ADDIS ABABA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

DEPARTMENT OF ACCOUNTING AND FINANCE

GRADUATE STUDIES

CHALLENGES AND BENEFITS OF IMPLEMENTING EXPECTED CREDIT LOSS MODEL FOR MICROFINANCE INSTITUTIONS IN ETHIOPIA: CASE STUDY ON SOME SELECTED MICROFINANCES

BY:

BITHANIA MAMO

ADVISOR: ABEBAW KASSIE (PH.D)

A THESIS SUBMITTED TO THE DEPARTMENT OF ACCOUNTING AND FINANCE IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN ACCOUNTING AND FINANCE

FEBRUARY 2024

Addis Ababa, Ethiopia

ADDIS ABABA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

DEPARTMENT OF ACCOUNTING AND FINANCE

GRADUATE STUDIES

CHALLENGES AND BENEFITS OF IMPLEMENTING EXPECTED CREDIT LOSS MODEL FOR MICROFINANCE INSTITUTIONS IN ETHIOPIA: CASE STUDY ON SOME SELECTED MICROFINANCES

BY:

BITHANIA MAMO

ADVISOR: ABEBAW KASSIE (Ph.D)

A THESIS SUBMITTED TO THE DEPARTMENT OF ACCOUNTING ANDFINANCE IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THEDEGREE OF MASTER OF SCIENCE IN ACCOUNTING AND FINANCE

FEBRUARY 2024

Addis Ababa, Ethiopia

STATEMENT OF DECLARATION

I the undersigned graduate student hereby declare that this thesis is my original work and that all sources and material used for this thesis have been acknowledged. This Thesis is submitted in partial fulfillment of the Degree of Master of Science in Accounting and Finance. No part of this research should be reproduced without my consent or that of Addis Ababa University.

Student Name: Bithania Mamo Beyene

ID No: GSR/2277/14

Phone. No: 0933-592610

Signature: ______________

Date: _________________

Supervisor

This thesis has been presented for examination with my approval as a university supervisor.

Name: ___________________

Signature: _________________

Date: ____________________

APPROVAL

Addis Ababa University

College of Business and Economics

Department of Accounting and Finance

Graduate Programs

Approval by the Examining Board

The undersigned certify that they have read and hereby recommend to Addis Ababa University to accept the thesis submitted by Bithania Mamo Beyene, entitled “challenges and benefit of implementing expected credit loss model for microfinance institutions in Ethiopia: case study on some selected microfinances” in partial fulfillment of the requirement for the award of a master’s degree in accounting and finance.

Approved by:

Dean, Graduate Studies: _____________ Signature _____________Date________________

Advisor: Abebaw Kassie (PhD) Signature _____________Date____________________

Internal Examiner: Sewale Abate (PHD): Signature _________Date _______________

External Examiner: Dakito Alemu (PHD) : Signature______________Date:____________

ENDORSEMENT

This thesis was submitted to the School of Graduate Studies of Addis Ababa University College of Business and Economics for examination with my approval as a university advisor.

Abebaw Kassie (PhD) ______________________ __________________

Signature Date

ACKNOWLEDGEMENTS

I would like to extend my deepest gratitude towards all those who supported and guided me throughout my thesis journey. Firstly, I am extremely grateful to my supervisor, Dr. Abebaw Kassie for his continuous support, immense knowledge, and motivation.

I would also like to thank all my friends, family, and respondents. Special thanks to my family, particularly my parents, whose unwavering faith in my capabilities propelled me to persevere and complete this thesis.

I'm wholeheartedly thankful to everyone who has been part of this journey. Their immense contributions have made this thesis what it is today.

ABSTRACT

According to Financial reporting proclamation 847/2014 ratified by House of people representative, both public and private interest entities were required to prepare their financial report in accordance with International Financial Reporting Standard. Pursuant on the proclamation issued financial Institutions adopted IFRS9 along with other standards. The new standard introduces the expected credit loss model, which is the new impairment model, to allow for up-to-date recognition of credit losses, estimated not only on the actual credit loss, as well as details on the present loan portfolio's prospects. The primary goal of this study was to investigate the challenges and benefits associated with implementing the International Financial Reporting Standard 9 (IFRS 9) Expected Credit Loss Model. Even though the purpose of ECL implementation is to simplify existing rules and increase investor confidence in financial institutions' financial statements, financial institutions confront numerous challenges during implementation. In order to achieve its goals descriptive research design is implemented along with non-probability purposive sampling. Both primary and secondary data gathering approaches are employed to answer the study questions and fulfill the research's goal. The study assessed five microfinance institutions on their implementation of expected credit loss. The research finds that lack of skilled personnel, inadequate data collection and management systems, challenges in obtaining reliable forward-looking information, difficulty in forecasting the expected cash flows of various assets, difficulties in developing suitable models for classifying loans, IT infrastructure related challenges, External challenges are identified as major challenge. This finding recommends the need for Data management systems, implementation of technology and tools, regular ECL model development and validation, Incorporation of scenario analysis and forward looking information, Staff training and Collaboration with external parties are proposed in order to minimize the challenges the institutions are facing.

Key words: International financial reporting standards (IFRS), IFRS 9, expected credit losses, Impairment, Credit Risk

Contents

List of Tables

List of Abbreviations and Acronyms

AABE	Accounting and Auditing Bord of Ethiopia
EAD	Exposure at default
ECL	Expected Credit loss
EY	Ernest & Young
FASB	Financial Accounting Standards Bord
IASB	International Accounting Standards Bord
IAS	International Accounting Standards
IFRS	International Financial Reporting Standard
KPMG	Klynveld Peat Marwick Goerdeler
LGD	Loss given default
LLP	Loan Loss provisioning
MFI	Microfinance Institution
NBE	National Bank of Ethiopia
PD	Probability of default
PWC	Price Waterhouse Coopers

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the study

The international financial crisis showed the insufficiency of current accounting principles in reporting financial instruments' fair value (Besmir et al., 2021). The historical phenomena that result in the issuance is the great depression that hit most of the countries and results in collapse of many banks in 2008. Following this event the G-20 countries recommend international Financial Standards to broaden its credit information for loan loss provision. IASB after receiving the recommendation from G-20 countries and financial stability board issued IFRS 9 to be effective form January 2018. Loan loss provisions in previous models were described as "too little, too late" in the professional language (Frykstrom & Jieying 2013). IFRS 9 was issued by the IASB in July 2014 and became effective in January 2018 by replacing International Accounting Standard (IAS) 39. The new standard makes three major changes: It classifies financial instruments, estimates credit loss, and uses hedge accounting.

One of the most significant distinctions between IFRS 9 and IAS 39 is the categorization and methodology for recognizing impairment. Expected credit loss is calculated for each year-end and the balance is adjusted to reflect the increment in credit risk and the holder of the financial asset must consider more timely, reasonable, and verifiable forward-looking data (Baghdasaryan & Mnatsakanyan, 2019). Although the standard defines its objective it doesn't prescribe detailed methods which resulted in the rise of the complication of implementing the standard.

However, the implementation of the ECL model has proven to be challenging for banks and other financial institutions (Awatef, 2021). As the standard requires significant changes in processes, systems, and risk models, needing extensive data history and forecasting capabilities (Deloitte,2020). Incomplete and Inadequate data, Model complexity, forecasting uncertainty, association of the standard with local requirements were identified as challenge during the implementation of the standard (Awuye& Taylor,2023). Furthermore, there are differences in interpretation and application of the standard, which can lead to inconsistencies in reporting.

Despite these challenges, the implementation of the ECL model also presents opportunities. It encourages financial institutions to advance their risk management practices and fosters greater transparency and accuracy in financial reporting (Stephen & Joshwa, 2022).

In Ethiopia, after the issuance of financial reporting proclamation 847/2014 all financial institutions were required to implement as IFRS as there financial reporting framework. Due to this microfinance were required to implement IFRS9 along with other standards. Research conducted in Ethiopia on challenges of expected credit loss implementation focuses mainly on banks. Research conducted by Berhanu& Getachew (2021) using comparative research approach by taking financial statements of commercial banks find that there is difference on models used among the banks which shows banks should carefully consider which model they use for the implementation of ECL model. Another research by Tesfaye and Mulugeta (2020) finds that data quality, Model complexity and regulatory compliance as a major challenge. This result shows that the need for further studies on this area to recommend better options to overcome the challenges.

Based on the brief explanation on the above paragraphs research has been made to identify the challenges and clarify benefits in implementing the ECL model. Such research was conducted by big organizations such as World Bank, and big 4 accounting companies such as EY, PWC, KAPLAN, and KPMG, individuals, and private entities.

Unlike recent studies, which focuses on banks, this research project covered detailed explanation of the challenges that Ethiopian micro finances face and the benefit that they get from implementing the ECL model. The research also includes recommendations for how to overcome the obstacles.

1.2. Problem Statement

In today's world, more than 100 nations have adopted the International Financial Reporting Standard (IFRS) 9. The new requirement of the standard improves reporting by providing timely information in a more responsive manner (Mohad, 2018). However, in the process of implementing the standard specifically the ECL model, financial institutions and supervisors faced several challenges mainly data availability and low data quality, modeling risk, and overreliance on managerial judgment (Ezio, Katia, Tatsiana and Juan, 2021).

Various pieces of research have been conducted on the implementation challenges and benefits of the ECL model in different countries by different organizations and individuals, but there are few studies undertaken in underdeveloped economies, particularly in Africa. As a developing economy, Ethiopia after the Financial Reporting Proclamation (847/14) requires financial institutions, of which Microfinance are part, to prepare their financial accounts in line with the International Financial Reporting Standards (IFRS) based on the Ethiopian Accounting and Auditing Board’s Road map. There is plenty of research made on the implantation of IFRS in Ethiopia but there is a very limited report made on specifically IFRS 9 Expected Credit Loss Model.

Under the research conducted by Tesfaye, D., & Girma, A. (2020) on challenges of expected credit loss implementation in Development bank of Ethiopia they identified inadequate data quality, lack of skilled manpower, and insufficient IT infrastructure as the major challenges and the other research conducted by Melaku (2021) on Challenges of Expected credit loss implementation evidence from commercial banks listed lack of skilled man power, inadequate data management system , staff capacity in terms of knowledge and experience, complexity of the model itself become the major challenges that banks are facing.

This research is conducted on the largest banks in the country such as Development bank and Commercial banks which can be considered as one drawback because they didn’t cover small financial institutions. Microfinance institutions are exposed to challenges with resources, human capital and technical assistance compared to banks. The second limitation is besides listing the challenges they lack detail analysis in specific technical challenges on IT and data quality. The third limitation is lack of assessment on external factors such as on regulatory body follow-up and guidance.

