ADDIS ABABA UNIVERSITY

COLLAGE OF BUSINESS AND ECONOMICS

DEPARTMENT OF BUSINESS MANAGEMENT

EFFECT OF ARTIFICIAL INTELLIGENCE ON CREDIT RISK MANAGEMENT OF DIGITAL LOAN: THE CASE OF COOPERATIVE BANKOF OROMIA S.C

A THESIS SUBMITTED TO COLLEGE OF BUSINESS AND ECONOMICS

INPARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF ARTS IN BUSINESS ADMINISTRATION (MBA)

BY: REBIRA BIRHANU

ADVISOR: ABERA LEGESE (Ph.D.)

JUNE, 2024

ADDIS ABABA ETHIOPIA

DECLARATION

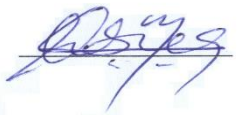
I, the undersigned, hereby declare that, as a requirement for earning a Master's of Arts in Business Administration (MBA), I completed the research project "Effect of Artificial Intelligence on Credit Risk Management of Digital loan: The Case of Cooperative bank of Oromia S.C." in 2023–2024 under the supervision of Abera Legese (PhD). Lists of references are provided, and the information taken from the literature has been properly recognized in the texts. This thesis has never been submitted in part for credit toward any other degree or at any other Institution.

Rebira Birhanu _____ 30/06/2024

Name of Author Signature Date

ADVISOR APPROVAL SHEET

This certifies that Rebira Birhanu worked under my supervision on his thesis, "Effect of Artificial Intelligence on Credit Risk Management of Digital Loan: The Case of Cooperative bank of Oromia S.C.," which was turned in as partial fulfillment of the requirements for the Master of Arts (Master in Business Administration) degree in the graduate program of the department of Business Management. As a result, I advised that the student submit the thesis to the department as it had met the requirements.



Abera Legese (Ph.D.) _____ 30/06/2024

Name of Advisor Signature Date

ADDIS ABABA UNIVERSITY

COLLEGE OF BUSSINESS AND ECONOMICS

DEPARTMENT OF BUISNESS MANAGEMENT

APPROVAL SHEET FOR THE BOARD OF EXAMINERS

This is to certify that the thesis prepared by Rebira Birhanu, entitled: "Effect of Artificial Intelligence on Credit Risk Management of digital loan: The Case of Cooperative bank of Oromia S.C. and submitted in partial fulfillment of the requirements for the Degree of Master of Arts in Business Administration (MBA) complies with the regulations of the University and meets the accepted standards with respect to originality and quality. Approved by the examiners

Desta Mulugeta (Ph.D.)		4/7/2024
Name of external Examiner	Signature	Date
Dejene Tulu (Ph.D.)		4/7/2024
Name of internal Examiner	Signature	Date
Abera Legese (Ph.D.)		30/06/2024
Name of Advisor	Signature	Date

ACKNOWLEDGMENT

Firstly I’m very grateful to God, the Almighty, for providing me with the health, fortitude, and perseverance necessary to carry out and complete this research. Second, I want to sincerely thank my advisor Abera Legese (Ph.D.) for his insightful counsel, critical comments and inspiring words that direct and motivated me to finish this thesis. Additionally, I would like to thank my wife Shewaye Lema for her unwavering support, unforgettably kind care, and inspiration during the challenging times of my studies. I sincerely thank the respondents of Coop Bank's head office and branch staffs for giving up their valuable time to complete the survey. I also want to thank all of my staffs who helped me by offering me leisure time, comments and advice that helped me to complete my thesis work.

.

Table of Contents

LIST OF TABLES

LIST OF FIGURES

ACRONYMS

AI -Artificial Intelligence

COOP Bank- Cooperative Bank of Oromia

S.C- Share Company

CLMR-Classical Linear Regression Model

ML -Machine learning

FIs- Financial Institutions

NBE -National Bank of Ethiopia

NPL -Non-Performing Loan

IBM -International Business Machines

RPA- Robotic Process Automation

AML -Anti Money Laundry

MSMES-Micro, Small and Medium Enterprises

SME-Small and Medium Enterprises

CAPM-Capital Asset Pricing Model

ANN-Artificial Neural Networks

LR-Logistic Regression

SVM-Support Vector Machines

HO-Head Office

SPSS-Statistical Package for Social Sciences

AAPOR-According to America Association for Public Opinion Research

OLS-Ordinary Least Squares

BLUE-Best Linear Unbiased Estimators

VIF-Variable Inflammatory Factors

ABSTRACT

Artificial Intelligence is a computer integrated and developed system that accomplish jobs that previously used human intelligence which includes identify models, making decision and speech recognizing. However, empirical studies aimed at addressing the effect of Artificial Intelligence on credit risk management of digital loan is not well studied. Specifically there is no any researches conducted either in Ethiopian banking industry or Coop bank till this study is proposed to do. As a result, the major objective of this research is to assess the effect of Artificial Intelligence on credit risk management of digital loan. Artificial Intelligence Applications on digital lending are independent variables (Artificial Intelligence Credit scoring, lending decision and personalized loan offering), while the dependent variable is Credit risk management. The study targeted a population of Coop bank employees found in head office and branches. The study was employed close ended structured questionnaires that was prepared by the five points Likert scale form. The explanatory research design was employed in the study to ascertain the association the cause and effect between independent and dependent variables descriptive analysis was employed to analyze Indicators of central tendencies such as mean, standard deviation, frequency, and percentage. A quantitative research approach was used in this study. This study was used primary data gathered by a researcher using a questionnaire. The multiple regression results indicated that all of the three Independent variables have positive significant relationship with dependent variable. Finally, depending on the finding from the study, a researcher was recommended the studied bank and the future studies to expand the topic and related measurements.

Key words: *Artificial Intelligence, Digital Lending, Credit risk management, credit scoring, lending decisions and personalized loan*

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Artificial Intelligence (AI) is a computer integrated and developed system that accomplish jobs which previously used human intelligence that includes identify models, making decision and speech recognizing (Copeland, 2020)

AI in financial service sectors is highly transforming the industry to technology from its ground break. AI gives data backed and better informed decision on assessment of potential borrowers that minimize time and less cost. AI provides Credit scoring depend on supplementary complex and advanced rules than the traditional scoring system. It supports financial providers to identify credit worthiness with or without credit history and predict probability of exposure to default risk (Bachir, 2021).

Most of the time to verify creditworthiness and access personalized loan alternative online lenders, banks and other credit provider use alternative data machine learning (ML) algorithms such as Smartphone connection (Arthur, 2019). Its system were reforming experiences of customers, that include the way to contact with service sectors such as, robotic advisor, chatbot, automated house mortgage and advance. It also includes identity check such as picture recognition. AI and ML are changing the financial institutions daily activities (operations), automating systems by minimum cost, and risk management, compliance with regulations, fraud detection effectiveness and improve product. Bachir (2021) stated that Artificial Intelligence and Machine lending systems also helps regulatory bodies and national banks to improve follow up and risk mitigations.

Credit risk management defined by Aduda (2011) is an organized method for handling uncertainties through risk identification, mitigation with managerial resources and the creation of strategies like shifting risk, avoiding, minimizing the risk's negative effects, and accepting a portion or all of the consequences of a specific risk. Schmidt and Roth (1990) defined risk management as the coordination of actions intended to reduce the adverse consequences

associated with uncertainty over possible losses or a methodical process used to determine and techniques required to assess the degree of exposure.

Credit risk is the issue that negatively affects financial institutions' viability and overall performance (Bhattarai 2019). It is the possibility of financial loss arising from a counterpart's inability to meet its contractual obligations or a higher chance of default the transaction's lifetime. Financial institutions historically modeled credit risk using traditional, probit, logit and linear regressions (Altman, 1968). However, the proof of shortcomings conventional approaches has led to a renewed interest from institutions in leveraging AI and machine learning approaches to improve credit risk management procedures.

Banks face a variety of risks in the dynamic and uncertain economic climate of today, including default or credit risk, liquidity, operational, market, foreign exchange, and interest rate risks (Tole et al. 2019). The principal objective of the banking industry is to collect public funds for the purpose of granting credit, facilitating business expansion and fostering a flourishing economy. Nevertheless, the possibility of debtors' default presents a noteworthy obstacle for banks, given its impact on the overall stability of the financial system (ALrfai et al. 2022). After the financial crisis of 2007 to 2008, the Basel III accord was created to reinforce bank capital requirements by boosting bank liquidity and lowering bank leverage, which incentivizes banks to assess the credit risk of their portfolios (Morris, 2001). A sound or sufficient risk management system's definition is always evolving as new technology allows for greater information and innovation and as market efficiency rises. By utilizing AI and machine learning approaches, credit risk management techniques can be substantially improved because of their capacity to analyze unstructured data semantically (Aziz and Dowling, 2019).

Digital lending is defined as the implementation of technology to originate, renew and repayment of loans in order to provide lending decision and faster financial service (Mohammed, et al. 2021). The financial institutions are gaining more important in minimizing expense, quick and effective decision making, customer excellence, marketing access and consistent loan system from the digitalization of lending system. It has become increasingly popular in recent years due to its convenience and accessibility for borrowers. However, recently due to the users of digital loan are expanding as a bank as well as a country the risk of bad debit loan or non-performing loan (NPL) also increase. According to Iqbal and Mirakhor (2007), banks can improve their competitiveness in the market and lower their exposure to risks by implementing a strong risk

management system. Thus implementation of AI technology that gives accurate credit score, personalized loans and gives good lending decision before disbursement will be seen to be a key to minimize a risk in digital lending.

1.2 Background of the Organization

The history of Ethiopian banking was started in 1905 when the bank known Abyssinia was operated (Teklearegay, 2015). Till later it was changed to Bank of Ethiopian, It has been giving services in the countries at few towns. In 1931 Bank of Ethiopia was operated and started giving services by replacing the bank of Abyssinia. In 1963 the bank was divided to the commercial and National bank of Ethiopia.

Private banking investment in Ethiopia was legally licensed by banking and monitory proclamation number 18/1994 in 1994 and some of the private banks currently operating in Ethiopia such as Awash Bank (1994), Dashen Bank (1995), Bank of Abyssinia (1996), Wegagen Bank (1997), United Bank (1998), Nib international Bank (1999) and Cooperative bank of Oromia (2004) are respectively registered and started their operation thought the country (NBE, 2023).

Cooperative banking industry was started in the world in 19th Century when a lot of peoples from rural populations, those have small and medium level income and farmers was challenged by inadequate financial services. At the time as a result of the expansion of manufacturing industries, larger mining enterprises and highly growth of cities the financial service was highly concentrated to the organizations those have high monetary capacity, and as a result the financial crises was happened among the community. The case for that time was bring the inauguration for the Cooperative society's organization that was operated to mitigate the rise of market price by a group and to improve the large population of rural areas and lower income city communities those does not have larger capacity, and following to that the cooperative banking is also started in European countries and later expanded to the Asian, Africa and the rest of the world.

In Ethiopia the Coop bank of Oromia was operated in 2004 with commercially licensed. The bank has broad and diversified ownership base. Majority of share-holders are Cooperatives such as primary cooperatives, cooperative unions and cooperative federations and non-cooperatives

such as organizations associations and individuals (Coop, 2023). Coop bank was started giving collateral less digital lending service known as Michu which is Artificial Intelligence (AI) based platform in 2022 in collaboration with Kifiya Financial Technology provider to provide digital lending solution that individual, and enterprise to reach a mass of large populations, those needs a loan but not have capacity to give collateral. Michu was accessed the loan depending on the AI based Credit scoring which were received from the borrowers characteristics of credit worthiness (Coop, 2022). UNDP (2024) stated that, micro, small and medium-sized enterprises (MSMEs) in Ethiopia, which account for 70% of jobs in the country's urban regions, obtaining loans can be difficult due to high interest rates, protracted processing periods, stringent collateral requirements and a lack of bank branch locations. However, digital lending services such as Michu from the Coop Bank, is offering a promising and potentially revolutionary answer to this problem in Ethiopia.

1.3 Statement of the problem

UNDP (2024) stated that, Ethiopia is one of Africa's fastest-growing economies, with a population of over 123 million. However, access to financial services is frequently difficult for persons who live in rural areas and those have lower incomes in urban areas. A big challenge to this is getting loans, especially for micro, small, and medium enterprises (MSMEs) that account for about 70% of jobs in urban areas of the country. However, digital lending services such as Michu from the Coop Bank, is offering a promising and potentially revolutionary answer to this problem in Ethiopia. The primary objective of digital lending is to provide a loan for MSMEs and individuals to meet a short term financial needs via uncollateralized online lending system. However, most of the time the traditional or manual credit scoring is time consuming and leads to loan defaults. Specially, as the digital loan is naturally uncollateralized most of the time there’s seen a high default rate. Yitbarek (2023) on his study of Loan repayment performance and its determinants: evidence from micro and small enterprises operating in Dire-Dawa, Ethiopia stated that 41.5% of the loans provided for MSEs were found defaulted.

Yao (2019) stated that credit risk is the possibility that, for a variety of reasons, borrowers or debtors won't be able to pay back loans or complete contractual commitments on time, resulting a losses on banks or creditors. Because of the enormously negative effects that financial institution collapse would have on financial system and global economy, risk management is a

distinctive element of financial institution management (Natufe et al., 2023). Wang et al. (2019) studied how financial accessibility was improved by the credit scoring of AI. The research was showed the reduction of loan loss and raise in the disbursement rate was improved as the organization was implemented the AI. Similarly Remesh (2021) from his study of the role of AI in Banking indicated that AI digital lending system calculates and gives a decision on a borrower repayment capacity that will reduce default that might cause Non-performing loan. Nabila (2019) on his study of Impact of AI in Moroccan credit scoring shows that artificial intelligence and machine learning are digitally transforming financial industry by solving concrete problems associated with efficiency, time and cost saving especially in credit scoring performance. Noah (2013) indicated that AI provides improvements in asset management, regulatory compliance's, credit risk assessment, client services and crime detections.

In Ethiopia, Daniel (2019) studied Loan Risk Prediction Using Machine Learning Algorithms in micro finance institutions in Ethiopia. Tsega et al. (2023) also studied the use of machine learning technology to create a classification model that assigns contracts a high or low risk category in order to forecast loan default trends at Awash Bank. But the study was limited to the microfinance or traditional banks' lending system and its impact on the digital lending system was not studied or not well touched as a topic. This shows that there's seen a lack of studies regarding the effect of AI on the digital loans, specifically as the digital lending system was the newly started credit providing mechanism in Ethiopia there's no studies yet conducted on the topic till this study is proposed to conduct. Therefore this research targeted to study the effect of AI applications (AI credit scoring, AI based personalized lending and AI lending decision) on digital loan credit risk management specifically on Coop bank's digital lending service to fill the literature gap of existing studies.

1.4 Research questions

The problem that the researcher wants to evaluate is reflected in the study questions. According to Johnson and Christensen (2004), research questions are more precisely defined as interrogative statements that serve as "explanation for the objective of the study, specifically the main questions that needs answer". This study was targeted to give answer for the following questions.

- What is the effect of Credit scoring by Artificial Intelligence on credit risk management of digital loans?
- To what extent the lending decision by Artificial Intelligence have significantly effect on credit risk management of digital loans?
- What is the effect of personalized loan offerings by Artificial Intelligence application on credit risk management of digital loans?

1.5 Objectives of the study

1.5.1 General Objectives

The major objective of this research is to study how the artificial intelligence (AI) affects the banks credit risk management of digital loan.

1.5.2 Specific objectives

Four particular objectives were identified by a researcher in order to address the major objective.

- To analyze the effect of credit scoring by Artificial Intelligence application on credit risk management of digital loans.
- To determine how lending decision by Artificial Intelligence application impacts the credit risk management of digital loans.
- To examine the effect of Artificial Intelligence application based personalized loan offerings on credit risk management of digital loan.

1.6 Significance of the study

As mentioned in the above section the use of AI on banking industry is rising in recent years. Banks are gradually changing their traditional teller banking system to the digitalized services. One of and more important banks service that have direct contribution to its profit is loan. Currently most of the banks in the world are accessing digital lending system to their customers, a few commercial banks and other financial service sectors in Ethiopia are also interring to this era. However most of the time there's seen the probability of the borrower will default their loan repayment and the banks was faced credit risk. This research was prepared to study the role of AI on the credit risk management of digital loans on digital loan providers in Ethiopia specifically Coop bank.

The finding from this research was expected to add knowledge by determining the effect of AI on credit risk management of digital loans that includes credit scoring, lending decisions and personal lending for the organization Coop bank and other banks else were giving similar services. As the role of AI based application on credit risk management of digital loan is not well studied as a subject matter in the previous research studies, this research were expected to fill the literature gap of existing studies on the mentioned topic.

