Predicting Financial Inclusion and Access to Credit in Kenya

By

Chebet Tanui

051687

Masters of Science in Data Science and Analytics

2024

Predicting Financial Inclusion and Access to Credit in Kenya

By

Chebet Tanui

051687

Submitted in Partial fulfilment of the Requirements for the Degree of Master of Science in Data Science and Analytics at Strathmore University

Institute of Mathematical Sciences

Strathmore University

Nairobi, Kenya

JUNE 2024

Declaration and Approval

Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Student's Name: **Chebet Tanui**

Sign: ..... Date: 25/03/2024

Approval

The thesis of **Chebet Tanui** was reviewed and approved for examination by the following:

..... Date: 25/03/2024

Dr. John Olukuru

Institute of Mathematical Sciences,

Strathmore University

Dedication

This dissertation is dedicated to my beloved parents, Daniel Tanui and Stella Tanui, whose unwavering support has been invaluable throughout this journey. To my siblings, Chirry, Chemu, and Junior, and to my niece, Nataana Tai, your presence and encouragement have lightened the burden and enriched every step of the way. To my dad, Daniel Tanui, your guidance and wisdom have been a source of strength and inspiration. Thank you, from the depths of my heart, for believing in me.

Acknowledgements

My sincere gratitude goes to everyone that has supported me during the dissertation and the entire Masters Programme. I thank God for His mercies and grace which have guided me throughout.

My Friends, Classmates and Colleagues who motivated and supported me throughout the process. My Supervisor Dr John Olukuru, the faculty at Institute of Mathematical Sciences and Strathmore University, whose invaluable guidance steered me to completion.

Abstract

Financial inclusion, particularly access to credit, is a crucial aspect of economic development in Kenya. This study aims to investigate the determinants of financial inclusion and access to credit in Kenya, employing logistic regression modeling to predict financial inclusion patterns; and construct a forecast model that can support policymakers and financial organizations in boosting financial inclusion. The study analyzed several factors including demographics, technology adoption, financial services usage and barriers to assess their impact on financial inclusion and access to credit.

The results revealed that the use of mobile phones and the internet as technological indicators of financial inclusion were the most effective predictors. Contrary to previous studies, gender was not found to significantly affect financial inclusion in this context. The development of a machine-learning model achieved an overall prediction accuracy of 90.9%. An interactive user dashboard was also developed using flexdashboard in R and hosted in the web, with visualizations and regression models to provide insights into the key factors driving financial access in Kenya

The results showed that demographics, technology adoption, financial services usage and barriers to financial inclusion were the most significant factors that impacted financial inclusion; however, there were no significant correlations between these factors and financial inclusion as a whole.

This research study will offer insights into the causes of financial exclusion in the country and how to overcome them.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

ATM	Automated Teller Machine
AUC	Area under Curve
CHFS	China Household Finance Survey
KNBS	Kenya National Bureau of Statistics
TAM	Technology Acceptance Model

CHAPTER ONE: INTRODUCTION

1.1 Study Background

Financial inclusion is an act of ensuring that people who have been conventionally shut out of the conventional financial system, have financial services access including banking, credit, and insurance (The World Bank, 2011). A growing body of research evidence indicates that inclusive financial markets assist in the reduction of poverty and the wealth divide. Providing people and families with the means of managing their finances, pay their bills, obtain bank loans, and obtain insurance coverage assists in attaining this goal (Pomeroy, 2022; Zeqiraj *et al.*, 2022; Cicchiello *et al*., 2021 & Mader, 2018). The World Bank (2021) reports that close to 2.5 billion individuals worldwide are financially excluded, mainly due to reasons such as high fees, distrust, or inadequate financial products. However, since the World Bank Group began monitoring global financial service accessibility through the Global Findex database in 2011, there has been a significant increase in financial inclusion (Hall, 2022). Adults who have a bank account have increased in number from 51% in 2011 to 69% in 2017, an addition of 515 million people (The World Bank, 2021).

In the United Kingdom, statistics indicate that 14.1% of the adult population (7.1 million people) are financially marginalized (Elliot, 2022). This includes 5.8 million people without operational bank accounts. A study by Cambridge University linked ethnicity to financial exclusion in the UK (Adami, 2022). Additionally, a report by the UK parliament revealed that a third of the population (about 17 million people) lacked financial education and capability, which resulted in financial exclusion (UK Parliament, 2017). The Financial Inclusion Commission's goal in the UK is to foster a financially inclusive community where people can readily access financial services that are user-friendly, convenient, and can be tailored to their evolving needs over time. Financial inclusion index as measured by India's Reserve Bank stood at 53.9% as at March 2022 (Reserve Bank of India, 2022). According to the 2017 Global Findex Report, 80% of the Indian population owned a bank account which was approximately double the figure when compared to 42% of the adult population who owned bank accounts in 2014 (The World Bank, 2023). According to Department of Financial Services (2022), the Indian Government has implemented several initiatives promoting financial inclusivity and granting financial access for individuals who currently lack them. Access to money is changing because to the India Stack, which provides a digital ID card and eliminates barriers to entry for financial services (International Monetary Fund, 2021).

Financial inclusivity has received increasing attention in policy discussions in several African nations. As stated by Beck *et al.* (2014), access to finance has gotten better in African nations, mainly due to emerging market foreign banks aiding in this process. The usage of mobile money transactions has been widely adopted in the continent, leading to significant advancements in financial inclusion in the region. The financial sector in South Africa is very advanced, and financial inclusion is assessed based on accessibility. In 2017, over 67 percent of adults held accounts with official financial institutions, whereas the average for Sub-Saharan Africa was 39 percent. (Demirguc-Kunt, *et al*., 2018). Through the introduction of the Msanzi account concept, attempts have also been made to provide banking services to rural communities (National Treasury, 2020; Jameson, 2014).

According to CARE International's report in 2014, more than half of Uganda's adult population, around 54%, were able to use formal financial services in 2013. However, a considerable number of 2.6 million adults, approximately 15%, were still unable to access such services. A study conducted by Finscope in 2018 on financial inclusion in Uganda noted that 76% of adults resided in the rural areas (Finscope, 2018. In Tanzania, a report on the status of financial inclusion revealed that 16.7% of the adult population used bank services, 48.6% did not operate bank accounts but used other formal services, 6.7% did not operate bank accounts but used informal services while 28% were financial excluded (National Financial Inclusion Strategy, 2018).

The 2021 Global Findex Database of the World Bank shows that Kenya has achieved the highest financial inclusion rate in Africa, scoring 82.9%. The high score has been linked to M-PESA success that has resulted in a tremendous financial inclusion (Ventures Africa, 2016). Among the East African countries, it leads in financial inclusion through the advancing of mobile transactions platforms and the widespread usage (Johnson, 2016). Further, Johnson (2016) observes that at least 73% of Kenya’s adult population are financially included of which 98% of that population operate mobile money accounts. Consequently, over 66% of rural residents have access to banking services and utilize mobile transactions to make payments and send and receive money domestically.

The overarching objective of financial access is to bring in the segment of the society that lack bank accounts or integration of financial services into the formal financial system. This would get them to have unrestricted access to affordable and appropriate financial instruments. Kenya has experienced remarkable progress in financial inclusion since 2006, when only a small

group of adults, approximately 27%, took advantage of formal financial services and products that were available to them. This is a great contrast to 2021 where 84% had access to the basic financial services (Makunda & Heyer, 2022).

1.2 Problem Statement

Although there have been efforts to enhance the availability of formal financial services, a considerable proportion of people still do not have access to such services. This is a worldwide issue, with about 2 billion people lacking access to such services, and a large portion of these individuals reside in rural places in developing countries (Demirguc-Kunt *et al*., 2015). There is a widespread agreement that granting the majority of individuals access to fundamental financial services can bring about beneficial effects on household livelihoods (Mujeri 2015). However, the current financial infrastructure in developing countries is underdeveloped, inefficient, and offers limited options for individuals. In contrast to developed nations where there is a wide-ranging choice of financial services available, including debit and credit cards, among others internet banking services, and an efficient payment system, most developing countries, particularly those in sub-Saharan Africa, do not have as many readily available financial services. Although there has been substantial growth in the financial industry in sub-Saharan Africa, financial services accessibility is still limited for a considerable number of people. For instance, in Kenya, only 55.2 % of adult people have access to formal financial accounts, while 43.8 % do not, and a large portion of these individuals reside in rural regions, according to Demirguc-Kunt *et al.* (2015). The actual number of individuals who use these financial services may be even lower, but there is no data available on voluntary exclusion. Individuals who lack access to financial services encounter challenges in acquiring credit and saving, which hinders their ability to make substantial contributions to the development and growth of their respective economies. Financial inclusivity is a vital aspect of addressing poverty, achieving financial stability, and fostering economic growth. In order to tackle financial exclusion among a section of the population, it is critical to identify the elements that impact financial inclusion, analyse the function of informal financial services and technology, and recognize the obstacles to financial inclusion in Kenya.

1.3 Research Aim

The general aim goal of this research is to identify the crucial elements that impact financial inclusion in Kenya, and construct a forecast model that can support policymakers and financial organizations in boosting financial inclusion in the nation

1.4 Research Objective

a) To identify the key factors that influence financial inclusion and access to credit in Kenya.
b) To examine the relationship between technology adoption and financial inclusion in Kenya.
c) To examine how informal financial services contribute to advancing financial inclusion and access to credit in Kenya.
d) To identify potential barriers to financial inclusion in Kenya.

1.5 Research Questions

a) What are the key factors that influence financial inclusion in Kenya?
b) What is the influence of technological adoption on financial inclusion in Kenya?
c) How do informal financial services contribute to advancing financial inclusion in Kenya?
d) What are the potential barriers to financial inclusion in Kenya?

1.6 Significance of Study

First, Kenya like many other nations, has a sizable population that is socially and economically disenfranchised. Therefore, this research study will offer insights into the causes of financial exclusion in Kenya and how to overcome them. Furthermore, the study's results will assist policymakers in determining the appropriate policies and measures required to improve financial inclusion in Kenya. The study may highlight certain regions or demographic groups that are especially susceptible to financial exclusion and recommend focused interventions. Additionally, financial service providers can gain insights into the demands and preferences of prospective clients through the study, enabling the creation of financial instruments that are better adapted to the requirements of population segments that don't have access to the banking system.

1.7 Scope of Study

This study aims to examine the pertinent variables linked to financial inclusion in Kenya utilizing the dataset from Central Bank of Kenya on FinAccess Household Survey and to explore the connections between these variables to address the research queries. The study will concentrate on the financial sector in Kenya, taking into account the context of the Kenyan

financial market and the social, economic, and political aspects that impact financial access in the nation. The study will offer valuable insights into the aspects that foster financial inclusion in Kenya, as well as identifying and promoting financial access in the country, it is necessary to identify and tackle any potential barriers that may hinder its progress.

CHAPTER TWO: LITERATURE REVIEW

2.1 Overview

The term "financial inclusion," also referred to as outreach in the banking sector, has a broad definition. Sarma and Pais (2011) define financial inclusion as offering essential financial services to all citizens at a reasonable cost, in a convenient form, and without discrimination in terms of time and place. The main aim is providing formal financial services to those living in poverty who lack access to them, addressing market inefficiencies that prevent less privileged persons from participating in the financial system. Financial inclusion creates new opportunities to combat poverty, promote inclusive development, and achieve the Millennium Development Goals by enabling people to engage with the formal financial system. According to Thankom and Rajalaxmi (2015), for countries to achieve economic growth, it is necessary to prioritize the implementation of financial inclusion policies that promote small-scale businesses. Mutegi and Phelister (2013) found that many adults struggle to sustain their daily livelihood due to financial policies that limit their access to financial services. The World Bank (2017) advocates that financial inclusion for both individuals and enterprises are crucial for countries worldwide to achieve economic stability and advancement. Several studies, including DemirgüçKunt and Klapper (2012) and Allan *et al*. (2012), suggest that making financial services available to low-income workers, unbanked populations, and other disadvantaged individuals can boost a country's economic growth.

2.2 Theoretical Review

The study will be fixed on two theories namely: Capability Approach Theory and Technology Acceptance Model.

2.2.1 Capability Approach Theory

The capability (capabilities) approach theory was conceived by Amartya Sen and Martha Nussbaum in the 1980s. The theory emphasises how important it is for people to have the freedom to pursue happiness and get just compensation. By giving priority to resources, usefulness, and thorough assessment, the Capability Approach seeks to address a variety of concerns with contemporary well-being measurement techniques. Additionally, it considers various life circumstances, making it more inclusive when assessing people's financial capacity.

The capability approach directs attention away from the resources and public goods that individuals possess and towards what they can accomplish and attain through the use of those resources and goods. This change is justified because merely having resources and goods does not guarantee that individuals can transform them into actual doings and beings. Even if two people have similar sets of resources and goods, they may still attain different outcomes depending on their situation.

The capacity approach can be used to evaluate how financial inclusion affects disadvantaged groups' ability to acquire appropriate credit and develop the required capabilities and functioning (Kuriakose & Kylasam Iyer, 2015). This strategy enables a thorough review of many positive aspects, as well as the evaluation of current social norms or actual data on financial inclusion (Robeyns & Byskov, 2021). (Kimhur, 2020). Additionally, it can be used to assess the impact of housing regulations or programmes on people's capacities (Kimhur, 2020). The current study can benefit from this theory as it offers a beneficial perspective on comprehending the idea of financial inclusion and the possible benefits it could bring.

2.2.2 Technology Acceptance Model (TAM)

The TAM theory, proposed by Davies in 1989, was created to anticipate and explain the adoption and acceptance of information technology by an organization and its users. Its aim is to use specific technology or services to describe attitudes. The TAM theory is a strong and valid model that has been widely applied in the field of technology acceptance. External variables such as ease of use and utility are considered, along with facilitating situations, subjective norms, and self-efficacy. Personal capacities are presented as variables that vary among investigations. The concept of perceived ease of use is a term used to describe to describe a person's perception of the amount of effort required to utilize technology. The behaviour intention predicts use in different versions of the Technology Acceptance Model, but the relationship between them is not deterministic. This model examines how people use technology based on their perceptions of its usefulness, ease of use, and level of acceptance. The TAM theory will be used in this study to explain an individual’s willingness to make use of fintech e-payments and other technological systems.

2.3 Empirical Review

Several prior research studies have investigated financial inclusion, each with specific research objectives. This section will provide a brief overview of these studies.

2.3.1 Factors Influencing Financial Inclusion

Gakii (2012) examined the factors affecting Kenyans' usage of mobile financial services, particularly those for money transfers in Nairobi. According to the research, the utilization of advanced financial instruments such as mobile banking and payments, is influenced by variables such as gender, age, education, wealth, and service fees. To address this issue, the research proposed improving financial education in both urban areas and rural creating more inclusive financial products and services.

Kimutai's (2015) research looked at the agent outlets of the Kenya Commercial Bank in the Marakwet West Sub-County in order to determine what factors affect the financial inclusion in rural parts of Kenya. Researchers employed a survey research strategy to gather data from all KCB Mtaani agents in the study's sub-county. They used questionnaires and interview guides to gather information from 113 KCB Mtaa agents. Financial inclusion in rural areas of Marakwet West Sub-County was found to be significantly influenced by variables like infrastructure, agent quality, financial education, and network connectivity. The study provides a foundation for the current study on predicting financial inclusion by identifying the key factors that need to be considered in the predictive model.

Nanda (2018) conducted an evaluation of the determinants of financial inclusion in India using existing literature and empirical studies. The study utilized secondary data, including surveys and empirical evidence, to investigate the association between various factors and financial inclusion. The research found that in India, financial integration is influenced by several factors, including income levels, educational attainment, gender, social status, financial services access, and institutional factors. The research highlighted that encouraging financial inclusion requires such elements as the accessibility of financial facilities and financial literacy. The research outcome could offer useful perspectives on the aspects that might impact financial inclusion in Kenya.

Mhlanga and Denhere (2020) carried out research to evaluate the primary factors behind the promotion of financial access in South Africa. Data collection was achieved using a structured questionnaire. The study used the logit model whereby it was established that the education level, gender, age, race, total salary (income proxy) and marital status influenced financial inclusion. The study further established that gender unlike the other factors negatively influenced financial inclusion. By identifying the factors that drive financial inclusion in

specific countries, researchers can better understand how to promote financial inclusion across the continent, particularly in areas with similar economic, social, and political contexts.

Nyasani (2021) conducted a study carried out research to assess the factors that impacted financial inclusion among SME owners in Nairobi County. Data collection was achieved through questionnaires. Stratified random sampling was employed to select 384 SME owners. Structured questionnaires were utilized in collecting original data, which was then analysed using various statistical techniques. The research outcomes indicated that the demographic aspects were important in determining the financial inclusion level among SME proprietors in the county.

2.3.2 The Influence of Technology Adoption and Financial Inclusion

To better appreciate the impact of wireless communication in financial inclusion, Mulwa (2012) specifically focused at mobile banking services in Makueni County. The research utilized a qualitative approach to explore and comprehend the idea of mobile banking. The study gathered data through interviews, focus group discussions, and questionnaires. The study's findings showed that adapting products to fit the local context was essential for successful implementation, and that the stability of the products relied on the interplay between all relevant actors, both human and nonhuman. Moreover, the study identified three crucial factors to consider in mobile banking, which are avoiding network control by a single actor, ensuring an adequate number of users and access points for long-term viability, and determining the most suitable mobile banking model before implementation. The research provided various recommendations, including revising regulations to promote market growth, enhancing awareness programs and offering financial literacy workshops for rural populations, and providing training and financial assistance to agents. This study is relevant to the current research as it will provide valuable insights relating to the aspects of mobile technology on financial access.

Prasad *et al*. (2013) investigated how Information Technology (IT) impacted financial inclusion. The research found that IT played a crucial role in cutting down the costs associated with providing banking services, especially in rural areas and for financially marginalized populations. The significance of IT was highlighted due to its ability to serve remote locations at lower costs and its greater population penetration, which is a vital requirement for achieving financial inclusion.

In 2018, Mwania conducted research to investigate the factors influencing the adoption of technology on financial inclusion in Machakos County, Kenya. Descriptive research methodology was employed to determine a connection between the variables tested. Technology adoption, transaction costs, collateral, the study's regression analysis revealed a positive correlation among perceived value, financial inclusion, and other variables. This study elucidates the elements that influence small business adoption of technology and financial services in a given area.

