small and large organizations suffer from financial risks, the study also indicated the difficulty of determining financial risks by use of financial rations only given that there could be other factors that cause financial risks. Makini researched on the Altman's Z-SCORE Model's validity in predicting the Financial Risks of Listed Companies at the Nairobi Securities Exchange (NSE) and made recommendation for the use of Altman's Z-SCORE Model by various organizations to help investors know the financial position of the companies they are investing in.

2.3 Conceptual Framework



Independent Variable **Dependent Variable**

Figure 2.1 Conceptual Framework

2.4 Summary of Literature Review

From the above literature review, it was evident that there existed knowledge gap concerning factors that caused credit default or financial distress. MFIs played a crucial role in economic developments especially in emerging economies like Kenya as they served credit customers. Although MFIs empowered people economically, they also suffered a lot of losses due to default.

Many factors had been highlighted that caused default in credit lending. According to Ofori et al., (2014), Marital Status, Age, Gender, Residential Status, Loan Amount, Income level, Number of Defendants, and Tenure were significant in determining default. However, Aslam et al., (2019) found that Age, Education levels, monthly revenue, extra income, number of dependents, and type of business were seen as indifferent in default prediction.

Several models had been used to predict financial risks and each model gave mixing results. Altman's model of prediction of financial risk was still relevant and recommended for financial institutions to predict credit default. Makini, P.A. (2015) in his study showed that the Z-Score Model of Altman was still appropriate in determining the probability of financial crisis of firms.

Many studies reviewed were based on banks or bank clients and to the best of the researcher's knowledge, there were few studies done on MFIs credit customers in predicting credit default and financial distress. Manousaridis (2017) recommended in his study a further study on financial institutions to get an understanding of default prediction.

Based on the above literature review, this research bridged the gaps by conducting a study on Predicting credit default of microfinance credit customers in ECLOF Kenya limited.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the Research Design, Target Population, Sample Design, Data Techniques, and Data Analysis are discussed.

3.2 Research Design

The study aimed at predicting credit default of microfinance credit customers in ECLOF Kenya Limited. A descriptive Research Design was used to realize stated research objectives in the study.

According to Munyua (2016), descriptive research usually enables to obtain information related to the phenomena's present status and it describes it as it exists with respect to factors or variables of a given scenario. In the descriptive design, the researcher can observe and describe an event in order to answer the 'who', 'what', 'how', and 'when' questions with accuracy and precision. The descriptive design was considered since it enabled the gathering of accurate and reliable data that was appropriate to establish which factors were important in predicting default risk in ECLOF Kenya Microfinance credit customers.

3.3 Population of Interest

The research aimed at predicting the credit risk of microfinance credit customers targeting ECLOF Kenya Limited Customers. The population elements were the credit borrowers and the target population was the credit customers at ECLOF Kenya Limited in Kisumu Branch.

The study focused on the Kisumu Branch of Elcof Kenya Ltd which had around 2000 credit borrowers.

3.4 Sampling Plan

A sample is the subject of the population which is used to make inferences to the study population. The sample enables save cost and time expenses associated with analyzing every character of the population (Haregewayin 2017).

Credit customers volunteer their personal data when they apply for loans in ECLOF Kenya Ltd. Hence the study used the successful loan applications of the individuals who borrowed credit between Jan 2018 to Dec 2018. Using stratified random sampling, loans were then separated into two categories of non-defaulted loans and defaulted loans. And, for each category of the loans, 35 defaulted loans and 35 non-defaulted loans were randomly selected to form the sample size of 70 cases.

3.5 Data Collection.

Secondary data was used and was extracted from the sample of successful loan forms applied by the borrowers. These successful loan forms were the loan applications that met the loan requirements and proper credit scores of the customers at the time of application and disbursements. Normally when customers apply for loans, they give their personal information that is usually captured in the loan forms. The researcher then used the borrower's data extracted from the loan application forms in the loan file. The data collected was related to such factors as Gender, Age, Marital Status, Guarantor, LSF Contribution, Loan Amount, Loan Term, Weekly Loan Installments, Loan Purpose, and Number of Loan Cycles for analysis. The loan application forms of both defaulters and non-defaulters were retrieved for data collection through a Data Collection Instrument from the period January 2018 to December 2018.

This data was qualitative and captured the client factors that were used to establish which of such factors were important in establishing default risk.

3.6 Data Analysis.

Discriminant Analysis Model was used as the data analysis technique in the study. The discriminant analysis is related to Altman Model which used multivariate Discriminant Analysis in financial crisis prediction. The model aided in discriminating between Non-Default credit customers and Default credit customers using predictor factors observed from the borrowers. The analysis sought to minimize the within-group variance and maximize the between-group variance and then give the relationship between a dependent predictive variable and a group of predictors called independent variables.

In discriminant analysis, all the predictive variables were analyzed simultaneously irrespective of the discriminant power of the factors. The borrower and loan factors such as Gender, Age, Marital Status, Guarantor, LSF Contribution, Loan Amount, Loan Term, Weekly Loan Installments, Loan Purpose, and Number of Loan Cycles that were analyzed to determine the probability of default. Data was analyzed using SPSS (IBM SPSS statistics 23) and Discriminant Analysis in the research. Discriminant function showed default status as the dependent variable while borrower and loan characteristics formed the independent variables.

In the analysis, the Eigenvalue and Canonical Correlation were used to know the predictive power of the Discriminant Analysis. The eigenvalue was useful to get the ratio between the explained and unexplained variable in the analysis hence the bigger the value (>1) the better the discrimination. A higher value of Canonical Correlation explains the high association between the groups indicating the confidence that the selected borrowers were either defaulters or non-defaulters.

The validity of the Discriminant Analysis Function was confirmed by Wilk's Lambda. Wilk's Lambda gave a value that ranges from zero (0) to one (1) and it helped test the Discriminant Function's significance; the discriminatory strength of the MDA is strong when the value of Wilk's Lambda is smaller. The standard canonical discriminant function coefficients indicated the significant contribution for every independent variable and direction of their relationships. Variables with high coefficients values were the strongest predictors of credit default. Again, structure matrix correlations showed the independent variables that have a stronger relationship with the discriminatory variables.