1.7 Scope of the study

1.7.1 Methodological scope

Studies on the Artificial Intelligence show that AI applications are used in many sectors and it is a key technology in the financial service providers to estimate credit worthiness of the requesting client. This study was determined the Artificial Intelligence Applications (AI credit scoring, AI lending decision and AI Personalized loan offerings) as independent variable and their effect on dependent variable, credit risk management of digital loan. The study was used explanatory and descriptive research method to analyze the relationship between variables. A quantitative research approach was used in this study. The study was used primary data gathered by a researcher using a questionnaire. Correlation and regression analysis was employed to measure relationship between variables.

1.7.2 Temporal scope

This study was focused on the banking industry specifically the Coop bank of Oromia and the respondents were selected from the banks digital lending, risk management and central finfine district branches, which means all are physically located in Addis Ababa.

1.8 Limitations of the study

This study was geographically limited to the Coop bank S.C. The reason that the researcher was selected to take on this organization is that it is the first bank by giving digital lending service in Ethiopia and the leading bank by this service in the country till this study was proposed to conduct. This could be limiting the boundary of the study to be conducted on only the Coop bank S.C to protect quality of data. However, other commercial banks and every financial sector that gives same service may use the finding of the research.

1.9 Challenges of the study

As there is no more studies conducted on the topic so far or the previous researcher were not touched well the topic and specifically no research done in Ethiopia on the topic the research was faced lack of sufficient secondary data that allow for further analysis. As the digital lending technology is the new for the country there's seen challenge of getting sufficient information from respondents.

1.10 Operational Definition of Terms

Definitions of important operational terms used in this study are:

a) **Artificial Intelligence (AI):** the term artificial intelligence (AI) in this study refers to the computer integrated theory and algorithm that is used to analyzed loans data and decision making which have been traditionally demanded human intelligence.
b) **Digital Lending:** the term digital lending in this study is the process of loan applying, disbursement, collection and management through digital channels.
c) **Credit risk:** credit risk in this study refers to the financial loss that happened when obligor, customer or partner will not be able to meet its contractual loan financing obligations or default the loan repayments.
d) **Risk management:** risk management in this study is a management strategy that aids in optimizing an institution's rate of return by limiting its financial risk vulnerability within reasonable bound.
e) **Credit scoring:** The term credit scoring in this study refers to the estimates of an individual's creditworthiness by gathering more detailed information from raw data, including credit history, expected incomes, education, employment and transaction history to give credit capacity of borrower for approval.
f) **Lending decision:** In this study, "lending decision" refers to the lender's final determination of whether or not to provide the loan in line with the credit worthiness, contract terms and conditions.
g) **Personal Lending:** the term personal lending in this study refers to the unsecured credit provided via online self-service lending system of lending institutions depending on

requirements such as employment history, ability to repay debt, income level, occupation, and credit history.

1.11 Organization of the Study

This study report is generally organized into five chapters. The first chapter is the introductory of the research. The study background, problem statement, research questions, Objectives, Significance, challenges, limitations and scope of the study was studied in this chapter. The second chapter discussed the related literature reviews. It includes the theoretical review, empirical revises, studied conducted abroad Ethiopia, studies conducted in Ethiopia, the researches gap and conceptual framework was studied by articulating the major AI applications on digital lending and their effect on credit risk management from previous studies. The third chapter discussed the research methodology. The research design; population, sampling techniques and sample size; data collection and instruments; Validity and reliability of instruments; method of data analysis and ethical consideration was studied. Chapter four studied about data presentation, discussion and analysis. The final fifth chapter summarizes the findings and recommendation of the study.

CHAPTER TWO

LITERATURE REVIEWS

2.1 Theoretical Reviews

2.1.1 Definition of Artificial Intelligence (AI)

Artificial Intelligence (AI) is the advancement, theory and algorithms for computers that are capable of performing tasks which have traditionally demanded human intelligence, like recognition of speech, recognition of patterns, and decision-making. According to Kaplan, artificial intelligence is the capacity of a system to learn from external data and interpret it to accomplish certain tasks and goals through adaptable change (Kaplan, et.al. 2019). Natural language processing (NLP) deep learning and machine learning are just a handful of the technologies that are included in the wide category of artificial intelligence (AI).According to International Business Machines (IBM), artificial intelligence (AI) is a discipline that integrates large datasets and computer science to facilitate problem-solving. The terms artificial intelligence (AI) and its subfields, deep learning, natural language processing, and machine learning are often used interchangeably. AI algorithms in the current generation's technology are developing expert systems that process classification or prediction from given input data. (IBM, 2023)

2.1.2 Major importance of Artificial Intelligence in financial sector

Minzhen (2019) categorized the implementation of machine learning (ML) and artificial intelligence in the banking industry into four primary domains. First, there are applications that are focused on clients (front-end) such as credit scoring, focused on clients service robots, and insurance; second, there are applications that are management-level (the database) such as risk management, financing enhancement, and economic impact assessment; third, there are applications that are related to financial markets, such as handling portfolios and financial market interactions; AI also has applications in the banking industry for "RegTech" and by regulatory agencies for "SupTech."Riteshkumar and Uma (2023) discussed applications of AI in banking industry as follows:

a. Credit scoring: Artificial intelligence is a critical component of alternative financial institutions' creditworthiness assessment processes, assisting them in developing innovative lending programs backed by dependable credit scoring models, regardless of individuals or

businesses with little or no credit history. Artificial intelligence gathers and analyzes data from a wide range of conventional and non-traditional source materials. Two of the most common uses of AI are in analytics for forecasting and broad-application semantic and natural language applications are important for loan evaluation (Eno Gregory, 2022).

b. Reduced Risks: Foreign global variables including currency rate swings, political unrest, and catastrophic events have a big influence on the banking and investment sectors. In these unpredictable times, it is critical to exercise additional prudence when considering business decisions. Interacting with people, there is one common disadvantage. Errors happen frequently and can have detrimental effects. Even with knowledgeable personnel in charge.AI-driven statistics offer a somewhat accurate prediction for upcoming occurrences, which helps with planning and prompt decision-making (Riteshkumar and Uma, 2023).

c. fraud detection and Cyber security: The banking industry must step up its efforts in these areas when a wide variety of digital activities, including bill payment, cash withdrawals, and verification of identity via apps or online accounts, occur. Yashoda (2018) stated that AI can help banks to reduce risk, find flaws in their systems, and improve the security of online banking. Artificial intelligence (AI) combined with machine learning can detect fraudulent activity with ease and notify banks and customers. One important area where artificial intelligence (AI) may improve banking operations is risk management through enhanced portfolio management, fraud detection, repayment plan optimization, speedy identification, and credit rating.

d. Lower time and costs: AI accomplish large scale automation with less time that will reduce costs. In fact, AI can overall overhead expenses. Studies shows increase in the number of a loan borrower was raised as the finance sector used the AI application process, that allow to perform huge transactions as well as bill payments in minimum cost and less time (Bart, 2017).

e. Better Loan Evaluation: The usual use of deposit rankings to determine financing eligibility is based on outdated data, misclassification, and inaccuracies. But these days, a lot more information is readily available online that might provide a more realistic picture of the person or business that is being evaluated. Even in cases where the party, whether private or business, has less paperwork, an AI-based system can propose recommendations for approval or denial by considering other factors (Hodgkinson and Walker, 2003). Some AI systems can also help banks

securely store and analyze the vast volumes of data they are required by law to collect in order to handle their customer transactions. In the past, one of the earliest uses of AI in the banking industry was credit rating, particularly with the application of machine learning. By looking at past behavioral patterns and data to predict future behavior and rule out human error, AI also helps detect risky applications by estimating the likelihood that a customer will fail on a loan (David, 2020).

f. Personalized Finance: By giving clients access to the most recent credit data, artificial intelligence enables them to make quick and informed financial decisions. This service is also including chatbot (a software programs which mimic textual human conversation through interfaces), (Eno, 2022),

2.1.3 AI on Credit Applications

According to Hichamet al. (2022), older methods to credit assessment in finance integrate a number of data pre-processing techniques with generic statistical methods, such as logistical regression scoring, that provide dependable results. Because of the way AI algorithms work, they only provide marginally better performance with some productivity increases if the volume of data remains constant. But since AI has been around, the foundation of data has altered. This is because of big data new information sources that could not have been included into conventional credit risk management system because of their size, can now be mobilized. Without always knowing why, these new AI-mobilized data sources enable the acquisition of weak signals, such as interactions or non-linearity's, which appear to improve the evaluation of a customer's creditworthiness.

Hodgkinson and Walker (2003) built an expert system based on rules that helps banking intuitions in deciding about whether to approve or reject requests for cooperative credit financing. Yashoda (2018) stated the areas that ML used include fraud detection, sentimental analysis, wallet share estimation, query expansion and etc. Hicham et al. (2021) on their study of "Artificial intelligence and financial institutions loan analysis: A review" indicated on their study indicated that fraud identification, handling risks, improving credit scoring, investing, collecting on loans planning improvement, quick identification and evaluation of signals of troublesome clients, and financial framework building are just a few of the key areas where artificial intelligence enhances banking activities. Ngai et al. (2011) offer a comprehensive summary of

the fundamental AI methods utilized in banking fraud detection, highlighting decision trees and neural networks as the two primary methods. Bart (2017) claimed that AML/CFT fraud detection: Some businesses utilize AI for AML/CFT and fraud detection at financial institutions in an effort to boost productivity while lowering costs and risks at the same time and adhering to laws. Additionally, businesses can employ machine learning to monitor credit and reduce risk.

According to David (2020), artificial intelligence (AI) has a significant impact on financial inclusion through digital means in areas including risk assessment, evaluation, and monitoring; resolving communication inequity; providing client service and helpdesk via chatbots; and fraud and online security surveillance.

2.1.4 Digital Lending

Digital lending is a fairly recent and growing development in the banking and credit business. Digital platform lending begins with the reception of loan applications and continues through loan disbursement, and collections. Thanks to the use of new technology, inclusive approaches, and credit assessment algorithms, digital lending was growing quickly (Ravikumar et al. 2019).

In recent years, FinTech, or financial technology, has Financial Technology (FinTech) has been a major player in the financial industry during the past several years. Fin Tech has entirely changed the way that business is conducted. In order to deliver financial solutions that are far more efficient than those offered by traditional financial institutions, financial technology essentially combines finance with technology. Alternative lending is another name for digital lending. Digital platforms offers low cost loans that are easily accessible to the vast untapped market segment are referred to as alternative lending. The digital lending market known as "alternative lending" is expanding and offers loans for a range of purposes, including working capital, payday, small- and medium-sized business, and consumer requirements. It functions as an asset class that is comparatively less volatile for institutional and retail investors. The sector is mostly made up of digital lending platforms and the enabler like white label services and alternative credit scorer that make these platforms possible (Thangaraj, 2019).

In the past several years, there has been a notable increase in the demand for digital financial services. This trend has been hastened by the Covid-19 outbreak, and as attention has turned to economic recovery, digital lending has taken center stage. Digital credit products give families

and micro, small, and medium-sized companies (MSMEs) access to financing by utilizing conventional and alternative financial and non-financial data (Christoph, 2021).

Because of the accessibility of sophisticated machine learning (ML) techniques that can precisely predict the financial health of an organization from the information that is available, lending activities especially for medium and small sized businesses (SMEs) are becoming more and more dependent on financial technologies (Golnoosh et al. 2022).

2.1.5 Digital Lending in Ethiopia

The Ethiopian financial inclusiveness performance is below average compared to the average for Sub-Saharan Africa and East African states (Lakew and Azadi, 2020). The national digital transformation strategy, Digital Ethiopia 2025, was approved by the Ethiopian Council of Ministers in June 2020. It uses cutting-edge technologies to guarantee social and economic development (Ousman, 2023).

Ethiopia's first uncollateralized digital lending product was introduced in early 2022 by Kifiya Financial Technology and the Coop Bank. The platform is known as Michu which is AIbased digital lending solution that provides individuals and enterprises access credit via online AI processed credit scoring system. It’s digitized means of applying for loan with Easy Repayment Method. Michu was designed to meet the funding requirements of medium-sized and small enterprises. The two claim that over 113,000 people and MSMEs (small and medium-sized businesses) have gotten minor loans totaling over 1.3 billion Birr in disbursements. Because traditional banking institutions and MFIs (microfinance institutions) rarely meet the funding needs of MSMEs, these organizations are the primary focus of digital lending. Kifiya hopes to increase the product's use case through Qena in order to meet people's requirements for financial access. (Coop, 2023)

Early in August 2023, Telebirr, a mobile money service offered by Ethiopian telecom, introduced its digital microcredit services with automated payout and notification mechanisms. Mela, a lending option, and Sanduk, an overdraft credit facility that allows users to make payments via telebirr and settle later, are the services offered. Telebirr, which is powered by Huawei mobile money technology, determines creditworthiness and credit limits by analyzing

telecom usage data from customers as well as Telebirr history. The website provides financing alternatives for any amount on a daily, weekly, and monthly basis (Ousman, 2023).

2.1.6 Definition of Credit

According to Sullivan et al. (2003), credit is the trustworthiness that permits one party to give money or resources to another party in which the recipient does not pay the first party back right away but instead makes plans to either return or refund the resources later. The resources provided may either be financial (in the form of money transfers, cash, and bill payment on behalf of borrower) or any other markup or cost plus finance service. Any type of postponed payment that a lender or creditor extends to a borrower or debtor is referred to as credit. Depending on the organization's term and tariff policy, the purpose and nature of credit have been divided into three categories: short term which has less than one year loan term, medium term most of the time one year to five years and long term loans that have more than five years term. Most of the time digital credits are categorized under short term loan which should have has to repay in short period of time as the risk compared to other loan type is high.

2.1.7 Credit Risk

Different scholars and studies defined risk depending on its content of measures. Yao (2019) stated that credit risk is the possibility that, for a variety of reasons, borrowers or debtors won't be able to pay back loans or complete contractual commitments on time, resulting in losses for banks or creditors. The likelihood that final outcomes will differ from predicted results is known as risk in the finance industry. Risk is defined as fluctuation in return in the Capital Asset Pricing Model (CAPM). According to the theory of "risk and return," more volatile investments should have more predictable returns to make up for their higher volatility and greater level of risk.

Ekaet al. (2023) was defines credit risk as a financial loss that happened when obligor, customer or partner will not be able to meet its contractual loan financing obligations. According to this definition, global credit risk is the failure of a company, organization, entity or individual to meet its obligations under its rules or original contract in a timely manner.

In financial discourse, risk is defined as uncertainty resulting from differences in expected result. Probability in risk suggests that risk can be calculated or evaluated using methods suitable for the type of risk that is anticipated. Because of the enormously negative effects that financial

institution collapse would have on any economy due to the intricately linked and interdependent nature of financial systems and global economies, risk management is a distinctive element of financial institutions (Natufe et al., 2023).

Tamplin (2023) defined that Credit risk is the potential for a borrower to default on their financial commitments. The lender or investor can suffer losses as a result of this. Since credit risk is a natural component of lending and investment, maintaining the stability of financial institutions depends on its efficient management. Financial institutions may increase their profitability, shield themselves from possible losses, and keep the confidence of investors and consumers by managing credit risk well.

2.1.8 Credit risk of Digital Lending

In recent years, digital lending has become a very popular substitute for conventional lending practices. The possibility of large profits and easier access to data attract banks and other lending institutions, allowing them to fund a larger range of borrowers. However, because of the speed at which innovation and change occur, lending organizations frequently deal with a changing set of risks, necessitating the use of efficient risk mitigation techniques in order to keep up with the quickness of cross-border transactions. Onay & Ozturk (2018) stated that, the risk management difficulties in the digital era have increased as the method of accessing loan is transforming to digital.

2.2 Applications of Artificial Intelligence on Digital Lending

According to studies, 1.5 billion individuals worldwide lack access to banking or other financial institution services. We refer to these people as "unbanked." Less than half of the people who are banked are eligible for lending to the rest of us. To improve the capacity of banks to provide credits, efficient and effective credit scoring platform, credit decision making process, limit assessment and fraud detection are evident. Artificial Intelligence based credit digital lending is the most promising, and relevant solution, especially for small and medium enterprises and individuals.

Intelligent technology enables BigTech businesses to continuously modify risk assessments using real-time information to process a huge volume of loan requests quickly. BigTech lenders

can restructure loans rapidly and in huge quantities thanks to the machine learning approach, which drastically reduces operating expenses. At the time of Covid-19, the BigTech financing model is especially resilient due to its "contact-free feature" in every operation, including client recruiting, loan risk assessment, and rescheduling (Yiping et al., 2020).

Credit scoring is transformed by artificial intelligence. Traditional credit scoring does not account for the complexity and variety of individual financial activities. However, AI is capable of processing enormous volumes of data, spotting trends, and accurately processing credit scoring in a matter of minutes. This makes it possible to evaluate creditworthiness fairly and more individually. By taking into account alternative data during the scoring process, AI credit scoring also has the ability to increase credit prospects for disadvantaged populations from finance or loan service, such as individuals with weak credit files or recent credit applicants. Furthermore, AI is utilized to identify frauds involving dubious source data.