Fanta and Makina conducted a cross-sectional study in 2019, utilizing quantitative methods and secondary data sourced from the World Bank's Global Findex database. The study aimed to examine the correlation between financial access and technology in Africa, specifically focusing on the usage of mobile phones and the internet as technological indicators of financial inclusion. By utilizing a logistic regression model, the researchers analysed publicly accessible datasets from the database. Based on the results, it was evident that ATM and internet technologies had a notable and favourable effect on financial accessibility and usage. Despite the positive correlation between having mobile and telephone subscriptions and using financial services, the connection was not deemed statistically significant. The study's conclusion emphasized the importance of technology in increasing access and utilization of financial services, thus supporting the idea that technology and financial inclusion are connected. This research is significant as it provides valuable insights into the potential impact of mobile technology on financial inclusion.

Alabi and Olaoye conducted a study in 2022 to evaluate the influence of the usage of technology on financial inclusion in China and Nigeria, using a cross-country panel analysis methodology. The research analysed World Bank Global Findex data and the International Telecommunication Union (ITU) for the period 2011-2017, using publicly available datasets gathered through surveys conducted by the World Bank and ITU. The focus was on mobile phones and internet utilization as indicators of the use of technology related to financial inclusion. However, the findings indicated that the impact on financial inclusion was not significant despite the use of internet, mobile phone subscriptions, and ATMs. In contrast, the technology factors had a significant positive influence on financial inclusion in other non-specific nations included in the panel. The study provides insights into how technology adoption can be an effective tool for promoting financial inclusion, which is valuable in forecasting financial inclusion.

2.3.3 The Influence of Informal Financial Services in Promoting Financial Inclusion

A study by FinScope (2018) in Uganda revealed that 56% of the adult population (10.3 million) used informal financial services of which 6.7 million additionally used formal financial services. The report which examined the financial inclusion status in Uganda utilized data from the FinScope 2018 Survey. The research gathered information from a nationwide survey comprising of more than 5,000 participants, alongside focus group conversations and interviews with key informants in the financial industry to ensure representation. The report evaluated different metrics of financial inclusivity, such as the availability and utilization of formal financial services such as bank accounts and mobile money. It was also discovered that 76% of the adult population lived in rural areas and preferred to use informal financial services. Therefore, the informal financial services contributed to increased financial inclusion among the rural based population.

Alhassan *et al*. (2019) utilized a quantitative research approach to investigate the influence of formal financial access on monetary preferences and informal financing. The study analysed the association between the utilization of formal and informal financial instruments and cash preferences as indices of financial inclusion utilizing the 2014 World Bank Global Findex panel data and Afrobarometer surveys. The methods of data collection involved accessing and analysing publicly available datasets, which were gathered through surveys conducted by the World Bank and Afrobarometer. The study applied a fixed-effects regression model to investigate the relationship between mainstream banking inclusion and informal financial facilitation. The results revealed that informal financial services played a significant role in mobilizing resources through channels such as family members, friends, and self-help groups. Furthermore, the financially excluded individuals can make use of informal intermediations to meet their financial needs.

Agabalinda and Steel (2021) analysed the impact of training and informal financial services in enhancing financial inclusion and literacy in Uganda. The study collected data through a randomized controlled trial involving more than 1,000 participants, focus group discussions, and interviews with financial sector stakeholders. The research assessed various indicators of financial literacy and inclusion, such as financial knowledge, usage of formal financial services, and saving behaviour. The findings revealed that financial training was significantly related to financial literacy and this in turn resulted in increased usage of both informal and

formal financial services. The study concluded that the promotion of the use of informal financial services compared to training was more efficient in promoting financial inclusion.

2.3.4 Potential Barriers to Achieving Financial Inclusion

Fungacova and Weill (2014) conducted a study that sought to highlight various aspects of financial inclusion in China. The research employed a quantitative research approach by utilizing China Household Finance Survey (CHFS) data and conducting regression analysis to examine the variables that influenced financial inclusion. Data from the CHFS, a nationally representative survey that collected information on household finance and economic behaviour was used. The research examined various metrics of financial inclusion, such as the access and utilization of mainstream financial services such as credit and bank accounts. The study identified several hurdles that study participants identified as impeding their ability to use formal bank accounts, including lack of funds, especially among the impoverished, inadequate documentation, elevated expenses associated with operating bank accounts and related services, and distance to banking institutions, particularly among older adults.

Ahmed and Jianguo (2014) employed qualitative research techniques to investigate financial inclusion in Tanzania and the associated challenges. Semi-structured interviews were conducted to gather the data from policymakers, financial institutions, and other stakeholders in the financial sector, as well as focus group discussions with members of the public. The study examined various financial inclusion indicators, including mainstream financial services. The findings suggested that although financial inclusion had increased in the country, a big segment of the population still required access to formal banking. The study identified obstacles such as high costs, regulatory requirements, lack of advanced technology, and limited awareness that were hindering financial inclusion in Tanzania.

Varghese and Viswanathan (2018) conducted a study on financial inclusion in India, focusing on its opportunities, issues, and challenges. The research employed a literature review methodology, using existing research and publications to gather data. The methods of data collection involved reviewing existing literature on financial inclusion, including academic research, policy documents, and reports from international organizations. The research identified supply and demand issues that acted as obstacles to financial inclusion. The demand challenges identified included a lack of technological and financial literacy, a large unbanked population spreading across a vast area and limited access to credit facilities. Among the supply challenges identified is the reluctance of banks to provide credit facilities to people with small

and irregular incomes, high transaction costs and documentations such as birth and income certificates, which the rural poor could not easily produce.

2.3.5 Access to Credit

Bhanot *et al.* (2012) conducted a study with the objective of determining the significant elements that impact financial inclusion in remote geographical locations and recommending expansion strategies for banks into underserved markets. Using a standardized questionnaire, primary data was gathered from 411 families in the states of Meghalaya and Assam in northeast India. Using a logistic regression model, the important contributors to financial inclusion were identified. The research revealed that financial inclusion in northeast India was exceedingly low. Income, having access to financial information through several channels, familiarity with self-help groups (SHGs), and education were identified as crucial factors in promoting inclusion. In addition, the proximity to postal office banks increased inclusion probability. Location and receipt of government assistance did not help integration on their own, though recipients of government assistance in plain regions indicated a higher degree of integration.

Óskarsdóttir *et al.* (2019) investigated the potential of utilizing phone networks as a novel source of data to improve credit scoring models. The study employed sophisticated social network analysis techniques to estimate influence ratings, and combined call-detail data with credit and debit account information to provide credit card applicants with scorecards. The study's findings indicated that integrating call-detail records into credit scoring models enhances their performance, especially in terms of AUC, with calling behaviour features proving to be the most effective predictors. The study also raised concerns regarding the ethical use of call-detail information, regulatory compliance, and data privacy. Additionally, the characteristics of calling behaviour were found to be the most effective statistical and economic predictors in other models. These findings have important ramifications for the ethical usage phone logs, regulatory rules, financial inclusion, information exchange, and privacy concerns.

Gomber *et al.* (2018) examined the recent technological advancements and process disruptions in the financial services industry, including the rise of fintech startups seeking to improve business models, customer experiences, and services transformation. The authors argued that experts viewed these developments as a revolution, with the industry requiring significant improvements in efficiency, customer focus, and knowledge. The authors further suggested a new fintech innovation mapping methodology to study developments and adaptations in four financial services domains: operational management, technology advances, and

transformations in the financial regulatory environment, lending and deposit services, and investment and financial markets, which are influenced by various innovations, such as P2P lending, social media use, cryptocurrencies, blockchain, and robo-advisory services.

2.4 Research Gaps

Various research studies have investigated financial inclusion. However, Kimutai's (2015) study specifically concentrated on the factors that impacted financial inclusion in the rural regions of Kenya, with a specific focus on Kenya Commercial Bank agent outlets located within Marakwet West Sub-County, which may limit the generalizability of the findings to other rural areas in Kenya or other countries. Also, the research only identified the factors that significantly impacted financial inclusion in the rural regions of Marakwet West Sub-County however, no causal association was established between these characteristics and financial inclusion. Additionally, Nanda's (2018) study, which examined financial inclusion in India, may not be relevant to Kenya or other nations due to unique cultural, economic, and political factors. Mhlanga and Denhere's (2020) research on the determinants of financial access in South Africa was based solely on structured questionnaires, which might not offer an in-depth comprehension of the variables influencing financial inclusion in the country. Qualitative data, such as interviews or focus groups, may provide deeper insights into the experiences and perceptions of individuals regarding financial inclusion.

The study by Mulwa (2012) specifically focused on mobile banking services in Makueni County. The study presents several research gaps, which include a limited geographic scope focusing only on Makueni County, lack of quantitative data using only a qualitative research approach; this might not offer a thorough comprehension of how wireless communication affects financial inclusion. A limited scope focusing only on mobile banking services, and did not explore other forms of wireless communication, such as internet-based banking or digital wallets. An examination of these alternative types of wireless communication may offer a more comprehensive illustration of how wireless communication affects financial inclusion.

Alabi and Olaoye's (2022) research evaluated how the adoption of technology affects financial inclusion, and it uncovered several areas that require further investigation. These include a narrow emphasis on particular technological metrics such as mobile phone usage, the internet, and ATMs as indicators of technology adoption for financial inclusion. Secondly, the study had a limited sample size examining data only from two countries, China and Nigeria, which may not be representative of other countries or regions. To obtain a more in-depth

understanding of the influence of technology adoption on financial inclusion, future studies could scrutinize a broader range of nations with different economic, social, and political settings. Additionally, contextual elements like regulatory frameworks, infrastructure, and cultural norms that might impact the connection between technology adoption and financial inclusion were not explored in the present study. The upcoming research will aim to address these gaps.

2.5 Conceptual Framework

This is an illustration that depicts the variables being studied in research (Mugenda & Mugenda, 2003). The diagram helps the researcher understand and connect with the concepts being analysed, and it displays how the variables are related to each other. The study's independent variables are factors influencing financial inclusion, technology, informal financial services and barriers to financial inclusion. The dependent variable is financial inclusion. Factors influencing financial inclusion will be measured by sociocultural, economic, infrastructural, regulatory and policy indicators. The indicators of technology are mobile phone penetration, internet access, ATMs and Electronic Payment Systems. The informal financial services are measured by savings/rotating groups, mobile money, informal remittance services and money lenders. The lack of physical financial services access is an indicator of obstacles to financial inclusion, limited financial literacy and high costs of financial services. Financial inclusion is indicated by access, usage and affordability.

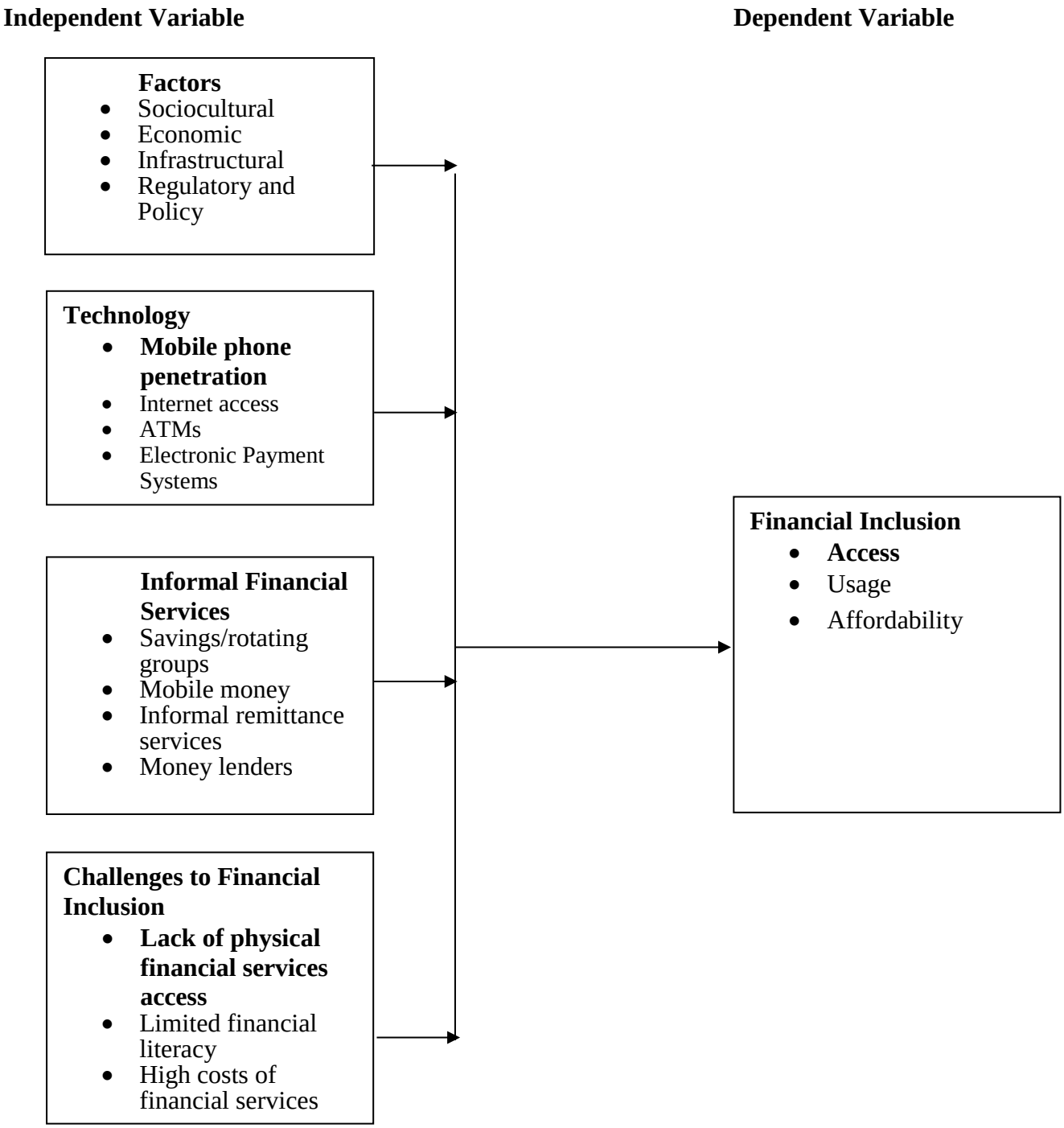


Figure 2-1: Conceptual framework

CHAPTER THREE: METHODOLOGY

The research design, data understanding, data preparation, modelling, evaluation/performance metrics and deployment tools is presented in this section.

3.1 Research Design

For this study, a descriptive research design will be implemented, which is fitting as it will enable the identification of the variables in their current state without attempting to manipulate them, as explained by Mugenda and Mugenda (2013). The design is well-suited as it focuses on describing and summarizing the data to identify trends, patterns, and relationships between the variables of interest. This design is especially useful when working with large datasets, such as the 2021 FinAccess Household Survey dataset, which will be analysed in this study.

3.2 Data Understanding

The 2021 FinAccess Household Survey dataset found in Kenya National Bureau of Statistics (KNBS) website (https://finaccess.knbs.or.ke/reports-and-datasets) contains data here linked Anonymised and weighted dataset - FinAccess Household Survey 2021 - (EXCEL FORMAT). The dataset comprises of 22,024 respondents and has 2,326 variables from rural and urban Kenya. The dataset comprises a broad spectrum of topics encompassing financial behaviour, access to financial services, demographics, and socio-economic status. It contains categorical, binary, and continuous variables. To better understand the variables in the dataset, the data will be grouped into the following categories: financial behaviour, financial services access, demographics and socio-economic status. The study's independent variables are factors influencing financial inclusion, technology, informal financial services and barriers to financial inclusion. The dependent variable is financial inclusion. Indicators of financial inclusion include sociocultural, economic, infrastructural, regulatory and policy aspects. The indicators of technology are mobile phone penetration, internet access, ATMs and Electronic Payment Systems. Indicators for the informal financial services are savings/rotating groups, mobile money, informal remittance services and money lenders. Indicators of barriers to financial inclusion include financial exclusion, limited financial literacy and high costs of financial services. Financial inclusion is measured by access, usage and affordability.

3.3 Data Preparation

To allow effective processing and evaluation during data analysis, data preparation entails gathering, collecting, structuring, and arranging the data (Manikandan, 2010). The data will be

examined for missing entries, which could result from skipped questions or non-responses, during data preparation. The missing values will be replaced by the mode and descriptive analysis done for each research objective by use of frequency. Some variable categories were recoded to attain the required sample size required for inferential analysis.

3.4 Modelling

To create a financial inclusion prediction model, logistic regression was utilized in this study. This technique is employed to create a statistical model that shows the relationship between a binary outcome variable and one or more predictor factors (Zhang, 2016). Inferential analysis by use of generalized linear model (GLM) for the binomial family and logit link was utilized. Bivariate logistic regression was carried out between the predictor and outcome variables. Using significant variables at p-value = 0.05 from the bivariate binary logistic regression models, a multivariable binary logistic regression model was fitted to identify the independent predictors of financial inclusion. The strength of association was measured by odds ratio with 95% confidence intervals. Variables with $p<0.05$ in the multivariable logistic regression model were considered as significant factors associated with financial inclusion. The logistic regression model was established by using maximum likelihood estimation, and the Hosmer-Lemeshow test was employed to evaluate the model's goodness of fit. The odds ratio (OR) was employed to gauge the magnitude of the predictor variables' effect in the model. A significance level of $p < 0.05$ was utilized to determine the statistical significance of both the model and predictor variables. The logistic model for predicting financial inclusion and access to credit can be represented by the equation:

$P(y=1) = 1 / (1 + e^{(-z)})$

where $P(y=1)$ is the probability of financial inclusion, z is the linear combination of predictor variables, and e is the exponential function.