Finally, the Classification of Results helped the researcher to know the prediction power of the Discriminant Function in predicting the default and non-default status of the credit customers.

Therefore, the results from the Data Analysis were used for the purpose of drawing conclusions as to which factors were important in establishing default risk and also evaluating the relative degree of the importance of each of the factors in this study of predicting credit risk of microfinance credit customers.

CHAPTER FOUR

DATA ANALYSIS, FINDINGS AND DISCUSSIONS

4.1 Introduction

This chapter shows the Data Analysis carried out, research findings plus the interpretation of results. The research objective was to find factors that are important in establishing credit default in MFI customers and to evaluate the relative degree of importance of such factors in default prediction. Data collection was done from a sample that contained 35 Non-Default and 35 Default cases for analysis, and the following factors were considered in the analysis: Gender, Age, Marital Status, Guarantor, Loan Amount, Loan Term, Weekly Installments, LSF Contribution, Loan Purpose, and Number of Loan Cycles. Discriminant Analysis was conducted using SPSS version 23 software and the findings were presented as descriptive statistics.

4.2 Descriptive Analysis.

In Discriminant Analysis, the aim is to predict membership in each group using multiple predictor variables. The group is the dependent variable which is either Default or Non-Default. The Predictors are the independent variables which are the borrower and loan factors. The analysis helped to discriminate the credit customers into good or bad payers using the borrower and loan characteristics.

4.3 Data Analysis Presentation

Table 4.3.1 Analysis Case Processing Summary

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		70	100.0
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Total	0	.0
Total		70	100.0

Source: Researcher (2022)

Table 4.3.1 presents Analysis Case Processing Summary which shows that there are 70 valid cases. There wasn't excluded case in the analyzed data.

Table 4.3.2 Group Statistics.

Group Statistics

Payment Status		Mean	Std. Deviation	Valid N (listwise)	
				Unweighted	Weighted
Non-Default	Gender	.37	.490	35	35.000
	Age	40.86	11.178	35	35.000
	Marital status	1.29	.710	35	35.000
	Guarantor	.43	.502	35	35.000
	LSF Contribution	31.83	9.319	35	35.000
	Loan Amount	98714.29	70610.186	35	35.000

	Loan Term	52.94	14.408	35	35.000
	Loan Installment	1744.61	927.122	35	35.000
	Loan Purpose	.91	.284	35	35.000
	Loan Cycles	4.63	3.557	35	35.000
Default	Gender	.23	.426	35	35.000
	Age	36.80	10.892	35	35.000
	Marital status	1.14	.601	35	35.000
	Guarantor	.63	.490	35	35.000
	LSF Contribution	15.73	10.367	35	35.000
	Loan Amount	49171.71	33306.468	35	35.000
	Loan Term	48.00	6.306	35	35.000
	Loan Installment	1009.20	622.564	35	35.000
	Loan Purpose	.94	.236	35	35.000
	Loan Cycles	1.34	.684	35	35.000
Total	Gender	.30	.462	70	70.000
	Age	38.83	11.145	70	70.000
	Marital status	1.21	.657	70	70.000
	Guarantor	.53	.503	70	70.000
	LSF Contribution	23.78	12.710	70	70.000
	Loan Amount	73943.00	60215.460	70	70.000
	Loan Term	50.47	11.317	70	70.000
	Loan Installment	1376.91	867.006	70	70.000
	Loan Purpose	.93	.259	70	70.000
	Loan Cycles	2.99	3.034	70	70.000

Source: Researcher (2022)

Table 4.3.2 indicates Group Statistics. The standard deviations (Std) and the means of predictive variable of Default groups together with Non-Default group are highlighted. The combined group standard deviations and group means for the variables are as follows: Number of Loan

Cycles presented a mean value of 2.99 with a standard deviation value of 3.0 while LSF Contribution showed a mean value of 23.78 with a standard deviation of 12.71. The findings indicated Loan Purpose had a mean of .93 with a standard deviation of .259, Weekly Loan Installments' mean is 1376.91 with a standard deviation of 867.0 and Loan Amount's group mean was 73,943 with a standard deviation of 60,215.46. The predictor variable Guarantor's mean is .53 with a standard deviation of .503, Marital Status' mean was 1.21 and a standard deviation value of .657, Age presented a mean of 38.83 with a standard deviation of 11.145, while Gender gave group mean value of 0.3 with 0.462 as the standard deviation.

Table 4.3.3 Tests of Equality of Group Means.

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
Gender	.976	1.693	1	68	.198
Age	.966	2.365	1	68	.129
Marital status	.988	.825	1	68	.367
Guarantor	.960	2.843	1	68	.096
LSF Contribution	.593	46.719	1	68	.000
Loan Amount	.828	14.094	1	68	.000
Loan Term	.952	3.457	1	68	.067
Loan Installment	.818	15.178	1	68	.000
Loan Purpose	.997	.210	1	68	.648
Loan Cycles	.702	28.802	1	68	.000

Source: Researcher (2022)

Table 4.3.3 above shows the level of significance of each of the predictor variables. The Number of Loan Cycles, LSF Contribution, Weekly Loan Installments, and Loan Amount had all sig, value of 0.000 indicating that the variables were statistically significant meaning that these variables discriminate between the clients that defaulted and clients that did not default their loans. The other variables were not statistically significant with their sig. values being above 0.05 significant levels.

Table 4.3.4 Test of Results.

Test Results

Box's M		198.813
F	Approx.	3.048
	df1	55
	df2	14932.332
	Sig.	.000

Tests null hypothesis of equal population covariance matrices.

Source: Researcher (2022)

Table 4.3.4 gives the test of results and shows a significance of 0.000 from the Box's M. This means that there are unequal group variances hence the null hypothesis can be rejected.

4.4 Test of Results Summary of Canonical Discriminant Functions.

Table 4.4.1Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.622[a]	100.0	100.0	.787

a. First 1 canonical discriminant functions were used in the analysis.