Based on the above limitations identified this research tries to fill the gap by focusing on small financial institutions, detail and in-depth analysis on technical challenges. In addition to these technical challenges, the ECL model's implementation is also subject to varying regulatory environments and the financial institutions' preparedness to adopt. These issues is covered by this research.

In general, there is a need for a better understanding of the constraints and benefits that microfinance faces in implementing expected credit loss to ensure the implementation complies with IFRS and propose possible way outs that shall be carried out that don't contradict with IFRS.

The study answered the following major questions:

Research Question

1. What does the process of Expected credit loss model implementation look like in the institutions?
2. What external challenges influence the ECL model's implementation?
3. What internal environment elements have an impact on the ECL model's implementation?
4. What are the major benefits of implementing and using the ECL model in institutions?

1.3. Objective of the study

1.3.1. General Objective

The overall goal of this study was to uncover problems and benefits associated with applying the ECL model in Microfinance institutions, as stated in the problem described above.

1.3.2. *Specific objective*

The specific objectives of the study that emanate from the general objective are:

1. To assess the ECL implementation process in the institutions
2. To determine the external challenges that influence the ECL model's implementation.
3. To examine the internal challenges that influence the ECL model's implementation.
4. To investigate the benefits of implementing the ECL model

1.4. Significance of the study

The study was focused on in-depth analysis of challenges and benefits of implementing the expected credit loss model in microfinance institutions. Furthermore, the study's findings can be used by:

Practitioners- Including auditors and consultants can have information from the finding of the research on the barriers and benefits of implementing expected credit loss model by identifying the variables that become obstacle for the implementation of the model and providing the alternative ways to overcome the challenges faced by those institutions.

Regulators- The finding of the research can assist the regulators in identifying the areas that the institutions are facing challenges and results can be used as an input for further policy making, assessment if trainings are needed and assess the possibilities if national database is required for the macro-economic variables.

Future researchers- The findings of the study might be used as a reference for future researchers who want to conduct research in this area and also can be used as a steppingstone to further analyze the topic under consideration.

1.5. Scope of the study

The scope of the research focuses on Addis Credit and Saving institution S.C, Somali Microfinance institution, Meklit Microfinance institution, Dire Microfinance institution and Metemamen Microfinance. These Microfinances are selected based on the size, amount of loan portfolio and nature of operations. Addis Credit and saving institution has the biggest in size and loan portfolio while Metemamen is relatively smaller in two parameters. Based on nature of operations Somali Microfinance is an Islamic microfinance while the rest three are not. Respondents of the research are Finance managers, Operational Managers, IT department, and IFRS implementation team leaders. The reason for selection of these departments because they are the ones that are engaged on implementation of ECL other than other departments. As the research on challenges and benefits of ECL implementation these parties face the real-life struggles to meet the requirements of the standard.

This study covered only on their IFRS 9 ECL model adoption challenges and benefits and covers the year 2020, which is the year after the adoption period.

1.6. Limitation of the study

The study is limited only to assessing the challenges and benefits of ECL model implementation. The specific model analysis isn’t made, and model recommendations is not proposed and the ECL model impact on their financial performance not included and analyzed.

1.7. Organization of the study

This research contains a total of five chapters. Chapter one of the study focused on introductory aspects including the background of the study, statement of the problem, objectives of the study, significance, scope, and limitation of the study. Chapter two presented a review of related literature. Chapter three presented the research design and methodology including the data source and method of data collection, sampling techniques used, and measurement and analysis parts, the chapter focuses on data analysis interpretation, and also the final chapter five presents the finding, conclusion, and recommendation.

CHAPTER TWO

2. LITRATURE REVIEW

This chapter presents a review of related literature and empirical facts. The following subsections include the theoretical background of what expected credit loss means and how to calculate under International financial reporting standards, as well as a look at the actual obstacles and opportunities considering different countries' experiences.

2.1. Theoretical Review

International Financial Reporting Standard (IFRS) is accepted in more than 167 Jurisdictions around the globe. Ethiopia is among the countries that require the adoption of IFRS. To this effect, the Parliament issued Proclamation no. 847/2014 also known as Financial Reporting Proclamation to support the adoption and impose responsibility on the responsible government organs that are solely established to execute the adoption.

Currently, the International Financial Reporting Standard has 43 active standards. International Financial Reporting Standard (IFRS) 9 is among the active standards with the effective date for annual periods beginning on or after 1 January 2018 replacing the previous International Financial Reporting Standard (IFRS) 39.

As an IFRS adopter, Ethiopia also adopted IFRS 9 with the other 42 standards. The standard is composed of three sections this is Financial Instrument classification, Measurement, and Hedge Accounting. Under the measurement section, we find the impairment model of the standard. This standard's impairment method is mainly used for financial institutions' loan loss provisioning (LLP). Banks, Insurance companies, Microfinance institutions, Credit and Saving Institutions, and other deposit-taking and lending financial institutions are supposed to implement this standard fully.

Under the theoretical review section, Meaning, assumptions, and parameters of the Expected Credit Loss Model and compare it with existing National Bank of Ethiopia provisioning requirements are covered. Before looking at IFRS theories the first section covers the two popular accounting theories, Normative and Positive accounting theories, and identify the association with the topic on hand.

2.1.1. Normative and Positive accounting theories

The two popular accounting theories are discussed briefly as follows:

Normative Accounting Theory: This type of theory often expresses how things should be done according to theoretical standards. Normative accounting research makes policy recommendations and provides certain designs for accounting systems based on subjective and theoretical analyses. The main goal is to provide a mechanism for decision-making processes and help with better financial reporting (Watts & Zimmerman, 1979).

Positive Accounting Theory: Contrary to normative theory, positive accounting theory seeks to explain and predict actual accounting practices. This theory doesn't tell us how things should be, instead it describes how things are. It is empirical, aiming to accurately forecast real-world events and translate them into accounting practices. It is often used to predict which choices companies can make regarding accounting practices and standards (Ijiri, 1975)

International Financial Reporting Standards (IFRS) are more closely linked to normative accounting theory. This is because IFRS offers a set of rules and guidelines on how companies should report their financial results, which aligns with the 'should do' aspect of normative theories (Hudson & Muller, 2018)

However, the adoption and implementation of IFRS in different countries and companies can be studied using positive accounting theory. Researchers using this theory might examine why countries adopt IFRS, how companies implement these standards, and what effects its adoption has on financial reporting practices. So, while IFRS itself is normative, the study of its implementation can fall under positive accounting theory (Stevanovic et al., 2019).

2.1.2. Historical Background of Expected Credit Loss

Following the international financial problems in 2009, the G-20 issued a recommendation to the International Accounting Standards Board (IASB). The G-20 recommended accountants "strengthen accounting recognition of loan-loss provisions by using a broader range of credit information" (G20 2009). After receiving the recommendation International Accounting Standards Board (IASB) from G20 leaders and Financial Stability Board IFRS 9 was issued in July 2014 and became effective in January 2018 by replacing IAS 39. By replacing the incurred credit loss model in IAS 39, the new standard created a new impairment model called Expected Credit Loss.

There were three main phases to replacing IAS 39 with IFRS 9 by IASB. Each phase-completed chapter was added in IFRS 9 and the chapter was canceled from IAS 39. The three main phases are listed below:

Phase one: Classification and measurement of financial assets and liabilities

In 2009 IASB issued the classification and measurement of financial assets. Financial assets are classified based on their business model and contractual cash flow (IFRS 9 P. 4.1.1-4.1.5). Following this in 2010 IASB issued the second amendment on the classification and measurement of financial assets. Incorporating credit risk components in their classification and measurement.

Phase Two: Impairment

In July 2014 IASB issued the full and amended version of the impairment chapter of IFRS 9. The new standard was released as an exposure draft three times from 2009-2013. The first draft was issued by IASB in 2009. This exposure draft proposes for the first time the concept of expected credit loss rather than incurred loss model but most of the reviewers commented that the first exposure draft model was too complex and ECL recognition on initial recognition raises doubts among the reviewers. The second draft was issued proposing an alternative ECL model by FASB that ECL can be calculated through the lifetime of all financial assets. In 2013 IASB incorporating all the comments forwarded by the reviewers issued the third exposure draft, that entities should recognize loss allowance at an amount equal to 12-month credit loss for all financial assets..

Phase three: Hedge Accounting

In 2013 IASB released the hedge accounting chapter of the standard. Its requirement aligns hedge accounting with risk management.

In response to international organizations' recommendations, IFRS 9 fully replaces IAS 39 and was enforced in 2018 for its full implementation.

2.1.2. Modeling Principles of Expected Credit Loss

The expected Credit Loss model of IFRS 9 focuses on default risk rather than the actual loss incurred (Mojca, 2020). The ECL model recognizes impairment not only based on historical and current data but also on future forward-looking information (Banu, 2018). Entities can also use estimations and judgments to support their data and improve their model (Mohad, 2018).

Incorporating forward-looking information added to the complexity of the model for calculating loan loss provision. The standard impairment section proposed two approaches for calculating loan loss provision. These are General Approach and the Simplified Approach.

Simplified Approach:

This approach is mainly used for trade receivables and impairment is computed by using a provision matrix. The matrix is developed based on historical data and each receivable is grouped based on their age group and provision is computed based on pre-determined rates.

General Approach:

This approach covers those financial assets that are measured at amortized cost. This approach is used by financial institutions as they have the longest financial assets, Loan Receivable. The impairment objective of this standard is to recognize lifetime expected credit loss for those financial assets with increasing credit risk since initial recognition (Paragraph 5.5.4 of IFRS 9).

If the credit risk declined after the reporting period then the loss allowance can be calculated in an amount less than 12 months of expected credit loss (Paragraph 5.5.5 of IFRS 9).

In general, the General approach proposes two ways of measurement of financial instrument impairment. These are Lifetime expected credit loss and 12-month expected credit loss.

The standard not only recommends an approach for impairment approach but also assists in classifying the financial instruments into stages. Credit risk increment is one of the reasons for the classification of financial assets into categories.

The general approach allows dividing the financial instrument into significant risk and non-significant risk through stages.

Stage 1: It applies to existing loans with no significant increase in credit risk since their initial recognition or has the lowest credit risk at the reporting date. 12-month expected credit loss is recognized in profit or loss.

Stage 2: If a loan's credit risk has increased significantly since initial recognition and is not considered low. Financial instruments in this stage are not yet claimed as default. Lifetime ECL is recognized.

Stage 3: If the loan's credit risk increases to the point where it is considered credit-impaired. Financial instruments in this stage are assessed individually.

At initial recognition 12 month expected credit loss can be calculated and subsequently lifetime expected credit loss is calculate as the credit risk of the instruments increase significantly.