$z = bo + b1x1 + b2x2 + b3x3 + b4x4$

And;

x_1 = Factors
x_2 = Adoption of technology
x_3 = Use of informal financial services
x_4 = Potential barriers to financial inclusion

3.5 Evaluation/Performance Metrics

In evaluating the effectiveness of predictive models, evaluation measures are essential (Hossin & Sulaiman, 2015). In this study, the logistic regression's performance was evaluated using a variety of metrics that assess the model's accuracy, precision, recall, and F1 score. Accuracy refers to the proportion of correct predictions made by the model (Li, 2017).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

According to Steyerberg *et al*. (2010), precision gauges the ratio of accurate positive predictions to the overall number of positive predictions. In this research, precision will gauge the ratio of correctly predicted individuals with financial inclusion to the total number of individuals predicted to have financial inclusion. A high precision means that the model is generating fewer false-positive predictions.

$$Precision = \frac{TP}{TP + FP}$$

Conversely, recall measures the ratio of correctly predicted individuals with financial inclusion to the total number of individuals who have financial inclusion. A high recall value signifies that the model is making fewer false-negative predictions.

$$Recall = \frac{TP}{TP + FN}$$

The harmonic mean of Recall and Precision is the F-score.

$$F - score = \frac{Recall * Precision}{Recall + Precision}$$

3.6 Dashboard Development Using R

3.6.1 Tool Selection

R was used as the primary tool for dashboard development due to its versatility in statistical analysis and visualization. The Flexdashboard and plotly libraries were employed to create an interactive and user-friendly dashboard.

3.6.2 Dashboard Design

The dashboard was designed to present key findings from the logistic regression analysis in an intuitive and visually appealing manner. Graphs, charts, and tables were used to communicate the relationships between different variables and their impact on financial inclusion.

3.6.3 Integration of Logistic Regression Results

The dashboard will include the logistic regression analysis's findings, such as coefficients, odds ratios, and statistical significance. Users have the ability to interactively assess the variables impacting financial inclusion and obtain supplementary information regarding the model.

3.7. Deployment and Accessibility

3.7.1 Deployment Tools

Data analysis was done using Python whereby the python libraries were used to clean and pre-process the data, explore the FinAccess Household Survey dataset and identify patterns, and generate descriptive statistics.

3.7.2 Deployment Platform

To make the dashboard accessible to a broad spectrum of users, it was implemented on a web platform. Accessibility factors such as ease of manoeuvring from one web page to another or accessing various components of the dashboard were considered in order to support users with varying levels of technological proficiency.

3.7.3 Documentation

To help users interpret the data, comprehend the methodology, and make the most of the dashboard, extensive documentation was supplied alongside it.

CHAPTER FOUR: RESULTS

This chapter presents the study results, which have been analyzed in line with the study objectives. The first section presents the demographic profile of respondents, and the subsequent sections present the analysis, presentation, and interpretation of the factors under investigation in the current study. Descriptive analysis was first done for each research objective by use of frequency. It was then followed by inferential analysis by use of generalized linear model (GLM) for the binomial family and logit link. Bivariate logistic regression was carried out between the predictor and outcome variables. Using significant variables at p-value = 0.05 from the bivariate binary logistic regression models, a multivariable binary logistic regression model was fitted to identify the independent predictors of financial inclusion. The strength of association was measured by odds ratio with 95% confidence intervals. Variables with $p<0.05$ in the multivariable logistic regression model were considered as significant factors associated with financial inclusion.

4.1 Demographic characteristics of respondents

The participants' mean age was 38.9 years (SD=17.2), most of the respondents were between 26-35 years (27.3%), male (59%), married or living with their partners (54.5%), had primary school as their highest level of education (40.2%), were from the poorest wealth quintile (26.1%) and were residing in the rural areas (65.6%). The summary of the demographic characteristics is shown in the table below.

Table 1: Demographic characteristics of respondents

	Total	
Variables	**n**	**%**
Age(mean and SD)*	38.9	17.2
Age		
16-17	1115	5.1
18-25	4382	19.9
26-35	6022	27.3
36-45	4065	18.5
46-55	2404	10.9
>55	4036	18.3
Gender		
Female	9026	41.0
Male	12998	59.0
Marital status		
Single/never married	5801	26.3
Married/living with partner	12004	54.5

Divorced/separated	1612	7.3
Widowed	2582	11.7
Don't know	13	0.1
Refused to answer	12	0.1
Highest Education Level		
None	3987	18.1
Other	25	0.1
Primary school	8846	40.2
Secondary school	6631	30.1
Tertiary education	2535	11.5
Wealth quintile		
Middle	4600	20.9
Poorest	5742	26.1
Second poorest	4609	20.9
Second wealthiest	3804	17.3
Wealthiest	3269	14.8
Residence		
Rural	14455	65.6
Urban	7569	34.4

The table 4-1 above is a summary of the demographic characteristics of the respondents, classified according to age, gender, marital status, education level, wealth quantile and residence.

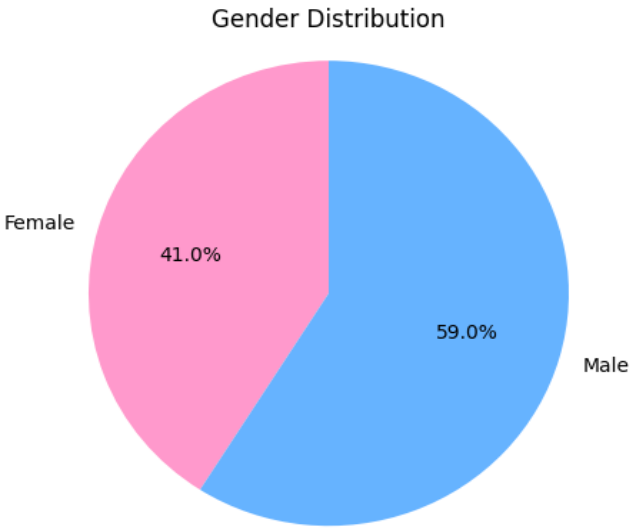


Figure 4-1: Pie chart of gender distribution

The male respondents accounted for 59% (12,998) compared to females who were 41% (9,026).

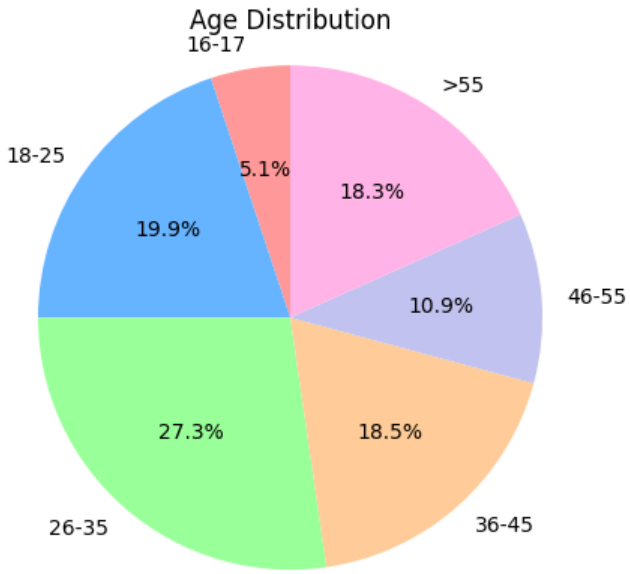


Figure 4-2: Pie chart of age group distribution

The highest proportion of respondents, 27.3% (6,022) were within the age group of 26-35 years while the lowest proportion, 5.1% (1,115) was recorded within the age group of 16-17 years.

4.2 Factors influencing financial inclusion and access to credit

Majority of the respondents who reported to have access to financial services; used any credit institutions (35.2%), did not use formal digital credit services (63.7%), had access to mobile money services (56.2%), no mobile money savings account (34.3%), no mobile banking savings account (61.8%), and currently have formal savings account (32.5%).

Table 2: Factors influencing financial inclusion and access to credit

	Financial Inclusion			
	Yes		No	
Variables	**n**	**%**	**n**	**%**
Uses any Credit institution				
No	7209	32.7	3078	14.0
Yes	7742	35.2	3995	18.1
Formal digital credit users				
No	14029	63.7	6167	28.0
Yes	922	4.2	906	4.1
Access to mobile money services				
No	2582	11.7	378	1.7
Yes	12369	56.2	6695	30.4
Mobile money savings				
No	7564	34.3	2078	9.4
Yes	7387	33.5	4995	22.7
Mobile banking savings				

No	13607	61.8	5302	24.1
Yes	1344	6.1	1771	8.0
Formal savings account				
Currently have	7162	32.5	5250	23.8
Never had	6302	28.6	1278	5.8
Used to have	1487	6.8	545	2.5

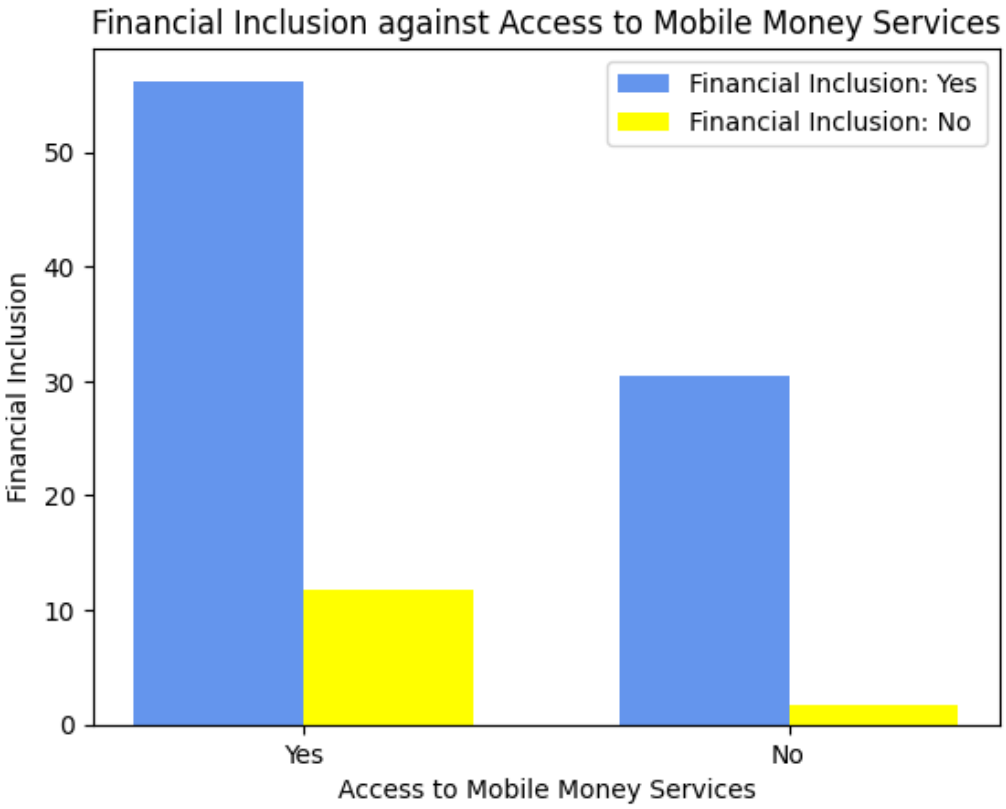


Figure 4-3: Bar graph of financial inclusion against access to mobile money services

4.3 Association between the factors and financial inclusion and credit access

Respondents within the age group of above 55 years were 1.35 times more likely to have access to financial services and credit compared to those aged between 16 and 17 years (AOR =1.35, 95% CI=1.082-1.686, P-value=0.008). Additionally, those who resided in urban areas were more than two folds more likely to have access to financial services and credit compared to those in the rural areas (AOR =2.88, 95% CI=2.675-3.102, P-value=<0.001). Participants whose highest level of education were primary, secondary and tertiary were more than four times more likely to have access to financial services and credit compare to those who had no education (AOR =4.10, 95% CI=3.531-4.753, P-value=<0.001; AOR =5.51, 95% CI=4.723-6.425, P-value=<0.001; AOR =18.14, 95% CI=15.160-21.703, P-value=<0.001).

Respondents who used formal digital credit services were approximately two times more likely to have access to financial services and credit compared to those who do not (AOR =2.01, 95% CI=1.360-2.967, P-value=<0.001). Participants who currently have and used to have formal savings account had higher odds of accessing financial services compared to those who never had (AOR =2.63, 95% CI=2.193-3.148, P-value=<0.001; AOR =1.47, 95% CI=1.172-1.849, P-value=0.001). Respondents who had mobile banking savings account had higher odds of accessing financial services and credit compared to those who did not have (AOR =1.29, 95% CI=1.163-1.426, P-value=<0.001). Those who subscribe to any credit institution were 0.49 folds less likely to have access to financial services and credit compared to those who do not (AOR =0.49, 95% CI=0.333-0.710, P-value=<0.001).

Table 3: Association between the factors, financial inclusion, and credit access

	Financial Inclusion			
Variable	**COR(95%CI)**	**P-value**	**AOR(95%CI)**	**P-value**
Age				
16-17	REF	REF	REF	REF
18-25	1.81(1.549 -2.112)	<0.001	1.00(0.829-1.212)	0.981
26-35	2.17(1.862-2.518)	<0.001	1.17(0.957-1.441)	0.124
36-45	1.86(1.589-2.171)	<0.001	1.16(0.935-1.434)	0.178
46-55	1.5(1.265-1.765)	<0.001	1.08(0.861-1.353)	0.509
>55	1.11(0.945-1.300)	0.206	1.35(1.082-1.686)	**0.008**
Gender				
Female	REF	REF	REF	REF
Male	1.14(1.075-1.207)	<0.001	1.07(0.986-1.155)	0.106
Residence				
Rural	REF	REF	REF	REF
Urban	3.66(3.449-3.887)	<0.001	2.88(2.675-3.102)	**<0.001**
Marital status				
Single/never married	REF	REF	REF	REF
Married/living with partner	0.92(0.858-0.979)	0.009	0.91(0.816-1.007)	0.067
Divorced/separated	0.76(0.674-0.857)	<0.001	0.98(0.833-1.154)	0.814
Widowed	0.45(0.402-0.502)	<0.001	1.03(0.869-1.216)	0.748
Highest Education Level				
None	REF	REF	REF	REF
Primary school	5.21(4.51-5.964)	<0.001	4.10(3.531-4.753)	**<0.001**
Secondary school	9.65(8.425-11.054)	<0.001	5.51(4.723-6.4250	**<0.001**
Tertiary education	41.09(35.211-47.951)	<0.001	18.14(15.160-21.703)	**<0.001**
Formal digital credit users				
No	REF	REF	REF	REF
Yes	2.24(2.030-2.462)	<0.001	2.01(1.360-2.967)	**<0.001**
Uses any credit institution				

No	REF	REF	REF	REF
Yes	1.21(1.142-1.280)	<0.001	0.49(0.333-0.710)	**<0.001**
Formal savings account				
Never had	REF	REF	REF	REF
Currently have	3.61(3.371-3.876)	<0.001	2.63(2.193-3.148)	**<0.001**
Used to have	1.81(1.611-2.028)	<0.001	1.47(1.172-1.849)	**0.001**
Mobile money savings				
No	REF	REF	REF	REF
Yes	2.46(2.317-2.615)	<0.001	1.08(0.852-1.372)	0.521
Mobile banking savings				
No	REF	REF	REF	REF
Yes	3.38(3.129-3.655)	<0.001	1.29(1.163-1.426)	**<0.001**

4.4 Influence of technology adoption on financial inclusion

The table below shows responses on adoption of technology on financial inclusion. Among the respondents who reported to have access to financial services 39.6% had access to internet, 59.5% used ATM, 56.2% used electronic payment systems, and 58.8% had access to a mobile phone.

Table 4: Influence of technology adoption on financial inclusion

	Financial Inclusion			
	Yes		No	
Variables	**N**	**%**	**n**	**%**
Internet access				
No	6209	28.3	319	1.5
Yes	8700	39.6	6709	30.6
Don't know	9	0.0	2	0.0
Refused to answer	3	0.0	2	0.0
Uses ATM				
No	1850	8.4	1867	8.5
Yes	13095	59.5	5195	23.6
Uses electronic payment				
No	2582	11.7	378	1.7
Yes	12369	56.2	6695	30.4
Mobile phone access				
No	2008	9.1	255	1.2
Yes	12943	58.8	6818	31.0

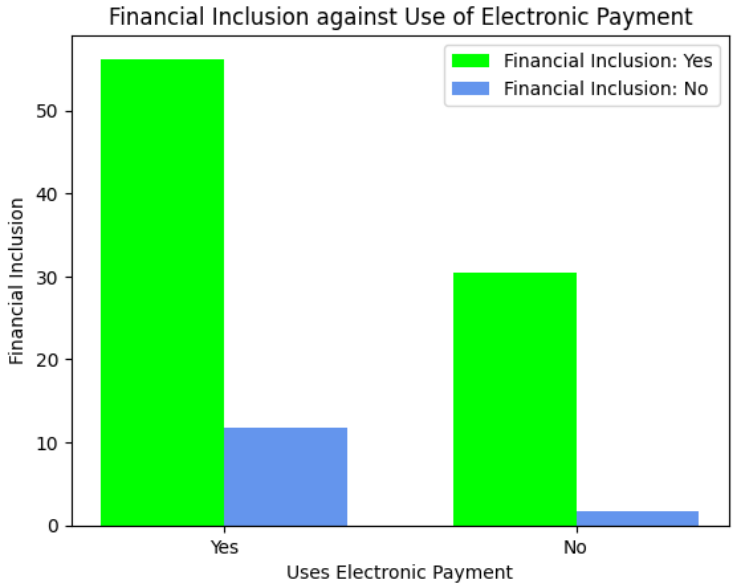


Figure 4-4: Bar graph of financial inclusion against use of electronic payment

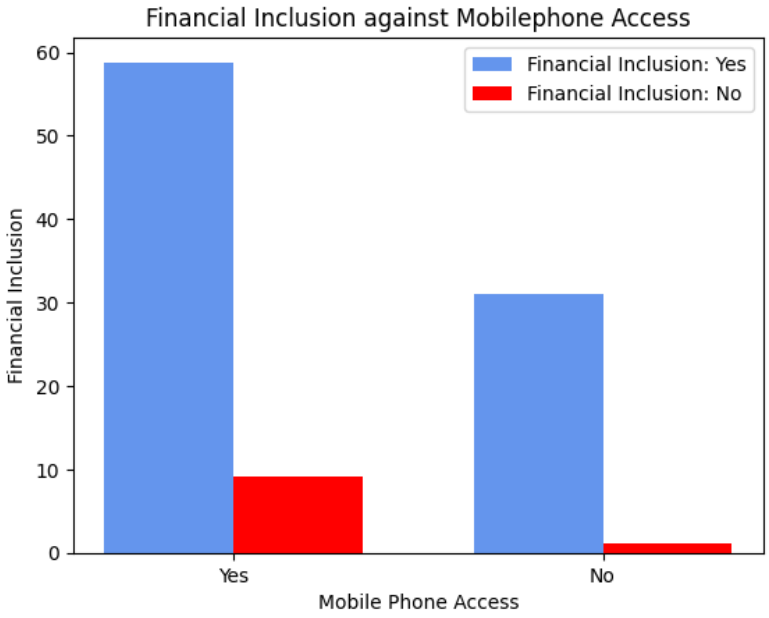


Figure 4-5: Bar graph of financial inclusion against mobile phone access

4.5 Association between technology adoption and financial inclusion

Participants who reported to have access to internet were more than ten folds more likely to have access to financial services compared to those who do not have access (AOR =12.84, 95% CI=11.325-14.566, P-value=<0.001). Conversely, participants who used ATM were 0.75 less likely to access to financial services compared to those who do not (AOR =0.75, 95% CI=0.683-0.820, P-value=<0.001).