Source: Researcher (2022)

In table 4.4.1, the Eigenvalue is 1.622 with a Canonical Correlation of 0.787 which explains the more variance in dependent variable.

Table4.4.2 Wilks' Lambda

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.381	60.729	10	.000

Source: Researcher (2022)

In table 4.4.2, the Wilks' Lambda is 0.381 and the significance value is 0.000. This indicated that the prediction model was significant statistically at $\lambda = .381$, $\chi 2 = 60.729$, $p < .001$. The predictors significantly discriminated between the Default and Non-Default groups in the analysis.

Table4.4.3 Standardized Canonical Discriminant Function Coefficients

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Gender	-.091
Age	-.060
Marital status	-.021
Guarantor	-.348
LSF Contribution	.790
Loan Amount	-.845
Loan Term	.074
Loan Installment	1.137
Loan Purpose	-.152
Loan Cycles	.611

Source: Researcher (2022)

In this Table 4.4.3, the capability of each predictor variable in predicting the group membership of default or non-default is indicated for the Discriminant Model. The variables Weekly Loan

Installments, Loan Amount, LSF Contribution, and Number of Loan Cycles have the highest coefficients of 1.137, -.845, .790, and 0.611 respectively and they were more weighed than Gender, Age, Marital Status, Guarantor, Loan Term and Loan Purpose.

Table4.4.4 Structure Matrix

Structure Matrix

	Function
	1
LSF Contribution	.651
Loan Cycles	.511
Loan Installment	.371
Loan Amount	.357
Loan Term	.177
Guarantor	-.161
Age	.146
Gender	.124
Marital status	.086
Loan Purpose	-.044

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions

The variables within the function are ordered by absolute size of correlation.

Source: Researcher (2022)

Table 4.4.4 on Structure Matrix, LSF Contribution and Number of Loan Cycles variables have the highest predicting power in the model with values of 0.651 and 0.511 respectively. This is followed by Weekly Installments (0.371) and Loan Amount at 0.357. The rest of the variables have lower predicting capability with Loan purpose being the least with -0.044 as the predicting value.

Table4.4.5 Canonical Discriminant Function Coefficients

Canonical Discriminant Function Coefficients

	Function
	1
Gender	-.199
Age	-.005
Marital status	-.033
Guarantor	-.702
LSF Contribution	.080
Loan Amount	.000
Loan Term	.007
Loan Installment	.001
Loan Purpose	-.582
Loan Cycles	.239
(Constant)	-2.585

Unstandardized coefficients

Source: Researcher (2022)

The results of Table 4.4.5 above present the coefficients of Discriminant Function for every independent variable in the Discriminant Model. The linear discriminant analysis model presents a combination of variables in a linear form as below:

$Z=\alpha + \beta 1X1 + \beta 2X2 + \beta 3X3 + \ldots\ldots.. + \beta nXn$

Z= -2.585 -.199Gender -.005Age -0.033Marital Status -0.702Guarantor +0.08LSF Contribution +0.000 Loan Amount +0.007 Loan Term in Weeks +0.001Weekly Loan Installments -0.582Loan Purpose +0.239Number of Loan Cycles.

The short form of the Discriminant Function is as below:

Z= -2.585 -.199Gen -.005Ag -0.033MaSt -0.702Guar +0.08LSFC +0.000LoAm +0.007 LTW +0.001WLI -0.582LoPu+ 0.239NLC.

Table4.4.6 Classification Resultsa,c

Classification Results[a,c]

		Payment Status	Predicted Group Membership		Total
			Non-Default	Default	
Original	Count	Non-Default	31	4	35
		Default	3	32	35
	%	Non-Default	88.6	11.4	100.0
		Default	8.6	91.4	100.0
Cross-validated[b]	Count	Non-Default	31	4	35
		Default	6	29	35
	%	Non-Default	88.6	11.4	100.0
		Default	17.1	82.9	100.0

a. 90.0% of cases were correctly classified from the original grouped cases.

b. 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.

c. 85.7% cases were correctly classified for the cross-validated grouped cases.

Source: Researcher (2022)

Table 4.4.6 above on Classification Results[a,c] indicate how well the model was predicting group membership. From Cross-Validated Count, The model predicted 88.6% of the clients classified as Non-Defaulters into the Non-Default group and it predicted 82.9% of the defaulted clients into the Defaulted group. This is a strong model that was able to predict the groups of Non-Default and Default Group.

4.5 Discussions of Findings

From the results of data analysis in table 4.3.1 on the Analysis Case Processing Summary, there were 35 Non-Default cases and 35 Default cases giving a total of 70 cases for the analysis. . All the 70 cases were valid for the analysis and correctly classified into Non-Default and Default groups. Table 4.3.2 showed an equal number of successful cases for both Non-Default and

Default. The findings indicated the variables' means and variables' standard deviations for Non-Default, Default, and Total groups. In comparison, The Number of Loan Cycles, LSF Contribution, Weekly Installments, Marital Status, Age, and Gender had higher means and standard deviations in the Non-Default group than in the Default group. Loan Purpose had almost the same mean and standard deviation in both Default and Default groups.

Table 4.3.3 indicated Tests of Equality of Group Means showing that Number of Loan Cycles, LSF Contribution, Weekly Loan Installments, and Loan Amount variables significantly discriminated the Default and Non-Default groups in the model. The Number of Loan Cycles, LSF Contribution, Weekly Loan Installments, and Loan Amount had a strong statistical significance with a value of significance being 0.000, hence they discriminated against the clients that defaulted and clients that did not default their loans. On the other hand, Gender, Age, Marital Status, Guarantor, Loan Term, and Loan Purpose had significance values of 0.198, 0.127, 0.367, 0.098, 0.067, and 0.648 respectively which is above significance value of 0.005 making them statistically insignificant in predicting credit default. These findings support the research done by Aslam et al., (2019) that showed Age and Loan Purpose were indifferent in predicting default status. However, the results of the study do not agree with Ofori et al., (2014) findings where Ofori concluded that Marital Status, Age, Gender are significant in determining default.