Component of ECL model

Expected credit loss has mainly three components this are Probability of default (PD), Exposure at default (EAD) and loss given at default (LGD). Commonly used formula to calculate ECL is:

$ECL = PD\% \times LGD\% \times EAD \times$ EIR……………………………………………………..*1

Probability of default (PD) - is the key parameters in the formula. It is the probability of a borrower can default before paying the debt.

Loss Given Default (LGD) - LGD estimates the rate of loss arising on default, it is the difference between expected cash flows that are due and the expected amount from collaterals divided by exposure at default (Ernst & Young, 2014).

Exposure ate Default (EAD) - It can be seen as an estimation of the extent to which the financial entity may be exposed to counterparty in the event of a default and at the time of the counterparty's default (PWC, 2018; Nadia and Rosa, 2014).

Effective Interest rate (EIR) – To discount lifetime expected credit loss to present value.

As shown in the above formula entities can calculate the ECL by multiplying the four components all information can be adjusted based on any change in information. LGD is mostly constant so the model heavily relies on PD and EIR. To estimate those parameters companies shall use internal credit rating and macroeconomic assumptions.

Steps to calculate impairment in IFRS 9

To apply Expected credit loss there are certain steps that should be followed these are:

- **Portfolio Segmentation:**
  Firms typically partition portfolios based on business lines, product types, and risk factors for the sake of loan loss projection. According to IFRS 9, portfolio segmentation must be more granular and dynamic. Firms must combine financial assets based on shared credit qualities, forward-looking information, and macroeconomic elements that normally react in a similar manner to the current environment (Moody, 2015).A forward-looking computation for financial instruments should be based on precise estimates of current and future cash flows, as well as macroeconomic data (Adamu, 2018).
- **Determining significant increases in credit risk:**
  Increase in credit risk may be computed using general approach if individual data is not available (Moody, 2015). The assessment of significant credit risk deterioration should incorporate a different stages and holistic approach (Dirk and Sammar, 2015). Other changes in the rates or terms of an existing financial instrument, such as a significant change in internal pricing, or other factors, judgment can be used to determine a considerable risk escalation. Furthermore, there have been significant shifts in external

market indicators (credit spreads, credit default swap prices, the duration that the fair value is less than the amortized cost, and other market information about the borrower), significant changes in the credit rating, internal credit rating downgrade, and significant changes in the value of the collateral can be used as a base for the Judgment.

According to Petr and Jiri study three determinants were identified for determining significant increase in credit risk. Determinants include macro-economic environment, idiosyncratic factors and change in model estimates.

- **Expected Credit Loss Calculation:**

  In IFRS 9, projected credit loss is calculated in stages. Assigning financial instruments to a specific impairment Stage, defining the value of credit risk components PD, LGD, and EAD, defining ECL value for each Impairment Stage, and calculating the reserve amount that corresponds to the aggregative value of ECL for all Impairment Stages are all stages in this process. (Alfiya and Elvina, 2019).

2.1.3. Transitioning from NBE directives to IFRS 9

National Bank of Ethiopia is entrusted to control the financial health of the country in general and jurisdiction over financial institutions. NBE controls all financial institution; Microfinance institutions are included in this study. One of the areas that NBE oversees is to set limit on loan, repayment period and provisioning requirements. The Bank sets its own conservative provision requirements for loan reserves (Directive mfi28/2016).

Category	Number of days Past due	Minimum provision
Substandard	91-180 days	25%
Doubtful	181-365 days	50%
Loss	Over 365 days	100%

Table 2.1: NBE Provision Matrix

Loan receivables is grouped based on their number of days past due for reckoning provision. This means it is assumed that the credit risk might increase after 90 days. Provision is calculated on outstanding amount, but the directive also permits Microfinances to deduct cash deposits and Federal Government securities held as collateral.

Microfinances compute LLP based on this directive until 2019. After the adoption of IFRS by Ethiopian government these institutions are obligated to follow other LLP determining mechanism called Expected credit loss.

During the transition from NBE directives to IFRS 9 ECL requirements have broad differences. Main dissimilarity between the approaches is listed below:

Parameters	IFRS 9 ECL Model	NBE Provision Requirements
Credit Risk	30 days rule of thumb is sated. But there are number of factors that have impact on significant increase in credit risk. Internal and External factors need to be analyzed.	Any loan that is not repaid for more than 90 days can be considered as an increase in credit risk. No other assumptions and inputs needed.
Categorization	All Loans can be categorized as stage 1, 2 and 3 based on their credit risk increment.	Loans only past due more than 90 days can be classified as standard, substandard and Loss/Doubtful.
Collateral	All collaterals for that specific loan can be included by their Fair Value.	Only Cash deposits and Federal Government Securities can be considered
Computation	Using the 3 main components of ECL. Probability of default, exposure at default and Loss Given Default and Effective interest rate.	Categorize outstanding loans by their age category then multiply them by predetermined rates

Table 2.2: Comparison between NBE Provision Matrix and ECL model

From the above table we can grasp main differences between the two approaches. To calculate Loan loss provision using ECL model entities need to have large and detail data for the analysis. Internal credit rating, Fair Value of Collateral, Macro economic factors and other inputs are required to the best outcome of the model.

The standard doesn't provide any model that should be used by the institutions. Model depends upon type of instrument and data availability (Banu, 2018). But the standard requires specific information stated below (IFRS 9 paragraphs 5.5.17):

- an unbiased evaluation of a range of possible outcomes and their probabilities of Occurrence (probability-weighted amount);
- the time value of money; and
- reasonable and supportable information that is available without undue cost or effort About past events, current conditions and reasonable and supportable forecasts of Future economic conditions.

Institutions are required to have sufficient data to use the model and held provision. Transitional challenges and benefits are the area that is covered in this study.

2.2. Empirical Review

The new IFRS 9 expected credit loss model has got a widespread application in many countries. As the standard is recent phenomena limited research are conducted in nation and international perspective.

2.2.1. Challenges of Implementing Expected Credit Loss

The introduction of the new standard and impairment model demands organizations to deploy professional accountants with the skill to overcome the challenges they face in the implementation process (Gulyas and Somogyi, 2019).

In the survey conducted by Gulyas & Somogyi (2019) in Hungarian banks from July –September 2018 conducted using questioner-based survey on 100 specialists in 30 credit institutions observed that challenges faced by those institutions are immaturity of IT system, large information requirements, Shortage of time, generation of data and issues related taxation. The other research conducted by Schutt et al. (2020) described that as the standard is principle-based there are no prescribed specific methodologies for expected credit loss estimation by the standard becomes a challenge for those who implement this standard to choose which approach and methodology to follow.

Baghdasaryan & Mnatsakanyan (2019) in a study aimed at identifying the challenges of implementing IFRS 9 impairment requirement in post-soviet countries banks points out the main challenges small banks and credit organizations face. Grouping exposures into segments based on shared credit characteristics such as identifying default and large increases in credit risk, selecting a suitable ECL model, and integrating macro-economic forecasts and forward-looking information are among the problems identified. The paper recommends that small banks need official guidance to overcome the challenges they face.

Moody (2015), In the process of implementing the IFRS impairment model banks have been assessed for the challenges they face. The major identified problems in this regard are the requirement in capturing historical data to track credit risk ratings, product features, historical probability default, and economic scenario variables. Banks likely face challenges if they don't collect data for impairment modeling and if the data is available but not adequate (Mohad, 2018). The study classifies the challenges into two broad categories as methodological and analytical problems. Moreover, the study puts solutions to overcome the challenges and identifies possible qualitative and quantitative measures to identify significant risks, possible ways of developing models internally, and simplified ways of gathering forward-looking information. Similarly, modeling risk, data availability, low data quality, limited staff capacity, lack of appropriate analytical tools, regulatory treatment of accounting provisioning, difficulties with constraining managerial judgment, and lack of enforcement from a supervisor are identified as major challenges on the survey conducted in 184 countries (Ezio et al., 2021). The study conducted by Wolfgang (2015) stated that the main challenging requirement if that consideration of forward-looking information including macroeconomic factors and unavailability of reliable data and Quantitative and qualitative information to disclosure is rare and these requirements are challenging to the banks especially smaller ones (Wolfgang, 2015).

In 2016 two accounting firms KPMG and Deloitte have made research separately. The former summarizes the Global Public Policy Committee (GPPC) study on challenges from the audit committee perspective and listed some of the factors affecting new standards such as high time and effort to implement, increased complexity for preparers, and diverse range of approaches and outcomes weighted the most while Deloitte on its six global IFRS banking survey which covers 91 banks in Europe, Middle East, Africa, America, and Asia pacific 40% of the participants responded that they are facing data quality is sued mainly on estimation of the probability of default while the rest 60% couldn't quantify the transitional effect of IFRS 9 (KPMG, Deloitte: 2016). According to Deloitte's recent survey on the UAE banking industry in 2020, they find out that unavailability of historical data and Data quality, Challenges in bridging global models to regional and macroeconomic data, limited control over model specification and justifications to use certain forward-looking macroeconomic factor were identified as a major challenges banks in UAE Middle East are facing (Deloitte, 2020).

Due to the transition to IFRS 9, Banks are not only required to calculate LLP according to Expected Credit Loss but also should assume changing how they do business, allocate capital, and manage the quality of loans and provision at origination (Hassan et al., 2020). During the development of the model and computation of provision companies among all other parameters, macroeconomic forecasts play a great role but this area is identified as a main challenging area for financial institutions (Petr and Jiri, 2020).

Pastiranováa and Witzanya (2021) studied the impact of the implementation of IFRS 9 on the Czech banking sector covering the challenges banks face using empirical research. The study finds that the new standard brings some negativity such as the complexity of the new methodology and potential issue of the volatility of allowance and necessity of a model for the calculation of ECL and new categorization, Significant increase in credit risk, and so on have an impact on banks (Olga and Jori, 2021).

Pucci & Skaeraek conducted their research in 2019 using document analysis and interview data to perform a study on the co-preformation of financial economics in accounting standard-setting: A study of the translation of the expected credit loss model in IFRS 9 finds that struggles of increasingly complex forward-looking models in financial reporting standards and Primarily reliance on the conceptual framework provides an insufficient base of convergence.

The supervisory institution also has to be involved in eradicating the challenges that banks face. Gerald (2016) in his article Supervisors' key roles as banks implement Expected Credit Loss Provisioning stated that encouraging industry and supervisory participation in seminars, requiring banks to periodically present updates that enable supervisors to monitor their ECL implementation, encouraging those charged with bank governance to achieve a greater understanding of IFRS 9 and encouraging auditors to achieve an understanding of IFRS 9 are listed as a supervisors role to assist institutions to overcome implementation challenges (Gerald,2016).