Table 5: Association between technology adoption and financial inclusion

	Financial Inclusion			
Variable	**COR(95%CI)**	**P-value**	**AOR(95%CI)**	**P-value**
Internet access				
No	REF	REF	REF	REF
Yes	14.84(13.216-16.671)	<0.001	12.84(11.325-14.566)	**<0.001**
Uses ATM				
No	REF	REF	REF	REF
Yes	0.39(0.366-0.423)	<0.001	0.75(0.683-0.820)	**<0.001**
Uses electronic payment				
No	REF	REF	REF	REF
Yes	3.70(3.346-4.135)	<0.001	0.97(0.818-1.161)	0.771
Mobile phone access				
No	REF	REF	REF	REF
Yes	4.15(3.629-4.741)	<0.001	1.18(0.981-1.424)	0.079

4.6 Informal financial services contribution to advancing financial inclusion and access to credit

The table below shows responses on informal financial services and the magnitude of their contribution to advancing financial inclusion and access to credit. The largest proportion of respondents who reported to have access to financial services had never used Shylock money lenders (67.3%), were not informal credit users (45.9%), never had informal savings account (48.6%), never used informal remittance services (31.2%), did not use informal digital credit (37.5%).

Table 6: Informal financial services contribution to advancing financial inclusion and access to credit

	Financial Inclusion			
	Yes		**No**	
Variables	**n**	**%**	**n**	**%**
Informal savings account				
Currently have	3353	15.2	2605	11.8
Never had	10698	48.6	3996	18.1
Used to have	900	4.1	472	2.1
Informal remittance services				
Currently use	6654	30.2	4696	21.0
Never use	6877	31.2	1864	8.5
Used to use	1419	6.4	573	2.6
Informal digital credit users				
No	8258	37.5	4040	18.3
Yes	6693	30.4	3033	13.8
Shylock money lenders				
Currently use	41	0.2	59	0.3
Never used	1485	67.3	6930	31.5

Used to use	84	0.4	81	0.4
Informal credit users				
No	10099	45.9	5780	26.2
Yes	4852	22.0	1293	5.9

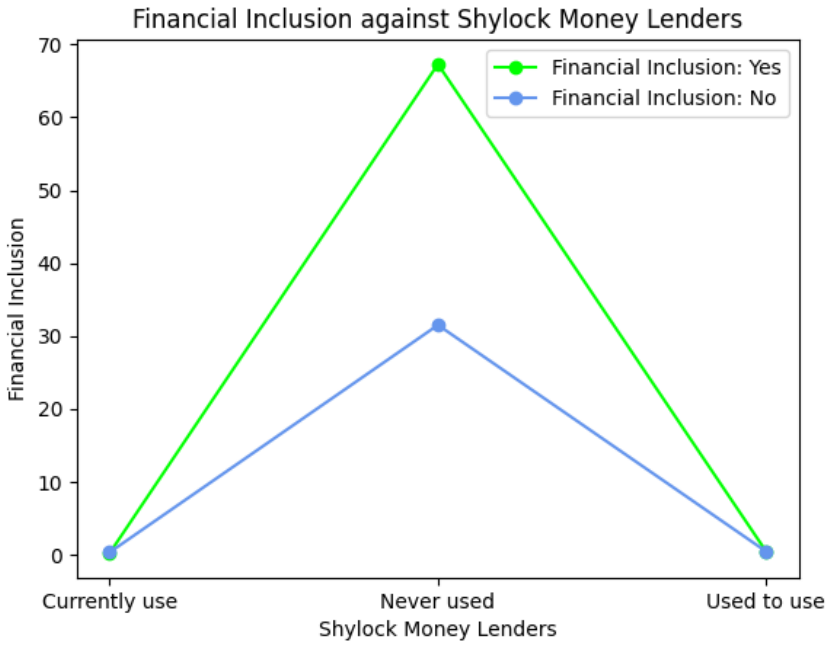


Figure 4-6: Line graph of financial inclusion against shylock moneylenders

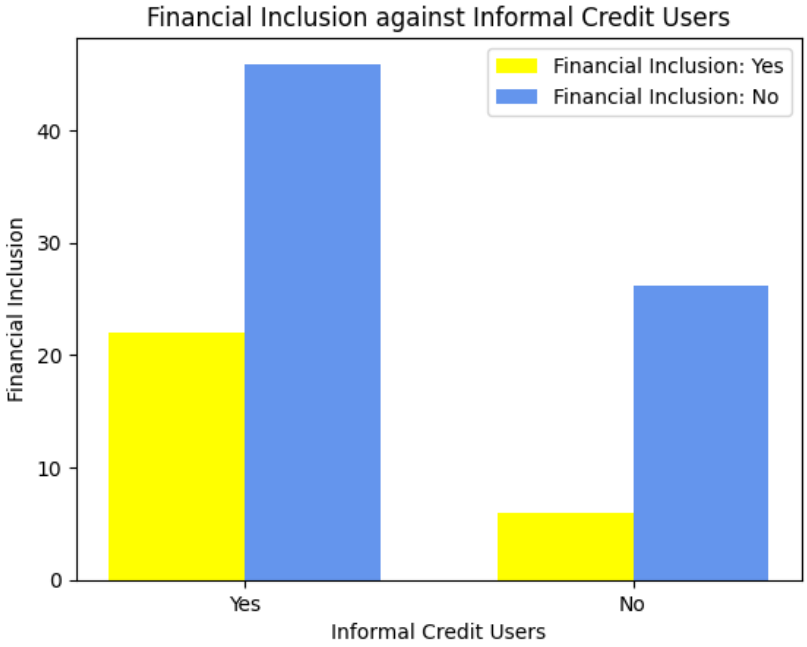


Figure 4-7: Bar graph of financial inclusion against use of informal credit

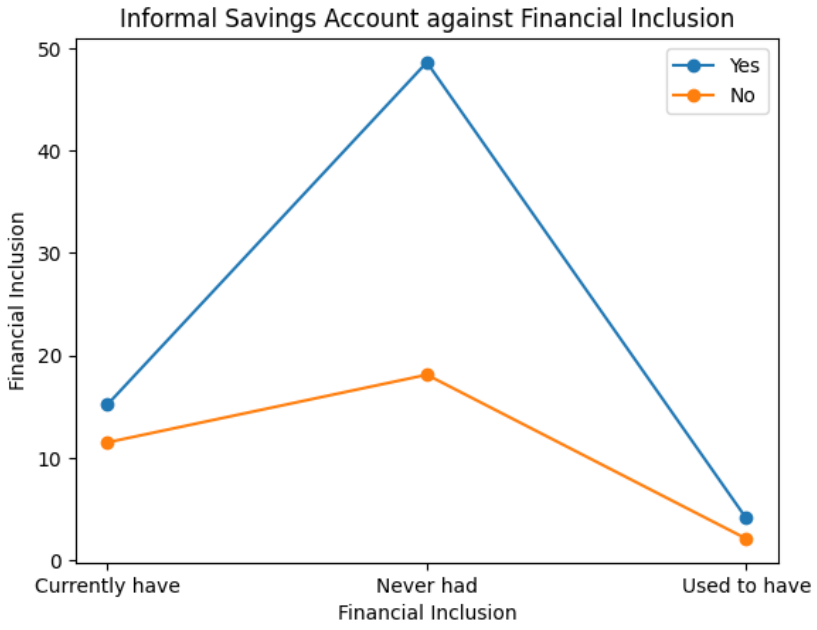


Figure 4-8: Line graph of financial inclusion against informal savings account

4.7 Association between informal financial services and advancement of financial inclusion and access to credit

Participants who currently have and used to have informal savings account had higher odds of accessing financial services compared to those who never had (AOR =1.64, 95% CI=1.511-1.785, P-value=<0.001; AOR =1.18, 95% CI=1.021-1.369, P-value=0.025). Those who currently use informal remittance services were 0.65 less likely to access financial services and credit compared to individuals who do not (AOR =0.65, 95% CI=0.486-0.857, P-value=0.002). Moreover, respondents who currently use shylock money lending services were 2.01 times more likely to have access to financial services and credit compared to those who had never used the services (AOR =2.01, 95% CI=1.223-3.313, P-value=0.006). Those who used informal credit services were 0.70 times less likely to have access to financial services and credit compared to those who do not (AOR =0.70, 95% CI=0.627-0.784, P-value=<0.001). Individuals who used informal digital credit services were 1.68 folds more likely to have access to financial services and credit compared to those who do not (AOR =1.68, 95% CI=1.144-2.458, P-value=<0.001)

Table 7: Association between informal financial services and advancement of financial inclusion and access to credit

		Financial Inclusion		
Variable	**COR(95%CI)**	**P-value**	**AOR(95%CI)**	**P-value**
Informal savings account				
Never had	REF	REF	REF	REF
Currently have	2.08(1.953-2.215)	<0.001	1.64(1.511-1.785)	**<0.001**

Used to have	1.40(1.249-1.579)	<0.001	1.18(1.021-1.369)	**0.025**
Informal remittance services				
Never had	REF	REF	REF	REF
Currently use	2.57(2.413-2.739)	<0.001	0.65(0.486-0.857)	**0.002**
Used to use	1.49(1.335-1.662)	<0.001	0.81(0.623-1.061)	0.128
Informal digital credit users				
No	REF	REF	REF	REF
Yes	0.93(0.875-0.981)	<0.001	1.68(1.144-2.458)	**0.008**
Shylock money lenders				
Never used	REF	REF	REF	REF
Currently use	3.08(2.064-4.589)	<0.001	2.01(1.223-3.313)	**0.006**
Used to use	2.06(1.518-2.802)	<0.001	1.18(0.806-1.737)	0.391
Informal credit users				
No	REF	REF	REF	REF
Yes	0.47(0.434-0.499)	<0.001	0.70(0.627-0.784)	**<0.001**

4.8 Potential barriers to financial inclusion and access to credit

The table below shows the responses on the potential barriers to financial inclusion and access to credit. Majority of respondents who had a monthly income of between 3001 and 7500 Kenyan shillings (18.6%), were financially literate (62.1%) and had no limited access to credit (43%) reported to be financially included and able to access credit. Conversely, those who earned between 7501 and 15000 Kenyan shillings monthly (8.4%), were financially literate (21.4%) and had no limited access to credit (21.5%) reported to be financially excluded and unable to access credit.

Table 8: Potential barriers to financial inclusion and access to credit

	Financial Inclusion			
	Yes		**No**	
Variables	**n**	**%**	**n**	**%**
Monthly income				
0-100	52	0.2	7	0.0
101-1500	2547	11.6	506	2.3
1501-3000	3541	16.1	881	4.0
3001-7500	4093	18.6	1677	7.6
7501-15000	2169	9.8	1845	8.4
15001-30000	639	2.9	1008	4.6
30001-70000	103	0.5	443	2.0
70001-200000	13	0.1	89	0.4
200001-400000	1	0.0	3	0.0
Don't know	1746	7.9	528	2.4

Refused to answer	46	0.2	85	0.4
Financially illiterate				
No	13684	62.1	4719	21.4
Yes	1267	5.8	2354	10.7
Limited access to credit				
No	9467	43.0	4737	21.5
Yes	5484	24.9	2336	10.6

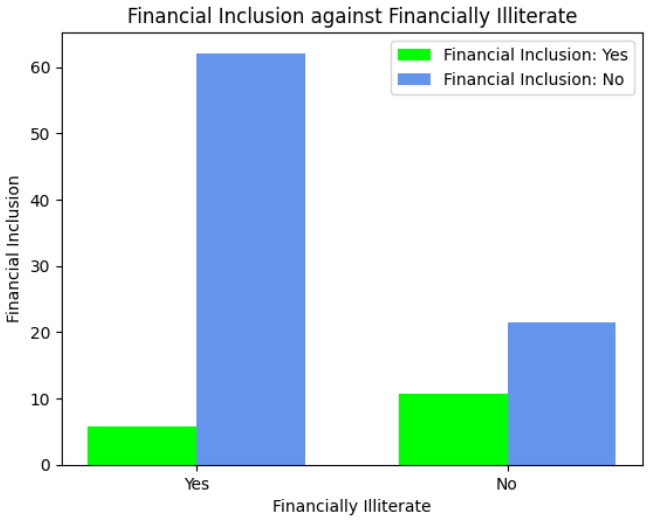


Figure 4-9: Bar graph of financial Inclusion against financial illiteracy

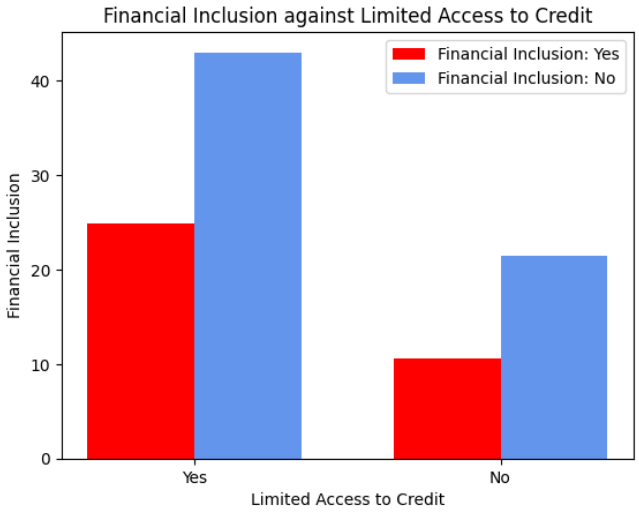


Figure 4-10: Bar graph of financial Inclusion against Limited Access to Credit

4.9 Data Product - Dashboard

4.9.1 The Overview

The data product is an interactive dashboard that carefully breaks down all financial inclusion issues in Kenya for practical use. This potent tool is systematically separated into different pages, which focus on various areas of the research.

Therefore, it is a strong means that links complicated output of logistic regression with meaningful information for banking practitioners, policy makers and academia.

It summarizes important performance measures depicting at a glance the level of accuracy, precision, recall and F1-score of the logistic regression model under study.

4.9.2 Demographic Statistics Page

The Demographic page has various tabs that illuminates demographic information revealing intricacies surrounding Gender, marital status, Residence , wealth quartile, informal savings, monthly income, education, urbanization, and financial incorporation for the population of interest.

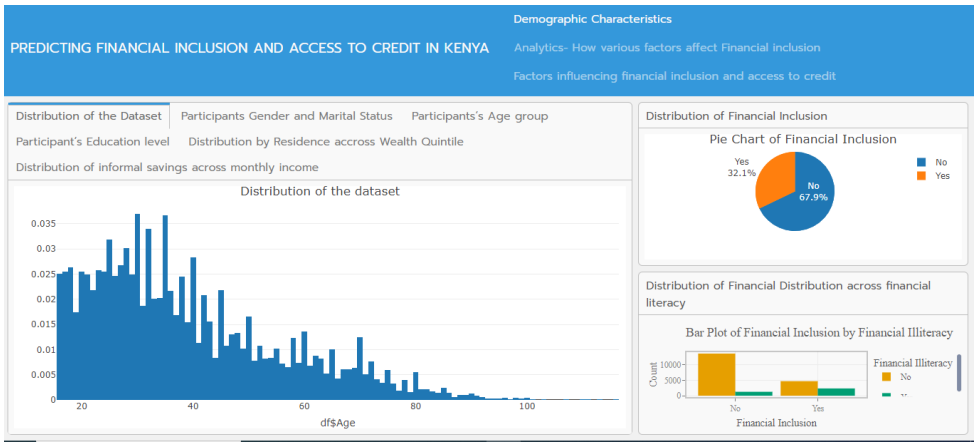


Figure 4-11: Demographic Statistics Page

4.9.3 Analytics Page

This page has five tabs that contains distribution of factors affecting financial inclusion.

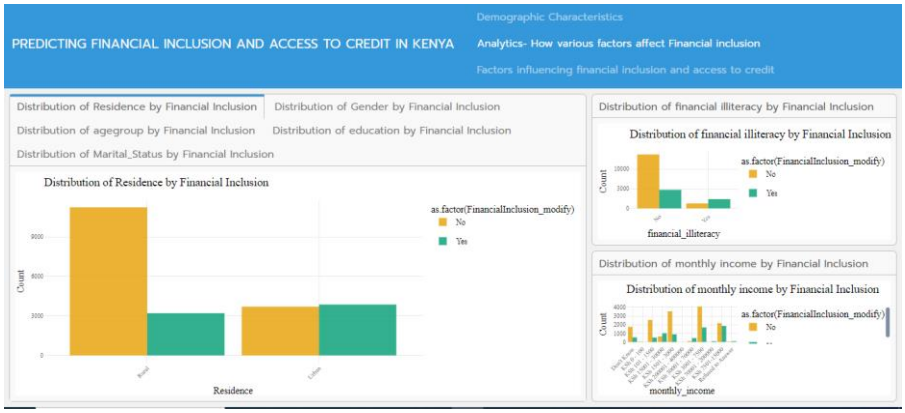


Figure 4-12: Analytics Page

4.9.4 Logistics Regression Page

The logistics regression page communicates the logistic regression model's findings through visual representations, emphasizing the significance of predictor variables and their impact on financial inclusion.