In table Table 4.3.4 on Test of Results, the Box's M has a 0.000 value of significance that is lower than 0.001 sig. value, meaning that there is unequal group variance and the default status of the credit clients can be predicted. The Eigenvalues of 6.22 in table 4.4.1 is large enough with Canonical Correlation value of 0.787 giving an Effect Size of 0.7872 which explains more variance in the dependence variable (Repayment Status). Therefore, the function has high discriminating power and is able to differentiate the Non-Default and Default groups better. Table 4.4.2 showed Wilks' Lambda as significant, $\lambda = .381$, $\chi2 = 60.729$, $p < .001$, and it indicated that including all the ten independent variables, the model significantly discriminated against the Default and No-Default groups. Table 4.4.3 presents coefficients of Standardized Canonical Discriminant Function that show the comparative importance of the predictor variables. These predictor variables; Weekly Installments, Loan Amount, LSF Contribution, and Number of Loan Cycles with coefficient values of 1.137, -0.845, 0.790, and 0.611 respectively contributed most to the differentiating those clients that defaulted and those that did not default. This is consistent with table 4.4.4 which shows LSF Contribution, Number of Loan Cycles, Weekly Loan Installments and Loan Amount have the highest predicting power in the model with values of 0.651, 0.511, 0.371and 0.357respectively. However, Gender (0.124), Age (0.146), Marital Status (0.086), Guarantor (-0.161), Loan Term (0.177), and Loan Purpose (-0.044) have lower predicting capability.

Lastly, the findings of the study in table 4.4.6 of Classification Results[a,c] indicated how well the discriminant analysis model was able to predict group membership of Non-Default and Default. From the original sample, 88.6% of Non-Default cases were predicted as Non- Default, and 91.4% of Default cases were predicted as Default. The model presented a high specificity than sensitivity because there were few Non-Default cases in the Default group.

On the question of the model's ability to predict the results accurately, the Discriminant Analysis model predicted the group membership accurately. From the cross-validation, the model correctly predicted 88.6% of Default cases and 82.9% of No-Default cases. The results indicated that the Model was fairly strong with a high prediction rate that can be used to predict the default status of credit clients given the predictive variables. The findings of this study were in line with the findings of Katam (2018) which found that the Discriminant Analysis Model was effective with a classification percentage of 82.9% in the assessments of financial performance of the NSE listed Kenyan manufacturing firms.

Therefore, the study results presented that Weekly Installments, Loan Amount, LSF Contribution, and Number of Loan Cycles predictor variables classify the group membership of Default and Non-Default. In conclusion, when such variables as Weekly Loan Installments, Loan Amount, LSF Contribution, and Number of Loan Cycles are known in advance for the potential borrowers, the default status of credit customers of MFIs can be predicted. The Discriminant Analysis Model is able to discriminate between "good-borrowers" and "bad-borrowers" to enable the management of MFIs make informed decisions to manage default risk before lending.

4.3 Explanation of Important Variables

4.3.1 Weekly Loan Installments

The loans are mostly repaid on weekly basis. Therefore, Weekly Loan Installments mean the amount of loan and interest borrowers pay every week as they service their loans. This variable was statistically significant in determining the default status of the credit customers. Clients with smaller installments were more likely to default on their loans than the clients with bigger weekly installments. This could be that the borrowers' ability is low hence borrowing smaller amounts of loans to fund small businesses that are not yet established. This could be startup businesses or struggling businesses whose cost of operation are relatively high. Clients with higher weekly installments were likely to repay well. This is attributed to established businesses that enable clients with bigger loans to maximize the returns hence serving the loans well

4.3.2 Loan Amount

This is the amount of loan a credit customer intends to borrow from the MFI. The factor enabled discriminate Non-Default and Default cases in the analysis. The Loan Amount is an indication that smaller loans were prone to default than bigger loans. The majority of the new customers take small loans for the first time in a way to test their ability to repay loans. Smaller loans end up being defaulted because of asymmetry of information resulting in moral hazard and adverse selection. Clients with bigger loans mostly have established businesses that are running and they have undergone tests of time to continue generating income to repay borrowed loans and they have a low default rate.

4.3.3 LSF Contribution Factor

This is mandatory weekly savings a client makes before and during the entire period of the loan term as cash collateral. The ability to save regularly by the credit customer determines the probability of defaulting loans advanced. When a client stops or skips to save into their LSF account, the chances of such a client defaulting loan is high. LSF contribution is a commitment of the client to ensure that they service their loans without default.

4.3.4 Loan Cycles

The loan cycle means the number of loans that the client had previously serviced in full before borrowing another loan with the same institution. This factor contributed to the prediction of default status. The clients with many number of loan cycles were likely to pay their loans well than the clients with a fewer number of loan cycles. It is also an indication of how long the clients have stayed with the MFI to develop loyalty to the organization. First-time borrowers and clients with a lower number of loan cycles had higher default risk.

CHAPTER FIVE

SUMMARY CONCLUTIONS AND RECOMMENDATIONS

5.1 Introduction

Chapter five deals with the summary of the study findings, research conclusions and recommendations. It also discusses the study limitations and suggestions for further research.

5.2 Summary of Findings

This study was carried out with an aim of predicting credit default among microfinance customers. The study objective was to find the factors that are important in establishing default risk among MFI credit customers. Again, the study evaluated the relative degree of the importance of each of the factors that affect default. The clients of ECLOF Kenya Limited microfinance institution were sampled for this research. A descriptive design was used to conduct the research. Secondary data was extracted from the file of loan applications that were applied for the year 2018. Using stratified random sampling, loans were then separated into two categories of non-defaulted loans and defaulted loans. And for each category of the loans, 35 defaulted loans and 35 non-defaulted loans were randomly selected to form the sample size of 70 cases.

The research was guided by Credit Risk Theory and Information Asymmetry theory while studies on financial distress and default were reviewed.