Other challenges also can be seen as after implementing ECL it is observed that it causes volatility in loan loss reserve (Barbara and Tamin, 2018). This volatility is due to changes in market discipline. Any change in the macroeconomic parameters such as interest rate and inflation result in a change in parameters in the model. The unavailability of a uniform model also results in non-comparability among institutions.

In Ethiopia due to the recent development of Expected credit loss in general and IFRS implementation there are limited research conducted. Tesfaye & Girma (2020) conducted their research on “Expected Credit Loss Model Implementation and Its Challenges: The Case of Development Bank of Ethiopia” using mixed method research design, including survey questionnaires and interviews, to collect data from DBE staff members. The study identifies several challenges in the implementation of the ECL model. The main challenges include inadequate data quality, lack of skilled manpower, and insufficient IT infrastructure. Another research conducted by Melaku G. under the title "The Challenges of Implementing the Expected Credit Loss Model in Ethiopia: Evidence from Commercial Banks" find out that lack of skilled manpower, inadequate data management system, limited awareness of IFRS 9 standards, complexity of the ECL model and high cost of implementation become among the major constraints that commercial banks are facing.

2.2.2. Benefits of Implementing Expected Credit Loss

IFRS implementation leads to high-quality, transparent, and fairly presented financial statements for users. More specifically IFRS 9 provides timely and forward-looking information on financial instruments so that investors have predicted information (Stephen and Joshua ,2022).

The following is a list of ECL model benefits: -

- Transparency: Expected credit loss provisioning enhances transparency on incomes and profits. The standard allows both internal and external users to have a clear picture of the financial instrument of the entity not only historical but also forecasted values.
- Reduce non-systematic risk: by nature, non-systematic risk is specific to a company or industry the standard allows the company to identify risk areas and diversify its portfolio as required.
- Reduction in non-performing loans: As the ECL model filters out non-performing or doubtful accounts the company take action on those accounts and strengthens its control for those balances with increasing credit risk.

The above three are the major benefits that companies get by implementing expected credit loss according to the study conducted by Stephen & Joshua (2022). In addition, it brings principle-based financial statements and brings cross-border investment.

2.3. Summary and Research Gap

In general, in recent years IFRS has gain attention from researchers, government and organizations, as the standard play crucial role in bringing harmonized system globally, transparency, and easy comparison of company rating. More specifically IFRS 9 has gain momentum on 2009 by the initiation of G-20 countries with effective date of 1 January 2018. This research could contribute to the field of study by pointing out the main challenges to smooth transition to the full implementation of the standard. The reviewed literatures are conducted from 2015-2022 and the geographical distribution is mainly in Europe, Middle east and some in Africa specifically in Ethiopia.

The reviewed literatures share almost the same findings on the main challenges of implementing the Expected Credit Loss (ECL) model. One of the major identified challenges is the need for high-quality and comprehensive data, which is essential for accurately estimating credit risk Which includes, historical data of borrowers, credit ratings, and macroeconomic factors. The second challenge identified by the research are selecting the appropriate methodology for estimating the probability of default (PD), loss given default (LGD), and exposure at default (EAD) components of the ECL model. The third identified problems are meeting regulatory requirements, lack of sufficient IT infrastructure and lack of skilled manpower are among the items identified challenges by the research.

The research's reviewed uses variables to base their research such as data quality and availability, IT infrastructure and systems, level of expertise and knowledge, regulatory environment, and size of financial institutions. Research conducted and reviewed under the literature review section has the following four major gaps in common. The first gap is limited focus on the impact of expected credit models on smaller financial institutions, such as microfinance organizations in which results the results may not be representative of the challenges faced by smaller organizations. The second gap identified is limited attention to developing economy, while most of the existing research is on developed countries. The third gap identified by the researcher is lack of in-depth analysis of specific technical challenges. The fourth gap identified is insufficient research on the role of regulatory oversight and support.

This research "Challenges and benefits of implementing expected credit loss model for microfinance institutions in Ethiopia: case study on some selected microfinances" try to fill the major identified existing literature gaps. The research uses the same variables used by the previous research because the major identified gap is less attention to microfinance institution and assess it in the microfinance institutions perspective so we have a complete picture on the challenges of implementing Expected credit loss model.

CHAPTER THREE

3. RESEARCH DESIGN AND METHODOLOGY

The research design, sample methodologies, data collection, Data Presentation and Analysis, and Ethical Considerations are all covered in this chapter.

3.1. Research Design

The study's goal is to investigate the problems and opportunities associated with implementing an expected credit loss model in microfinance institutions. The research strategy to be used in this research is survey research. A survey is a method of collecting data from a population of interest to describe, compare, or explain their knowledge, attitudes, and behavior. Surveys are used in a variety of settings, including marketing, public opinion research, and social science research (Uma & Roger, 2016).

Among the data collection instruments, self-administered survey, in which respondents complete a questionnaire on their own, is used in this research. To achieve the objective descriptive type of research is used because it describes the characteristics of objects, people groups, organizations, or environments and answers who, what, when, where, and how questions.

3.2. Research Approach

A combination of qualitative and quantitative methods is used in this research to capture more of a complete picture of the research area. The qualitative approach helps in analyzing non-numerical data for beliefs opinions and experiences and assists to gather more in-depth insights into the problem. Quantitative research helps to generalize results to the whole population and to critically observe the pattern.

3.3. Sample Design

3.3.1. Population

There are more than 38 microfinance institutions licensed and operating in Ethiopia. Among 38 of them, only four (5) institutions are selected and used for the research purpose. The institutions are selected based on the size, amount of loan portfolio and nature of operations. The data are collected from those who works in Finance department, Operational department and IFRS team leaders. Overall, the population is 75 people who are involved in the implementation within 5 institutions.

3.3.2. Sampling Frame

The institutions selected for this research are based on their total capital, ownership, and type of services rendered. Addis, Somlai and Dire MFI are government owned while Melkit and Metemamen are privately owned. Based on capital distribution Addis credit and saving have the highest and Metemamen relatively the lowest.

Selected employees from the whole population are based on their position and involvement in IFRS implementation.

3.3.3. Sampling Unit

The sampling unit of the research is Finance managers, Operational Managers, IT department, and IFRS implementation team leaders of the institutions.

3.3.4. Sampling Technique

Non-probability sampling is used so that all members of the population don't have equal chance to be selected. More specifically purposive sampling is used to select that is most useful to the purpose of the research. To avoid misinformation respondents are selected based on their involvement in implementation.

3.3.5. Sample Size

Of the total population, 75 respondents from Finance, IT, Operations and IFRS committee that are directly related to data collection and analysis is used.

3.4. Sources of data

This study relied on both primary and secondary data. Both types of data are used in the way the research questions are achieved, and the objectives met.

3.4.1. Primary Data Sources

The primary source of the data is gathered through structured questionnaires on 5 microfinance institutions from 75 respondents which work on Finance, IT, Operations and IFRS committee. The Questioner was designed in a way to address the specific objectives of the research. assess what challenges they faced in the project and what benefits and drawbacks they encountered in the implementation.

3.4.2. Secondary Data Sources

Secondary data are collected from AABE reviews, IFRS Green Book, Journal articles, related research, Government Reports, Financial reports of the institution sent to supervisory authority (National Bank of Ethiopia and Accounting and Auditing Board of Ethiopia) are used.

3.5 Data collection Method

Quantitative and Qualitative data are collected through a self-administered questionnaire. The questioners are distributed to the selected staff of the institutions.

The main way data collected for this study was through self-administered questionnaires. Questions are developed in the questionnaire by reviewing related literature and making sure they addressed each of the variables the researcher is interested in studying.

The questioner was distributed to 75 respondents. The questioner used close ended questions, and it helped the respondents to respond easily. a five-point Likert scale was included in the questionnaire, which asked them to rate their level of agreement with the following ratings: Strongly Agree (5), Agree (4), Neutral (3), Disagree (2), and Strongly Disagree (1) are the five levels of agreement.

The questioner is composed of 4 Parts. The first part intended to collect general information of the respondent and consists of 6 close ended questions. Their educational background, department they are currently working on, and level of involvement on ECL implementation is covered on the first part. The second part meant to assess internal challenges they are currently facing on the implementation of ECL model which has a total of 27 questions. The third part covers external challenges on implementation of ECL 12 questions. The last part of the questioner covers the benefits of ECL and have a total of 5 questions.

3.6. Data Analysis and Interpretation

The data collected for this study is analyzed using both qualitative and quantitative methods. Qualitative analysis was used to assess the opinions, feelings, experiences, and behavior of the respondents. Quantitative analysis was used to analyze and interpret the data using IFRS standards and statistical techniques. The results of the quantitative analysis is presented in tables, percentages, and charts.

Qualitative analysis is a research method that involves the collection and analysis of non-numerical data. This type of data can be in the form of text, images, or audio recordings. Qualitative analysis is often used to understand the experiences and perspectives of individuals or groups. Quantitative analysis is a research method that involves the collection and analysis of numerical data. This type of data can be in the form of numbers, percentages, or rates. Quantitative analysis is often used to measure the frequency, distribution, or magnitude of a phenomenon. Statistical techniques are a set of methods that are used to analyze data. These methods can be used to describe data, to test hypotheses, and to make predictions. Statistical techniques are often used in quantitative research (C.R. Kothari, 1990).

The analysis is made mainly using IFRS standards. IFRS 9 is the one that is used extensively for this purpose. Eash responses are measured in light with the IFRS 9. The result of the quantitative analysis is presented in tables, percentages, and charts. This helped to make the results more understandable and easier to interpret. The tables show the raw data, and the percentages show the proportion of respondents who gave each answer.

3.7. Ethical Considerations

In terms of the respondents' privacy, their responses are kept totally confidential and utilized solely for academic purposes.

CHAPTER FOUR

4. DATA ANALYSIS, PRESENTATION AND DISCUSSION

Based on the methods discussed in chapter three, the researcher's inquiry outcomes are presented in this chapter. It comprises an overview of the respondents' backgrounds, a thorough description of the four main goals, and an examination of descriptive statistics. Responses are presented using tables and percentages are used to show the distribution. Interpretation of the responses are based on IFRS requirements.

4.1. Questionnaire Response Rate

Generally, questioner was distributed for 75 individuals who are directly associated with the implementation of Expected Credit loss. Even though it takes three weeks to gather the data all respondents submitted their responses on the provided questioners.

4.2. Reliability and Validity Assessment Results

In the realm of research, reliability refers to the degree of consistency or precision in the techniques and findings of an examination. It refers to getting the same outcomes after carrying out the same steps multiple times. Thinking on reliability in terms of consistency is also helpful on explaining the data is reliable for future uses.