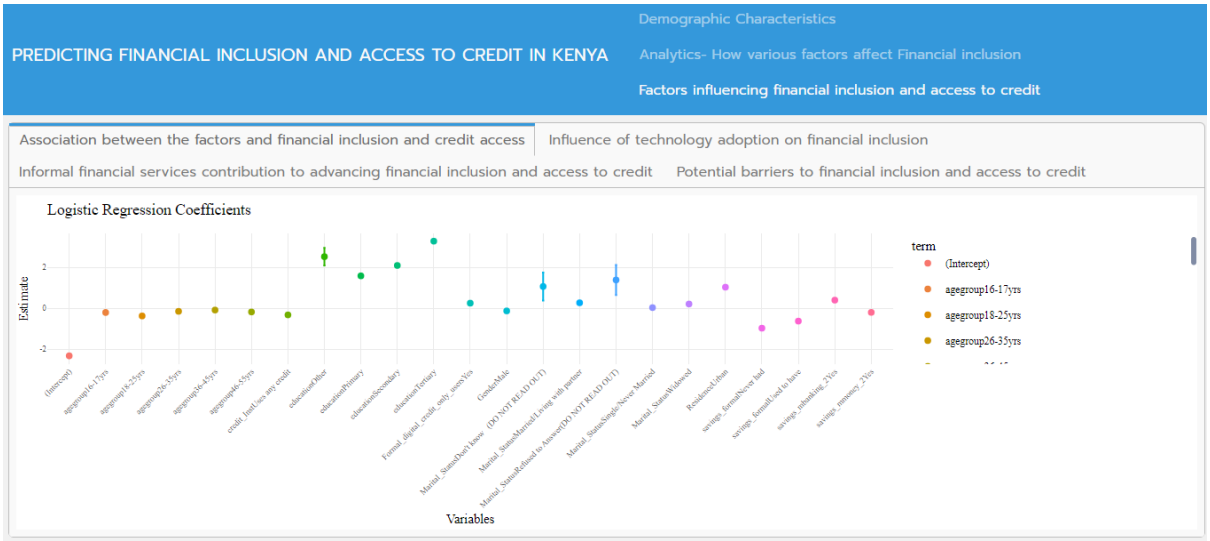


Figure 4-13: Logistics Regression Page

4.9.5 User-Centric Design:

Simplicity and Accessibility:

User-centric design ensures clarity and simplicity, making statistical insights accessible to both experts and non-experts alike.

Web Deployment:

Accessible on a web server, the dashboard accommodates universal access from various devices and locations.

Dissemination and Impact:

Stakeholder Engagement:

The dashboard will be shared with policymakers, financial institutions, and researchers, offering a comprehensive view of financial inclusion dynamics.

Documentation and Support:

Accompanied by thorough documentation, the dashboard provides guidance on interpretation and exploration.

Future Development:

For iterative enhancement; planned continuous updates and refinements will be based on emerging research, policy changes, and user feedback, ensuring the dashboard remains a relevant and valuable resource.

This analysis looks at phase 1 of the work. Preparation of a data lake/ data warehousing can be done where data is automatically fed to a dashboard

Summary of Results

The financial inclusion dashboard reveals that overall access to formal financial services in Kenya is low at just 44% and there are significant disparities across demographic segments - with higher education, urban, younger, and male populations having much higher inclusion. Key barriers are lack of income and financial literacy. While informal financial mechanisms partially fill the gap, over-reliance on them limits inclusion. Digital financial services like mobile money and electronic payments are strongly linked to higher financial inclusion, especially in enabling access to credit and savings. The dashboard analysis provides critical insights on the target groups, barriers, and opportunities to guide policy and product decisions to enhance financial inclusion. The recommendations outline how to build on this static view and develop a full dynamic data architecture and machine-learning pipeline to create an end-to-end solution.

The dashboard can be accessed through https://rpubs.com/Chebet/1146800

CHAPTER FIVE: DISCUSSION

5.1 Factors influencing financial inclusion and access to credit

Consistent with Gakii (2012) and Nanda (2018), the study shows that respondents who had higher levels of education were more likely to have access to financial services and credit. The results indicate that individuals with primary, secondary, and tertiary education were more than four times more likely to have access compared to those with no education.

Similarly, the study findings align with Kimutai (2015), as it shows that participants residing in urban areas were more likely to have access to financial services and credit compared to those in rural areas. The odds of access were more than two times higher for urban residents, consistent with the higher infrastructure, connectivity, and agent quality found in urban settings.

Contrasting with Mhlanga and Denhere (2020), the study found that gender did not significantly influence financial inclusion. The literature review indicated that gender had a negative impact on financial inclusion, whereas the current findings do not support this relationship.

The study also highlights the importance of digital financial services. Consistent with Gakii (2012), the results show that individuals who used formal digital credit services were more likely to have access to financial services and credit. Additionally, the findings align with Nyasani (2021), as respondents who had mobile banking savings accounts were more likely to access financial services and credit compared to those who did not.

In contrast to the literature review, the study found that participants with subscriptions to any credit institution were less likely to have access to financial services and credit. This result contradicts the findings of Gakii (2012), which suggested that utilizing advanced financial instruments, such as mobile banking and payments, would increase financial inclusion.

5.2 Influence of technology adoption on financial inclusion

Fanta and Makina (2019) found that ATM technologies had a notable and favorable effect on financial accessibility and usage. However, the study's results suggest a contrasting finding, indicating that participants who used ATMs were 0.75 times less likely to have access to financial services compared to those who did not use ATMs. This contrasting result suggests that the impact of ATM usage on financial inclusion might be more complex and context-dependent.

On the other hand, the finding that participants who reported having access to the internet were more than ten times more likely to have access to financial services aligns with the literature. Prasad et al. (2013) highlighted the crucial role of Information Technology (IT), including internet access, in reducing costs and improving access to financial services, particularly in remote areas and for marginalized populations. This finding reinforces the significance of internet technology as a facilitator of financial inclusion.

5.3 Informal financial services contribution to advancing financial inclusion and access to credit

The findings indicate that a significant proportion of respondents did not use informal financial services, which contrasts with previous studies that have shown the widespread usage of such services in Uganda (FinScope, 2018). However, the study found that individuals who currently or previously had informal savings accounts had higher odds of accessing financial services compared to those who never had such accounts, which is consistent with the findings of Alhassan et al. (2019). On the other hand, those who currently use informal remittance services were less likely to access financial services and credit, which is inconsistent with the study by FinScope (2018) that found informal financial services to contribute to increased financial inclusion among the rural population.

Additionally, the results showed that individuals who currently use shylock money lending services were more likely to have access to financial services and credit, which is consistent with the study by Agabalinda and Steel (2021) that found the promotion of the use of informal financial services to be more efficient in promoting financial inclusion. Furthermore, individuals who used informal credit services were less likely to have access to financial services and credit, which is consistent with the findings of Alhassan et al. (2019). The study found that individuals who used informal digital credit services were more likely to have access to financial services and credit, which is consistent with the results of Agabalinda and Steel (2021) that found financial training to be significantly related to financial literacy, resulting in increased usage of informal and formal financial services.

5.4 Potential barriers to financial inclusion and access to credit

In the study conducted by Fungacova and Weill (2014) in China, they identified several barriers to financial inclusion, including lack of funds, inadequate documentation, high expenses, and distance to banking institutions. These barriers were particularly significant for the impoverished and older adults. The finding that lack of funds was a barrier to financial

inclusion aligns with the result mentioned in the findings. It states that respondents with a monthly income between 3,001 and 7,500 Kenyan shillings, who were financially literate and had no limited access to credit, reported being financially included and able to access credit. This suggests that having a higher income can positively impact financial inclusion by providing individuals with the necessary funds to access financial services.

On the other hand, the study by Varghese and Viswanathan (2018) in India identified limited access to credit facilities as a supply-side challenge to financial inclusion. They mentioned that banks were often reluctant to provide credit to individuals with small and irregular incomes. This finding aligns with the findings that respondents earning between 7,501 and 15,000 Kenyan shillings monthly, who were financially illiterate, reported being financially excluded and unable to access credit. It suggests that despite having a higher income than the previous group, these individuals may still face challenges in accessing credit due to factors such as limited financial literacy.

5.5 Machine Learning Model

The developed machine learning model achieved an overall prediction accuracy of 90.9%. This means that the model correctly classified individuals as financially included or not in Kenya with an accuracy of nearly 91%. Moreover, the precision score of 86.9% indicates the proportion of true positive predictions out of all positive predictions made by the model. In other words, when the model predicted an individual to be financially included, it was correct around 86.9% of the time. The recall score of 84.4% indicates that the model's ability to correctly identify financially included individuals among the total population is approximately 84%. The F1 score, which combines both precision and recall, was calculated to be 85.6%. This score provides a balanced measure of the model's performance, considering both its ability to correctly classify positive instances and its overall accuracy.

CHAPTER SIX: CONCLUSION AND RECOMMENDATION

6.1 Conclusion

In conclusion, the findings highlight several factors that influence financial inclusion and access to credit. Higher levels of education were found to be positively associated with access to financial services and credit, emphasizing the importance of education in improving financial inclusion. Urban residence is also a significant factor, with urban areas offering better infrastructure and connectivity that facilitate access to financial services. Gender, contrary to some previous studies, was not found to have a significant influence on financial inclusion in this study. Digital financial services, such as formal digital credit services and mobile banking savings accounts, were found to be associated with increased access to financial services and credit. However, the study also revealed a contradictory finding that participants with subscriptions to any credit institution were less likely to have access to financial services and credit, challenging the notion that advanced financial instruments automatically enhance financial inclusion. The impact of ATM usage on financial inclusion appears to be more complex and context-dependent. While some studies have shown positive effects, this study suggests that ATM usage may be associated with reduced access to financial services. Conversely, access to the internet is found to be a significant facilitator of financial inclusion, aligning with previous research highlighting the role of information technology in improving access to financial services. The contribution of informal financial services to financial inclusion and access to credit varied. While the usage of informal savings accounts was associated with higher odds of accessing financial services, current users of informal remittance services were less likely to have access. The promotion of informal financial services, particularly shylock money lending services, was found to be efficient in promoting financial inclusion. However, the usage of informal credit services was associated with reduced access to financial services and credit. The study also identified potential barriers to financial inclusion and access to credit. Lack of funds and limited access to credit facilities were significant challenges. Higher income levels were found to positively impact financial inclusion, while limited financial literacy posed obstacles to accessing credit. These findings underscore the importance of addressing supply-side challenges and improving financial literacy programs to enhance financial inclusion.

For the dashboard, it provides insightful visualizations and analysis into the key factors driving financial access in Kenya, based on survey data.

The interactive charts allow users to explore financial inclusion across different demographics like gender, age, education level, and residence. The regression models quantify the direction and magnitude of influence of various factors.

Key takeaways are:

i. Formal financial account ownership is still low, highlighting the need for greater financial inclusion
ii. Digital financial services and technology adoption are strong enablers for improving access
iii. Younger, educated, urban populations have higher financial inclusion
iv. Women and rural groups need tailored products to address their lower access
v. Barriers like low income, lack of credit, and financial illiteracy need to be addressed

Below are responses to the Research Objectives:

Research Objective 1) To identify the key factors that influence financial inclusion and access to credit in Kenya.

This research objective has been successfully achieved. The study analyzed several factors including demographics, technology adoption, financial services usage and barriers to assess their impact on financial inclusion in Kenya. Key factors that were found to have a significant influence include - education level, location type, use of digital financial services and access to credit. The results align with multiple past studies such as Nanda (2018) and Gakii (2012) that also identified socioeconomic indicators as drivers of financial inclusion. Thus, the objective of recognizing major determinants of financial access has been adequately accomplished based on the analytical outcomes.

Research Objective 2) To examine the relationship between technology adoption and financial inclusion in Kenya

The objective to examine the technology-financial inclusion relationship has been partially fulfilled and allows scope for further investigation. Measures for technology adoption mainly comprised mobile phone ownership, internet access and digital payments systems. Significant positive association was discovered between internet access and higher likelihood of financial

inclusion. However, usage of ATMs was linked to lower access contrary to some prior research. While indicative of the role of technology, studying more intricate metrics like frequency and purpose of technology use could provide greater insight. Follow up work should explore the contextual and demographic nuances around technology usage.

Research Objective 3) To examine how informal financial services contribute to advancing financial inclusion and access to credit in Kenya

The impact assessment of informal financial services achieved substantial coverage through metrics like savings groups, lending services and remittances but remains slightly incomplete. Current usage of some informal mechanisms like lending services showed increased financial inclusion probability. However, directions were mixed across different services warranting additional focus into service-specific effects. Comparisons with other developing country contexts could also highlight the unique financial culture influencing preference for formal or informal access channels in Kenya. Thus, while informative patterns have emerged, more targeted probing is required into distinct traditional financial instruments.

Research Objective 4) To identify potential barriers to financial inclusion in Kenya

The identification of barriers restricting financial access has been fulfilled based on the study's findings. Major obstacles recognized include lack of income, high costs of financial services, remote locations with accessibility challenges, and inadequate financial awareness. The results align with barriers uncovered in similar developing country contexts by studies like Varghese & Viswanathan (2018) and Fungacova & Weill (2014). Significant gaps in financial inclusion exist across income levels, geographies, literacy status and access to credit channels. Addressing these pain points through policy reforms, infrastructure improvement and tailored financial products is pivotal to enhance usage and affordability of formal financial services among the unbanked population. Thus, the fourth objective to highlight impediments to universal financial inclusion provides critical recommendations for targeting reforms.

6.2 Recommendation

Given the positive association between education and financial inclusion, efforts should be made to strengthen financial literacy programs. Providing accessible and comprehensive financial education initiatives will empower individuals with the knowledge and skills necessary to make informed financial decisions, access financial services, and effectively

manage credit. Urban areas have shown better infrastructure and connectivity, enabling easier access to financial services. To bridge the urban-rural divide, it is crucial to invest in developing infrastructure in rural areas. This includes establishing physical branches or agents, expanding digital connectivity, and ensuring adequate banking infrastructure to extend financial services to underserved regions. The study highlights the positive impact of digital financial services on financial inclusion. Policymakers and financial organizations should continue to promote the adoption of formal digital credit services and mobile banking savings accounts. This can be done by creating an enabling regulatory environment, encouraging partnerships between financial institutions and technology providers, and raising awareness about the benefits and accessibility of digital financial services. The study identifies several barriers to financial inclusion, such as lack of funds, limited access to credit facilities, and low financial literacy. To overcome these challenges, policymakers should focus on addressing the supply-side issues, including improving access to affordable credit and expanding the availability of credit facilities. Additionally, investing in targeted financial literacy programs, particularly in underserved areas, can help individuals overcome the obstacles posed by limited financial knowledge.

6.3 Future Work

Future studies on financial inclusion and access to credit should consider further exploration to understand the specific aspects of education that contribute to improved access to financial services, emphasizing the importance of educational interventions and financial literacy programs. Additionally, it will be valuable to investigate the context-specific factors that influence the impact of digital financial services and ATM usage on financial inclusion, as conflicting findings were observed. More research is needed to understand the role of informal financial services in promoting or hindering financial inclusion, particularly regarding different types of services such as savings accounts and credit services. Likewise, future studies should focus on addressing the barriers to financial inclusion, such as limited access to credit facilities and low financial literacy levels, and develop strategies to overcome these challenges.

The current financial inclusion dashboard developed is a static visualization based on a one-time sample dataset. To enhance its value and capabilities, a full end-to-end data architecture could be implemented, comprising of continuous data collection from relevant sources, a cloud data lake and warehouse, automated data transformation pipelines, machine-learning

models that run periodically to predict financial inclusion, a dynamic visualization layer with user input capabilities, and an API layer to serve real-time data/models. This would convert the dashboard from a basic static report to an intelligent data-driven application that provides the latest insights and trends on financial inclusion in Kenya. Developing this full solution would require cross-domain expertise spanning data engineering, cloud infrastructure, machine learning, and full-stack development. It offers significant scope for an organization to take this initial visualization and turn it into an impactful data product.

References

Adami, R. (2022). Financial Exclusion in the UK: Evidence on Ethnicity. *Social Policy and Society*, 1–19. https://doi.org/10.1017/s1474746422000252

Agabalinda, C., & Steel, W. F. (2021). Training vs. informal financial services for the promotion of financial literacy and inclusion in Uganda. *Enterprise Development and Microfinance*, *32*(1), 107–122. https://doi.org/10.3362/1755-1986.20-00011

Ahmed, M. S., & Jianguo, W. (2014). Financial Inclusion and Challenges in Tanzania. *Research Journal of Finance and Accounting*, *5*(21), 1–6.

Alabi, A. W., & Olaoye, F. O. (2022). The Effect of Technology Adoption on Financial Inclusion: A Cross-country Panel Analysis between China and Nigeria. *European Journal of Business and Management Research*, *7*(2). https://doi.org/10.24018/ejbmr.2022.7.2.1314

Alhassan, A., Li, L., Reddy, K., & Duppati, G. (2019). The impact of formal financial inclusion on informal financial intermediation and cash preference: evidence from Africa. *Applied Economics*, *51*(42), 4597–4614. https://doi.org/10.1080/00036846.2019.1593316

Allen, F., Demirguc-Kunt, A., Klapper, L., & Soledad, M. (2012). The Foundations of Financial Inclusion: *Understanding Ownership and Use of Formal Accounts*. World Bank Policy Research Working Paper No. 6593

Beck, T., Senbet, L., & Simbanegavi, W. (2014). Financial Inclusion and Innovation in Africa: An Overview. *Journal of African Economies*, *24*(suppl 1), 3–11. https://doi.org/10.1093/jae/eju031

Bhanot, D., Bapat, V., & Bera, S. (2012). Studying financial inclusion in north-east India. *International Journal of Bank Marketing*, *30*(6), 465–484. https://doi.org/10.1108/02652321211262221

CARE International (2014). CARE International in Uganda VSLA MIS (Management Information System) Data, 2014. https://www.care.org.au/wp-content/uploads/2014/12/Financial-Inclusion-in-Uganda-Nov-2014.pdf

Cicchiello, A. F., Kazemikhasragh, A., Monferrá, S., & Girón, A. (2021). Financial inclusion and development in the least developed countries in Asia and Africa. *Journal of Innovation and Entrepreneurship*, *10*(1). https://doi.org/10.1186/s13731-021-00190-4

Department of Financial Services. (2022). *Home | Department of Financial Services | Ministry of Finance | Government of India*. Financialservices.gov.in. https://financialservices.gov.in/

Demirgüç-Kunt, A. & Klapper, L. (2012) "*Measuring Financial Inclusion*: The Global Findex Database" Policy Research Working Paper, No. 6025.