A. AI credit scoring

Mohamed (2016) stated that credit scoring is the most widely used technical method for assigning scores that improve the process of classifying projected debtors into risk classifications. According to Nabila (2019), an AI model estimates an individual's credit capacity by gathering more detailed information from often more raw data, including credit history, expected incomes, education, and present and potential employment. A lot of people utilize artificial intelligence to enhance the credit risk evaluation procedures better.

Golnoosh et al. (2022) on the study titled “Explainable FinTech lending” stated that Lending activities, especially Artificial Intelligence (AI) effectively estimate the financial performance for individuals and SMEs from the available data sources. It showed that machine learning (ML) is capable of extracting patterns from massive databases, which can then be applied to lending data to produce creditworthiness estimations that are more reliable compared to those produced by traditional credit scoring algorithms.

As Jean et al. (2023) explained in his study of “Cost of Explain ability in AI: One important use of artificial intelligence is credit scoring, which makes predictions about the creditworthiness of current or prospective borrowers based on a variety of reasons, including the economy of the state. A grade or score that represents a borrower's default probability over a given time period or the duration of the credit risk (lifetime PD) is assigned by credit scoring algorithms. It is

employed in the estimation and underwriting of credit, management of risks related to credit, and computation of capital requirements for financial institutions as required by laws such as Solvency II and Basle IV.

The independent variable AI based credit scoring in this research was used questionnaires adapted from Eno Gregory (2022) to measure the effect of AI credit scoring on credit risk. It includes the applications AI in credit scoring that includes: instantaneous decisions, Predictive analysis, and market risk analysis, use of qualitative data for risk modeling, AI mitigate bias by improving fairness, It's transparent and compliance with regulations, Risk reporting, assess the creditworthiness of prospective borrowers and predict borrowers' defaults.

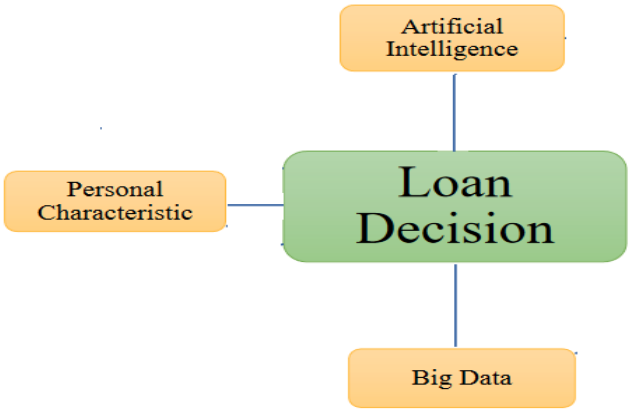
To answer the first research question the following hypothesis was prepared for test.

Hypothesis 1: AI based credit scoring has a positive and significant effect on credit risk management of digital lending

B. AI Lending decision

Making decisions involves methodically choosing the best option from a range of options in order to address issues. According to the study of Wang and colleagues (2019), between August 2017 and January 2018, conducted a study indicate that AI-based models may simultaneously lower the default rate and raise the approval rate.

Figure 2.1: Artificial Intelligence based loan decision.



Source: Maha, 2020

Maha (2020) in his study found a statistically significant positive correlation between the quality of loan decision making and the uses of artificial intelligence. According to Asongo et al. (2021), AI is utilized in credit risk models that financial institutions and the general public use to determine which loans to make.

To answer the second research question the following hypothesis was prepared for test.

Hypothesis 2: AI based lending decision has a positive and significant effect on credit risk management of digital loan

C. AI Personalized Loan offerings

Personalized digital financing services are one of the uses and advantages of AI in personalized banking. AI learns more about customers and their behavior to forecast creditworthiness based on previous interactions. This enables banks to tailor financial goods and services by adding personalized features and easy interfaces to provide relevant financial solutions and establish lasting connections with its consumer.

According to Shorouq et al. (2010), Jordanian banks can enhance their lending evaluation systems by employing artificial intelligence systems like neural networks. According to the study's findings, neural networks can be helpful for categorizing requests of loans because of the algorithm's precision. According to research by Eno (2022), the use of artificial intelligence (AI) for individualized finance improves the client experience and increases flexibility in customer care while offering additional features to a wider clientele.

To answer the third research question the following hypothesis was prepared for test.

Hypothesis 3: AI based personal loan offering had a positive and significant effect on credit risk management of digital loans.

2.3 Credit Risk Management

Credit risk management, as described by Casu et al. (2006), is a management strategy that aids in optimizing an institution's rate of return by limiting its financial risk vulnerability within reasonable bound. According to Raghavan (2003), the most importance of credit risk management are to “measure, identify and mitigate the high risk area of the bank”. According to

the description, credit risk management is critical to commercial organizations' analysis, observation, and assessment of the many actions taken to reduce credit risk.

Credit risk management, according to Kalapodas et al. (2005), is a management strategy that aims to eliminate, control, and minimize risks in order to maximize advantages while minimizing losses. Financial organizations can enhance their financial performance and avoid credit risk by using credit risk management. A comprehensive method for holistic risk mitigation includes good credit risk management, which is essential to a financial institution's health and stability. Financial institutions should put in place the right policies and procedures to ensure efficient identification, evaluation, measurement, monitoring, and handling or reduction of credit risk.

2.3.1 Credit Risk Measurements

Different authors give different ideas on Credit risk measurement. Some authors present summaries of information that should be obtained from credit agencies in order to make an informed decision. Other authors present mathematical and theoretical models for credit analysis that use the information gathered from business information authorities. In order to facilitate decision-making, Hodgkinson and Walker (2003) developed an expert system based on rules. This system aids financial institutions in making decisions regarding requests for credit on loans with cooperative credit.

Eka et al. (2023) measured credit risk using bad debit or none performing loans (NPL) which are obtained by comparing total credit limits with total credit amounts distributed to borrowers or debtor’s. In contrary, Golnoosh et al. (2023) on their study indicated that An organization's anticipated probability of default (PD), or the likelihood that it won't be able to pay back its debts, is the primary factor used to evaluate its credit risk. Typically, to address this issue, the credit score of every business is estimated, and an acceptable level is set to categorize it into two primary groups based on predicate criteria: non-default and default.

2.4 Empirical Reviews

Several research works have looked into how AI affects banks' credit risk. The points that follow is extremely useful for this study and pertinent to matches. Hicham et al. (2022) talked about the application of AI theories, such as big data, throughout the credit evaluation process for creditworthiness evaluations by banks as well as other lending organizations. The study

contrasted big data, an AI tool, with traditional methods pertaining to credit evaluation, such as data pre-processing and parametric statistical procedures like logistic regression scoring. According to the research, artificial intelligence (AI) technology increases financial inclusion and microloan availability for the most vulnerable borrowers. However, the associated risks necessitate the adoption of new generation finance

Khandani et al. (2010) created nonlinear and nonparametric predictive models of consumer's credit vulnerability using machine learning technologies. For a sample of clients of a major commercial bank, the research integrated client (transaction-level and account-balance information for specific individuals) and credit reporting agency information from January 2005 to April 2009. The study's findings demonstrate that machine learning projections are far more flexible and can identify the dynamics of shifting lending seasons as well as the total amount of credit defaults.

According to Diederick and W. Fred (2019), traditional logistic systems evaluate a customer's loan portfolio based on past behavior; however artificial intelligence gives lenders the chance to always track the development of each individual risk by using behavioral unorganized and organized information. Forecasting utilizing algorithms based on machine learning offers a useful way to assess systemic risk in one of the most significant and susceptible economic sectors in a number of financial services firms. The results indicate artificial intelligence predictions have a greater capacity for forecast and offer the potential to scale risk models throughout product categories and geographical areas.

Artificial neural networks (ANNs) are highly adaptable models that are utilized as a decision support system that continually recognize and give preference to "wrong" accounts for clients, (Viresh, 2007). It is possible to undertake consistent, objective evaluation that is devoid of emotion and human mistake. Additionally, it has been discovered that its algorithms accurately forecast credit risk ratings.

Eno (2022) highlighted the significance of artificial intelligence (AI) in credit risk mitigation, customized banking, and the difficulty of integrating AI factors. The study's conclusions included the following recommendations: banks should systematically implement AI as part of their overall business strategy, not just as a means of competition; the international financial community should actively work to establish and improve the AI financial market in order to

foster the advancement of new scientific and technological achievements; and AI can be used for credit risk management and personalized financial services experiences.

2.4.1 Studies conducted out of Ethiopia.

In a Tunisian commercial bank, Sihem and Boujelbene (2017) calculated the likelihood of default as a means of gauging credit risk. The study combined artificial intelligence approaches, such as support vector machines (SVM) and artificial neural networks (ANN), with the conventional method of logistic regression (LR) to score data. According to the study's findings, applying artificial intelligence approaches to credit risk assessment enhances the efficiency of credit decisions while reducing the expense and duration of application processing.

The Asongo group (2021) it is impossible to overstate how important credit risk models are to the banking industry and the economy as a whole when it comes to lending choices. Further research has revealed that very few Nigerian banks have knowledge of machine learning methods as an analytical instrument for credit risk prediction. The study suggests that machine learning techniques be deployed and applied for credit risk estimation in emerging economies, where they will serve as a neutral framework for evaluating loan applicants in place of the prejudicial system, which is primarily a subjective decision that is susceptible to mistake and human interference. Khemakhem and Boujelbene (2017) conducted a research on credit risk assessment by artificial neural network and support vector machine using the RBF model for credit scoring applications in the Tunisian. The study stated that the effectiveness of credit decisions is increased, application processing time and cost are decreased, and credit risk is evaluated using artificial intelligence approaches.

Reisa and Quinti (2023) conducted a research on evaluating Classical and Artificial Intelligence Methods for Credit Risk Analysis. The study analysis shows that the artificial intelligence methods outperformed than the statistical approaches. Miliunaite and Gerda (2022) studied the Role of Artificial Intelligence, Financial and Non-Financial Data in Credit Risk Prediction. The results indicated that non-financial data can improve credit risk prediction performance in credit risk prediction models, and AI techniques can make it possible to include non-financial as alternative data in credit prediction models.

2.4.2 Studies conducted in Ethiopia

Ousman (2023) Studied the Digital Financial Inclusiveness Through Financial Technology in Ethiopia: Case Study on TeleBirr. Tekle and Melaku (2023) conducted a research on Machine Learning based credit risk assessment for predicting loan defaulters in Ethiopian Banking industry. According to the research, data mining applications can be advantageous for the banking industry to comprehend loan client behavior when it comes to forecasting loan default tendencies.

Tamiru et al. (2022) studied Analyzing the effectiveness of machine learning and deep learning algorithms for the loan evaluation model. The study stated that machine learning algorithms exhibit superior classification accuracy compared to deep learning algorithms. Furthermore, machine learning algorithms are favored over deep learning techniques for classifying loan applications as either accepted or reject the loan.

2.4.3 The research gap

The above listed topics demonstrated the reviews of literature on artificial intelligence and its various implementations on credit risk managements. It shows that the papers constantly conducted on the AI application on financial sectors, the author will argue that the studies does not sufficiently conducted on credit risk management. A few researches in the literature claim that credit risk has been observed to be impacted by AI. But, its application on digital lending was not well studied. In addition, most of researches were conducted on organizations found outside of Ethiopia; however, as Ethiopian banks are relatively new to AI and the digital lending technology, no studies have been specifically conducted there regarding the effect of artificial intelligence on credit risk management of digital lending. Thus, the purpose of this study was to investigate how artificial intelligence (AI) affects the credit risk management of digital loans at Coop bank.

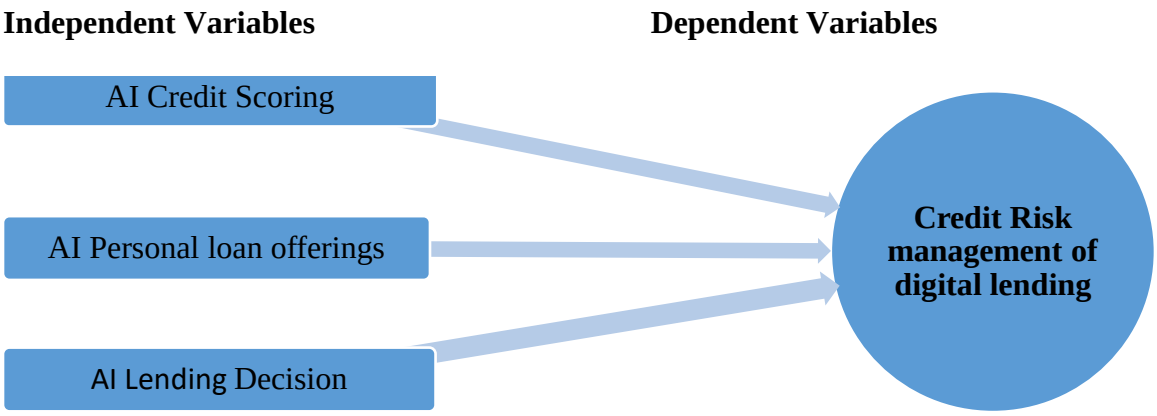
2.5 Conceptual framework

Gujarati (2004) stated that conceptual framework serves as the research project's blueprint, assisting the investigator in developing a mental grasp of the study and outlining the independent and dependent variables. Thus, the conceptual framework for this study will be created and described below based on the evaluated literature.

The purpose of this study was to investigate how artificial intelligence (AI) may impact Coop Bank's digital lending credit risk management. Thus, credit risk management is seen as a dependent variable and AI applications for digital lending (AI credit scoring, AI lending decision, and AI personalized lending) as explanatory or independent factors. In this study, a number of risk mitigation activities, including risk identification, assessment, monitoring, detection, control, and loan performance measurements, were used to gauge the effectiveness of credit risk management.

The foundation of the lending sector is credit scoring, which is used to assess borrowers' creditworthiness for loans (Wang et al. 2019). According to Lessmann et al. (2015), artificial intelligence (AI) has made it possible for new credit scoring tools to analyze intricate correlations between creditworthiness and borrower variables, including seemingly unimportant borrower characteristics. Determining a borrower's creditworthiness and approval status are key components of the lending decision-making process (Khaled, 2024). Making a final decision entails taking into account the findings of the credit risk assessment in addition to other elements like internal lending policies and market conditions. The detection of fraud in financial institutions can be made more dependable and effective with the application of artificial intelligence (AI). According to Joseph et al. (2021), the current credit administration and management practices used by banks for fraud detection aim to prevent false alarms. In 2019, Golda conducted research on artificial intelligence and found that neural networks a kind of learning model influenced by the activity of real neurons are used to identify fraud.

Figure 2.2: Conceptual framework



Source: Literature reviews, 2024

CHAPTER THREE

RESEARCH METHODOLOGY

Procedures and methods utilized in gathering, analyzing, and processing data was covered in this topic. In particular, it includes the following: an explanation of the subject area; study procedure; research design; target demographic; number of samples determination; data collection procedures; data interpretation techniques; sampling techniques and the application of ethical considerations.

3.1 Research Design

Gujarati (2004) defines research design as a blueprint or strategy that outlines the procedures for gathering and evaluating data relevant to a certain issue. Depending on the goals of each study, several research designs are employed, Ngalim (2018) stated that it is the research's conceptual framework. It offers the outline for conducting an investigation procedurally.

The explanatory research design was employed in the study to ascertain the association between the variables or to examine how the use of AI effects credit risk management. Chindler and Cooper (2003) stated that explanatory research attempts to clarify the causal relationship of events rather than just observing and characterizing the state. The goal of explanatory research is to identify cause and effect between independent and dependent variables. Descriptive analysis was employed to analyze Indicators of central tendencies such as mean, standard deviation, frequency, and percentage. The dependent variable in this study, credit risk management of digital loans, was examined in relation to three independent variables: credit scoring, lending decisions, and personalized loan offerings.

3.1.1 Research Approach

The impact of artificial intelligence on digital lending's credit risk management was demonstrated by this study. A quantitative research approach was used in this study. The association between an independent variable and a dependent or outcome variable within a population is ascertained through quantitative research studies (Muijs, 2010). Furthermore, quantification is stressed in quantitative research while gathering and analyzing data that can be represented as tables, percentages, or numbers (Babbie, 2010). Quantitative research also

involved the use of closed survey methodologies (Myers, 1997). The deductive method is also linked to quantitative research. Reliability, generality, and the application of limited sample results to the population from which the sample was obtained are all stressed by quantitative researchers (Collis, 2009).

In order to measure variables inferred from a sample of Coop Bank workers working in the digital lending department, risk management department, and branch offices under the banks central finfine district, this study employed a structured survey instrument. According to the methodological premise, deductive procedures, generalizations that result in explanations, forecasts, and understandings of the impact of AI in credit risk management of digital loans were conducted in this work. Consequently, the quantitative technique and positivist worldview were used for this investigation.

3.2 Target Population, Sampling Technique and Sample size

3.2.1 Target population

A target population, according to William (2011), is a collective word used to define the total number of samples or cases that the researcher would use in their study. In a similar vein et al. (2007) define a population as the group that the researcher is interested in and to which the findings are intended to be applied. Generally speaking, the sample is a subset of the population, which is the entire number of study participants.