Discriminant Analysis was performed using SPSS version 23 software where the independent variables represented loan and borrower's characteristics, and, the dependent variable (Z) was a dummy which equaled one (1) for the defaulted loan and zero (0) for the non-defaulted loan. The loan and borrowers' characteristics analyzed included Gender, Age, Marital Status, Guarantor, Loan Amount, Loan Term, Weekly Installments, LSF Contribution, Loan Purpose, and Loan Cycles.

5.2.1 Important factors in establishing credit customers' default risk

The main objective was the determination of factors that are important in causing default risk among credit customers of microfinance institutions. The study results clearly demonstrated a relationship that was statistically significant between loan characteristics and repayment status.

Loan Cycles ($p = 0.000 < 0.05$), LSF Contribution ($p = 0.000 < 0.05$), Weekly Installments ($p = 0.000 < 0.05$) and the Loan Amount ($p = 0.000 < 0.05$) were more important in discriminating default and non-default categories hence determining the credit default of the borrower. When such factors are known, borrowers can be classified into good or bad to enable the lenders to manage default risk through prudent lending.

The predictor Guarantor ($p = 0.096 > 0.05$) and Loan Term ($p = 0.067 > 0.05$) were indifferent in predicting the default status of the borrowers. However, factors such as Gender ($p = 0.198 > 0.05$), Age ($p = 0.129 > 0.05$), Marital Status ($p = 0.367 > 0.05$), and Loan Purpose ($p = 0.648 > 0.05$) were statistically insignificant in determining credit default. Hence from the Discriminant Analysis Model, Gender, Age, Marital Status, and Loan Purpose did not contribute to the discrimination of default and non-default status.

5.2.2 The degree of importance of factors that establish credit customers' default risk

The objective of evaluating the relative degree of the importance of the factors in determining default risk was analyzed. The weighting of each factor analyzed was shown in the structure matrix table.

LSF Contribution (0.651), Number of Loan Cycles (0.511), Weekly Installments (0.371) and Loan Amount at (0.357) had the highest predicting powers in the model. However, Loan Term (0.177), Guarantor (-0.161), Age (0.146), Gender (0.126), Marital Status (0.086), and Loan Purpose (-0.044) had the lowest predicting powers in the model.

5.2.3 The Discriminant Analysis Model's Prediction Power.

The study established that the Discriminant Analysis Model was able to predict default cases by 82.9% and non-default cases by 88.6% indicating that this is a strong model with a high prediction rate that can be used to predict the default status of credit clients by MFIs for best decision making in lending.

5.3 Conclusions

The researcher was seeking to establish the factors that influence the repayment status of MFI credit borrowers. ECLOF Kenya credit customers were sampled for the study using borrower and Loan characteristics. The borrowers' characteristics and loan characteristics were analyzed for the groups of default and non-default status. Borrower characteristics included such factors as Gender, Age, Marital Status, Guarantor, while Weekly Installments, LSF Contribution, Loan Amount, Loan Term, Loan Purpose, and Loan Cycles were loan characteristics. The study concluded that loan characteristics such as Weekly Installments, LSF Contribution, Loan Amount, and Loan Cycles determined the default status in ECLOF Kenya MFI. Loan Term was indifferent while Loan Purpose was statistically insignificant hence was not considered to determine default status of credit borrowers.

On borrowers' characteristics, Gender, Age, and Marital Status were statistically insignificant and the study concluded that such factors did not determine default status. However, the Guarantor factor was considered as indifferent in getting the probability of default hence it was not clear whether or not it determines the loan default status of the borrowers.

The study also found that the Altman Model- Discriminant Analysis is a strong model that can predict the default status of MFI clients. The model was able to predict default cases by 82.9% and non-default cases by 88.6% indicating that Altman Model- Discriminant Analysis was a strong model.

5.4 Recommendations

From the findings and conclusions of the study, the research recommends that MFIs need to consider factors that can determine borrowers' chances of default. Weekly LSF Contribution which is a mandatory saving as cash collateral to loans must be embraced by the customer before funding. There should be consistency in paying such LSF during the entire loan term to prevent default. The MFIs need to properly assess the first-time borrowers on their first loan cycles to avert adverse selection. Clients who graduate their loan cycles need to be served well given that their default rate is low. On weekly Loan installments, the clients' capacity to borrow has to be well-vetted to prevent default. Caution should be exercised by the MFIs especially when clients prefer to pay smaller loan installments because that could be an indication that their ability is small and are likely to default.

Loan Amount is a factor that MFIs need to consider before funding. Smaller loans have a high rate of default as they indicate the smallness of the business. Small businesses such as startups have no strong structures and have high failure rates. MFIs can support borrowers qualifying for bigger loans to reap loan benefits given that such loans have a high chance of non-default. The relatively big loans are an indication of established businesses with a minimal failure rate.

The Altman model was found to have a strong predictive power in determining default and non-default categories. Therefore, the study recommends the use of Altman Model-Discriminant Analysis by MFIs to discriminate good and bad borrowers so that they minimize default risk in lending. The Discriminant Model is very useful for scholars and academicians for continued study and evaluation of factors that affect credit default. This will help to bridge the knowledge gaps and transfer knowledge to other scholars. The policymakers can use the Altman Model and the findings of the study to guide further policymaking in the financial industry.

5.5 Limitations of the Study

The researcher had time constrain in the study. The study focused on the clients of the EKL Kisumu Branch for the year 2018 whereby time could not allow doing research in all the branches of EKL spread across Kenya. CRB scores were used to select applications for funding which meant borrowers with default history were not included in the study to give generalized results.

Most of the credit clients operated in groups and group methodology exerts pressure for loan payments even to the clients who were likely to default. Hence the dependent variable of group categories was not conclusive given that some borrowers paid well for their loans due to group pressure. Other good payers may have defaulted due to poor group mismanagement.

5.6 Suggestions for Further Research

This study focused on the data extracted from successful loan applications of EKL in the year 2018. The study recommends other MFIs to conduct studies that are similar to this research so as to get an in-depth understanding of the factors that affect default risk.