In general, the question of whether study results are reproducible is at the basis of reliability (Allen & Emma, 2011). The researcher conducted the research by carefully assessing if the same response is gathered with same sense questions but different ways of saying it.

4.3. Demographic Characteristics of the Respondents

The respondents' demographic features include gender, level of education and department they are currently working on. Table 4.1 below shows the frequency and percentage of respondents.

The demographic distribution as articulated under Table 4.1 gender distribution of the population compromises of 41% of female and 59% male respondents. On the other hand, the educational background of the respondents was consisting of 83% first degree holders and the rest 17% were above master’s degree.

The other variable under the demographic profile of the respondents was based on the department they are currently working in as it is directly associated with the data requirements. According to gathered data 49% of them work in the finance department, 39% in the operations department and the rest 12% work in the IT department. These three departments work closely on data collection associated with loans.

Table4.1 Demographics of Respondants

Indicators	Category	Frequency	Percent
Gender	Male	44	59%
	Female	31	41%
		75	100%
Educational Background	First degree	62	83%
	Master’s degree and above	13	17%
		75	100%
Department they are Currently woking	Finance Department	37	49%
	Operations Department	29	39%
	It Department	9	12%
Source: Survey Data(2023)		75	100%

This finding confirms that the study received appropriate input from knowledgeable staff members which is critical for the result and conclusion made based on that. The selection criteria were also purposive to avoid any biases and misinformation that might potentially mislead users of the outcome of this research.

4.4. Respondents level of involvement and understanding of ECL model

The other critical data that determines the validity of the data collection is the level of involvement and understanding of expected credit loss model. Based on gathered data 52% of the respondents involved on the data collection stage of ECL implementation, in which this stage is the most challenging and time taking stage because the standard requires recognition of impairment of loan commitments at each reporting period using General approach (IFRS 9 Pp. 5.5.3). To comply with the requirement of the standard companies were required to gather all customers data for the computation. 21% of the respondents are involved in data cleaning which is cleaning and reconciling data gathered by the data collectors. In this stage missed data is identified and communicated. 15% of the respondents were responsible for analyzing the cleaned data and calculating if there is existence of impairment on the loan commitments outstanding for that specific reporting period. The rest 12% were involved in support of the process in different stages.

Table 4.2 Level of Invlolvemnt on ECL Implemenation

Indicators	Category	Frequency	Percent
Stages Repondants involved on ECL	Data Collection	39	52%
	Data cleansing	16	21%
	Data analysis	11	15%
	Support	9	12%
		75	100%
Level of Undrstanding on ECL	Very familiar	18	24%
	Somewhat familiar	29	39%
	Not familiar at all	28	37%
Source: Survey Data(2023)		75	100%

As all the respondents are involved in different stages of implementing expected credit loss the other critical question can be familiarity with the conceptual framework of IFRS 9. Even though IFRS is principle based all models and analysis should take the principles into consideration. Of the total of respondents 24% of them are confident that they are very familiar with the concepts and principles while 39% claim that they are familiar but to a certain extent. At last, 37% indicated that they are not familiar with the standard, and they just imitate the work previously done by others. The result shows that most of the respondents are not confident they are familiar with or have knowledge in this area. This implies that there is a gap in knowledge and understanding of the model and has an impact on the data gathering analysis and presentation. Possible reasons for this might be lack of adequate training and lack of attention form the management as well as employee.

4.5. General Overview of Expected Credit Loss Implementation Practice

To make it simple and understandable the researcher classified the general overview into two major parts. The first part is the exitance of training. As indicated in the below Table 4.3, 77% of the respondents claimed that there is no consistent training while 23% indicated that they have continued capacity building training. The result indicates that there is a lack of continuous capacity-building training for the staff who are involved on IFRS 9 ECL model computation. This entail employees are not updated with latest development of the standard and the computation made for provisioning is not updated accordingly. The reason behind this might be since the report is prepared at each reporting date and employees and management are focused on the day-to-day activities of the institutions. This results in less attention for the model and IFRS in general. IFRS 9 involves complex financial reporting standards and evolves over time. It introduced significant changes in accounting for financial instruments, especially regarding loans and credit risk assessment. Therefore, employees involved in financial reporting must stay updated with these changes. Continuing training is important as to understand complex rules, Keeping up with changes, Consistent application, and Risk Management.

Table 4.3 General insight of ECL Implmentation practice of the institutions

Indicators	Category	Frequency	Percent
Existance of Continiious Capacity Building Tranings provided for the staffs	Yes	17	23%
	No	58	77%
		75	100%
Using Internally Developed Expected credit loss model	Yes	0	0%
	No	75	100%
		75	100%
The model currently using by the insititutions are developed by	Consultant	75	100%
	Regulatory Body	0	0%
		75	100%
Level of Knowledge on each components of the model	No, I don't	47	63%
	Yes, I do	11	15%
	I'm not sure	17	23%
Source: Survey Data(2023)		75	100%

The second part of Table 4.3 is associated with model. All financial institutions use models developed by consultants hired for the implementation of IFRS. This implies the respondents are not involved in the process of model development which leads to not understanding the model components and variables. This makes the results unadjusted, models not customized for their context and assumptions not aligned with the institutions conditions. Even though using the model is developed by consultants' employees working on the implementation need to know each component of the model developed. Possibly these results from consultants not sharing the whole model as they consider it as their property, Not training the staff accordingly and employees not giving attention at the beginning as it is handled by the consultants. The major advantage of using models developed by consultants is consultants likely have substantial experience in developing ECL models for various organizations, which can be extremely valuable. Speeding up the model development process as they likely already have well-established models and processes and providing training to staff and ongoing support as needed are the other major benefits. On the other hand, disadvantages associated with this are that the model might not be perfectly tailored to specific needs and risk appetite and maintaining the process and flexibility to modify and adapt the model as needed might be difficult.

4.6. Internal challenges faced by institutions in implementation Expected Credit Loss

Financial institutions may face various internal challenges during the implementation phase of the Expected Credit Loss (ECL) model. To make the analysis and interpretation easier the researcher classified internal challenges as major challenges and practical challenges. Major challenges list general challenges institutions face during the implementation and practical challenges shows the detail practical challenges.

4.6.1. Major Challenges faced by institutions in the process implementing ECL

I. Lack of Skilled personnel

From the total of respondents shown under Table 4.4 61% of them strongly agree that there is lack of skilled manpower while 23% agree and 5% was neutral and 11% disagree that lack of skilled manpower not a challenge by them. Overall lack of skilled manpower is a significant hurdle in implementing an Expected Credit Loss (ECL) model. This implies institutions may struggle to adapt to newer updates or upgrades in future. This might be result of lack of trainings and management support.

Table 4.4 Lack of Skilled Personnel

	Alternatives	Ranking	Frequency	Percent
Lack of skilled personnel to implement ECL model	Strongly Agree	1	46	61%
	Agree	2	17	23%
	Neutral	3	4	5%
	Disagree		8	11%
Source: Survey Data(2023)			75	100%

There are various ways that lack of skilled manpower affect implementation of expected credit loss. To name a few:

a. **Limited Expertise in Model Development**: An ECL model follows intricate mathematical and statistical methods. If organizations lack personnel with the necessary expertise in model construction and validation, it is challenging to reliably implement an ECL.

b. Data Handling: Extracting, curating, and managing data required for an ECL model necessitates a thorough understanding of data analysis and management. In the absence of skilled data professionals, Organization might struggle to accurately compile and interpret necessary data sets.

c. **Streamlining Processes:** Skilled manpower also ensures smooth integration of the new model into existing systems and processes. Without skilled personnel, distortions or errors might go unnoticed, leading to misinformed decision-making.

d. **Timely Updates and Adaptations:** ECL models need to be dynamic and evolve based on changing circumstances. Without trained staff, organizations could miss necessary updates or misinterpret information.

II. Data Availability

This section covered in depth on the second part of internal challenges. But as a general overview this section describes the major issues. Generally, form the total respondents 29% of them strongly agree believes that inadequate data collection and management systems are internal challenges they face and 44% of respondents agrees while 15% was refined from giving response on this and the rest 12% disagrees on this. The result indicate that inadequate data collection and management system is a challenge for the respondents. This implies that longer data collection time and time taking data validity period. The grounds behind might be lack of technological development to store data and retrieve it when needed.

Table 4.5 Data Availablity				
Inadequate data collection and management systems	Strongly Agree	1	22	29.3%
	Agree	2	33	44.0%
	Neutral	3	11	14.7%
	Disagree	4	9	12%
			75	100%
Poor data quality or inadequate data	Strongly Agree	1	27	36%
	Agree	2	32	43%
	Neutral	3	7	9%
	Disagree	4	9	12%
Source: Survey Data(2023)			75	100%

The other major challenge in relation to data availability is poor data quality or inadequate data. 36% of the respondents Strongly agree and 43% agrees with this as a major problem while 12% disagree that this is not the only case they are coming across and 9% of them are neutral. Results indicates that poor quality and in adequate data are a challenge for the respondents in the process of implementation of the standard. This implies poor quality and insufficient data have an impact on the outcome of the model as well because the model produces what is provided to it. Wrong and low-quality data could result in wrong analysis and implementation. This can also impact the financial report by breaching the fundamental conceptual framework of faithful representation.

III. Model development and usage

According to IFRS 9 Pp. 5.5.17, an entity shall measure expected credit loss of financial instrument in a way that reflects the;

a. an unbiased and probability-weighted amount that is determined by evaluating a range of possible outcomes.
b. the time value of money; and
c. reasonable and supportable information that is available without undue cost or effort at the reporting date about past events, current conditions, and forecasts of future economic conditions.

Each model should comprise the above three major components. In the below paragraphs we shows the responses in light with the above paragraphs of the standard.

For the first question raised for respondents which presents insufficient resources to implement ECL model total of 69% Strongly agree and 23% agrees that it is quite a challenge for them while 8% disagree in this matter. The result indicates that insufficient resources to implement the ECL model is a challenge for the respondent. This implies inability to calculate and anticipate expected credit loss accurately can considerably weaken a institutions risk management. The development a reliable ECL model relies on data about past financial conditions, risk factors, correlations, assumptions, and other parameters. The lack of high quality, clean, and robust data can lead to an inaccurate model that misstates credit loss expectations.

The Second question was challenges in obtaining reliable forward-looking information. For this question 44% of respondents Strongly agree and 36% of them agree that it is challenging them while 20% was neutral. The result shows that the institution doesn’t consider using forward-looking information. This implies that the major requirement to transit from IAS 39 to IFRS 9 is overlooked. This has a significant impact on the output of the model, financial reporting and decision making of potential investors. The ECL model considers potential future scenarios, which makes model predictions inherently uncertain. Building in these scenarios requires a deep understanding of potential economic outcomes and their likelihood.