Demirguc-Kunt, Asli, Leora Klapper, Dorothe Singer, Saniya Ansar, & Jake Hess. (2018). *The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution*. Washington, DC: The World Bank.

Elliot, S. (2022). *Financial Inclusion in the UK – LexisNexis Risk Solutions*. LexisNexis Risk Solutions | Transform Your Risk Decision Making. https://risk.lexisnexis.co.uk/insights-resources/article/financial-exclusion-in-the-uk#:~:text=One%20in%20seven%20financially%20excluded

Fanta, A. B., & Makina, D. (2019). *The Relationship Between Technology and Financial Inclusion: Cross-Sectional Evidence*. 211–230.

Financial Inclusion Commission. (2022, October). *Financial Inclusion Commission – Making financial inclusion a top political priority in the UK*. Https://Financialinclusioncommission.org.uk/. https://financialinclusioncommission.org.uk/

FinScope (2018). Report on banking and the status of financial inclusion in Uganda: Insights from FinScope 2018 Survey. https://fsduganda.or.ug/wp-content/uploads/2019/05/FSDU-Thematic-Report-on-Banking.pdf

Fungacova, Z., & Weill, L. (2014). Understanding Financial Inclusion in China. *SSRN Electronic Journal*, *34*(10). https://doi.org/10.2139/ssrn.2428151

Garg, S., & Agarwal, Dr. P. (2014). Financial Inclusion in India – a Review of Initiatives and Achievements. *IOSR Journal of Business and Management*, *16*(6), 52–61. https://doi.org/10.9790/487x-16615261

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. *Journal of Management Information Systems*, *35*(1), 220–265. https://doi.org/10.1080/07421222.2018.1440766

Hall, S. (2022, July 28). *4 things to know about financial inclusion around the world right now*. World Economic Forum. https://www.weforum.org/agenda/2022/07/global-digital-financial-inclusion-findex

Hossin, M., & Sulaiman, M. N. (2015). A Review on Evaluation Metrics for Data Classification Evaluations. *International Journal of Data Mining & Knowledge Management Process*, *5*(2), 01-11. https://doi.org/10.5121/ijdkp.2015.5201

International Monetary Fund. (2021). *The India Stack is Revolutionizing Access to Finance - IMF F&D*. Www.imf.org. https://www.imf.org/external/pubs/ft/fandd/2021/07/india-stack-financial-access-and-digital-inclusion.htm

James, D. (2014). "Deeper into a Hole?" Borrowing and Lending in South Africa. *Current Anthropology* 55: 17.

Johnson, S. (2016). Competing visions of financial inclusion in Kenya: the rift revealed by mobile money transfer. *Canadian Journal of Development Studies*, *37*(1), 83–100. https://doi.org/10.1080/02255189.2016.1140022

Kimhur, B. (2020). How to Apply the Capability Approach to Housing Policy? Concepts, Theories and Challenges. *Housing, Theory and Society*, *37*(3), 1–21. https://doi.org/10.1080/14036096.2019.1706630

Kimutai, J. B (2015). Factors influencing financial inclusion in rural Kenya: A case study of Kenya Commercial Bank Agent Outlets in Marakwet West Sub County. (Unpublished Master's Thesis). University of Nairobi, Kenya.

Li, J. (2017). Assessing the accuracy of predictive models for numerical data: Not r nor r2, why not? Then what? *PLOS ONE*, *12*(8), e0183250. https://doi.org/10.1371/journal.pone.0183250

Mader, P. (2018). Contesting financial inclusion. *Development and Change*, 49(2), 461–483.
World Bank Group. (2021, June 30). Drive for financial inclusion: The Global Findex database. Retrieved from https://ieg.worldbankgroup.org/sites/default/files/Data/reports/ap_driveforfinancialinclusion.pdf

Makunda, Lukania. G., & Heyer, A. (2022, November 3). *The Financial Inclusion Statistics Conference*. Financial Sector Deepening Kenya. https://www.fsdkenya.org/finaccess/finaccess-household-surveys/the-financial-

inclusion-statistics-conference/#:~:text=The%20report%20revealed%20remarkable%20growth

Manikandan, S. (2010). Preparing to analyse data. *Journal of Pharmacology and Pharmacotherapeutics*, *1*(1), 64. https://doi.org/10.4103/0976-500x.64540

Mhlanga, D., & Denhere, V. (2020). Determinants of Financial Inclusion in Southern Africa. *Studia Universitatis Babes-Bolyai Oeconomica*, *65*(3), 39–52. https://doi.org/10.2478/subboec-2020-0014

Mutegi, K., & Phelister, N. (2015). Financial literacy and its impact on loan repayment by small and medium entrepreneurs. *International journal of economics, commerce, and management the United Kingdom* Vol. 6 (12), 58 – 76.

Mwania, M. P (2018). Antecedents Of Technology Adoption and Financial Inclusion Among Micro Enterprises in Machakos County, Kenya. (Unpublished Master's Thesis). Kenya Methodist University, Kenya.

Nanda, K. (2018). Factors that Matter for Financial Inclusion: Assessment of Empirical Evidences, with Special Reference to India. *Abhigyan*, *36*(1), 52+.

National Treasury. (2020). *An Inclusive Financial Sector for All*. Available online: *www.treasury.gov.za* (accessed on 15 February 2022).

NFIF (2018) 'National financial inclusion framework, 2018 - 2022', pp. 2018–2022.

Nyasani, K. N. (2021). Factors affecting financial inclusion among Small and Medium Enterprises owners in Nairobi County, Kenya. (Unpublished Master's Thesis). Egerton University, Kenya.

Olajide, O. (2014), Understanding the Complexity of Factors which Influence Livelihoods of the Urban Poor in Lagos' Informal Settlements. (Unpublished Doctoral Dissertation), Newcastle University

Óskarsdóttir, M., Bravo, C., Sarraute, C., Vanthienen, J., & Baesens, B. (2019). The value of big data for credit scoring: Enhancing financial inclusion using mobile phone data and social network analytics. *Applied Soft Computing*, *74*, 26–39. https://doi.org/10.1016/j.asoc.2018.10.004

Ozili, P. K. (2020). Financial Inclusion in Nigeria: Determinants, Challenges and Achievements. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3557244

Pomeroy, R. (2022, September 9). *How "financial inclusion" can lift millions out of poverty: World Bank Economist*. World Economic Forum. https://www.weforum.org/agenda/2022/09/financial-inclusion-findex-radio-davos-world-bank-economist

Prasad, A., Deep, K., Dubey, O. P., & Singh, S. N. (2013). Role of Information Technology in Financial Inclusion. *SocPros 2013*. SocPros 2013, IIT Roorkee.

Reserve Bank of India. (2022, August 2). *Reserve Bank of India - Press Releases*. Www.rbi.org.in. https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=54133

Robeyns, I., & Byskov, M. F. (2021). *The Capability Approach* (E. N. Zalta, Ed.). Stanford Encyclopedia of Philosophy; Metaphysics Research Lab, Stanford University. https://plato.stanford.edu/entries/capability-approach/#Bib

Sarma M. (2010) Index of Financial Inclusion. *CITD Discussion Paper* 10-05.

Sarma, M. and Pais, J. (2011) Financial Inclusion and Development. *Journal of International Development*, 23: 613-628

Steyerberg, E. W., Vickers, A. J., Cook, N. R., Gerds, T., Gonen, M., Obuchowski, N., Pencina, M. J., & Kattan, M. W. (2010). Assessing the Performance of Prediction Models. *Epidemiology*, *21*(1), 128–138. https://doi.org/10.1097/ede.0b013e3181c30fb2

Thankom, A., & Rajalaxmi, K. (2015). Financial inclusion: Policies and practices the University of Central Lancashire, UK Indian Institute of Management, Bangalore, India.

The World Bank. (2011). *Overview*. World Bank. https://www.worldbank.org/en/topic/financialinclusion/overview

The World Bank. (2023, January 27). *The Global Findex Database 2021*. World Bank. https://www.worldbank.org/en/publication/globalfindex#data_sec_focus

UK Parliament. (2017). *House of Lords - Tackling financial exclusion: A country that works for everyone? - Select Committee on Financial Exclusion*. Publications.parliament.uk. https://publications.parliament.uk/pa/ld201617/ldselect/ldfinexcl/132/13206.htm

Varghese, G., & Viswanathan, L. (2018). Financial Inclusion: Opportunities, Issues and Challenges. *Theoretical Economics Letters*, *08*(11), 1935–1942. https://doi.org/10.4236/tel.2018.811126

Ventures Africa. (2016, August 19). *Here are 5 of Africa's most financially inclusive countries*. Ventures Africa. https://venturesafrica.com/here-are-5-of-africas-most-financially-inclusive-countries/

Zeqiraj, V., Sohag, K., & Hammoudeh, S. (2022). Financial inclusion in developing countries: Do quality institutions matter? *Journal of International Financial Markets, Institutions and Money*, *81*, 101677. https://doi.org/10.1016/j.intfin.2022.101677

Zhang, Z. (2016). Model building strategy for logistic regression: purposeful selection. *Annals of Translational Medicine*, *4*(6), 111–111. https://doi.org/10.21037/atm.2016.02.15

Schmitt, M. (2022). Deep Learning vs. Gradient Boosting: Benchmarking state of-the-art machine learning algorithms for credit scoring. University of Oxford, UK.

Appendix

Dashboard

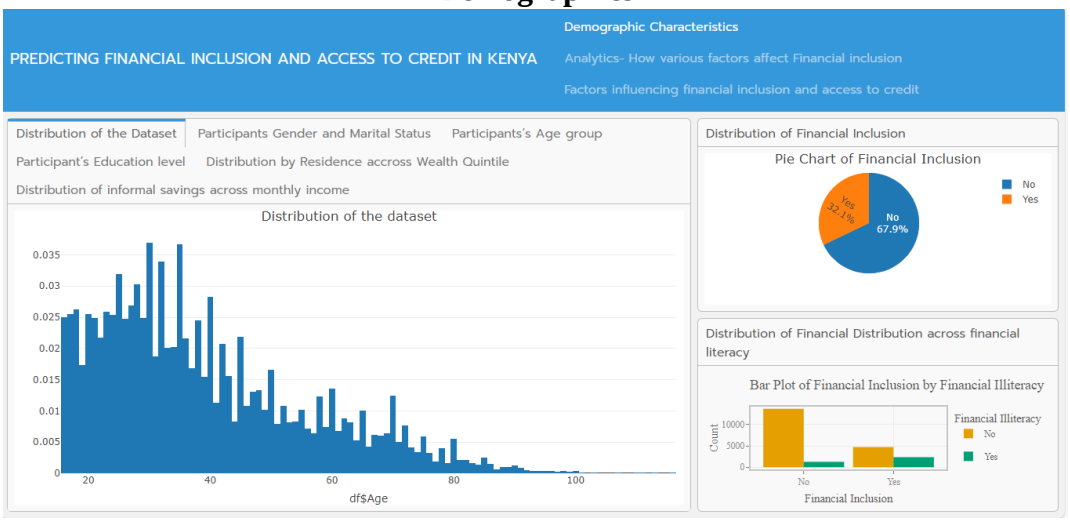
Appendix A: Dataset used

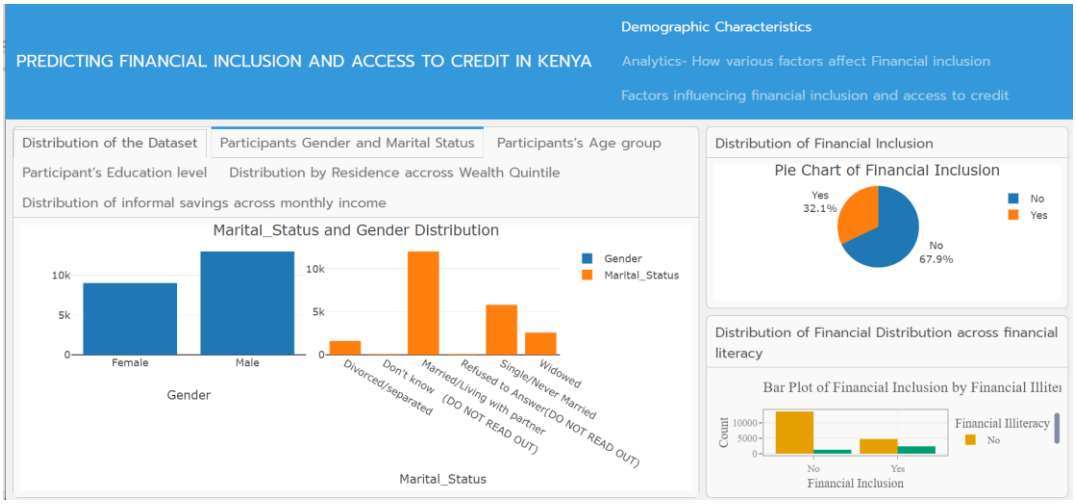
Variable	Description	Coding in Model
Serial Number	Unique respondent id	Not used in modeling
Gender	Male or Female	Converted to numeric category
Age	Respondent's age in years	Binned into age groups
agegroup	Predefined age groups	Converted ro numeric category
education	Highest education level	Converted to numeric category
Marital_Status	Marital status	Converted to numeric category
wealth_quintile	Wealth quintile based on assets	Converted ro numeric category
Residence	Rural or Urban	Converted to numeric category
Internet Access	Yes/No internet access	Converted to numeric category
ATM	Use ATM services - Yes/No	Converted to numeric category
Electronic payment	Use electronic payments - Yes/No	Converted to numeric category
savings_informal	Informal savings - Yes/No	Converted to numeric category
savings_formal	Formal savings account - Yes/No	Converted to numeric category
mobile_money_access	Use mobile money - Yes/No	Converted to numeric category
financial_illiteracy	Level of financial literacy	Converted to numeric category
monthly_income	Monthly income range	Hashed to numeric
Shylock money lenders	Use shylock lenders - Yes/No	Converted to numeric category
Informal_remittance_services	Use informal remittance services - Yes/No	Converted to numeric category
Informal_only_credit_users	Only use informal credit - Yes/No	Converted to numeric category
Formal_digital_credit_only_users	Only use formal digital credit - Yes/No	Converted to numeric category
NotFormal_digital_credit_only_users	Do not use formal/informal credit	Derived variable
credit_Inst	Use credit from formal institution - Yes/No	Derived variable
Limited Access to credit	Reported barrier to credit access	Converted ro numeric category
mobilephone_access	Has mobile phone - Yes/No	Converted to numeric category
savings_mbanking_2	Use mobile banking - Yes/No	Converted to numeric category
savings_mmoney_2	Use mobile money savings - Yes/No	Converted to numeric category
FinancialInclusion_modify	Financially included based on formal account ownership - Yes/No	Target variable (0(N0),1(Yes))

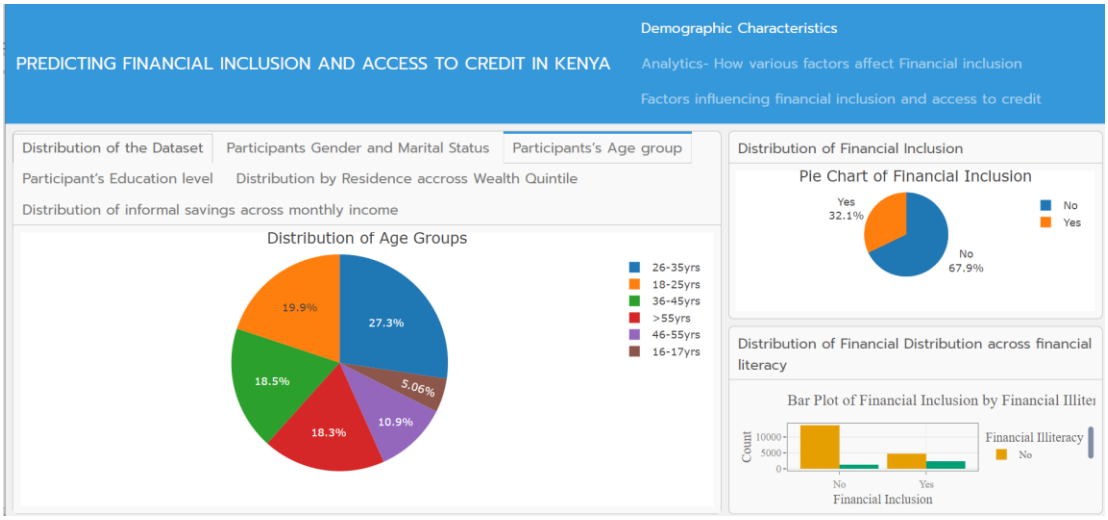
The dataset had 9000+ rows representing survey respondents. Categorical variables were encoded into numeric categories. String variables like income were hashed to numeric values.