In this research a researcher was used employees of Coop bank digital lending and risk management department at the head office and employees found under central finfine district branches. The total population of the study was 495 from which the sample size was selected.

3.2.2 Sampling Techniques

The process of choosing a sample size of individuals from a population in order to estimate the features of the entire population is known as sampling procedures. Sampling reduces the cost of data collecting and speeds up data acquisition. Every observation quantifies one or more characteristics of observable objects that can be identified as autonomous people (Robert, 2004; Kish, 1965). A sample design, according to Kothari (2006), is a well-defined strategy for obtaining a sample among the target population. In most research, it is obviously impractical and not practicable to examine the entire population. When a subset of participants, or a sample, is

chosen from the population that is representative of the entire population in terms of both number and size, the results gained are accurate inferences.

Employees at the head office and branches were selected for the study using two different sampling techniques. Using judgmental selection procedures, personnel from the central finfine district branches and two departments from head office the departments of digital lending and risk management were chosen in the first step. Judgmental or non-statistical sampling is applied for selecting a set of test items based on the experience, knowledge, and professional judgment of examiners to focus on areas that are known or likely to be at risk. Using lists of HO and Branch personnel as the sampling frame, simple or basic random sampling techniques were used in the second step to choose the sample unit from each department. The departments of digital lending and risk management, respectively, have 52 and 9 workers, and the central finfine district of the Coop bank employs 434 branch workers.

3.2.3 Sample Size

The study's power and precision, which may have an impact on the capacity to identify meaningful correlations or differences, are determined by the sample size. Even if a larger sample size study yields more trustworthy results, its cost and complexity are higher. The demographic under investigation, the research topics, and the study's accessibility resources may all influence the sample size. In this research Yemane's equation (Yemane, 1967) was used to calculate the required minimum sample size with a 95% confidence interval.

$$n = \frac{N}{1 + N(\mathrm{e})2}$$

Where: N represents the total population size,

n- Represent the sample size and

e-Denotes level of the precision at 95% confidence level (5% precision level).

This study sample size is

$$n = \frac{495}{1+495(0.05)2} = \mathbf{221}$$

The each stratum's (from each department's employees) sample size were determined as follows$Pi = \frac{ni}{N}$

Where: Pi – represents total proportion of population would be included in the stratum i,

ni-the number of sample size,

N= the overall number of population

Therefore, Pi=221/495=**0.446**

Table 3.1: Proportionate Sampling Determination

Departments	**Total Employees**	**Sample Size**
Digital lending	52	24
Risk Management	9	4
Total Clerical Employees under Central finfine district	434	193
Total	**495**	**221**

Source: Human Resource Department of Coop bank, 2024

3.3 Data Source and Collection Methods

3.3.1 Data Source

This study was used primary data gathered by a researcher using a questionnaire. The information that the researcher initially collects is known as primary data. Direct observations from respondents as well as surveys, questionnaires, and interviews may be used to gather it. This study's data sources were Digital lending and risk management department employees and selected branch employees under central finfine district of Coop bank. The study was employed close ended structured questionnaires (with prepared answer choices for responders) for survey. The five points Likert scales that ranges from one extreme attitude to another was applied.

3.3.2 Data Collection Instruments

Tools or methods for gathering and measuring data on certain variables are known as data collecting instruments. These are used to assess study outcomes and find answers to research questions. Data collecting instruments are used to gather data, process it, and arrange it in a methodical manner. Because it can collect data from an extensive range of respondents at a single point and is cost and time effective, the questionnaire was chosen as the primary data collection technique (Best and Kahn, 2005).

Questionnaires consist of two portions. The first portion of the questionnaire contains the respondent's personal characteristics such as information about their gender, age, education level, bank service year and current job position. The second part of questionnaire contains questions related with both independent and dependent variable of the research. Questions included in independent variables are AI credit scoring = 9 questions adapted from Eno (2022), AI Lending decision 7 questions received from Asongo et al. (2021) and AI based personalized loan offerings consists 9 questions used from Eno (2022). The dependent variable consists of 12questions adapted from Asongo et al. (2021) and Esker (2022) to measure credit risk management from risk mitigation and loan performance perspectives. The choices are formed by using a 5-point Likert format which is 1 represents Strongly Disagree, 2= represents Disagree, 3= represents Neutral (I have no idea), 4= represents Agree and5= represents strongly agree for both independent variables and dependent variable.

3.4 Research Procedures

The primary data for this study was gathered by using a comprehensive questionnaire which is fulfilled by the Coop banks digital lending and risk management employees and branch employees found under central finfine district branches. The questionnaire was prepared to prove for questions indicated in the statement problem of the study. The close ended structured questions was prepared using Likert scale format as it helps to assess respondents view on effect of Artificial Intelligence (AI) on credit risk management of digital loans (Upagade and Shende, 2012).

The researcher published the questionnaires using different research source that includes each variable questions and response choices. The researcher also attached formal letter from the AAU for approval of questionnaires by the banks management. The questionnaires were physically sent to all 221sample respondents of the bank. Before the researcher was collected the responses, the respondents had enough time (for two weeks) to finish the questions. Additionally, a pilot test was carried out to confirm the validity and reliability of the questionnaire; the specifics are provided in the upcoming topics.

3.5 Validity and Reliability of Data and Scale

A pilot, validity and reliability was conducted to evaluate quality of instrument.

3.5.1 Pilot Study

Pilot studies is mini survey that was conducted to pre-testing a specific study items or instrument, like an interview schedule or questionnaire, as well as small-scale versions of larger investigations (also known as feasibility studies). Before devoting additional resources and time to conducting a full scale survey, a pilot investigation is a small-scale survey designed to evaluate the survey's efficacy. A pilot study yields the data required to determine the sample size, evaluate the main study, reduce needless effort on the part of both investigators and participants, and allocate research resources. (Junyong (2017)

In this study, respondents from sample size were selected by simple random sampling method to conduct pilot study; those drawn from 221 members of Digital lending, credit management head office department and employees under central finfine district branches of Coop bank. The simple random sampling method was conducted and 22 respondents that account 10% of the total sample size were selected from Coop bank employees for pilot study. As Kothari (2004), the pilot study represents number of practical respondents (10% to 20% of the sample size).

Table 3.2: Pilot Study

Departments	**Number of respondent selected**
Digital Lending department	24*x10%=2.4 ≈2*
Risk management	*4x10%=0.4 ≈1*
Central Finfine district branch employee	193*x10%=19.3 ≈19*
Total	**22**

Source: Survey result, 2024

3.5.2 Reliability of the Instruments

According to Creswell (2005), an instrument is considered reliable if its scores are constant and stable. The scores must to stay constant and identical even when the piece of equipment is given multiple times at various times. Alternatively, as stated by Terwee CB and Dekker J, et al. (2007), it is the capacity to replicate a consistent result from various observers, exhibiting aspects on consistency, stability, and equivalency. It is among the main requirements for an instrument's quality. Put another way, instrument reliability is dependent on the circumstances and the population the instrument is utilized for; in other words, research settings determine the instrument's reliability. According to the Cronbach's Alpha test, the reliability coefficient that is closest to 1.00 or ≥0.60 is preferable.

The Cronbach's alpha reliability evaluation was used in this study among 22 pilot study participants to verify the reliability among the questionnaires. The findings indicated that all research items and questionnaires had Cronbach's Alpha values significantly greater 0.7, suggesting all the data collected were reliable.

Table 3.3: Cronbach Alpha Value

S/No	Variables	Number of items	Cronbach alpha
1	Credit Scoring	9	0.91
2	Personalized Loan Offerings	7	0.92
3	Lending decision	9	0.75
4	Constructs of Credit Risk Management	12	0.88

Source: Survey Results and SPSS output, 2024

3.5.3 Validity of the Instrument

When an instrument is considered valid, each of its individual scores has value and enables the researcher to make inferences from the population of samples under study (Crewell, 2005). In order to assess the validity of the instruments used in this study, seasoned educators of Addis Ababa University were asked to comment on the tool used. The instruments used was anticipated and modified based on their input before being given to the study's primary participants, with the goal of removing unnecessary elements and including pertinent ones.

3.6 Method of Data Analysis

Data organization, editing, and coding are all included in data analysis. Version 29.0.2.0(20) of the Statistical Package for Social Sciences (SPSS) was utilized for analysis in this study. Both explanatory and descriptive analytical techniques were used in the study. Indicators of central tendencies such as mean, standard deviation, frequency, and percentage calculations are part of descriptive analysis. In order to determine the impact of AI applications on the credit risk of digital loans, multiple linear regressions was employed as an inferential analysis technique, along with correlation analysis to assess the strength of the association among AI applications and credit risk management.

The study employed correlation analysis to evaluate the degree of relationship between two variables. The coefficient of correlation (r) indicates how strong a relationship is. According to Saunders et al. (2016), the value of r ranges from -1 to +1, where a value of +1 denotes an ideal positive connection (perfect positive correlations) and a value of -1 denotes an ideal negative correlation. The dependent variable in this study, credit risk management of digital loans, was compared to the independent factors (credit scoring, lending decision, and personal lending) using Pearson's correlation coefficient. This study's fourth chapter examined the detail.

Multiple linear regression analysis will be used when the data has two and above independent variables (Greene, 2012). For this study the AI Applications that include AI credit scoring, AI lending decision and AI personal loan offering that are postulated to influence credit risk management of the bank from risk mitigation measurements and loan performance. The detail was studied in chapter four of this research.

Assumption to use the correlation and multiple regression analysis was tested before employing them. According to C. Fein et al. (2022) the widely used technique in the classical linear regression model test are linearity, homoskedasticity, autocorrelation, multicollinearity, normality and significant Outliners and all of them are tested this study.
Oscar (2007) stated that a regression model's specification should be examined prior to estimation or testing the hypothesis. Model specification is referred to as the process of selecting which independent variables to include or exclude in a regression equation. In this study the

correlation analysis and multiple regression analysis was applied using model summary and ANOVA (analysis of variable) to test the validity and significance of the relationship between variables.

3.7 Ethical Consideration

An introductory letter from Addis Ababa University was utilized to request authorization from senior officials at the Cooperative Bank for the data collection process in order to uphold ethical standards. Since research is done with and about individuals by a person or organization, Dawson (2007) states that as researchers, we need to handle all those involved and the data that they supply with honesty and respect. This is because informed permission of participants and privacy are vital. Respondents must understand the motivation behind their disclosure of personal or other information. It enhances their willingness to actively contribute to data collection for research (Singh, 2007). As a result, the digital lending and risk management departments and branch employees under central finfine district was briefly informed during the survey about the objective of the study. Furthermore, it is kept confidential as well as used only for only academic purpose of the research objectives.

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS, AND INTERPRETATION

4.1 Data Presentation

The methods used to convert unprocessed data or raw source to analyzed summary of facts (information) are covered in this parts of chapter. It displays the results of the analysis of the survey questions. The study used quantitative data collection techniques to provide a thorough picture of how AI applications have reduced credit risk at Coop Bank. The core data for the study came from arranged and structured items or questionnaires that were used to gather data and the responses have been entered into SPSS Version 29.0.2.0(20) for processing and display. In the course of the analysis, each is subjected to first descriptive statistics, and then both the independent and dependent variable are correlated using a second correlation analysis. Finally, to determine the extent to which changes in independent variables (credit score) are responsible for the variation in the dependent variable (credit risk), a multiple regression approach was employed.

4.1.1 Questionnaire Response Rate

The response rate is defined as the percentage of research instruments having reporting units that are complete, divided by the total number of eligible reporting units in the sample, by the America Association for Public Opinion Research (AAPOR, 2011). In this research a total 221 questionnaires was distributed to digital lending and risk management employees at head office and branch employees under central finfine district of Coop bank. From this questionnaire 204 were filled and collected from respondents. This shows a response rate of 92.3% which is deemed sufficient for the study and the detail is presented in table 4.1 below. This indicates a 92.3% response rate, which is considered adequate for the study.

Table 4.1: Respondents response rate on survey questionnaires

Departments	**Distributed Questionnaires**	**Administered Percentage (%)**	**Received Questionnaires**	**Retrieved Percentage (%)**
HO. Digital Lending	24	10.86	20	9.05
HO. Risk management	4	1.8	3	1.35
Central finfine district employees	193	87.33	181	81.9
Total	**221**	**100**	**204**	**92.3**

Source: Survey result, 2024

In the above table the total numbers of 221questionnaires in all were distributed; of those, 204 were successfully retrieved, yielding a response rate of 92.3%. AAPOR (2011) states that a response rate of more than 50% is considered good, and more than 70% is extremely good. Additionally, Mugenda and Mugenda (2008) said that 50% of responses are appropriate for analysis. In a similar vein, Babbie (1990) states that a response rate of 60% is good and 70% are excellent. The sufficiency limit is set by Bailey (1996) at 75%, and Chen (1996) contends that the non-response error decreases with increasing response rate. A response rate of 92.3% was attained in this investigation. As a result, the study had a very high response rate.

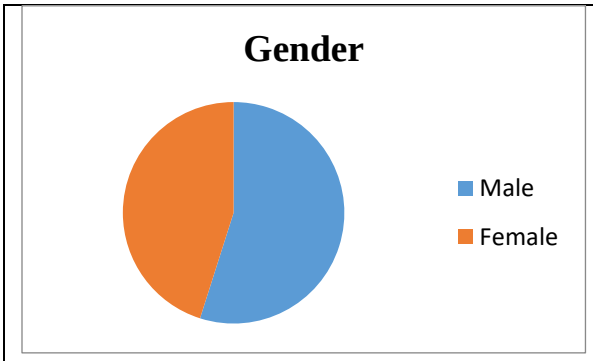
4.1.2. Respondents demographic characteristics

The study's respondents' age, gender, education level, work experience and present positions are among their general data. The summary for each of them was presented in distinct sections.

4.1.2.1 Gender

The goal of this heading is to determine the respondents' gender distribution from the Coop bank that is being reviewed. As a result, the results are displayed in Figure 1 below.

Figure 4.1: Gender distribution of respondents



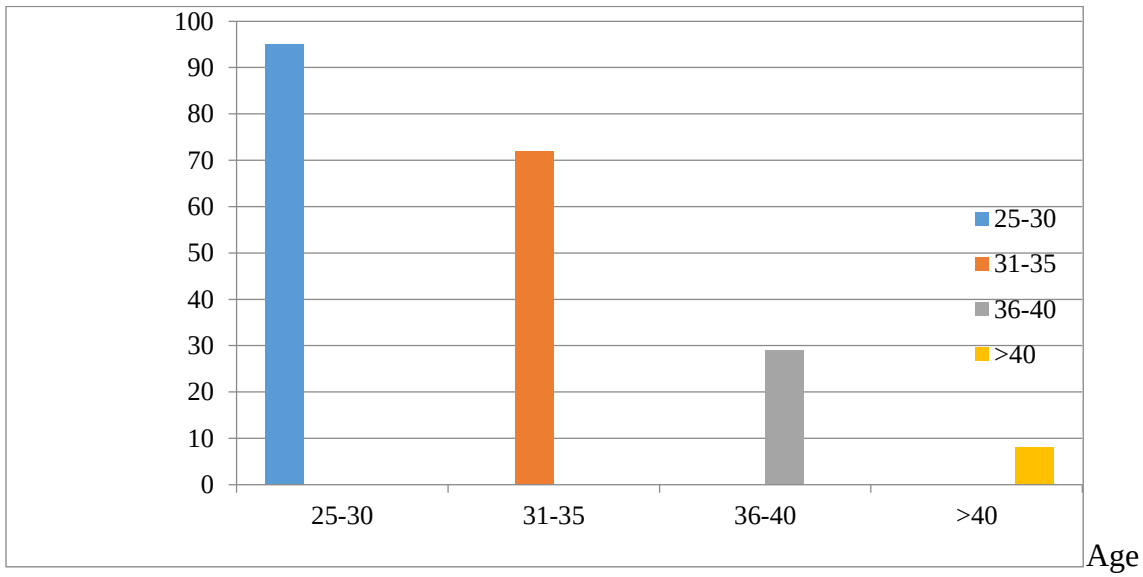
Gender	Frequency	Percentage (%)
Male	112	54.9
Female	92	45.1

Source: Survey result, 2024

The result on Gender distribution figure 3revealed that among respondents (54.9%) were male which shows majority of them and 45.1% of the respondents were female. This affirms that even if there's small variation between them it shows that the Organization was employed more men as it was compared the women's.

4.1.2.2 Age distribution of Respondents

Figure 3.2: Respondents Age



Source: Survey result, 2024

Most of the respondents age was between 25 and 35 or from age 25 up to 30 is 95 respondents that covers 46.6% of the total and between age 31 and 35 is 72 respondents which means 35.3% by percentage. A small number of respondents i.e., 29 (14.4%) and 8 (3.9%) were between the ages of 36 up to 40 and greater than 40 respectively. This implies majority of the respondent's age is found in a range of high production working force which only a few numbers are above 40.Studies show that younger work force is more flexible to adopt technology than others; from this table everyone may expect that the bank would have high opportunity to adapt the AI technology.