The other question was difficulty in forecasting the expected cash flows of various assets. Again 49% of the respondents strongly agree and 28% agree that it is a challenge while 23% of them are neutral. The results show that integrating the forecast of expected cash flow from various assets is a challenge for the institutions. This implies that integrating such information is relevant for financial reporting but failure to do so might question the quality of the results. The reason behind this might be the concept of ECL is new and institutions are on the way to adopt and understand each component it has. The fourth question for respondents was about difficulties in developing suitable models for classifying loans. 61% respondents agreed that it is a challenge in their organization while 32% of them disagree on this challenge. The result shows that classifying loans to make them suitable for the computation of provision is a challenge for them. This implies that unable to classify loans have impact on the analysis of provision by misplacing risk rates of the model.

Table 4.6 Model development and usage

Insufficient resources to implement ECL model	Strongly Agree	1	52	69%
	Agree	2	17	23%
	Disagree	4	6	8%
			75	100%
Challenges in obtaining reliable forward-looking information	Strongly Agree	1	33	44%
	Agree	2	27	36%
	Neutral	3	15	20%
			75	100%
Difficulty in forecasting the expected cash flows of various assets	Strongly Agree	1	37	49%
	Agree	2	21	28%
	Neutral	3	17	23%
			75	100%
Difficulties in developing suitable models for classifying loans	Strongly Agree	1	27	36%
	Agree	2	19	25%
	Neutral	3	5	7%
	Disagree	4	10	13%
	Strongly Disagree	5	14	19%
			75	100%

Source: Survey Data(2023)

It is known that the complexity of the model can be challenging for institutions. The reason why it is challenging is listed briefly below:

a. **Probabilistic Modeling:** ECL models require the estimation of potential losses for possible future scenarios, incorporating probabilities of default (PD), loss given default (LGD), and exposure at default (EAD). These calculations imply a detailed understanding of credit risk, financial products, market influences, and advanced statistical techniques.
b. **Macroeconomic Factors:** ECL models need to integrate macroeconomic factors and their influence on default rates. This integration further adds to the complexity, as economic factors can be hard to forecast and model.
c. **Data Requirements:** The ECL model requires extensive historical data on defaults, recoveries, and product-specific information. Gathering, cleaning, and managing such vast amounts of data can be a complex task.
d. **System Integration:** The implementation of an ECL model often implies a deep integration with existing IT systems for data extraction, processing, and reporting. These integrations add to the technical complexity of the model.

4.6.2. Practical institutional challenges for implementing expected credit loss

In this section, practical challenges faced by microfinance institution is covered. According to the general sense of collected data those challenges are classified in to two major parts.

I. Data Related Challenges

Implementing ECL in practice can often pose challenges due to data availability. According to table 4.7, 64% of respondents agree that there is a challenge in data sourcing and cleansing while 21% of them think that it is a medium impact challenge the rest 15% think that it has low impact. Which shows data sourcing and cleansing is one of the major challenges that internally facing. This denotes very hectic and time taking data sourcing and cleaning. This might be due to manual data handling and the very poor way of data storing. For the second question presented to respondents 69% agree that incomplete and insufficient data is the other major challenge associated with data while 17% think that it has low impact. This result indicates that incomplete and insufficient data is the other problem they came across. This implies that the inputs used for loan loss provision are not high quality and might result in compromised reliability of the LLP. The reasons rotate back to the previous reasonings, and it is low data handling technique. The other challenge pinned pointed by respondents is the challenge for accessing and retrieving data in which 39% of them agree that it is posing challenge while 43% think that it has medium impact and the rest 19% low impact. According to the responses challenges associated with accessing and retrieving data on the other hand is affecting them internally in the process of implementing ECL. This implies that populating data is time taking and data might be missed, and this leads to contradiction with completeness and freedom of error.

The respondents were required to rank lack of UpToDate information impact the process of implementing ECL. 56% think that it has high impact while 33% of them think that the impact is medium and 11% of them believe that the impact is low. This result shows that lack of UpToDate information does have high impact on implementation process. This implies enhancing qualitative characteristics of the conceptual framework. Lack of UpToDate data has impacted on the quality of the work performed. This might be a result of backward data handling techniques. The last question in relation to data availability was challenges associated with manually encoded and technological limitations to store data. 45% of them think it has high impact while 31% of them believe that it has medium impact and 24% rank it as it has low impact. Based on responses manually encoded and technological limitations to store data have high impact on ECL implementation. This implies that data migration to the model is time taking and challenging as it resulted to possibility of errors and misleading of the decision making.

Table 4.7 Data Related Challenges

Indicators	Category	Frequency	Percent
Difficulties in data sourcing and cleansing	High	48	64%
	Medium	16	21%
	Low	11	15%
		75	100%
Incomplete and insufficient data	High	52	69%
	Medium	10	13%
	Low	13	17%
		75	100%
Challenge for accessing and retrieving data	High	29	39%
	Medium	32	43%
	Low	14	19%
		75	100%
Lack of UpToDate customer information	High	42	56%
	Medium	25	33%
	Low	8	11%
		75	100%
Manually encoded and technological limitations to store data	High	34	45%
	Medium	23	31%
	Low	18	24%
Source: Survey Data(2023)		75	100%

To support and summarize the above analysis and result here are some challenges faced by institutions.

- **Lack of Historical Data:** ECL models rely heavily on historical data to predict future losses. However, many companies or banks may not have sufficient historical data on default rates, recovery rates, and other credit risk parameters. This can lead to an inaccurate prediction of ECL.

- **Data Quality:** Even if historical data is available, the quality of the data can be a significant challenge. It should be relevant, accurate, and consistent to effectively predict the ECL. Bad data can lead to inaccurate forecasting and ultimately, financial losses.

II. IT Related Challenges

Based on Table 4.8 below data was gathered for IT related challenges that the financial institutions are facing. For the first question presented to the respondents, which is to rate the status of their IT infrastructure, 36% believe that it is good while 48% agree that the stage is very low. This indicates that the institutions' IT facilities are very low. The result signifies that low IT facilities could lead to improper data management which is critical to successfully computing and managing credit risk. The second assessment question was to check how well their current accounting software accommodate ECL 68% of respondents agreed that their current accounting software has low performance on the accommodation of the model. This implies that their accounting system is not able to integrate the model. This implies the inability to integrate the ECL model and the accounting system can result in the reporting of inaccurate financial figures. The other question was raised to assess the efficiency of their IT infrastructure on the collection, processing, and analysis of ECL, 33% of the respondents think that the IT system is inefficient in the process of the data collection, processing, and analysis while 45% believe that it has medium impact. This indicates that their system is efficient but not in adequate level in the process of implementing ECL.

Table 4.8 IT Related Challenges			
Indicators	**Category**	**Frequency**	**Percent**
What is the Current state of your organization's IT infrastructure?	High	12	16%
	Medium	27	36%
	Low	36	48%
		75	100%
How well your current accounting software accommodate Expected Credit loss modeling?	High	8	11%
	Medium	16	21%
	Low	51	68%
		75	100%
How efficiently your IT infrastructure help you to collect, process and analyze expected credit loss model?	High	16	21%
	Medium	34	45%
	Low	25	33%
Source: Survey Data(2023)		75	100%

In general, ECL model requires well integrated IT infrastructure due to the following reasons:

- **Data Management:** ECL models require extensive data handling. From collecting and storing data on credit history to assessing and updating risk parameters, the accuracy of ECL models is highly dependent on the availability of high-quality data and reliable data management systems.
- **Model Calculation:** IT systems are required to execute the complex calculations involved in deriving the ECL. This includes computing the Probability of Default (PD), the Loss Given Default (LGD), the Exposure at Default (EAD), and the final ECL figure.
- **Integration with Existing Systems:** The ECL model needs to be integrated with the institution's existing credit risk management, financial reporting, and regulatory compliance systems.

4.7. External challenges faced by institutions in implementation Expected Credit Loss

In this section, the researcher tries to cover areas that are beyond the institution’s control. Those challenges are eternal but have a direct impact on the implementation of ECL. We can generally see them as Economic factors, government regulations and technological advancements. 56% of respondents believe that changes in economic conditions have high impact on the credit risk of the organization while 19% thought it has medium impact on the other hand 25% think that it has low impact. This result indicates that economic conditions have a high impact on the credit risk of the company. This entails the company credit risk is highly impacted by the change in economic conditions.

Table 4.9 External Challenges

Indicators	Category	Frequency	Percent
To what extent do changes in economic conditions impact our organization's credit risk?	High	42	56%
	Medium	14	19%
	Low	19	25%
		75	100%
How concerned are you about changes in government regulations affecting our organization's credit risk and expected credit loss?	High	39	52%
	Medium	22	29%
	Low	14	19%
		75	100%
In your opinion, how much of an impact do changing interest rates have on our organization's credit risk?	High	43	57%
	Medium	15	20%
	Low	17	23%
		75	100%
How much do external factors such as technological advancements, market disruptions (Inflation)or geopolitical events impact our organization's credit risk?	High	38	51%
	Medium	21	28%
	Low	16	21%
Source: Survey Data(2023)		75	100%

The other question raised for the respondents was to give their opinion on changing government regulation’s impact on credit risk. 52% of respondents think that it has high impact while 29% believe that it has medium impact and 19% low impact. The result shows that change in government regulation has a high impact on credit risk and expected credit loss. This implies change in government influences the financial position of the company.

The third question raised for the respondents was how much of an impact do changing interest rates have impact on an organization’s credit risk. 57% of respondents think that it has a high impact while 20% believe that it has medium impact and 23% low impact. The result shows that change in interest rate have impact on credit risk. The fourth and the last assessment question was to assess how much external factors such as technological advancements, market disruptions (Inflation)or geopolitical events impact organization's credit risk. 51% of respondents think that it has a high impact while 28% believe that it has medium impact and 21% low impact. The above result indicates that technological advancements, market disruptions (Inflation)or geopolitical events have high impact on credit risk.

The overall health of the economy directly impacts the ECL model. In times of economic downturn, job losses increase, and businesses face difficulties, which lead to higher default rates and hence increase expected credit losses. Changes in interest rates can also significantly impact on the ECL model since they directly affect the borrowers' capacity to repay loans.

On the other hand, Political events or instability can have a significant impact on economic factors such as unemployment, GDP, interest rates, and overall economic growth, affecting the financial capacity of borrowers to fulfill their credit obligations.