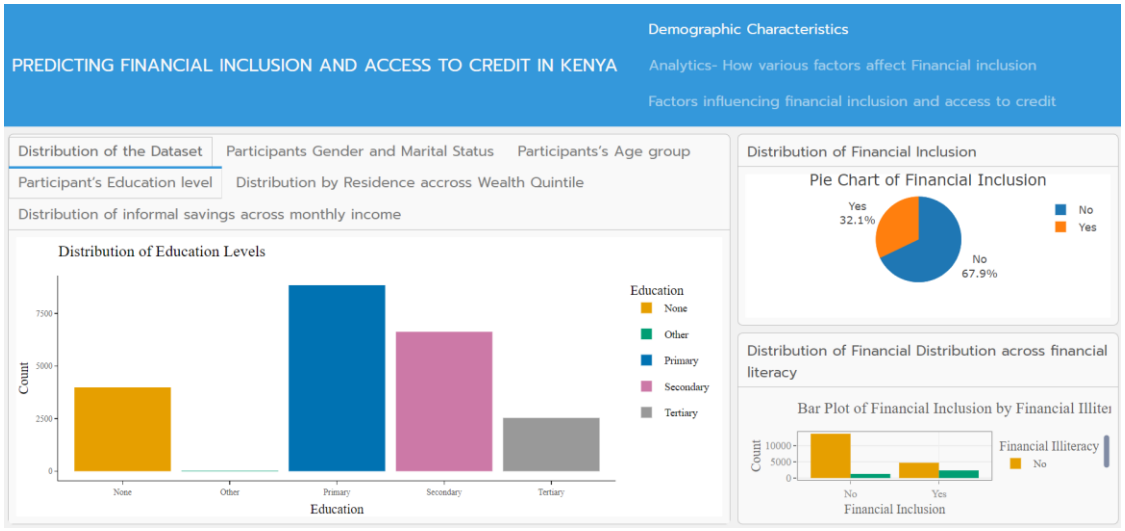
Appendix B: Dashboard Screenshots

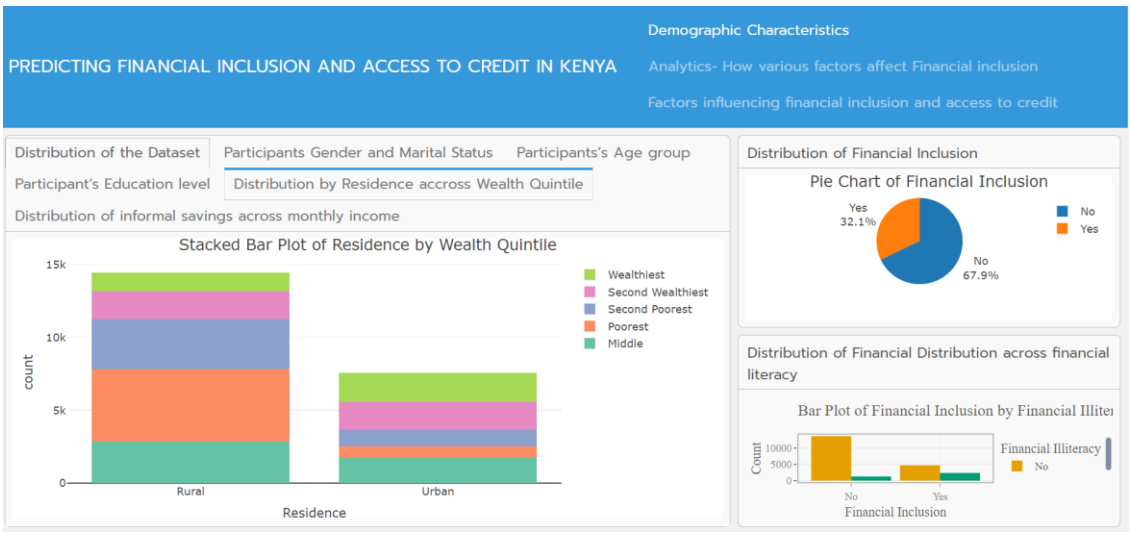
Demographics

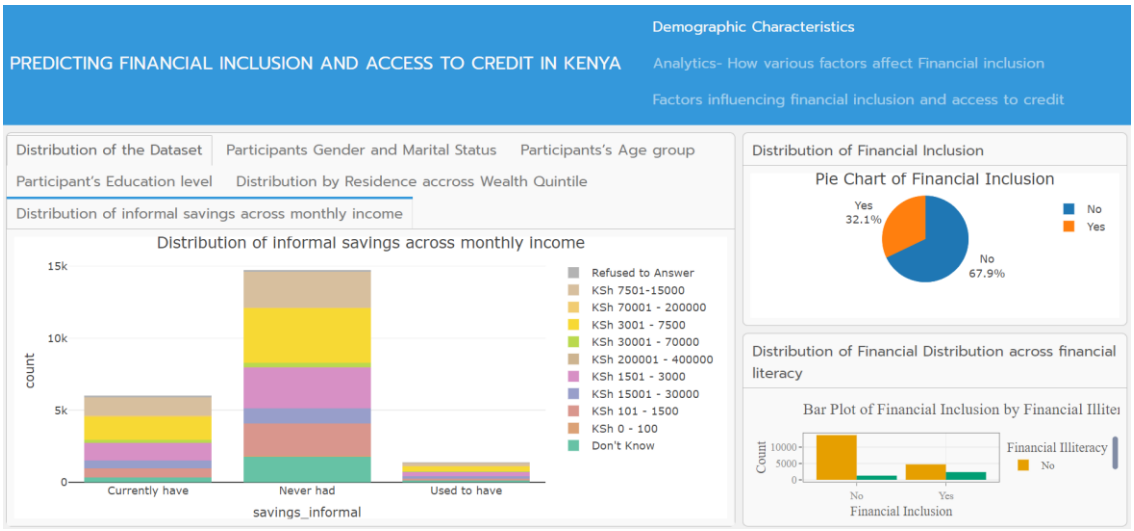




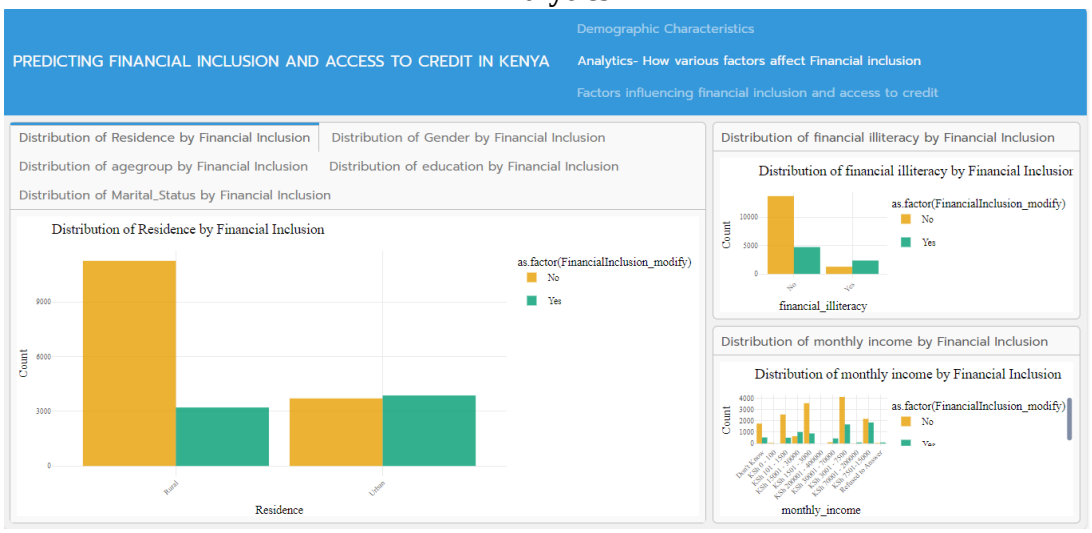


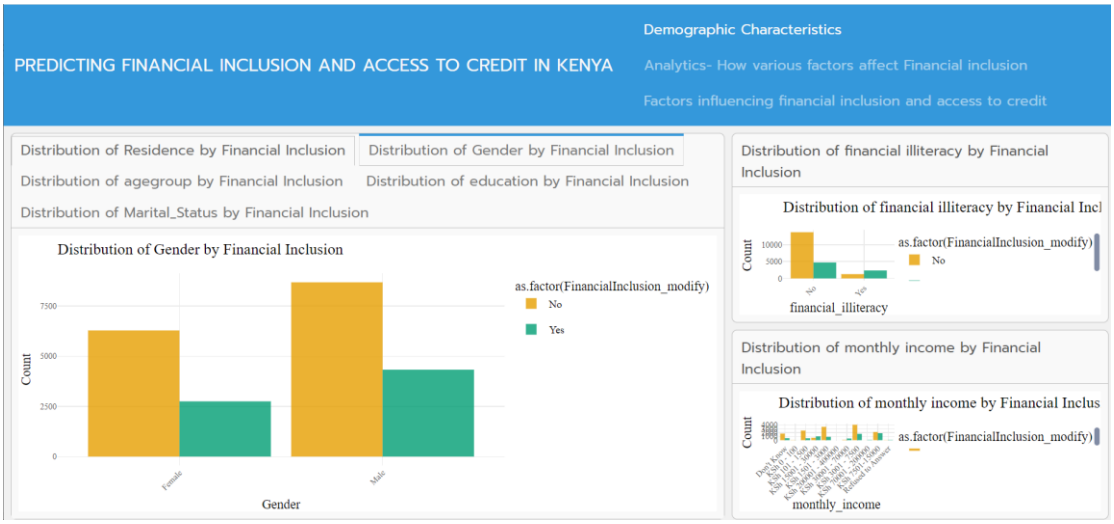

PREDICTING FINANCIAL INCLUSION AND ACCESS TO CREDIT IN KENYA
Demographic Characteristics
Analytics- How various factors affect Financial inclusion
Factors influencing financial inclusion and access to credit
Distribution of the Dataset
Participants Gender and Marital Status
Participants's Age group
Participant's Education level
Distribution by Residence accross Wealth Quintile
Distribution of informal savings across monthly income
Distribution of Education Levels
Education
None
Other
Primary
Secondary
Tertiary
Count
Education
Distribution of Financial Inclusion
Pie Chart of Financial Inclusion
Yes 32.1%
No 67.9%
No
Yes
Distribution of Financial Distribution across financial literacy
Bar Plot of Financial Inclusion by Financial Illite
Financial Illiteracy
No
Financial Inclusion

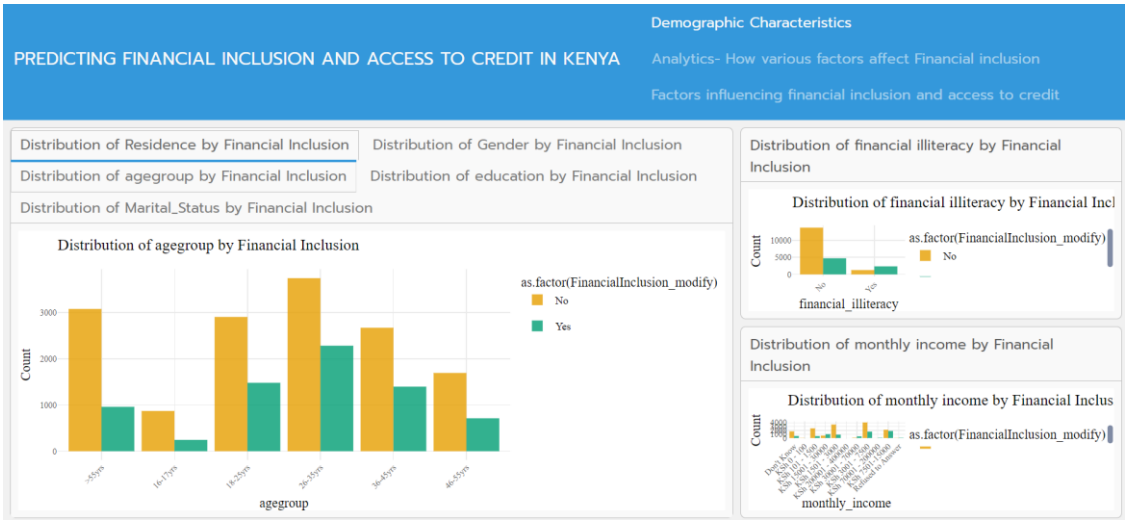

PREDICTING FINANCIAL INCLUSION AND ACCESS TO CREDIT IN KENYA
Demographic Characteristics
Analytics- How various factors affect Financial inclusion
Factors influencing financial inclusion and access to credit
Distribution of the Dataset
Participants Gender and Marital Status
Participants's Age group
Participant's Education level
Distribution by Residence accross Wealth Quintile
Distribution of informal savings across monthly income
Stacked Bar Plot of Residence by Wealth Quintile
Wealthiest
Second Wealthiest
Second Poorest
Poorest
Middle
count
Rural
Urban
Residence
Distribution of Financial Inclusion
Pie Chart of Financial Inclusion
Yes 32.1%
No 67.9%
No
Yes
Distribution of Financial Distribution across financial literacy
Bar Plot of Financial Inclusion by Financial Illite
Financial Illiteracy
No
Financial Inclusion

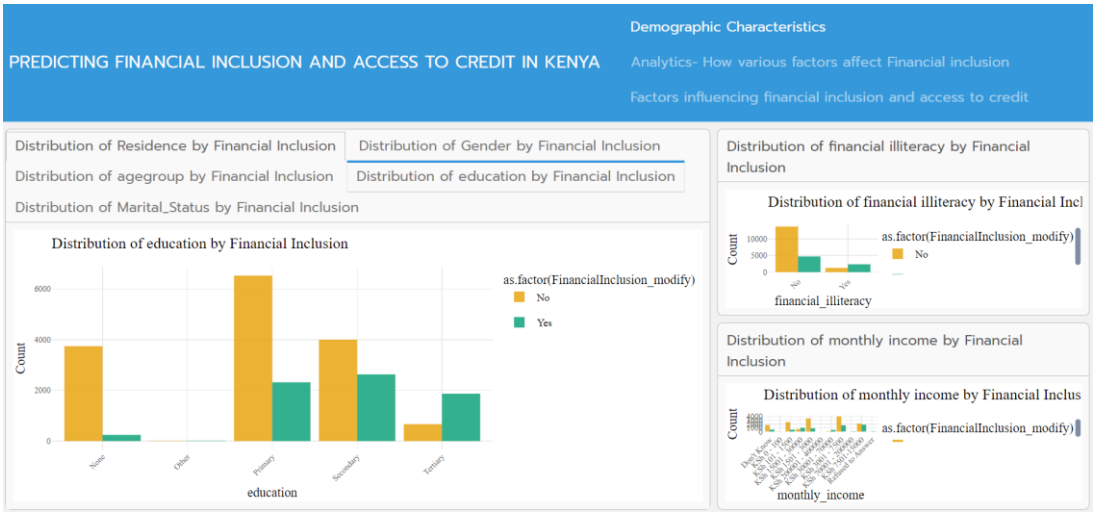

PREDICTING FINANCIAL INCLUSION AND ACCESS TO CREDIT IN KENYA
Demographic Characteristics
Analytics- How various factors affect Financial inclusion
Factors influencing financial inclusion and access to credit
Distribution of the Dataset
Participants Gender and Marital Status
Participants's Age group
Participant's Education level
Distribution by Residence accross Wealth Quintile
Distribution of informal savings across monthly income
Distribution of informal savings across monthly income
Refused to Answer
KSh 7501-15000
KSh 70001 - 200000
KSh 3001 - 7500
KSh 30001 - 70000
KSh 200001 - 400000
KSh 1501 - 3000
KSh 15001 - 30000
KSh 101 - 1500
KSh 0 - 100
Don't Know
count
Currently have
Never had
Used to have
savings_informal
Distribution of Financial Inclusion
Pie Chart of Financial Inclusion
Yes 32.1%
No 67.9%
No
Yes
Distribution of Financial Distribution across financial literacy
Bar Plot of Financial Inclusion by Financial Illite
Financial Illiteracy
No
Financial Inclusion

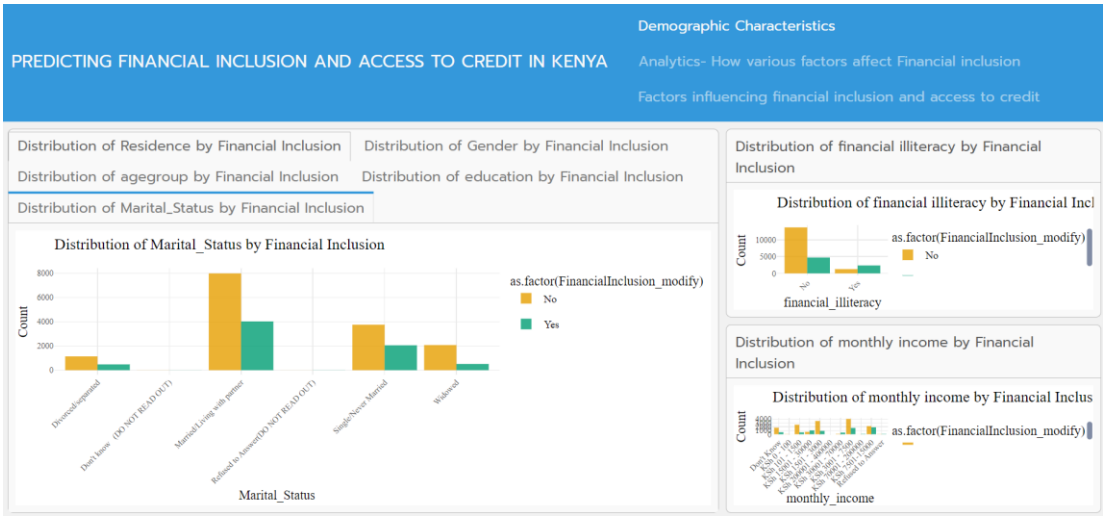
Analytics


PREDICTING FINANCIAL INCLUSION AND ACCESS TO CREDIT IN KENYA
Demographic Characteristics
Analytics- How various factors affect Financial inclusion
Factors influencing financial inclusion and access to credit
Distribution of Residence by Financial Inclusion
Distribution of Gender by Financial Inclusion
Distribution of agegroup by Financial Inclusion
Distribution of education by Financial Inclusion
Distribution of Marital_Status by Financial Inclusion
Distribution of Residence by Financial Inclusion
as.factor(FinancialInclusion_modify)
No
Yes
Count
Residence
Rural
Urban
Distribution of financial illiteracy by Financial Inclusion
financial_illiteracy
Distribution of monthly income by Financial Inclusion
monthly_income