Table 4.2: Current Position of employees

Position	**Frequency**	**Percentage**
Senior manager	3	1.18
Managers	28	13.9
Professional employees	124	60.78
Semiprofessional employees	49	24.32
Total	**204**	**100**

Source: Survey result, 2024

The result in above table 4.2 shows that 60.78% of the employees are professional and 24.32% of the employees are semiprofessional. The managers and senior managers are 13.9% and 1.18% respectively. This one can predict that the bank has a good pyramidal human resource structure that support the operations functionality.

4.1.2.3 Respondents Level of Education

Table 4.3: Education level of Respondents

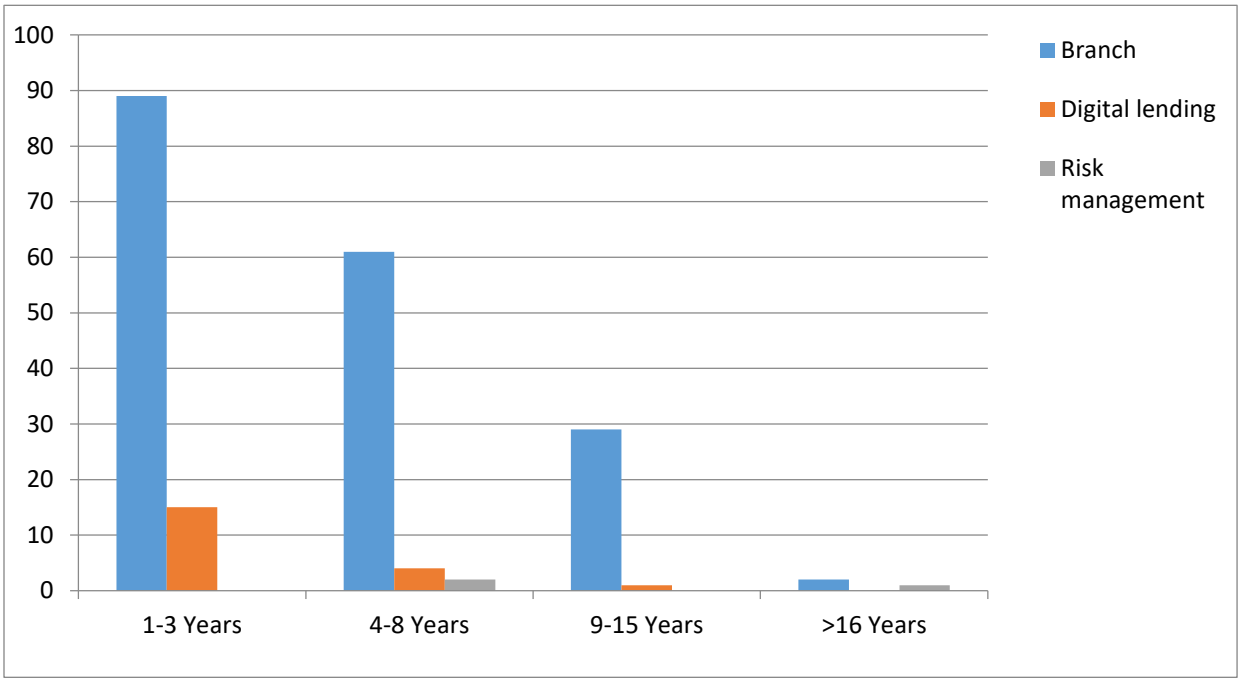
S. No	Level of Education	Risk Management		Digital Lending		Branch Employees		Total	
		F	%	f	%	F	%	f	%
1.	Diploma	0	0	0	0	0	0	0	0
2.	First Degree	1	33.3	17	85	153	84.5	171	83.8
3.	Master's Degree	2	66.7	3	15	28	15.5	33	16.2
4.	PhD	0	0	0	0	0	0	0	0
5.	Other	0	0	0	0	0	0	0	0
Total		**3**	**100**	**20**	**100**	**181**	**0**	**204**	**100**

Source: Survey result, 2024

The result in table 4.3 show that 2(66.7%) of the risk management HO employees highest level of respondents education is second (Master's) Degree and 1(33.3%) is first degree holder. Concerning Digital Learning employees, 17(85%) of them are first degree holder and 3(15%) have second degree (masters). 153(84.5%) of the Branch employees are first degree holders and only 28(15.5%) are master's degree holders. There's no employees who holds a diploma as well as a PhD. The finding affirmed that most of the employees are first degree holder.

4.1.2.4. Respondents experiences in Bank

Figure 4.3: Respondents experiences in Bank



Source: Survey result, 2024

According to the results of the respondents' experience working in banks, as seen in Figure 5 above, 104 (51%) of the respondents' work experiences fell between one and three years, followed by 67 (32.8%) in the range of four to eight years and 30 (14.7%) in the range of nine to fifteen years. Just 3 people, or 1.5%, have worked for more than 16 years. This showed that most bank workers have one to three years of job experience. The outcome also demonstrates that branch staff members have more relevant work experience than those in the department of digital lending. Two departments combined lack the experience of the risk management staff. This strongly suggested that the bulk of the study's Coop bank workers had fewer work experiences.

4.1.3 Descriptive Statistics of Variables

To determine the degree to which respondents agreed with statements regarding the application of artificial intelligence (AI) and credit risk management of digital loans, descriptive statistics were used to evaluate the raw data under this issue. A five-point Likert scale, with 1 denoting strongly disagree, 2 disagree, 3 neutral, agree, 4 agree, and 5 strongly agree, was used to develop the questionnaire for the aforementioned issue. In contrast, the results were reported using five

ranges based on the computed mean scores. A mean score of (1.0 – 1.5), (1.5 – 2.5), (2.5 – 3.5), (3.5 – 4.5), and (4.5 – 5.0) was therefore calculated, denoting, respectively, very poor, poor, undecided, high, and very high.

4.1.3.1 Descriptive statistics of Artificial Intelligence (AI) models

This section sought to establish applications of Artificial Intelligence models on digital lending at Coop bank. Essentially it is sought to establish credit scoring, lending decision and personalized loans.

A. AI Credit scoring

This section explains the detail of respondent's perception regarding the items to measure status of AI credit scoring model on digital lending of Coop Bank and details are presented on table 4.4 underneath with their respective mean and standard deviations.

Table 4.4: Descriptive Statistics of AI Credit scoring

S/No	Statement	N	Mean	Std. Deviation
1	Artificial Intelligence gives near instantaneous or quick lending decisions	204	4.09	1.072
2	Artificial Intelligence conducts Predictive analysis of potential risks and threats	204	4.01	1.101
3	AI assess the creditworthiness of prospective borrowers	204	4.18	1.100
4	AI Makes use of external data for risk measurement (e.g., government articles, annual reports, NBE directives and other sources)	204	3.78	1.209
5	AI application is transparent and compliance with regulations	204	3.72	1.099
6	AI Mitigate bias by improving fairness	204	4.10	.990
7	AI Application report any Risks that might exist	204	3.80	1.142
8	AI models predicts borrowers defaults accurately than traditional statistical models	204	4.10	.926
9	Artificial Intelligence conducts Market risk analysis	204	3.89	.982
	Aggregate Mean	**204**	**3.96**	**.831**

Source: Survey result, 2024

The first item's mean score is 4.09, with a corresponding standard deviation of 1.072, as can be seen in table 4.4 above. This shows that respondents agreed, on average, that artificial intelligence provides loan choices that are quite fast or nearly instantaneous. Similarly, participants said artificial intelligence performs a moderate predictive analysis of possible risk and threats. The mean score of 4.01 and the standard deviation of 1.101, respectively, serve as evidence for this. The third item mean score is 4.18, with a 1.100 standard deviation. These show that AI evaluates potential borrowers' creditworthiness in order to control the credit risk associated with digital loans. Similarly, for items number 4, 5, 6, 7, 8, and 9, the mean scores were 3.78, 3.72, 4.10, 3.80, 4.10, and 3.89, with standard deviations of 1.209, 1.099, 0.990, 1.142, 0.926, and 0.982, respectively. The findings show that artificial intelligence is moderate in its use

of external data for risk measurement (e.g., government articles, annual reports, NBE directives, and other sources); moderate in is transparent and compliance with regulations; high in Mitigate bias by improving fairness; moderate in reporting any potential risks; high in predicting borrowers defaults accurately than traditional statistical models; and moderate in carrying out market risk analysis.

Furthermore, the items' average standard deviation of 1.04 suggests that the deviation from the mean is too small, implying that each item's individual response is close to the others, which in turn indicates good precisions. The grand mean of 3.96 also revealed that the use of AI application in credit scoring is moderate in the digital lending of the firms under study. This leads one to the conclusion that, despite the potential of AI-based credit scoring systems, much work remains to be done to advance the bank's digital transformation program, which could ultimately improve credit risk management.

B. AI Lending Decision

This section explains the detail of respondent’s perception regarding the items to measure the status of AI Lending decision model on digital lending of Coop Bank and details are presented on table 4.5 underneath with their respective mean and standard deviations.

Table 4.5: Descriptive statistics of AI Lending decision

S/No	Statement	N	Mean	Std. Deviation
1	Decision to Give digital loans is based on AI Risk Assessment level of the borrower	204	4.17	.885
2	Disbursement is done only when the borrower meets the required criteria	204	4.01	.990
3	Artificial Intelligence based application gives approval or rejection tip for requested loans before disbursement	204	4.04	.930
4	Subjective (personal) Decisions leads to Mistake and high Default	204	4.24	1.010
5	Use of Artificial Intelligence for Default Prediction will loan loss	204	4.25	.978
6	Decision to Give Loans in the bank is currently is based on customer 5Cs(Character, Capacity, Capital, Collateral and Conditions)	204	3.98	1.012
7	Artificial Intelligence based application gives appropriate repayment schedule	204	4.10	.985
	Aggregate Mean	**204**	**4.11**	**.797**

Source: Survey result, 2024

Table 4.5 above confirms that in the AI lending decision of organization under study confirms that, Decision to grant digital loans is based on AI Risk Assessment Level of Borrower by a mean value of 4.17 and standard deviation of 0.885; Disbursement is made only when Customer meets requirements confirmed by a respondents by a mean of 4.01 and standard deviation of 0.990. Artificial intelligence based application provides approval or rejection tip for requested loans prior to disbursement by a mean score of 4.04 and standard deviation of 0.930. The descriptive statistics result of AI lending decision is also shows that; subjective (personal) decisions lead to error and high default, use of artificial intelligence for default prediction will reduce loan loss, decision to grant loans in the bank currently based on customer 5Cs (Character, Capacity, Capital, Collateral and Conditions) and Artificial Intelligence based application gives appropriate repayment schedule from the items number 4 to 7 with the mean scores of 4.24, 4.25, 3.98, and 4.10 and standard deviations of 1.010, 0.978, 1.012 and 0.985 respectively. In conclusion, the overall standard deviation of 0.797 suggests that each individual response

deviates little from the mean, indicating that the replies were somewhat near to one another. Furthermore, the grand mean score of 4.11 indicated that the majority of respondents agreed with the offered ranges of choices. This shows how the bank made a high-quality digital loan decision based on AI.

C. Artificial Intelligence Based Personal Loan Offerings

This section explains the detail of respondent's perception regarding the items to measure status of AI Personal Lending model on digital lending of Coop Bank and details are presented on table 4.6 underneath with their respective mean and standard deviations.

Table 4.6: Descriptive statistics of AI Personal Lending

S/No	Statement	N	Mean	Std. Deviation
1	Artificial Intelligence Supports Personal Planning	204	3.89	.494
2	Artificial Intelligence based application gives Virtual financial assistances	204	3.75	.694
3	Artificial Intelligence application has Chatbot service to handle customers need	204	3.90	.643
4	Artificial Intelligence application supports customer service with low cost and time	204	4.12	.888
5	Artificial Intelligence conducted Sentiment analysis of loan (Evaluating customer behavior and bank activities) for loan application and approval process	204	4.09	.883
6	Artificial Intelligence application has image recognition system to identify data.	204	4.06	.875
7	AI Natural language generation helped to analyze a large amount of loan data at less time and cost	204	4.17	.883
8	Artificial Intelligence Automated digital lending Transactions	204	4.25	.962
9	Artificial Intelligence application gives Personalized Reminders for repayments	204	4.13	.892
	Aggregate Mean	**204**	**4.04**	**.471**

Source: Survey result, 2024

The table displays the descriptive data for the AI personal lending measurements from 204 respondents. The typical mean scores for the AI application on personal based digital financing

range from 3.75 to 4.25. The range of the standard deviations is 0.494 to 0.962.Artificial Intelligence Automated digital lending Transactions scored the highest mean (4.25, SD=0.962) and closely followed by AI Natural language generation helped to analyze a large amount of loan data at less time and cost (4.17, SD=0.883). Artificial Intelligence application gives Personalized Reminders for repayments is also received the highest mean (4.13, SD=0.892) and AI supports customer services is also high (4.12. SD=0.888). The Artificial Intelligence Sentiment analysis of loan (Evaluating customer behavior and bank activities) for loan application and approval process and Artificial Intelligence applications image recognition system to identify data are high with a mean of 4.09 and 4.06 and standard deviation of 0.883 and 0.875 respectively. The three items of Personal Lending; Chatbot service to handle customers need, Supports Personal Planning and Virtual financial assistances is moderate with a mean of 3.9, 3.89 and 3.75 respectively and standard deviation of 0.643, 0.494 and 0.694 respectively.

The overall mean and standard deviation of 4.04 and 0.471indicates that the respondents are largely agree in each situation and their response deviation is little from the each other. Based on these results, it is possible to draw the conclusion that while the banks' AI-based application for personalized loans was encouraging, the customized system was only rated as moderate, necessitating further work to fully utilize advanced AI technology for online lending.

4.1.3.2 Descriptive statistics of Credit Risk management

This section explains the detail of respondent’s perception regarding the items to measure status of AI Personal Lending model on digital lending of Coop Bank and details are presented on table 4.7 underneath with their respective mean and standard deviations.

Table 4.7: Descriptive statistics of Credit risk management

S/No	Statement	N	Mean	Std. Deviation
1	In my organization the digital loans are repaid within the time frame specified in the loan agreement.	204	3.95	.864
2	In my organization the risk assessment of digital loan is promptly done	204	4.12	.950
3	The number of Non-Performing digital credit in my organization is declining from year to years.	204	3.91	.984
4	In my organization credit risks identification was done promptly to reduce the lose	204	3.97	.904
5	My organization has set clear strategy for dealing with nonperforming digital loans	204	3.75	.972
6	There is efficient credit risk monitoring system in my organization	204	3.99	.874
7	There's aggressive credit collection method in my organizations digital lending system.	204	4.03	.920
8	There's well trained lending personnel in your organization.	204	3.95	.875
9	There's efficient Policy and Procedure used for digital credit risk assessment in your bank.	204	3.74	.987
10	My organization is successful in managing non-performing digital loans	204	4.21	.846
11	My organization is aware of causes and effects of nonperforming loans	204	3.98	.506
12	There is an efficient control and evaluation that decreases credit risk risks	204	3.67	.874
	Aggregate Mean	**204**	**3.95**	**.589**

Source: Survey result, 2024

Based on the bank's credit risk management findings, the table above displays descriptive data for the credit risk management measurements from 204 respondents. The average score falls between 3.67 and 4.21, suggesting that the bank has managed the credit risk associated with its

digital loan satisfactorily. The range of the standard deviations is 0.506 to 0.987. The organization manages non-performing digital loans successfully has the highest mean score (4.21, SD=0.846). A quick risk assessment of digital loans is conducted within the organization, with a mean score of 4.12 and a standard deviation of 0.950. Additionally, the digital lending system's aggressive credit collection strategy has a mean of 4.03 and a standard deviation of 0.920.

The bank is moderate on the efficiency of credit risk monitoring system, aware of causes and effects of nonperforming loans, credit risks identification was done promptly to reduce the loss, digital loans are repaid within the time frame specified in the loan agreement, well trained lending personnel is available and level of Non-Performing digital Loan is declining from year to years by a means of 3.99, 3.98, 3.97, 3.95, 3.95 and 3.91 Standard deviations of 0.874, 0.506, 0.904, 0.864, 0.875 and 0.984 respectively. The strategy for dealing with nonperforming digital loans, availability of efficient procedure used for risk assessment of digital loan and availability of efficient control and evaluation are the items those have the lowest mean scores of 3.75, 3.74 and 3.67, with standard deviations of 0.972, 0.987 and 0.874 respectively.

The aggregate standard deviation of 0.589 indicate that the respondents perspective deviation is little on their credit risk management view and the grand mean of 3.95 indicate that they agree for the items indicted to measure the credit risk management of digital loan. From this, it is possible to conclude that the credit risk management of the organization is though encouraging still needs improvement.

4.2 Data Analysis and Interpretation

According to Jason and Elaine (2017), there are several advantages for the researcher when they verify the assumptions of multiple regressions. Errors of Type I and Type II can be prevented by ensuring that an analysis satisfies the related assumptions. Dealing with problems like low dependability, non-normality, and co-linearity attenuation frequently increases effect sizes, which is typically a desirable result.