The study successfully analyzed loan and borrower characteristics that determine the repayment status of the MFI borrowers. The study then recommended the incorporation of Institutional and Business factors in predicting default rates in MFI clients.

On methodology, the study used Discriminant Analysis to analyze the results. Other methods can be used for data analysis to determine whether there is a consistency of the findings on the loan and borrower factors that predict the credit default of MFI credit clients.

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APPENDICES

APPENDIX 1: DATA COLLECTION INSTRUMENT

LOAN APPLICATION CASE NUMBER:_________________			
DEPENDENT VARIABLE		Clients Default status (1 for Default and 0 for Non-Default)	
INDEPENDENT VARIABLE:			
X1	Gender	Client gender (0 for Female and 1 for Male)	
X2	Age	Dummy variables showing age group of the client.	
X3	Marital Status	Client marital status (0 for single, 1 for married and 3 for Not Applicable (Widow, Separated or otherwise)	
X4	Guarantor	Client personal guarantor for the loan(1 for spouse and 0 for else)	
X5	LSF Contribution	Dummy Variable showing percentage of savings contribution to loan Amount.	
X6	Loan Amount	Dummy Variable showing loan amount in Kenyan shillings borrowed.	
X7	Loan Term	Dummy Variable showing loan term in weeks for the loan contract period.	
X8	Loan Installments	Dummy Variable showing weekly loan installments for the loan contract.	
X9	Loan Purpose	Client purpose for the loan (1 for Business or Agri-	

		business activities and 0 for other purposes)	
X10	Loan Cycle	Number of loan graduations	

APPENDIX 2: SECONDARY DATA COLLECTED

Case Number	Days in Default	Payment Status	Gender	Age in Years	Marital status	Guarantor	Loan Amount	Loan Term in Weeks	Weekly Loan Installments	LSF Contribution	Loan Purpose	Number of Loan cycles
1	0	NON-DEFAULT	Male	43	Married	Spouse	90,000	48	1,875	34%	Agri/Business	3
2	0	NON-DEFAULT	Female	57	Married	Spouse	250,000	100	2,500	47%	Agri/Business	19
3	0	NON-DEFAULT	Male	41	Single	Non-spouse	200,000	70	2,857	26%	Agri/Business	4
4	0	NON-DEFAULT	Female	35	Married	Spouse	150,000	74	2,027	29%	Agri/Business	4
5	0	NON-DEFAULT	Male	25	Married	Spouse	200,000	74	2,703	26%	Agri/Business	10
6	0	NON-DEFAULT	Female	56	Not Applicable	Non-spouse	160,000	74	2,162	24%	Agri/Business	4
7	0	NON-DEFAULT	Female	39	Single	Non-spouse	40,000	44	909	28%	Agri/Business	2
8	0	NON-DEFAULT	Female	42	Not Applicable	Non-spouse	200,000	48	4,167	24%	Agri/Business	4
9	0	NON-DEFAULT	Male	47	Not Applicable	Non-spouse	40,000	48	833	32%	Agri/Business	4
10	0	NON-DEFAULT	Male	42	Married	Spouse	60,000	48	1,250	31%	Agri/Business	1
11	0	NON-DEFAULT	Female	32	Married	Spouse	50,000	48	1,042	27%	Agri/Business	2
12	0	NON-DEFAULT	Female	43	Not Applicable	Non-spouse	40,000	48	833	21%	Agri/Business	9
13	0	NON-	Male	35	Married	Spouse		35		36%	Agri/Business	5

		DEFAULT					50,000		1,429			
14	0	NON-DEFAULT	Female	29	Married	Spouse	150,000	61	2,459	40%	Agri/Business	4
15	0	NON-DEFAULT	Male	61	Not Applicable	Non-spouse	150,000	74	2,027	24%	Agri/Business	9
16	0	NON-DEFAULT	Female	35	Not Applicable	Non-spouse	30,000	37	811	32%	Others	4
17	0	NON-DEFAULT	Male	48	Not Applicable	Non-spouse	55,000	48	1,146	46%	Agri/Business	2
18	0	NON-DEFAULT	Female	42	Married	Spouse	100,000	35	2,857	25%	Agri/Business	3
19	0	NON-DEFAULT	Male	35	Married	Spouse	50,000	48	1,042	31%	Agri/Business	5
20	0	NON-DEFAULT	Female	32	Not Applicable	Non-spouse	200,000	74	2,703	25%	Agri/Business	2
21	0	NON-DEFAULT	Female	38	Not Applicable	Non-spouse	300,000	70	4,286	29%	Agri/Business	4
22	0	NON-DEFAULT	Female	45	Married	Spouse	35,000	44	795	60%	Agri/Business	6
23	0	NON-DEFAULT	Female	51	Married	Spouse	50,000	48	1,042	33%	Agri/Business	3
24	0	NON-DEFAULT	Male	32	Not Applicable	Non-spouse	40,000	48	833	38%	Agri/Business	4
25	0	NON-DEFAULT	Female	32	Single	Non-spouse	100,000	48	2,083	27%	Agri/Business	1
26	0	NON-DEFAULT	Female	31	Married	Spouse	90,000	48	1,875	22%	Agri/Business	11
27	0	NON-DEFAULT	Female	57	Not Applicable	Non-spouse	35,000	48	729	46%	Agri/Business	2
28	0	NON-DEFAULT	Male	65	Not Applicable	Non-spouse	70,000	44	1,591	44%	Agri/Business	8
29	0	NON-DEFAULT	Female	26	Single	Non-spouse	100,000	48	2,083	24%	Agri/Business	3
30	0	NON-DEFAULT	Female	29	Not Applicable	Non-spouse	30,000	48	625	24%	Agri/Business	1
31	0	NON-DEFAULT	Male	31	Not Applicable	Non-spouse	100,000	48	2,083	28%	Others	5
32	0	NON-DEFAULT	Female	62	Single	Non-spouse	100,000	48	2,083	49%	Agri/Business	2
33	0	NON-DEFAULT	Female	53	Married	Spouse	50,000	44	1,136	21%	Agri/Business	3