4.7.1. Regulatory organ involvement of institutions expected credit loss computation

The Accounting and Auditing Board of Ethiopia (AABE) and National Bank of Ethiopia (NBE) are the major regulatory organs for Microfinance institutions. In this section the researcher covered some of the involvement of these institutions in the implementation of ECL.

Table 4.10 Regulatory Organ Involvemnet

Indicators	**Category**	**Frequency**	**Percent**
Involvement in Expected credit loss implementation (technical assistance)	High	17	23%
	Medium	28	37%
	Low	30	40%
		75	100%
Monitoring and Supervision	High	56	75%
	Medium	12	16%
	Low	7	9%
		75	100%
Communications on Expected credit loss implementation	High	12	16%
	Medium	24	32%
	Low	39	52%
		75	100%
Provision of training and development	High	14	19%
	Medium	20	27%
	Low	41	55%
Source: Survey Data(2023)		75	100%

Respondents were questioned if there was technical assistance provided by the regulatory bodies during implementation. 40% of them claimed that there was low involvement of those bodies while 37% believed that there is medium level involvement. The result shows that there is low level of involvement of regulatory bodies on providing technical assistance. This implies that regulatory bodies' involvement is confined in review, supervision, and follow-up of the institutions' financial reporting. This might be a result of the regulatory bodies reason for establishments. When we see the monitoring and supervision aspect 75% of them think that there is high involvement while 16% think it is medium and 9% low involvement. This indicates that since they are regulatory organs that highly focus on monitoring and supervision. This might be due to their mission as institution. The communication on ECL implementation was assessed based on the respondent 16% of them think that there is high involvement while 32% think it is medium and 52% low involvement. This indicates that updates were not communicated among regulatory bodies and institutions. This implies that the supervisory authorities are responsible for reviewing the documents submitted and the institutions on just submitting and fulfilling the requirements. Regarding provision of training and development 55% of them believe that there is regulatory bodies involvement is very low. This implies that the regulatory bodies are expecting what they didn't shape the industry for.

4.8. Benefits of implementing Expected Credit loss model

The Expected Credit Loss (ECL) model is a critical element of financial and risk management for businesses. In this section the researcher assessed benefits of expected credit loss for the institutions. According to Table 4.11, 49% of the respondents believed that ECL model has high impact of improving identification of credit losses while 44% of respondents think that it has medium impact while 7% of them agree that it las low impact. The above result shows one of the major benefits of implementing ECL is it improves identification of credit losses. This entails better presentation and disclosure for financial instruments (loan commitment), fair presentation of statement for financial position and profit or loss. The respondents were asked if ECL provides a more accurate estimation of credit losses. 55% of the respondents believed that ECL model has high impact of giving more accurate credit losses while 24% of respondents think that it has medium impact while 21% of them agree that it las low impact. The result indicates that the model is giving them more accurate estimation of credit loss. This denotes that the financial reporting is improving from previously used frameworks. The reason is that the ultimate reason that the standard is issued is to improve quality of financial reporting in relation to financial instrument.

Table 4.11 Benefits of Implementing ECL			
Indicators	**Category**	**Frequency**	**Percent**
Improved identification of credit losses	High	37	49%
	Medium	33	44%
	Low	5	7%
		75	100%
More accurate estimation of credit losses	High	41	55%
	Medium	18	24%
	Low	16	21%
		75	100%
Better allocation of provisions for credit losses	High	58	77%
	Medium	17	23%
		75	100%
Improved understanding of credit risk distribution and concentration	High	48	64%
	Medium	22	29%
	Low	5	7%
		75	100%
Enhanced ability to manage credit risk	High	35	47%
	Medium	19	25%
	Low	21	28%
Source: Survey Data(2023)		75	100%

Better allocation of credit risk was also one of the questions given to be ranked by the respondents. 77% of the respondents believed that ECL model has a high impact on giving better allocation of credit losses while 23% of respondents think that it has medium impact. The result indicates that the ECL model has a high impact on better allocation of credit losses. This implies that losses are allocated in an efficient manner for each loan category. This results in better understanding of each loan category, credit risk and decision making.

64% of respondents believed that ECL has a high impact on improved understanding of credit risk distribution and concentration while 29% agree that it has medium impact and 7% of it has low impact. This result indicates that ECL has a high impact on improved understanding of credit risk distribution and concentration. This implies that the financial statements of the institutions are improved in the presentation of loan commitments. According to the above table 47% of respondents believed that ECL has a high impact on enhanced ability to manage credit risk while 25% think that it has medium impact and 28% with low impact.

The result indicates that ECL model allows companies to estimate potential losses from credit risk. This provides a more proactive and realistic assessment of credit risk by using predictive analysis on credit exposures over the life of a loan. Moreover, ECL accounting standards (like IFRS 9) provide more relevant information about changes in credit risk. They help users of financial statements understand the impact of credit risk on the amount, timing, and uncertainty of future cash flows.

Through regular ECL assessments and disclosures, stakeholders can gain a clearer picture of the company's credit risk profile, risk management practices, and financial health and by forcing institutions to recognize and provide for potential losses much earlier, the ECL model promotes financial stability. This helps protect the company and the broader financial system from shocks and downturns.

4.9. Results Discussion

According to research results and knowledge gap identified in chapter two. This subsection summarizes the findings with theories formulated.

The study finds that lack of skilled personnel, inadequate data collection and management systems, poor data quality or inadequate data, insufficient resources to implement ECL model as a key internal challenge this result aligned with the research findings of Tesfaye & Mulugeta (2020) in contrast challenges associated with forward looking data and forecasting future cashflows of assets are severe in which it proofs the results of Pucci& Skaeraek (2019), Wolfgang (2015) and (Deloitte, 2020). Their study shows that complex forward-looking models is one of the struggles of ECL model implementers.

The other challenges identified were related to IT infrastructure. Data sourcing and cleansing, incomplete and insufficient data, challenge for accessing and retrieving data, lack of UpToDate customer information, manually encoded and technological limitations to store data, System inefficiency, poor IT infrastructure, lack of IT system that can be used to store, manage, and retrieve data for whatever purposes are key challenges identified. The results of the study result aligned with the results of the Gulyas & Somogyi (2019). Poor and insufficient IT infrastructure is quite a challenge on implementation on ECL model. Schutt et al. (2020) results of lack of specific guidelines of the model are another challenge identified by this research.

Less regulators involvement, Volatile macroeconomic factors, unpredictable geopolitical events is also the results of the research conducted. The listed results are categorized as external challenges in the above paragraphs. Previously conducted research results by Gerald (2016), Petr & Jiri (2020), Barbara & Tamin (2018) also prove the existence of the challenges in global scale.

The results of the benefits of using ECL model Improved identification of credit losses, more accurate estimation of credit losses, better allocation of provisions for credit losses, improved understanding of credit risk distribution and concentration and enhanced ability to manage credit risk where the benefit of the model is underlined benefits of the research. This finding aligned with the first beginning result of IFRS9 which is improving confidence of the investor. Another research by Stephen & Joshua (2022).

CHAPTER FIVE

5. SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

Introduction

This chapter covers summary of findings, Conclusions and recommendations based on results and interpretations on the previous chapter.

5.1. Summary of the Findings and Conclusion

The assessment on challenges and benefits of implementing expected credit loss implementation on some selected microfinance was undertaken by the researcher. The below are core summary of findings.

The first objective of the research was to assess the ECL implementation process of the institutions. The researcher gathered and analyzed data on this regard and find out that there is lack of continuous capacity building trainings, ECL models used by the institutions are developed by consultant and staffs just imitate the process as there is lack of adequate knowledge for each component of variables in the model. This affects the subsequent reporting, and some variables are not updated to align with what happened at the reporting period.

The second objective was to examine internal challenges the institutions face during the implementation of the model. To make it clear and easily understandable the researcher classified it into two categories as major challenges and practical institutional challenges. Major challenges consist of lack of skilled personnel, data availability, and model development and usage. The researcher finds out that lack of skilled personnel, inadequate data collection and management systems, poor data quality or inadequate data, insufficient resources to implement ECL model, challenges in obtaining reliable forward-looking information, difficulty in forecasting the expected cash flows of various assets and difficulties in developing suitable models for classifying loans were major challenges they are facing. On the other hand, certain practical challenges ere also mentioned both related with data and IT support.

Difficulties in data sourcing and cleansing, incomplete and insufficient data, challenge for accessing and retrieving data, lack of UpToDate customer information, manually encoded and technological limitations to store data, System inefficiency, poor IT infrastructure, inability to integrate the model with accounting system were identified as practical challenges that the institutions are currently facing.

The third objective of the research is to assess external factors that impact model implementation. The researcher found that economic conditions such as inflation, technological advancements, geopolitical events, government regulation and interest rate have high impact on the institution impairment calculation on their loan commitments. These factors are beyond institutions' control and have impact on macro-economic variables.

The researcher also investigates regulators' involvement in the implementation process. The result shows that those regulators have minimal involvement in giving technical assistance, providing training and communications if there is update on the standard. The institutions focus mainly on monitoring and supervision.

The last objective was to assess how they benefited from implementing ECL. The result indicated that, Improved identification of credit losses, more accurate estimation of credit losses, better allocation of provisions for credit losses, improved understanding of credit risk distribution and concentration and enhanced ability to manage credit risk were the benefit of the model. Despite the challenges and the complexity of the model the benefits safeguard the interest of stakeholders on future cashflows of the entities.

In general, the above paragraphs showed that the results of the research conducted with the objective stated at the beginning of the research.

5.2. Recommendations

Based on the results of the research and identified gaps. The researcher suggests the below points to overcome the challenges.

- ***Data Management:*** The institutions should ensure that data of good quality, complete, and clean is available for accurate ECL calculations. They should create a data management plan that includes regular data validation and cleaning processes.
- ***Technology and Tools****:* Microfinance should implement tools and technology that are capable of managing, processing, and analyzing large datasets for ECL. They should

invest in the latest technologies in accounting software's that are capable of processing impairment or can be easily integrated with the model.

- ***Model Development and Validation:*** Build well studied models to estimate probability of default (PD), loss given default (LGD), and exposure at default (EAD), the three components of ECL. These models should be regularly validated and updated to reflect changing economic conditions.
- **Scenario Analysis and Forward-Looking Information:** Forward looking information was one of the major challenges and missing from the models of the institutions. The institutions should start to use multiple economic scenarios and forward-looking information to account for the uncertainty and volatility in future economic conditions.
- **Effective Governance and Control:** Implement strong governance structures to monitor and control the ECL estimation process. Regularly review models, assumptions, and estimates for accuracy and relevance.
- **Staff Training:** Invest in regular training for your staff so they can understand and effectively implement the ECL requirements. Foster a risk-aware culture within your organization that values accurate and timely risk reporting.
- **Regulatory Compliance:** Regularly review regulatory changes and standards to ensure your ECL model is compliant.
- **Collaboration with External Parties:** Collaborate with consultants, auditors, and regulators to ensure your ECL processes are sound and robust.