4.2.1 Diagnostic Tests of Assumptions of Correlation and Classical Linear Regression

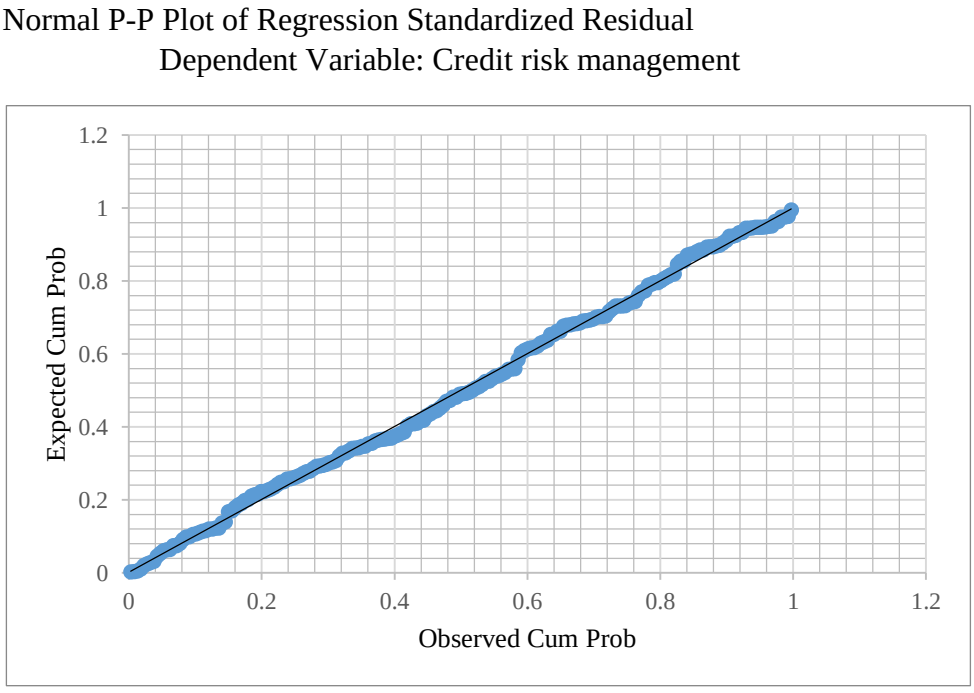
According to Brooks (2014), the Ordinary Least Squares (OLS) approach is a widely used technique in the classical linear regression model (CLRM) to find the Best Linear Unbiased

Estimators (BLUE) and fit a linear line to the data. The underlying assumptions of CLRM must hold in order to assess if the OLS yields the Best Linear Unbiased Estimators (BLUE) (Brooks, 2014; Gujarati and Porter, 2009; C. Fein et al., 2022). According to C. Fein et al. (2022) these presumptions are also crucial for performing correlation analysis.

a. Linearity Test.

As stated in CLRM's second assumption 2 the degree to which changes in the independent variables are correlated with changes in the dependent variable is known as linearity. To utilize OLS, a linear model that is, a relationship between x and y that can be written as a straight line must exist (Brooks, 2014). Plots of the regression residuals using SPSS Version 29 software were utilized to ascertain whether there was a relationship between the independent variables (AI Credit scoring, AI Lending decision, and AI Personal Loan Offering) and the dependent variable (credit risk management). This assumption has been met, and the relationship is regarded as linear.

Figure 4.4: Linearity Test



Source: Survey result, 2024

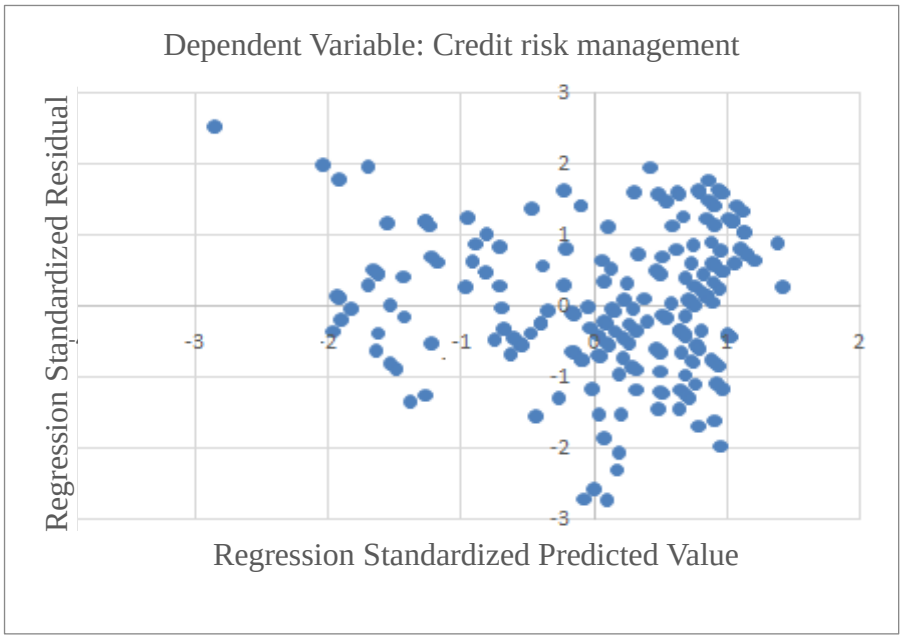
Figure 5 showed that all of the data are distributed close to the linear fit line, indicating a linear relationship between the dependent (criterion), independent (predictors), and variables. As a result, the study's premise to employ multiple regressions and Pearson product moment correlation is met

b. Homoskedasticity

For all values of x, the variance of the mistakes is constant and finite (Var (Ut) = σ2 < ∞). Regression analysis can be performed in practice under the assumption that there is no heteroscedasticity, according to Gujarati and Porter (2009). The residuals can then be examined postmortem to determine whether they show any regular patterns. In order to conclude that there is no heteroscedasticity issue and that the assumption of homoskedasticity is satisfied, a scatter plot was created for this study between the Regression Standardized Residual and the Regression Standardized Predicted Value. It reveals no discernible pattern or trend in the residuals' distribution.

Figure 4.5: Scatter plot

Scatter plot



Source: Survey result, 2024

c. **No Autocorrelation:** There is no association between the residuals because the errors are linearly independent of one another (Cov (Ui,Uj) = 0).The Durbin-Watson test is the most well-known method for identifying serial correlation, according to Gujarati and Porter (2009). According to Brooks (2014), a residual's Durbin-Watson value of 0 to 0.95 indicates positive autocorrelation, 0.95 to 1.15 indicates inconclusive, 1.15 to 2.85 indicates no autocorrelation, 2.85 to 3.05 indicates inconclusive, and 3.05 to 4 indicates negative autocorrelation.

For this investigation, the Durbin-Watson result was 1.32 (refer to Table 4.12). Model summary: This indicates that neither the residuals' autocorrelation nor the null hypothesis demonstrating the absence of autocorrelation will be rejected. Consequently, this presumption is taken into satisfied

d. Normality Test

According to Hemandez (2021), a normality test is a widely used technique in statistics and data analysis to calculate the likelihood that a random variable powering the collected information will be normally distributed and that the sample data was taken from a population that is normally distributed. More specifically, skewness and kurtosis are two shape metrics that can be used to verify normalcy (Garren et al., 2021). The degree of symmetry in a variable's distribution is measured by its skewness. Kurtosis, on the other hand, contrasts the dataset distribution with the standard distribution. In this investigation, skewness and

Table 4.8: Normality Test

Descriptive Statistics					
	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
AI Credit Scoring	204	-1.000	0.170	-0.167	0.339
AI Lending Decision	204	-0.842	0.170	-0.448	0.339
AI Personal Lending	204	-0.646	0.170	-0.505	0.339
Credit risk management	204	-0.216	0.170	-0.741	0.339
Valid N (listwise)	204				

Source: Survey result, 2024

In order to explain a normal univariate distribution, George and Mallery (2010) said that values for asymmetry (skewness) and kurtosis that was found existed between -2 and +2 are deemed acceptable. Table 4.8, skewness and kurtosis results show that every variable had a skewness value in the range of 1 to +1. As a result, it was discovered that the study's data had a normal underlying distribution, and the assumption was met.

e. Multicollinearity Test

When there is a strong correlation among independent or predictor variables, this is referred to as multicollinearity. This presumption suggests that the independent variables cannot have perfect multicollinearity. Predictive power "overlaps" or shares if there is a multicollinearity problem. However, when the variables that are autonomous are not independent of one another, multicollinearity happens. In this work, tolerance and variable inflammatory factors (VIF) are used to test multicollinearity. VIF and tolerance quantify the impact of independent variables on one another. VIF illustrates how multicollinearity inflates an estimator's variance (Gujarati and Porter, 2009).

For determining tolerance, a first linear regression evaluation is performed. For these first stage regression analyses, it has the definition $T = 1\text{-}R^2$. If the tolerance value is more than 1, it may indicate that there may be a multi-co linearity issue. The linear regression definition for variable inflammatory factors (VIF) is $VIF = 1/T$. There is an indicator of a multicollinearity concern when the VIF is more than 10. According to Gujarati (2015), if the VIF and tolerance are less than 10 and 1, respectively, it means that there isn't a significant multicollinearity problem with the particular independent variable used in the regression model.

Table 4.9: Collinearity Statistics of the Independent Variables

Model		Collinearity Statistics	
		Tolerance	**VIF**
1	AI Credit Scoring	0.287	3.484
	AI Lending Decision	0.998	1.002
	AI Personal Lending	0.287	3.481
a. Dependent Variable: Credit risk management			

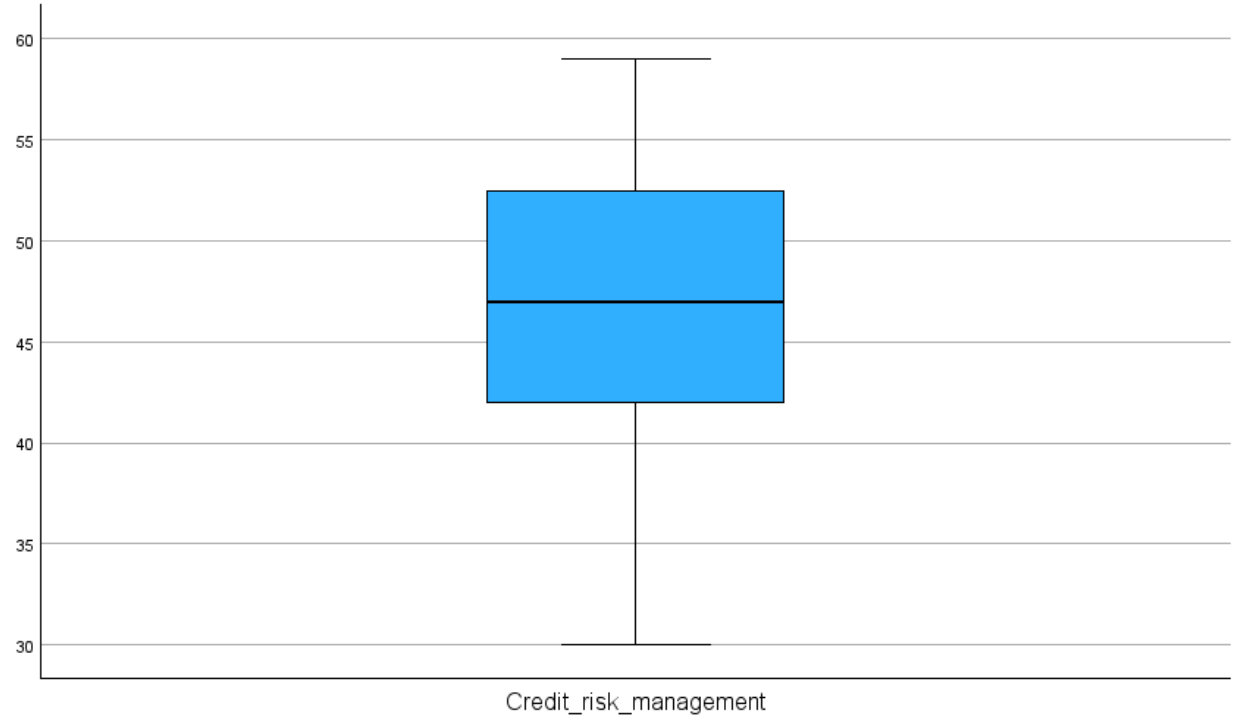
Source: Survey result, 2024

Table 4.9’s results showed that the tolerance and VIF values for all variables that are independent are significantly lower than the respective limits of 10 and 1. It demonstrates that there is little correlation between the study's independent variables. Therefore, the premise that numerous regressions should be used is satisfied as there's no multicollinearity issue.

f. No significant Outliners

There are no asterisks on either end of the box plot correspond ding to studentized deleted residual below, indicating the absence of outliners. For the purposes of this investigation, this assumption is therefore deemed met.

Figure 4.6: Boxplot of Studentized Deleted Residual



Source: Survey result, 2024

4.2.2 Correlation Analysis

According to Bluman (2008), correlation analysis is a statistical technique which measures the strength of the linear relationship among both the two variables. Correlation analysis's main goal is to evaluate linear relationship among two variables. A single figure known as the correlation coefficient helps to quantify the strength of this link (Walpole et al., 2017). According to Bluman (2008), the Pearson product-moment correlation coefficient (PPMC) is one sort of correlation coefficient that assesses the direction and strength of a linear relationship among both of the two

variables. Between ranges of -1 and 1, the correlation coefficient has a value. Strong positive linear relationships are shown by values closer to 1, and strong negative linear relationships are indicated by values closer to -1. Moreover, a number approaching 0 denotes the absence of a linear relationship or a very weak one.

Table 4.10: Correlation between AI Applications and Credit Risk Management

Correlations				
N:204	AI Credit Scoring	AI Lending Decision	AI Personal Lending	Credit risk management
AI Credit Scoring	1			
AI Lending Decision	0.027	1		
AI Personal Lending	.844**	0.002	1	
Credit risk management	.852**	0.09	.778**	1
**. Correlation is significant at the 0.01 level (1-tailed).				

Source: Survey result, 2024

The findings show a significant positive association between credit risk management and artificial intelligence applications, and a correlation between all the variables (sig. level $P<0.01$). In particular, AI Credit Scoring and Credit Risk Management have a substantially greater association, as seen by its highest correlation coefficient (0.852). With a correlation value of 0.788, AI Personal Lending and credit risk management also have a high association. Conversely, the correlation coefficient (0.09) between credit risk management and AI lending decisions is comparatively lower, indicating a weaker association.

4.2.3 Multiple Regression Analysis

A statistical method for examining the relationship between a group of independent or predictor variables and a dependent or criterion variable is regression analysis. Estimating the population mean of the dependent variable from the known values of the independent variables is the main goal of regression (Gujarati and Porter, 2009). Multiple regressions are widely used as statistical tools to determine the best prediction equation for a set of variables, i.e., to estimate the contribution of a particular variable or set of variables, i.e., identifying independent relationships, and to predict how much of the variation in the dependent variable is due to predictors

(independent) variables. Multiple linear regressions, or MLRs, are primarily used to describe the linear relationship between the study's dependent variables, or response variables, and explanatory or independent variables.

Multiple regression analysis was used in this study to measure the amount of variance in the dependent variable caused by the independent variable. The AI Applications (AI Credit Scoring, AI Lending Decision, and AI Personal Lending) were the predictor variables for the regression analyses. Furthermore, as previously demonstrated, an examination of the underlying assumptions of the Classical Linear Regression Model (CLRM) and Correlation Analysis demonstrated that none of the assumptions were broken. As a result, the results of the multiple regression models that show the strength of the correlation between the independent and dependent variables are shown in Table 4.12. The Goodness of Fit (R square or R^2) gauges how well the regression model genuinely matches the data. It is always between 0 and 100% and represents the percentage of the dependent variable variation that a linear model explains. The smaller discrepancies between the fitted values and the observed data are indicated by greater R2 values.

4.2.4 Model Specification and Interpretation

The model specification to test the hypothesis is given as follows in table 4.11.

Table 4.11: Model Specification

Where	AI CS	Artificial Intelligence Credit Scoring
	AI LD	Artificial Intelligence Lending Decision
	AIPL	Artificial Intelligence Personal Loan Offerings
	CRM	Credit Risk Management
	B	Coefficient of the slope of regression model
	A	Constant term
	E	Error term

Source: Survey result, 2024

Table 4.12: Model summary

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.862[a]	0.743	0.739	3.617	1.323
a. Predictors: (Constant), AI Personal Lending, AI Lending Decision, AI Credit Scoring.					
b. Dependent Variable: Credit risk management					

Source: Survey result and own computation, 2024

According to the above model summary, R shows a significant positive relationship of 0.862 which is 86.2%. The value of R^2 is 0.743 meaning 74.3% of the variation in the model can be predicted using independent variables and 25.7% of the variance in credit risk management is due to other factors that was not included in this research. This is indicated by the Adjusted R Squared value of 0.743, which takes the number of independent variables into account and is a more accurate measure of the Goodness of Fit.