34	0	NON-DEFAULT	Male	26	Not Applicable	Non-spouse	50,000	48	1,042	29%	Others	3
35	0	NON-DEFAULT	Female	33	Married	Spouse	40,000	35	1,143	34%	Agri/Business	6
36	157	DEFAULT	Female	42	Married	Spouse	150,000	48	3,125	0%	Agri/Business	3
37	162	DEFAULT	Female	35	Married	Spouse	35,000	48	729	1%	Agri/Business	1
38	163	DEFAULT	Female	34	Not Applicable	Non-spouse	20,000	22	909	16%	Agri/Business	1
39	165	DEFAULT	Female	24	Not Applicable	Non-spouse	30,000	48	625	20%	Agri/Business	1
40	169	DEFAULT	Female	38	Married	Spouse	30,000	48	625	3%	Agri/Business	2
41	169	DEFAULT	Male	24	Not Applicable	Non-spouse	50,000	48	1,042	13%	Agri/Business	1
42	170	DEFAULT	Female	41	Not Applicable	Non-spouse	20,000	48	417	20%	Agri/Business	1
43	171	DEFAULT	Female	30	Not Applicable	Non-spouse	30,000	48	625	21%	Agri/Business	1
44	177	DEFAULT	Male	28	Married	Spouse	70,000	48	1,458	28%	Agri/Business	3
45	178	DEFAULT	Female	34	Married	Spouse	50,000	48	1,042	1%	Agri/Business	2
46	179	DEFAULT	Female	30	Married	Spouse	100,000	48	2,083	24%	Agri/Business	1
47	190	DEFAULT	Female	36	Married	Spouse	50,000	48	1,042	12%	Agri/Business	1
48	192	DEFAULT	Female	33	Not Applicable	Non-spouse	40,000	48	833	1%	Agri/Business	3
49	199	DEFAULT	Female	56	Single	Non-spouse	30,000	48	625	1%	Agri/Business	1
50	205	DEFAULT	Female	42	Married	Spouse	40,000	48	833	15%	Agri/Business	1
51	205	DEFAULT	Female	39	Not Applicable	Non-spouse	50,000	48	1,042	14%	Agri/Business	1
52	221	DEFAULT	Male	64	Not Applicable	Non-spouse	100,000	48	2,083	21%	Agri/Business	2
53	228	DEFAULT	Male	34	Single	Non-spouse	20,000	48	417	23%	Agri/Business	1
54	233	DEFAULT	Female	20	Married	Spouse		48		30%	Agri/Business	1

							20,000		417			
55	233	DEFAULT	Female	59	Married	Spouse	30,000	48	625	29%	Agri/Business	1
56	240	DEFAULT	Female	33	Married	Spouse	20,000	48	417	32%	Agri/Business	1
57	247	DEFAULT	Female	35	Married	Spouse	20,000	48	417	33%	Agri/Business	1
58	247	DEFAULT	Female	38	Married	Spouse	40,000	48	833	1%	Agri/Business	1
59	247	DEFAULT	Female	39	Married	Spouse	30,000	48	625	13%	Agri/Business	1
60	249	DEFAULT	Female	33	Married	Spouse	120,000	48	2,500	23%	Agri/Business	1
61	268	DEFAULT	Female	32	Single	Non-spouse	40,000	48	833	19%	Agri/Business	1
62	268	DEFAULT	Female	44	Married	Spouse	50,000	48	1,042	18%	Agri/Business	1
63	268	DEFAULT	Male	26	Single	Non-spouse	140,000	74	1,892	21%	Agri/Business	3
64	288	DEFAULT	Male	27	Married	Spouse	46,010	48	959	12%	Others	2
65	296	DEFAULT	Female	60	Married	Spouse	30,000	48	625	25%	Agri/Business	1
66	302	DEFAULT	Male	26	Not Applicable	Non-spouse	50,000	48	1,042	0%	Others	1
67	302	DEFAULT	Female	31	Married	Spouse	50,000	48	1,042	22%	Agri/Business	1
68	338	DEFAULT	Female	34	Married	Spouse	30,000	48	625	16%	Agri/Business	1
69	347	DEFAULT	Male	58	Married	Spouse	50,000	48	1,042	25%	Agri/Business	1
70	149	DEFAULT	Female	29	Married	Spouse	40,000	48	833	1%	Agri/Business	1

APPENDIX 3: SPSS OUTPUT

```
DISCRIMINANT
 /GROUPS=PaymentStatus(0 1)
 /VARIABLES=NumberofLoancycles SavingstoLoanage LoanPurpose
WeeklyLoanInstallments LoanTerminWeeks
   LoanSizeinKsh Guarantor Marritalstatus AgeinYears Gender
 /ANALYSIS ALL
 /SAVE=CLASS PROBS
 /PRIORS SIZE
 /STATISTICS=MEAN STDDEV UNIVF BOXM COEFF RAW CORR TABLE
CROSSVALID
 /CLASSIFY=NONMISSING POOLED.
```

Discriminant

Notes

Output Created		27-NOV-2021 14:00:30
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	70
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing in the analysis phase.