4.3. Implications for Future Research

This study was conducted to assess the challenges and benefits of expected credit loss model. The sample was taken from 5 microfinance institutions for data collection purposes. This limits the generalization to the whole microfinance institutions. Future researchers can add more microfinance to their sample to make it more generalizable.

The other gap of this research that future researchers can assess is that it doesn't provide detail model assessment. It is only limited to assessing the challenges both internal and external as well as the benefits of the model in their specific companies. Future researchers can study each variable individually and make their recommendations.

REFERENCE

Adamu, J. A. (2018). IFRS 9 Measurement of Financial Instruments 2018: Jameel's Non-Normal Brownian Motion Models are Indeed IFRS 9 Complaint Models. Journal of Economics and Management Sciences,1(1), p92.

Albian Albrahim (2020). Loan loss provisioning and market Discipline: Evidence from the IFRS 9 Adoption. SSRN Electronic Journal.

Baghdasaryan L. and Mnatsakanyan H.(2019) .Implementation challenges of IFRS 9 impairment requirement in post-soviet countries' banks. Grant Thornton Armenia, Yerevan, Republic of Armenia.

Banu (2018). Expected Credit Loss model by IFRS 9 and its possible early impact on European and Turkish Banking Sector. Bilkent University, Faculty of Business Administration.

Barbara Seitz and Tamin Dinh (2018). Understanding Loan loss reserves under IFRS 9: A simulation based approach. Advances in Quantitative Analysis of Finance and Accounting, Volume 16(2018), pp.311-357.

Beerbaum Dr., Dirk Otto and Ahmad, Sammar, Credit Risk According to IFRS 9: Significant Increase in Credit Risk and Implications for Financial Institutions (September 1, 2015).

Caruso, Ezio; D'Hulster, Katia; Kliatskova, Tatsiana; Ortiz, Juan. 2021. Accounting Provisioning Under the Expected Credit Loss Framework : IFRS 9 in Emerging Markets and Developing Economies - A Set of Policy Recommendations. Equitable Growth, Finance and Institutions Insight;. World Bank, Washington, DC. © World Bank.

Çoll, Besmir & Ahmeti, Skender & Aliu, Muhamet. (2021). IFRS 9 TRANSITION EFFECT ON FINANCIAL STABILITY OF KOSOVO COMMERCIAL BANKS. Prizren Social Science Journal. 4.

Deloitte (2016). Six Global IFRS banking survey.

Deloitte (2020). Challenges of IFRS 9 Modeling in the UAE banking industry, Middle East point of View.

Ernst & Young Global Limited, Applying IFRS Impairment of financial instruments under IFRS 9.

Eva Gulyas (2019). Experience relating to the introduction of IFRS 9 in the banking sector. Economy & Finance, Vol. 6 Issue 3.

Ezio Caruso, Katia D'Hulster, Tatsiana Kliastskova and Jutan Ortiz (2021). Accounting Provisioning under the expected credit loss framework: IFRS 9 in emerging markets and Developing economies-A set of policy Recommendation. International Bank for Reconstruction and Development / The World Bank.

Frykström, N., & Jieying, L. (2018). IFRS 9 – the new accounting standard for credit loss recognition. Economic Commentaries.

G20. 2009. “Declaration on Strengthening the Financial System.” London Summit declaration, April 2.

Gerald A. Edwards (2016). Supervisor’s key roles as bank implement Expected Credit Loss Provisioning. SEACHEN Financial Stability Journal, Volume 7.

Gulyás, Éva and Somogyi, Cintia (2019) Experiences Relating to the Introduction of IFRS 9 In the Banking Sector. ECONOMY AND FINANCE: ENGLISH-LANGUAGE EDITION OF GAZDASÁG ÉS PÉNZÜGY, 6 (3). pp. 266-295.

Hassan Rkein etal. (2020) Toward a Framework for Examining the Implementation of IFRS 9 in Banking Industry: An Assessment from Lebanon. Volume 2 - Issue 1.

IFRS 9. 2018. “Financial Instruments.” IFRS website. https://www.ifrs.org/issued-standards/list-ofstandards/ ifrs-9-financial-instruments.

KPMG (2016). Implementing IFRS 9 considerations for systematically important banks.

Mohad Yaziz (2018). ADOPTION OF IFRS 9 IMPROVES REPORTING. Universiti Tun Abdul Razak.

Moody's analytics, "IFRS 9 Impairment Regulations: Implementation Challenges and Potential Solutions" December 2015.

Oday Tamimia & Ildiko Orban (2020). Accounting model for impairment under IFRS 9 and its Impact on loss allowance. European Research Studies Journal, Volume XXIII, Issue 4, pp. 1259-1277.

Oľga Pastiranováa, Jiří Witzanya (2021). Impact of implementation of IFRS 9 on Czech banking sector. Faculty of Finance and Accounting, Prague University of Economics and Business.

Petr Polak and Jiri panos (2020). The impact of expectation of IFRS 9 loan loss provisions. Czech National Bank.

Pucci R. & Skærbæk P. (2019). The co-preformation of financial economics in accounting standard-setting: A study of the translation of the expected credit loss model in IFRS 9. Inland Norway University of Applied Sciences.

PwC, "In depth expected credit losses", August 2014.

Setepehn Ongalo and Joshua Wanjare (2022). International Financial reporting standard IFRS 9 ABD The financial performance of commercial banks in Keya. European Journal of Business and Management Research, Vol 7, Issue 6, pp. 221-226.

Tesfaye, D., & Girma, A. (2020). Expected Credit Loss Model Implementation and Its Challenges: The Case of Development Bank of Ethiopia. International Journal of Academic Research in Accounting, Finance, and Management Sciences.

Vasilyeva, Alfiya and Frolova, Elvina A., Methods of Calculation of Expected Credit Losses Under Requirements of IFRS 9 (2019). Journal of Corporate Finance Research, Vol. 13, No. 4, pp. 74-86.

Wolfgang Reitgruber (2015). Methodological thoughts on expected credit loss for IFRS 9 Implement hidden reserves, cyclical loss predictions and LGD back testing. V3, forthcoming in credit technology 92.

APPENDIX

Addis Ababa University

Collage of Business and Economics

Department of Accounting and Finance

My name is Bithania Mamo. I am currently enrolled in Master of Science in Accounting and Finance department in Addis Ababa University. In order to fulfil the requirement to obtain my second degree I am conducting research under the title "***CHALLENGES AND BENEFITS OF IMPLEMENTING EXPECTED CREDIT LOSS MODEL FOR MICROFINANCE INSTITUTIONS IN ETHIOPIA: CASE STUDY ON SOME SELECTED MICROFINANCES***". This questioner will be only for academic purpose and your information is confidential.

I. General Information

a. Gender

Male ☐ Female ☐

b. Educational Background

Highschool Certificate ☐
Diploma ☐
Degree ☐
Masters ☐
PHD ☐

c. In which Department you are currently working on?

Finance Department ☐
Operations Department ☐
It Department ☐

d. Did you involve in implementation of Expected Credit Loss (IFRS 9) implementation?

Yes ☐ No ☐

e. In which stage did you involve in the implementation process?

Data Collection ☐

Data cleansing ☐

Data analysis ☐

Other Specify___________________________________

f. What is your level of understanding of ECL models? (Select one)

Very familiar ☐

Somewhat familiar ☐

Not familiar at all ☐

II. Assessment of internal challenges of Expected Credit Loss implementation.

1. Do you have continuous capacity building training on latest developments of IFRS 9?

Yes ☐ No ☐

2. Did you develop the model you are currently using?

Yes ☐ No ☐

3. If your answer is no for Q.2, Please choose who developed the model for you?

Consultant ☐ Regulatory Body ☐

Other Please specify, ___________________________________

4. Do You know each component of the developed model?

No, I don't ☐ Yes, I do ☐

I'm not sure ☐

5. What are the major challenges in implementing ECL models in your organization?

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Lack of skilled personnel to implement ECL model					
Inadequate data collection and management systems					
Poor data quality or inadequate data					
Insufficient resources to implement ECL model					
Challenges in obtaining reliable forward-looking information					
Difficulty in forecasting the expected cash flows of various assets					
Compliance with regulations and accounting standards					

6. Have you encountered any difficulties during the implementation of the ECL model in your organization?

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Difficulties in data sourcing and cleansing					
Difficulties in developing suitable models for classifying loans					
Difficulties in including forecasting in the model					
Poor Management Support					
Lack of Skilled Man power					
Poor IT infrastructure					

7. Have you encountered the following challenges in relation to Data Availability and cleanse? Please tick them with the defined range?

	High	Medium	Low
Incomplete and insufficient data			
Challenge for accessing and retrieving data			
Lack of UpToDate customer information			
Manually encoded and technological limitations to store data			

8. How did you come up the problem?

9. Have you encountered the following challenges in relation to IT infrastructure? Please tick them with the defined range?

	High	Medium	Low
What is the Current state of your organization's IT infrastructure?			
How well your current accounting software accommodate Expected Credit loss modeling?			
How well the data collection system integrated with your accounting software?			
How efficiently your IT infrastructure help you to collect, process and analyze expected credit loss model?			

10. How did you come up the problem?

III. Assessment of external challenges of Expected Credit Loss implementation.

11. Did you incorporate external forward-looking data for forecasting?

Yes ☐ No ☐

12. If your answer in Q. 11is no, why you didn't use the forward-looking data?

13. If your answer in Q. 11is yes, which data did you use?

GDP ☐ Interest Rate ☐

Unemployment rate ☐ Other; Please specify, _______________

14. Did you face any Problem associated with incorporation of forward-looking data?

15. How well does the regulatory organ involve in the implementation of ECL?

	High	Medium	Low
Involvement in Expected credit loss implementation (technical assistance)			
Monitoring and Supervision			
Communications on Expected credit loss implementation			
Provision of training and development			

16. Which external factor will have impact on your credit Risk?

	High	Medium	Low
To what extent do changes in economic conditions impact our organization's credit risk?			
How concerned are you about changes in government regulations affecting our organization's credit risk and expected credit loss?			
In your opinion, how much of an impact do changing interest rates have on our organization's credit risk?			
How much do external factors such as technological advancements, market disruptions (Inflation)or geopolitical events impact our organization's credit risk?			

IV. Benefits of Expected Credit loss implementation

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Improved identification of credit losses					
More accurate estimation of credit losses					
Better allocation of provisions for credit losses					
Improved understanding of credit risk distribution and concentration					
Enhanced ability to manage credit risk					