As a result, the built-in AI applications (such AI personal lending, AI lending decision making, and AI credit scoring) are good explanatory variable for credit risk management of digital loans. A goodness of fit value of less than 0.1 is regarded as poor fit, 0.11 to 0.30 as modest fit, 0.31 to 0.50 as moderate fit, and >0.50 as strong fit, according to Muijs (2004). The goodness of fit R^2 value in this study is 0.74, indicating a strong fit between the models independent variables and the dependent variable credit risk management of digital loans.

Table 4.13: Anova

ANOVA[a]						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	7547.437	3	2515.812	192.321	0.000[b]
	Residual	2616.269	200	13.081		
	Total	10163.706	203			
a. Dependent Variable: Credit risk management						
b. Predictors: (Constant), AI Personal Lending, AI Lending Decision, AI Credit Scoring						

Source: Survey, 2024

The model's overall adequacy is indicated by the analysis of variance (ANOVA) result, which is displayed in the above table. It can be concluded that the regression model used is adequate because the null hypothesis, which states that all the independent variables are jointly insignificant (i.e., the coefficients of the independent variable are zero), is rejected based on the resulting F ratio, F (3, 200) = 192.321, P = 0.000 < 0.05, which shows that the p-value is less than the test significance level of 0.05.

Table 4.14: Model Coefficients

Model Coefficients[a]							
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Zero-order (r)
		B	Std. Error	Beta			
1	(Constant)	9.199	2.828		3.252	0.000	
	AI Credit Scoring	0.634	0.063	0.671	10.016	0.000	0.852
	AI Lending Decision	0.090	0.046	0.071	1.987	0.048	0.090
	AI Personal Lending	0.353	0.112	0.212	3.167	0.002	0.778
Dependent Variable: Credit risk management							

Source: Survey result, 2024

The regression analysis results for the model are shown in the above table; the constant term value of 9.199 indicates that, on average, the value of credit risk management would be 1.792 if all other variables held a value of zero. The unstandardized coefficient Beta of AI credit scoring (0.634) indicates that, on average, a unity increase in AI credit scoring means a 0.634 unit increase in credit risk management, and the relationship is statistically significant at 1%. A unity increase in AI Lending Decision means, on average, a 0.090 unit increase in Credit risk management of digital loans, according to the unstandardized coefficient Beta of AI Lending Decision, which is 0.090. The relationship is statistically significant at 1. With all other factors held constant, an increase of one unit in AI Personal Lending translates into a rise of 0.353 units in credit risk management, according to the unstandardized coefficient Beta of AI Personal Lending (0.353). This association is statistically significant at 1%.

In conclusion, AI Credit Scoring has the highest standardized coefficient (0.671) of all the statistically significant AI applications, suggesting the strongest positive impact on credit risk management. AI Personal Lending is next with a standardized coefficient of 0.212, indicating a weaker positive significant effect on credit risk management. Finally, AI Lending decision has a standardized coefficient of 0.071.

Thus, the Model Equation can be expressed as follows using the regression model coefficients displayed in Table 4.14 as a basis:

Credit Risk Management (CRM) = $\beta_0 + \beta_1 AICS + \beta_2 AILD + \beta_3 AIPL + \varepsilon$

CRM = 9.199+0.634AICS+ 0.090AILD + 0.353AIPL+ 2.828

Furthermore, based on the above mentioned table 4.12 (model summary), The value of R^2 is 0.743 meaning 74.3% of the variation in the model can be predicted using independent variables in other words, from this study, the created independent variables account for 74.3% of the explanation of credit risk management.

The following formula was used to determine the extent to which credit risk management is explained by each independent variable.

$(R^2)(100) = (\beta \text{ AICS } \chi \text{ ϒAICS} + \beta \text{ AILD } \chi \text{ ϒAILD} + \beta \text{ AIPL } \chi \text{ ϒAIPL})$

$0.743(100) = (0.671 \chi 0.852 + 0.071 \chi 0.090 + 0.212 \chi 0.778)$

$74.3\% = 57.16\% + 0.6\% + 16.49\%$

This result shows that 57.16%, 0.6% and 16.49% of the change in credit risk management is due to AI Credit scoring, AI Lending decision and AI personalized loans. The results of regressions analysis explained that there is statistically significant positive relation between AI application and credit risk management of digital loan.

4.3 Discussion and Hypothesis Testing

AI Give credit A number of scoring metrics, such as almost rapid loan decisions, are conducted predictive evaluation of possible dangers and hazards, performs Utilizing qualitative data in risk modeling, analyzing market risk, verifies and backtests credit risk models. Forecast financial or economic factors utilized in risk management, highlight potential risks, evaluate potential borrowers' creditworthiness, and predict defaults by borrowers with a forecasting accuracy that is higher than that of conventional statistical models. AI Credit Scoring and Credit Risk Management had a comparatively greater positive link, according to the correlation analysis ($r=0.852$). This was further supported by the regression study, which showed that, in comparison to all other AI Applications, this one had the largest beneficial impact on credit risk management (Regression: $\beta=0.671$, $p<0.05$). This is consistent with earlier research by Eben and Ayuns (2024) showing that AI-powered models for credit scoring can enhance risk management procedures and lead to more equitable and inclusive credit assessments.

AI lending decisions include risk assessment of the customer, disbursement only upon meeting the necessary requirements, based on the customer's 5Cs (character, capacity, capital, collateral, and conditions) and approval or rejection tips for requested loans prior to disbursement. Subjective (personal) decisions result in mistakes and high default rates. AI Lending Decision and Credit Risk Management had a weakly positive link, according to the correlation analysis ($r=0.09$). The results of the regression analysis likewise show that there is a substantial, albeit weakly positive, link between the two (regression: $\beta=0.071$, $p<0.05$). This suggests that while

respondents are generally in agreement regarding AI lending decisions, AI lending decisions by themselves are insufficient to have a meaningful impact on credit risk management which means it have a weak positive effect. Instead, credit risk management is shaped by the interaction of other dimensions, such as AI credit scoring and AI personal lending. This is consistent with earlier research by Maha (2020), which found a positive association between the quality of loan decision and the use of artificial intelligence.

Artificial intelligence (AI) personal lending capabilities include picture recognition, chatbot services, and natural language generation for large-scale data analysis, and sentiment analysis of loans, virtual financial aid, and supports customer service with low cost and time. AI Facilitates automated digital lending transactions, personalized payback reminders, and the borrower's personal planning. AI Personal Lending and credit risk management showed a strong positive link, according to the correlation analysis ($r=0.778$). According to the regression analysis, AI Lending Decision had a positive significant influence on digital credit risk management that was second only to AI Credit scoring ($p<0.05$, regression coefficient: $\beta=0.353$). A possible reason behind this is that, according to research done by people like Vijaya (2024), consumers are a company's lifeblood indicating that AI-based personalization model in the digital finance ecosystem positively affects credit risk mitigation which in turn enhancing trust among the customers and the financial institutions. As a result, the AI personal lending or AI Based personal loan offering contributes to a higher level of credit risk management of digital lending.

Generally, the finding emphasizes the importance of AI based digital lending system have positive significant effect on credit risk management of digital loans.This is consistent with earlier research done by Khemakhem and Boujelbene (2017) that states the use of artificial intelligence techniques in the evaluation of credit risk improves the effectiveness of credit decision, minimizes processing cost and time by personalized lending and credit scoring model.

Table 4.15: Summary of Hypotheses testing and results

S.N	Hypotheses	Result	Reason
1	H1: AI credit scoring has a positive and significant effect on credit risk management of digital lending	H1: Accepted	β>0 and Sig=0.000 P<0.05
2	H2:AI based lending decision has a positive and significant effect on credit risk management of digital loan	H2: Accepted	β>0 and Sig=0.048 P<0.05
3	H3: AI personal loan offering had a positive and significant effect on credit risk management of digital loans.	H3: Accepted	β>0 and Sig=0.002 P<0.05

Source: Survey result and own elaboration, 2024

Thus, the research questions are addressed based on the data analysis as:

- **What is the effect of Credit scoring by Artificial Intelligence on credit risk management of digital loans?**

The results show that the Coop bank's credit risk management of digital lending and its artificial intelligence-based credit scoring model have a strong and favorable correlation. So, it would be concluded that the AI credit scoring have a significant and positive effect on credit management of digital loan.

- **To what extent the lending decision by Artificial Intelligence have significantly effect on credit risk management of digital loans?**

The results show that Artificial Intelligence based lending decision have a positive but weak significant effect on digital loans risk management.

- **What is the effect of personalized loan offerings by Artificial Intelligence application on credit risk management of digital loans?**

The results show that credit risk management of digital lending in the Coop bank and artificial intelligence personal lending, or personal loan providing model, have a substantial and favorable

link. This concludes AI personal Loan offering have positive as well as significant effect on digital loans credit risk management.

CHAPTER FIVE

SUMMARY, CONCLUSION, ANDRECOMMENDATIONS

A synopsis of the study's findings, inferences, and suggestions are explained in this chapter.

5.1 Summary of Findings

The first specific objective of this study was to analyze the effect of credit scoring by Artificial intelligence application on credit risk management of digital loans. The result shows that the strongest association was found between AI credit scoring and digital loan credit risk management, as evidenced by the greatest correlation coefficient. Particularly its application on near instantaneous or quick lending decisions, predictive analysis of potential risks and threats, assess the creditworthiness of prospective borrowers and predict borrowers' defaults was received positive feedback from the bank employees respondents and it's transparent and compliance with regulations, risk reporting, market analysis and makes use of external sources for risk assessment are needs improvement

The second specific objective this study was to determine how lending decision by Artificial Intelligence application impacts the credit risk management of digital loans. The result shows that AI Lending decision was viewed favorably, including Risk level Assessment of the Customer, Disbursement criteria, approval or rejection tip, Subjective (personal) Decisions, Reduce default and appropriate repayment schedule. However, there was a need for improvement considering the customers5Cs (Character, Capacity, Capital, Collateral and Conditions) while a decision was given for a loan.

The third specific objective of the study was to examine the effect of Artificial Intelligence application based personalized loan offerings on credit risk management of digital loan. The study result showed that AI personal Lending was positively perceived, including aspects such as analyze a large amount of loan data, Artificial Intelligence conducted Sentiment analysis, image recognition, Supports Personal Planning, Personalized Reminders for repayments and automated digital lending Transactions.

The credit risk management status of the organization was successful as the digital loans are repaid within the time frame specified in the loan agreement; risk assessment of digital loan is promptly done; awareness for causes and effects of nonperforming loans; the level of Non-Performing digital Loan in the bank is declining from year to years; credit risks identification was done promptly to reduce the loss; existence of efficient credit risk monitoring system and existence of aggressive credit collection method. But, existence of clear strategy for dealing with nonperforming digital loans; existence of well-trained lending personnel; existence of efficient Procedure used for digital credit risk assessment; and efficient control and evaluation that decreases credit risk of digital loans are needs improvement.

The general objective of the study was to analyze the effect of AI applications on credit risk management of digital loan. The study's correlation analysis result shows that the AI-based digital lending dimensions indicated in this research have positive significant effect on credit risk management of digital loan. From the three AI based credit scoring models, AI credit scoring system and AI Personal loan offerings have significant and positive effect on credit risk management of digital loans and AI lending decision has a weak significant effect.

5.2 Conclusion

Based on the aforementioned major finding results, it is possible to draw the conclusion that an AI-based digital lending system plays a crucial role in credit risk management for digital loans on Coop Bank S.C. Furthermore, it's possible to draw conclusion that among the AI based digital lending dimensions used in this research the effect AI credit scoring on credit risk management of digital loan was ranked firsts as 67.1% of the success of credit risk management was a result of change in AI credit scoring. This was implied that the organization must be gave more attention for AI credit scoring than the other dimensions. The second variable that has significant positive effect on credit risk management of digital loan was AI Personalized lending. 21.1% of the banks success in credit risk management of digital loan was due to improve of AI personalized lending. The AI Lending decision has a standardized coefficient of 0.071. Which means a change in credit risk management was affected only by 7.1% change in lending decision.

In conclusion, this study was explained the importance of Artificial Intelligence (AI) based digital lending system and it positive impact on credit risk management of digital loan. The findings shows the implementation of AI based digital lending applications to mitigate credit risk of digital loan that improve the loan performance of the bank would be encourage. The implementation of AI based digital lending system is crucial for banks to enhance credit risk mitigation which in turn improve the bank's loan performance. This was expected to give insights to the topic by explaining the empirical evidence of the relationship between AI applications and credit risk management of digital loans.

5.3 Recommendations

The researcher sent the following recommendations based on the aforementioned findings.

5.3.1 Recommendations for the Studied Bank

- The findings revealed that Artificial Intelligence application have significant positive effect on credit risk management of digital loan. Therefore, the bank should boost its AI based lending system.
- The finding revealed that the bank were relatively low in terms of its AI transparent and compliance with regulations and availability efficient policy and procedure used for digital credit risk assessment. Therefore, a researcher will recommend the bank and regulatory bodies should formulated a clear AI based digital lending framework that will improve accountability and responsibility among the lender and borrower to minimize credit risk of digital loan.

5.3.2 Recommendations for Future Studies

- As the both Artificial Intelligence and digital lending technology is at the birth stage for Ethiopia, the researcher will recommend the future studies to be done by expanding the topic across a wider bank industry and using another variables such as AI fraud detection, AI financial innovations and AI customer experiences and their effect on loan performance or organization performance etc.

REFERENCE

Natufe, O. and Esther, I. (2023). Credit Risk Management and the Financial Performance of Deposit Money Banks: Some New Evidence. *Journal of Risk and Financial Management. Vol 16: 302.*

Christoph, S. (2021). Addressing the challenges of digital lending for credit markets and financial systems in low- and middle-income countries: *Transformation of Economic and Social Systems'. German Development Institute. Vo.10.23661/bp23.*

Copeland, B. (2020). Artificial intelligence. Encyclopedia Britannica.

Arthur, B. (2019). 'The Growing Impact of AI in Financial Services: six examples"

Thangaraj, R. (2019). 'Digital Lending: Is It Alternative Lending Revolution?. *International journal of scientific and technology research. Volume 8ISSN 2277-8616.*

Bachiret al. (2021). Powering the Digital Economy: Opportunities and Risks of Artificial Intelligence in Finance. *IMF departmental Papers. Vol: 024.*

Coop bank S.C. (2023). Annual report. coopbankoromia.com.et

Wang, E.(2019). 'Does AI-based Credit Scoring Improve Financial Inclusion? *Evidence from Online Payday Lending'. Vol. ICIS Proceedings. 20.*

VP, Remesh. (2021). 'Role of AI in Banking'

Nabila, H. (2019). Impact of AI and Machine Learning on Financial Industry: Application on Moroccan Credit Risk Scoring. *Journal of Adv. Research in Dynamical and Control Systems. Vol. 11*

Noah, K. (2023). The Impact of AI on the Banking Industry. University of Twente, the Netherlands.

Hicham. A. (2022). Artificial intelligence and bank credit analysis: A review *Cogent Economics and Finance, Vol. 10:1, 2023262, DOI: 10.1080/23322039.2021.2023262*.

Riteshkumar, P. and Uma M. (2023). Artificial intelligence: a tool for enhancement of lending facilities in banking institution. *EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal Volume: 9,*

Minzhen, X. (2019). 'Development of Artificial Intelligence and Effects on Financial System' *J. Phys.: Conf. Ser. 1187 032084*

L, Hodgkinson. And E, Walker. (2003). an expert system for credit evaluation and explanation. *Consortium for Computing Sciences in Colleges, vol. 19(1): 62-72.*

Eka et al. (2023). The Role of Credit Risk, Management Risk and Capital on the Profitability of Indonesian Banks'. *International Social Sciences and Humanities UM Jember Proceeding Series. Vol. 2 No 3: 861-871*

Golnoosh, B. and Emanuela, R. (2022).Explainable Fin Tech lending. *Journal of Economics and Business. Vol. 125-126 106126*

NBE. (2023). Annual report.www.nbe.gov.et

Lessmann et al. (2015). Benchmarking State of the art Classification Algorithms for Credit scoring: An Update of Research. *European Journal of Operational Research. Vol. 247(1), pp. 124–136.*

Khaled, A. (2024). Rethinking SMEs lending decisions making: a two-stage model integrating AI approaches. *Migration Letters. Vol. 21(3), 1-5.*

Joseph et al. (2021). Artificial intelligence based system for bank loan fraud prediction. *International Conference on Hybrid Intelligent System. Vol. 463-472.*

Yiping et al. (2010). Fintech Credit Risk Assessment for SMEs: Evidence from China. *IMF Working Paper.*

Yashoda, K. (2018). The role of Artificial Intelligence (AI) in making accurate stock decisions in E-commerce industry. *International Journal of Advance Research, Ideas and Innovations in Technology.*

Bart, V. (2017). Machine Learning: A Revolution in Risk Management and Compliance? *The Capco Institute Journal of Financial Transformation.*

Maha, A. (2020). The role of artificial intelligence and big data on loan decisions. King Abdulaziz University. Saudi Arabia. *Growing Science, Canada.* Accounting 6-1291–1296

David, M. (2020). Industry 4.0 in Finance: The Impact of Artificial Intelligence on Digital Financial *Inclusion'. University of Johannesburg.*

Khandani, E. (2010). 'Consumer credit-risk models via machine learning algorithms. *Journal of Banking and Finance. Vol. 34: 2767-2787.*

Diederick, V. and Fred V. (2019). 'Artificial Intelligent Credit Risk Prediction: An Empirical Study of Analytical Artificial Intelligence Tools for Credit Risk Prediction in a Digital Era. *Journal of Accounting and Finance Vol. 19(8).*

Viresh, M. (2007). 'Credit Risk Analysis using Artificial Intelligence: Evidence from a Leading South African Banking Institution. *University of South Africa.*

Eno, G. (2022). 'Integration of Artificial Intelligence Applications for Financial Process Innovation by Commercial Banks in Nigeria'.*AkwaIbom State University.*

Asongoet, Al. (2021). 'The assessment of financial institutions awareness and application of machine learning techniques for credit risk prediction- the *case of Nigeria'.Adama University*.