	Cases Used	In the analysis phase, cases with no user- or system-missing values for any predictor variable are used. Cases with user-, system-missing, or out-of-range values for the grouping variable are always excluded.
Syntax		DISCRIMINANT /GROUPS=PaymentStatus(0 1) /VARIABLES=NumberofLoancycles SavingstoLoanage LoanPurpose WeeklyLoanInstallments LoanTerminWeeks LoanSizeinKsh Guarantor Marritalstatus AgeinYears Gender /ANALYSIS ALL /SAVE=CLASS PROBS /PRIORS SIZE /STATISTICS=MEAN STDDEV UNIVF BOXM COEFF RAW CORR TABLE CROSSVALID /CLASSIFY=NONMISSING POOLED.
Resources	Processor Time	00:00:00.08
	Elapsed Time	00:00:00.26
Variables Created or Modified	Dis_1	Predicted Group for Analysis 1
	Dis1_1	Probabilities of Membership in Group 0 for Analysis 1
	Dis2_1	Probabilities of Membership in Group 1 for Analysis 1

Number of unweighted cases written to the working file after classification	70

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		70	100.0
Excluded	Missing or out-of-range group codes	0	.0
	At least one missing discriminating variable	0	.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	.0
	Total	0	.0
Total		70	100.0

Group Statistics

Payment Status		Mean	Std. Deviation	Valid N (listwise)	
				Unweighted	Weighted
Non-Default	Number of Loan cycles	4.63	3.557	35	35.000
	Savings to Loan %age	31.83	9.319	35	35.000
	Loan Purpose	.91	.284	35	35.000
	Weekly Loan Installments	1744.61	927.122	35	35.000
	Loan Term in Weeks	52.94	14.408	35	35.000
	Loan Size in Ksh.	98714.29	70610.186	35	35.000
	Guarantor	.43	.502	35	35.000

	Marrital status	1.29	.710	35	35.000
	Age in Years	40.86	11.178	35	35.000
	Gender	.37	.490	35	35.000
Default	Number of Loan cycles	1.34	.684	35	35.000
	Savings to Loan %age	15.73	10.367	35	35.000
	Loan Purpose	.94	.236	35	35.000
	Weekly Loan Installments	1009.20	622.564	35	35.000
	Loan Term in Weeks	48.00	6.306	35	35.000
	Loan Size in Ksh.	49171.71	33306.468	35	35.000
	Guarantor	.63	.490	35	35.000
	Marrital status	1.14	.601	35	35.000
	Age in Years	36.80	10.892	35	35.000
	Gender	.23	.426	35	35.000
Total	Number of Loan cycles	2.99	3.034	70	70.000
	Savings to Loan %age	23.78	12.710	70	70.000
	Loan Purpose	.93	.259	70	70.000
	Weekly Loan Installments	1376.91	867.006	70	70.000
	Loan Term in Weeks	50.47	11.317	70	70.000
	Loan Size in Ksh.	73943.00	60215.460	70	70.000
	Guarantor	.53	.503	70	70.000
	Marrital status	1.21	.657	70	70.000
	Age in Years	38.83	11.145	70	70.000
	Gender	.30	.462	70	70.000

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
Number of Loan cycles	.702	28.802	1	68	.000
Savings to Loan %age	.593	46.719	1	68	.000
Loan Purpose	.997	.210	1	68	.648
Weekly Loan Installments	.818	15.178	1	68	.000
Loan Term in Weeks	.952	3.457	1	68	.067
Loan Size in Ksh.	.828	14.094	1	68	.000
Guarantor	.960	2.843	1	68	.096
Marrital status	.988	.825	1	68	.367
Age in Years	.966	2.365	1	68	.129
Gender	.976	1.693	1	68	.198

Analysis 1

Box's Test of Equality of Covariance Matrices

Log Determinants

Payment Status	Rank	Log Determinant
Non-Default	10	41.157
Default	10	32.212
Pooled within-groups	10	39.608

The ranks and natural logarithms of determinants printed are those of the group covariance matrices.

Test Results

Box's M		198.813
F	Approx.	3.048
	df1	55
	df2	14932.332
	Sig.	.000

Tests null hypothesis of equal population covariance matrices.

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.622[a]	100.0	100.0	.787

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.381	60.729	10	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Number of Loan cycles	.611
Savings to Loan %age	.790
Loan Purpose	-.152
Weekly Loan Installments	1.137
Loan Term in Weeks	.074
Loan Size in Ksh.	-.845
Guarantor	-.348
Marrital status	-.021
Age in Years	-.060
Gender	-.091

Structure Matrix

	Function
	1
Savings to Loan %age	.651
Number of Loan cycles	.511

Weekly Loan Installments	.371
Loan Size in Ksh.	.357
Loan Term in Weeks	.177
Guarantor	-.161
Age in Years	.146
Gender	.124
Marrital status	.086
Loan Purpose	-.044

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions

Variables ordered by absolute size of correlation within function.

Canonical Discriminant Function Coefficients

	Function
	1
Number of Loan cycles	.239
Savings to Loan %age	.080
Loan Purpose	-.582
Weekly Loan Installments	.001
Loan Term in Weeks	.007
Loan Size in Ksh.	.000
Guarantor	-.702
Marrital status	-.033
Age in Years	-.005
Gender	-.199

(Constant)	-2.585

Unstandardized coefficients

Functions at Group Centroids

	Function
Payment Status	1
Non-Default	1.255
Default	-1.255

Unstandardized canonical discriminant functions evaluated at group means

Classification Statistics

Classification Processing Summary

Processed		70
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		70

Prior Probabilities for Groups

		Cases Used in Analysis	
Payment Status	Prior	Unweighted	Weighted
Non-Default	.500	35	35.000
Default	.500	35	35.000
Total	1.000	70	70.000

Classification Function Coefficients

	Payment Status	
	Non-Default	Default
Number of Loan cycles	.432	-.167
Savings to Loan %age	.485	.284
Loan Purpose	9.410	10.871
Weekly Loan Installments	.104	.100
Loan Term in Weeks	4.711	4.695
Loan Size in Ksh.	-.002	-.002
Guarantor	-.033	1.728
Marrital status	8.528	8.610
Age in Years	.017	.031
Gender	-3.766	-3.266
(Constant)	-134.805	-128.316

Fisher's linear discriminant functions

Classification Results[a,c]

			Predicted Group Membership		
		Payment Status	Non-Default	Default	Total
Original	Count	Non-Default	31	4	35
		Default	3	32	35
	%	Non-Default	88.6	11.4	100.0
		Default	8.6	91.4	100.0
Cross-validated[b]	Count	Non-Default	31	4	35
		Default	6	29	35
	%	Non-Default	88.6	11.4	100.0
		Default	17.1	82.9	100.0

a. 90.0% of original grouped cases correctly classified.

b. 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.

c. 85.7% of cross-validated grouped cases correctly classified.