Jason W. Osborne and Elaine, W. (2017). Four Assumptions of Multiple Regressions Those Researchers Should Always Test. *North Carolina State University and University of Oklahoma.*

Garren, S. And Osborne, K. (2021). Robustness of T-test Based on Skewness and Kurtosis. *Journal of Advances in Mathematics and Computer Science, 102-110.*

George, D., and Mallery, M. (2010). SPSS for Windows Step by Step: A Simple Guide and Reference, 17.0update (10a Ed.) Boston: Pearson.

Bluman, A. (2008). Bluman, Elementary Statistics: A Step by Step Approach, Student Edition (Reinforced Binding) with Formula Card. McGraw-*Hill Education.*

Walpole, R, Myers, R. and Ye, K. (2017). Probability and Statistics for Engineers and Scientists. *Pearson. WBCSD Stakeholder Dialogue on CSR. (1998).*

Eben, R. and Ayuns, L. (2024). AI-powered credit scoring and risk assessment models. *University of Melbourne. Research Gate. vol. 378926461*

Vijaya, K. (2024). AI-based Personalization and Trust in Digital Finance. *Microsoft. USA. Research Gate. vol. 378493680*

Sullivan, A., Steven, M. and Sheffrin, S. (2003). Economics: Principles in action. Prentice Hall, Upper Saddle River

Kalapodas, E., and Thomson, M. (2006). Credit risk assessment: a challenge for financial institutions. *IMA Journal of Management Mathematics, Vol. 17(2), pp. 25-46.*

Teklearegay, H. (2015). Practice and Challenges of Balanced Scorecard. *St Mary' University*.

Daniel, B. (2019). Loan Risk Prediction Using Machine Learning Algorithms: The Case of Ethiopia's Micro-Finance Institution's. *St. Mary's University.*

Johnson, R. B., and Christensen, L. B. (2004). Educational Research: Quantitative, Qualitative, and Mixed Approaches. Boston, MA: Allyn and Bacon.

Hicham, N., Nassera, H., and Karim, S. (2022). Strategic framework for leveraging artificial intelligence in future marketing decision-making. *Journal of intelligent management decision, 2(3), 139-150.*

Ngai, E. W., Hu, Y., Wong, Y. H., Chen, Y., and Sun, X. (2011). The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. Decision Support Systems, 50(3), 559–569.

Casu, B., Giradone, C., and Molyneux, P. (2006). Introduction to banking. Pearson United Kingdom.

Shaorouq, F. and Saad, G. (2010). Applying Neural Networks for Loan Decisions in the Jordanian Commercial Banking System. Al Zaytoonah University of Jordan. IJCSNS International Journal of Computer Science and Network Security, VOL.10 No.1.

Jean, D., Nora, B., and Fabien, V. (2023). Cost of Explainability in AI: An Example with Credit Scoring Models. IESEG School of Management, Univ. Lille. CCIS 1901, pp. 498–516

Tamplin, T. (2023). Market Risk Definition, Importance, Types, and Strategies. Finance Strategists; Finance Strategists.

Raghavan, R. (2003). Risk management in banks. *Chartered Accountant-New Delhi, Vol. 51*(8), pp.841-851.

Sihem, K. and Boujelbene, Y. (2017) Predicting credit risk on the basis of financial and non-financial variables and data mining. Review of Accounting and Finance 17(3). Research gate. DOI: 10.1108/RAF-07-2017-0143

Golda, D. (2019). An efficient privacy preserving on high-order heterogeneous data using fuzzy K-prototype clustering. Journal of Ambient Intelligence and Humanized Computing. Vol 12. Springer Berlin Heidelberg

Gujarati, D. (2004). Basic Econometrics. Fourth edition. United States Military Academy, West Point.

Ngalim, V. (2018). "Dewey's Notion of Interest: Antithetic to or Sympathetic with Educational Development? In R. Heilbronn, C. Doddington, R. Higham (eds.), in Dewey and Education in the 21st Century: fighting back. Emerald Publishing, Cambridge. (201-215).

Yin, R. (2013). Validity and generalization in future case study evaluations. Evaluation, 19(3), 321–332.

Creswell, J. (2012). Educational research: Planning, conducting, and evaluating quantitative and qualitative research (4th Ed.). Boston, MA: Pearson.

Muijs, D. (2010). Doing quantitative research in education with SPSS. Sage. Munhall, P. (2011) Nursing research. Jones and Bartlett Learning. Chapter 3 (Quantitative Versus Qualitative Research, or Both?), pp. 35-52.

Babblie, E. (2010). The Basics of Social Research 5th (fifth) Edition. Published by Cengage Learning.

Myers, M. (1997). Qualitative Research in Information Systems. MIS Quarterly, 21, 241-242.

Collis, J. and Hussey, R. (2009). Business Research: A Practical Guide for Undergraduate and Postgraduate Students. 3rd Edition, Palgrave Macmillan, Basingstoke.

Wiliam, D. (2011). What Is Assessment for Learning? Studies in Educational Evaluation, 37, 3-14.

Kothari, C. (2004). Research methodology: methods and techniques. (2nd Ed.). New Delhi: New Age International (P) Limited Publishers.

Robert, M. (2004): Survey Errors and Survey Costs, ISBN 0-471-67851-1

Kish, L. (1965): Survey Sampling. New York: John Wiley and Sons, Inc. p. 78-94

Best, J. and Kahn, J. (2005). Research in education (10th Ed.). Boston: Pearson Education, Inc.

Kubwimana, J. and Kengere, A. (2023). Credit Risk Mitigation and Loan Performance of Financial Institution: A Case Study of Zigama Credit Saving Society. Journal of Finance and Accounting. Vol 7(8) pp. 89-104

Upagade, V. and Shende, A. (2012). Research methodology. 2nd edition. S. Chad and Company Ltd. Ram Nagar, New Delhi. Economics and Finance Review Vol. 5(02) pp. 14 – 23

Junyong, I. (2017). Introduction of a pilot study. Department of Anesthesiology and Pain Medicine, Dongguk University Ilsan Hospital, Goyang, Korea

Terwee, et al. (2007). Quality criteria were proposed for measurement properties of health status questionnaires. J Clin Epidemiol. Vol. 34-42.

Saunders, M., Lewis, P. and Thornhill, A. (2016). Research Methods for Business Students. 7th Edition, Pearson, Harlow.

Mohammed, et al. (2021). The role of digital platforms in revolutionizing the lending sector. International Journal of Innovative Research in Science, Engineering and Technology. Volume 10.

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy." The Journal of Finance 23:4: 589-609.

Saqib, A. and Michael, D. (2019). AI and machine learning for risk management. Rennes school of Business, France. SSRN Electronic Journal. DOI:10.2139/ssrn.3201337

Tole, Million, G. Mohammed, S. and Haymanot, A. (2019). Determinates of credit risk in Ethiopian commercial banks. Journal of Accounting, Finance and Auditing Studies 5: 196–212.

Bhattarai, B. (2019). Effect of credit risk management on the financial performance of commercial banks in Nepal. European Journal of Accounting, Auditing and Finance Research 7: 87–103.

Alrfai, Mohammad, M. Danilah, B. and Waeibrorheem, W. (2022). Empirical examination of credit risk determinant of commercial Banks in Jordan. Risks 10: 85.

UNDP, Ethiopia. (2024). Digital lending platforms, a step forward for financial inclusion for MSMEs in Ethiopia.

Tsegate, A. Melaku, B. and Tekle, D. (2023). Machine Learning-Based Credit Risk Assessment for Predicting Loan Defaulters in Ethiopian Banking industry. Wolaita sodo University. researchgate.net/publication/376834536.

Schmit, J. T. & Roth K. (1990).Cost Effectiveness of Risk Management Practices. Journal of Risk and Insurance. Vol. 57, No.3 pp. 455-470

Hassan, M. (2016). Risk management of banking sector: a critique review. American International Journal of Social Science. Vol. 5, No. 3

Aduda, J. (2011). The relationship between credit risk management and profitability among the commercial banks in Kenya. Journal of Modern Accounting and Auditing, 7(9), 034.

Morris, J. (2001). Diversification in the credit portfolio: An overview of country practices. IMF Working Paper, 5(1), 53.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15-25.

Ravikumar.T, Murugan.N, Suhashini.J. (2019). Digital Lending: Is It Alternative Lending Revolution? International journal of scientific & technology research volume 8, SSN 2277-8616.

Ousman, M. (2023). Digital Financial Inclusiveness through Financial Technology in Ethiopia: Case Study on TeleBirr. Arsi University, Ethiopia.

Cooper, D.R. and Schindler, P.S. (2003). Business Research Methods. 8th Edition, McGraw-Hill Irwin, Boston.

Tamiru, M., Tesfahun, B. Abdu M. and Assaye, W. (2022). Performance analysis of deep and machine learning algorithms for loan evaluation model. Bahirdar University, Ethiopia. Ethiopian journal of science and technology. 16(2): 101-114.

Khemakhem, S. and Boujelbene, Y. (2017). Artificial Intelligence for Credit Risk Assessment: Artificial Neural Network and Support Vector Machines. University of Sfax. ACRN Oxford Journal of Finance and Risk Perspectives 6.2:1-17

Bruno, R. and Antonio, Q. (2023). Evaluating Classical and Artificial Intelligence Methods for Credit Risk Analysis. Instituto Superior Tecnico, Universidade de Lisboa, Portugal. Journal of Economic Analysis 2023 2(3) 94-112.

Laura, M. and Gerda, Z. (2022). The Role of Artificial Intelligence, Financial and Non-Financial Data in Credit Risk Prediction: Literature Review. 17th Prof. Vladas Gronskas International Scientific Conference Kaunas: Vilnius University Kaunas Faculty.

Yitbarek, K. (2023). Loan repayment performance and its determinants: evidence from micro and small enterprises operating in Dire Dawa. JigJiga University, Ethiopia. Journal of Innovation and Entrepreneurship.13731-023-00271-6

APPENDIX

Addis Ababa University

College of Business and Economics

Department of Business Management

Artificial Intelligence (AI) and Credit risk management of digital loan Survey

Coop Bank

Dear Respondent,

First, I want to express my gratitude for agreeing to fill this questionnaire despite your incredibly job schedule. My name is Rebira Birhanu a graduate students at Addis Ababa University (AAU) School of Business and Economics. Currently I am carrying out a research study entitled" The Effect of Artificial Intelligence (AI) on Credit risk management of digital loan for partial fulfillment of Master's degree in Business Management.

The information provided will be used only for academic purpose and will be treated with strict confidentiality. If you have any questions or concerns about completing the questionnaire, you can raise questions at any moment. By completing and submitting the survey, you are indicating your consent to participate in the study. Your participation is appreciated and I would like to thank in advance.

Kind regards,

Rebira Birhanu

Phone: 0991745938 or Mail: rabibkitata@gmail.com

General Instructions

- ✓ There is no need of writing your name.
- ✓ In all cases where answer options are available please tick (√) in the appropriate box.

Part I: Background Information of the Respondents

S.N	Variables	Parameters	Answer
1	Gender	Male	
		Female	
2	Age (Years)	<25	
		25-30	
		31-35	
		36-40	
		Above 40	
3	Education Level	College Diploma	
		Bachelor's(BA/BSC) Degree	
		Master's Degree	
		PhD	
		Other	
4	Experience in bank (in years)	>1	
		1-3	
		4-8	
		9-15	
		Above 16	
5	Current Position in the organization	Officer/semi-professional	
		Manager	
		Senior manager	

Part II: Main Survey Questionnaire

This section sought to examine AI Applications and credit risk managements. Please put a **"√"**mark in the appropriate column. The options range from 1(strongly disagree), 2(disagree), 3(I have no opinion), 4 (agree), and 5 (strongly agree).

2.1 AI Credit scoring

S.N	**Application artificial intelligence (AI) in credit Scoring**	**Level of Agreement**				
		5	4	3	2	1
1	Artificial Intelligence gives near instantaneous or quick lending decisions					
2	Artificial Intelligence conducts Predictive analysis of potential risks and threats					
3	AI assess the creditworthiness of prospective borrowers					
4	AI Makes use of external data for risk measurement (e.g., government articles, annual reports, NBE directives and other sources)					
5	AI application is transparent and compliance with regulations					
6	AI Mitigate bias by improving fairness					
7	AI Application report any Risks that might exist					
8	AI models predicts borrowers defaults accurately than traditional statistical models					
9	Artificial Intelligence conducts Market risk analysis					

2.2 AI Lending Decision

S.N	AI Application based digital lending decision	Level of Agreement				
		5	4	3	2	1
1.	Decision to Give digital loans is based on AI Risk Assessment level of the borrower					
2.	Disbursement is done only when the borrower meets the required criteria					
3.	Artificial Intelligence based application gives approval or rejection tip for requested loans before disbursement					
4.	Subjective (personal) Decisions leads to Mistake and high Default					
5.	Use of Artificial Intelligence for Default Prediction will loan loss					
6.	Decision to Give Loans in the bank is currently is based on customer 5Cs(Character, Capacity, Capital, Collateral and Conditions)					
7.	Artificial Intelligence based application gives appropriate repayment schedule					

2.3 AI Personalized Lending

S.N	Application artificial intelligence (AI) in Personalized Lending experience	Level of Agreement				
		5	4	3	2	1
1	Artificial Intelligence Supports Personal Planning					
2	Artificial Intelligence based application gives Virtual financial assistances					
3	Artificial Intelligence application has Chatbot service to handle customers need					
4	Artificial Intelligence application supports customer service with low cost and time					
5	Artificial Intelligence conducted Sentiment analysis of loan (Evaluating customer behavior and bank activities) for loan application and approval process					
6	Artificial Intelligence application has image recognition system to identify data.					
7	AI Natural language generation helped to analyze a large amount of loan data at less time and cost					
8	Artificial Intelligence Automated digital lending Transactions					
9	Artificial Intelligence application gives Personalized Reminders for repayments					

2.4 Credit Risk Management

S.N	Credit Risk management	**Level of Agreement**				
		5	4	3	2	1
1	In my organization the digital loans are repaid within the time frame specified in the loan agreement.					
2.	In my organization the risk assessment of digital loan is promptly done					
3.	The number of Non-Performing digital credit in my organization is declining from year to years.					
4.	In my organization credit risks identification was done promptly to reduce the lose					
5	My organization has set clear strategy for dealing with nonperforming digital loans					
6.	There is efficient credit risk monitoring system in my organization					
7.	There's aggressive credit collection method in my organizations digital lending system.					
8.	There's well trained lending personnel in your organization.					
9.	There's efficient Policy and Procedure used for digital credit risk assessment in your bank.					
10.	My organization is successful in managing non-performing digital loans					
11.	My organization is aware of causes and effects of nonperforming loans					
12.	There is an efficient control and evaluation that decreases credit risk risks					

አዲስ አበባ ዩኒቨርስቲ
የቢዝነስና ኢኮኖሚክስ ኮሌጅ
ማስተርስ ኦፍ ቢዝነስ አድሚንስትሬሽን

Addis Ababa University
College of Business & Economics
Masters of Business Administration

Ref. NO:- CBE/MBA/42 /2023/24

Date: 20/03/2024,

To Cooperative Bank of Oromia S.C

Student Rebira Birhanu, is undertaking a research project title, "

The Effect of Artificial Intelligence On Credit ውሳኔ of digital loan "

She/he is taking this opportunity of research project for a partial fulfillment of MBA in Finance /Management.

We believe that result of the research project would have practical application and be of value to you, to us and to the community at larger. Hence we would be very grateful if your organization could support us in this endeavor.

Besides, we promise you that data will be kept confidential and used for academic purposes only. Further, we can send to you all the summary and findings when the undertaking is completed.

We appreciate your anticipated cooperation.

With best Regards

Dereje Workie
Coordinator, MBA Program
College of Business and Economic
Addis Ababa University

☎ 251-011-1-22-96-91 ✉5563