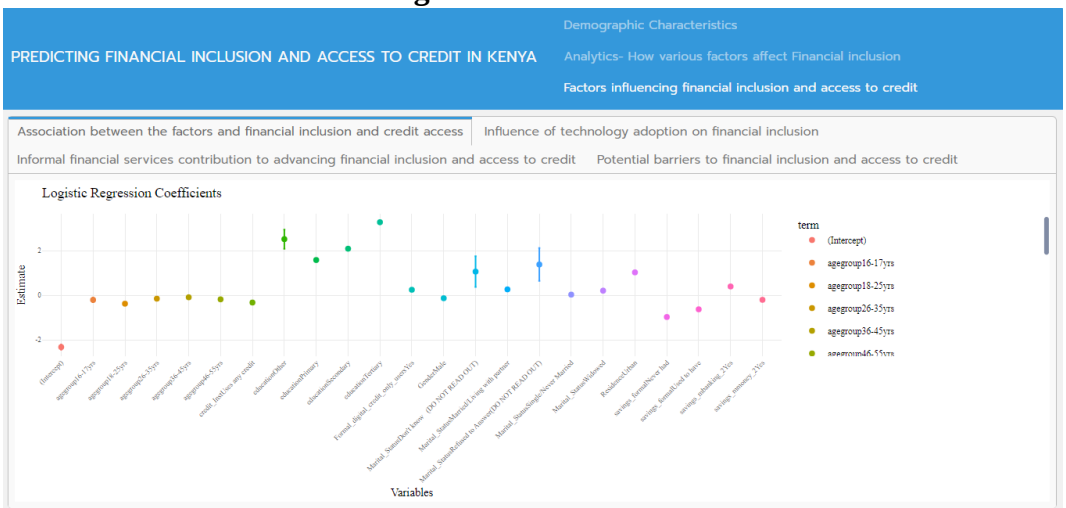

PREDICTING FINANCIAL INCLUSION AND ACCESS TO CREDIT IN KENYA
Demographic Characteristics
Analytics- How various factors affect Financial inclusion
Factors influencing financial inclusion and access to credit
Distribution of Residence by Financial Inclusion
Distribution of Gender by Financial Inclusion
Distribution of agegroup by Financial Inclusion
Distribution of education by Financial Inclusion
Distribution of Marital_Status by Financial Inclusion
Distribution of Gender by Financial Inclusion
as.factor(FinancialInclusion_modify)
No
Yes
Count
Gender
Female
Male
Distribution of financial illiteracy by Financial Inclusion
financial_illiteracy
Distribution of monthly income by Financial Inclusion
monthly_income

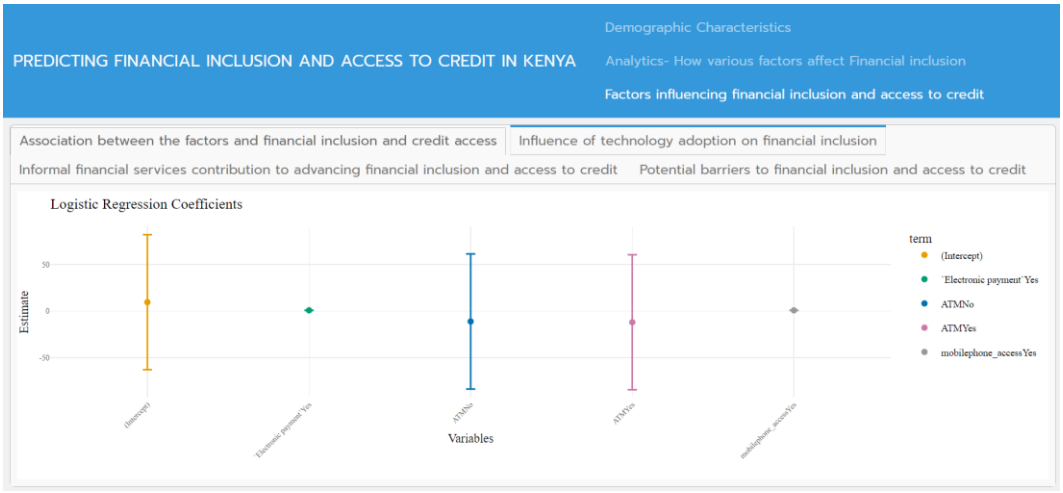

PREDICTING FINANCIAL INCLUSION AND ACCESS TO CREDIT IN KENYA
Demographic Characteristics
Analytics- How various factors affect Financial inclusion
Factors influencing financial inclusion and access to credit
Distribution of Residence by Financial Inclusion
Distribution of Gender by Financial Inclusion
Distribution of agegroup by Financial Inclusion
Distribution of education by Financial Inclusion
Distribution of Marital_Status by Financial Inclusion
Distribution of agegroup by Financial Inclusion
as.factor(FinancialInclusion_modify)
No
Yes
Count
agegroup
Distribution of financial illiteracy by Financial Inclusion
financial_illiteracy
Distribution of monthly income by Financial Inclusion
monthly_income

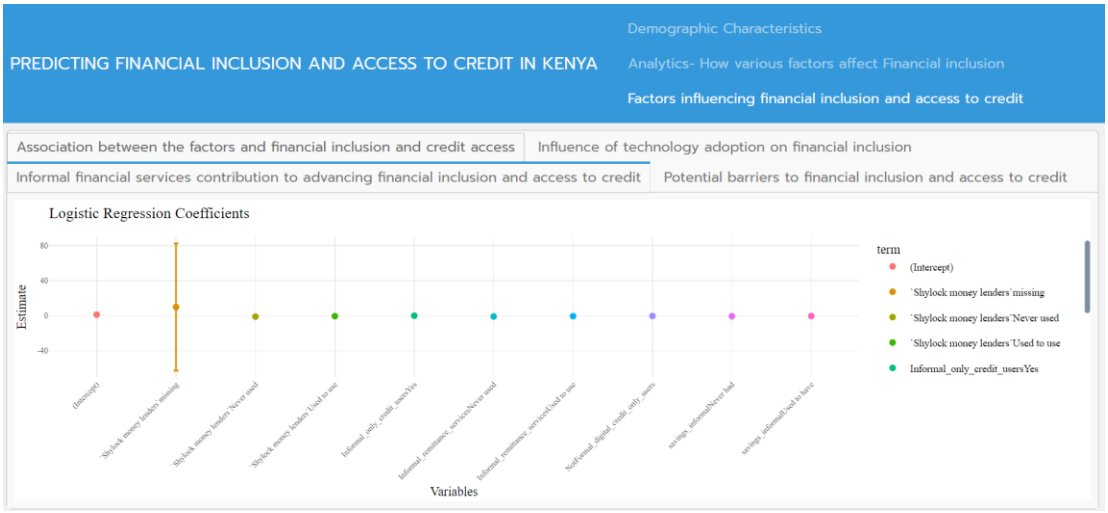


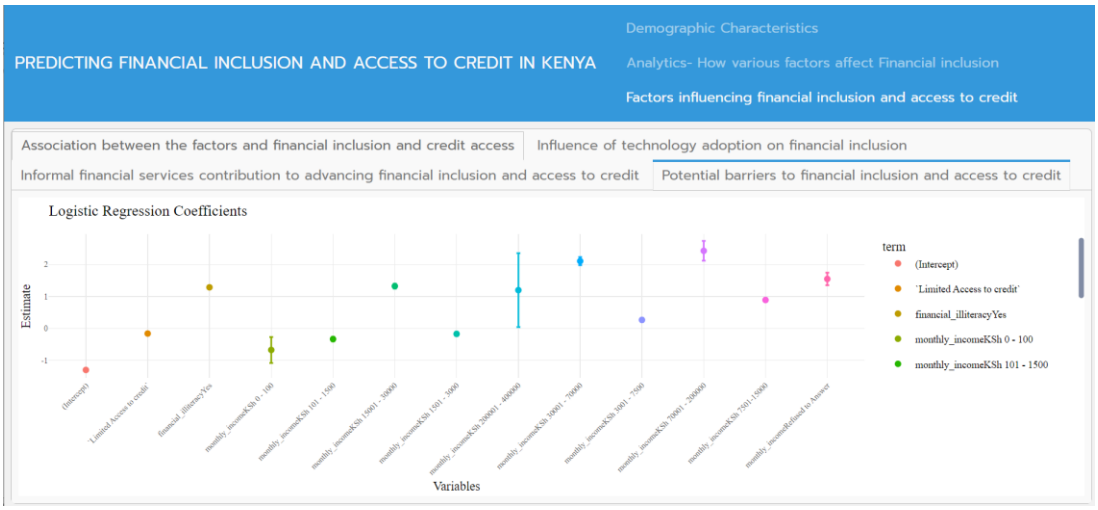


Factors influencing financial inclusion access to credit




PREDICTING FINANCIAL INCLUSION AND ACCESS TO CREDIT IN KENYA
Demographic Characteristics
Analytics- How various factors affect Financial inclusion
Factors influencing financial inclusion and access to credit
Association between the factors and financial inclusion and credit access
Influence of technology adoption on financial inclusion
Informal financial services contribution to advancing financial inclusion and access to credit
Potential barriers to financial inclusion and access to credit
Logistic Regression Coefficients
Estimate
Variables
term
(Intercept)
'Electronic payment' Yes
ATMNo
ATMYes
mobilephone_accessYes


PREDICTING FINANCIAL INCLUSION AND ACCESS TO CREDIT IN KENYA
Demographic Characteristics
Analytics- How various factors affect Financial inclusion
Factors influencing financial inclusion and access to credit
Association between the factors and financial inclusion and credit access
Influence of technology adoption on financial inclusion
Informal financial services contribution to advancing financial inclusion and access to credit
Potential barriers to financial inclusion and access to credit
Logistic Regression Coefficients
Estimate
Variables
term
(Intercept)
'Shylock money lenders' missing
'Shylock money lenders' Never used
'Shylock money lenders' Used to use
Informal_only_credit_usersYes


PREDICTING FINANCIAL INCLUSION AND ACCESS TO CREDIT IN KENYA
Demographic Characteristics
Analytics- How various factors affect Financial inclusion
Factors influencing financial inclusion and access to credit
Association between the factors and financial inclusion and credit access
Influence of technology adoption on financial inclusion
Informal financial services contribution to advancing financial inclusion and access to credit
Potential barriers to financial inclusion and access to credit
Logistic Regression Coefficients
Estimate
Variables
term
(Intercept)
'Limited Access to credit'
financial_illiteracyYes
monthly_incomeKSh 0 - 100
monthly_incomeKSh 101 - 1500

Appendix C: R Dashboard Codes

````
title: "PREDICTING FINANCIAL INCLUSION AND ACCESS TO CREDIT IN KENYA"
output:
  flexdashboard::flex_dashboard:
    theme:
      bg: "#F9F9F9"
      fg: "#333333"
      primary: "#3498DB"
      base_font:
        google: Prompt
      code_font:
        google: JetBrains Mono
    orientation: columns
    vertical_layout: fill
---

```{r setup, include=FALSE}
library(flexdashboard)
# Install thematic and un-comment for themed static plots (i.e., ggplot2)
 thematic::thematic_rmd()

library(ggplot2)
library(plotly)
library(dplyr)
library("ggpubr")
theme_set(
  theme_bw() +
    theme(legend.position = "top")
  )
```

```{r}
library(readr)
df<- read_csv("FinAccess data 3.csv")
attach(df)

```

Demographic Characteristics
==========================================


Column {data-width=650 .tabset}
-----------------------------------------------------------------------

### Distribution of the Dataset

```{r}
````
````

```
# Create a histogram
fig <- plot_ly(x = ~df$Age,
               type = "histogram",
               histnorm = "probability density")



# Add a title
fig <- fig %>% layout(title = "Distribution of the dataset")

# Show the interactive plot
fig


```

Participants Gender and Marital Status

```{r}
# Load necessary libraries
library(plotly)
library(dplyr)

# Assuming df is your data frame

# Create a bar plot for Gender
plot1 <- df %>%
  count(Gender) %>%
  plot_ly(x = ~Gender, y = ~n, type = 'bar', name = 'Gender') %>%
  layout(title = "Gender Distribution")

# Create a bar plot for Marital_Status
plot2 <- df %>%
  count(Marital_Status) %>%
  plot_ly(x = ~Marital_Status, y = ~n, type = 'bar', name = 'Marital_Status') %>%
  layout(title = "Marital_Status and Gender Distribution")

# Create a subplot with the two plots
subplot(plot1, plot2, nrows = 1, shareX = TRUE, titleX = TRUE)


```
Participants's Age group

```{r}
# Load necessary libraries
library(plotly)

# Create a pie chart for agegroup
agegroup_counts <- df %>%
  count(agegroup) %>%
```

```
  mutate(prop = n / sum(n) * 100)

agegroup_plot <- plot_ly(agegroup_counts, labels = ~agegroup, values = ~prop, type = 'pie') %>%
  layout(title = "Distribution of Age Groups",
         xaxis = list(showgrid = FALSE, zeroline = FALSE, showticklabels = FALSE),
         yaxis = list(showgrid = FALSE, zeroline = FALSE, showticklabels = FALSE))

# Display the plot
agegroup_plot

```
Participant's Education level

```{r}
# Create a bar plot for education
education_plot <- df %>%
  count(education) %>%
  ggplot(aes(x = education, y = n, fill = education)) +
  geom_bar(stat = "identity") +
  labs(x = "Education", y = "Count", fill = "Education",
       title = "Distribution of Education Levels") +
  theme_classic()

# Convert to interactive plot
education_plot <- ggplotly(education_plot)
education_plot

```


Distribution by Residence accross Wealth Quintile

```{r}
# Load necessary libraries
library(plotly)

# Create a grouped data frame of Residence and wealth_quintile
grouped_df <- df %>%
  group_by(Residence, wealth_quintile) %>%
  summarise(count = n())

# Create an interactive stacked bar plot
plot_ly(grouped_df,
        x = ~Residence,
        y = ~count,
        color = ~wealth_quintile,
        type = 'bar') %>%
  layout(barmode = 'stack', title = "Stacked Bar Plot of Residence by Wealth Quintile")


```

Distribution of informal savings across monthly income

```{r}

# Create a grouped data frame
grouped_df <- df %>%
  group_by(savings_informal, monthly_income) %>%
  summarise(count = n())

# Create an interactive stacked bar plot
plot_ly(grouped_df,
        x = ~savings_informal,
        y = ~count,
        color = ~monthly_income,
        type = 'bar') %>%
  layout(barmode = 'stack', title = "Distribution of informal savings across monthly income")


```

Column {data-width=350}

Distribution of Financial Inclusion

```{r}

# Load the necessary library
library(plotly)

# Convert the variable to a factor
df$FinancialInclusion_modify <- as.factor(df$FinancialInclusion_modify)
levels(df$FinancialInclusion_modify) <- c("No", "Yes")

# Create a pie chart
fig <- df %>%
  count(FinancialInclusion_modify) %>%
  plot_ly(labels = ~FinancialInclusion_modify, values = ~n, type = 'pie') %>%
  layout(title = "Pie Chart of Financial Inclusion") %>%
  add_trace(textinfo = 'label+percent',
            insidetextorientation = 'radial')

# Show the interactive plot
fig
```
Distribution of Financial Distribution across financial literacy

```{r}

# Convert the variables to factors
df$FinancialInclusion_modify <- as.factor(df$FinancialInclusion_modify)
```

```
df$financial_illiteracy <- as.factor(df$financial_illiteracy)

# Create a bar plot
p<-ggplot(df, aes(x=FinancialInclusion_modify, fill=financial_illiteracy)) +
  geom_bar(position="dodge") +
  labs(x="Financial Inclusion", y="Count", fill="Financial Illiteracy", title="Bar Plot of Financial
Inclusion by Financial Illiteracy")

ggplotly(p)

```
Analytics- How various factors affect Financial inclusion
==

Column {data-width=650 .tabset}

Distribution of Residence by Financial Inclusion

```{r}
library(ggplot2)

# Creating a bar plot for 'Gender' filled by 'FinancialInclusion_modify'
p<-ggplot(df, aes(x = Residence, fill =as.factor(FinancialInclusion_modify))) +
  geom_bar(position = "dodge", alpha = 0.8) +
  labs(title = "Distribution of Residence by Financial Inclusion",
       x = "Residence", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
ggplotly(p)

```
Distribution of Gender by Financial Inclusion

```{r}
# Creating a bar plot for 'Gender' filled by 'FinancialInclusion_modify'
p<-ggplot(df, aes(x = Gender, fill =as.factor(FinancialInclusion_modify))) +
  geom_bar(position = "dodge", alpha = 0.8) +
  labs(title = "Distribution of Gender by Financial Inclusion",
       x = "Gender", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
ggplotly(p)

```
Distribution of agegroup by Financial Inclusion

```{r}
# Creating a bar plot for 'Gender' filled by 'FinancialInclusion_modify'
p<-ggplot(df, aes(x = agegroup, fill =as.factor(FinancialInclusion_modify))) +
  geom_bar(position = "dodge", alpha = 0.8) +
```

```
  labs(title = "Distribution of agegroup by Financial Inclusion",
      x = "agegroup", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
ggplotly(p)

```
Distribution of education by Financial Inclusion

```{r}
# Creating a bar plot for 'education' filled by 'FinancialInclusion_modify'
p<-ggplot(df, aes(x = education, fill =as.factor(FinancialInclusion_modify))) +
  geom_bar(position = "dodge", alpha = 0.8) +
  labs(title = "Distribution of education by Financial Inclusion",
      x = "education", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
ggplotly(p)

```
Distribution of Marital_Status by Financial Inclusion

```{r}
# Creating a bar plot for 'Marital_Status' filled by 'FinancialInclusion_modify'
p<-ggplot(df, aes(x = Marital_Status, fill =as.factor(FinancialInclusion_modify))) +
  geom_bar(position = "dodge", alpha = 0.8) +
  labs(title = "Distribution of Marital_Status by Financial Inclusion",
      x = "Marital_Status", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
ggplotly(p)

```
Column {data-width=350}

Distribution of financial illiteracy by Financial Inclusion
```{r}
# Creating a bar plot for 'financial_illiteracy' filled by 'FinancialInclusion_modify'
p<-ggplot(df, aes(x = financial_illiteracy, fill =as.factor(FinancialInclusion_modify))) +
  geom_bar(position = "dodge", alpha = 0.8) +
  labs(title = "Distribution of financial illiteracy by Financial Inclusion",
      x = "financial_illiteracy", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
ggplotly(p)

```
Distribution of monthly income by Financial Inclusion

```{r}
```

```
# Creating a bar plot for 'monthly_income' filled by 'FinancialInclusion_modify'
p<-ggplot(df, aes(x = monthly_income, fill =as.factor(FinancialInclusion_modify))) +
  geom_bar(position = "dodge", alpha = 0.8) +
  labs(title = "Distribution of monthly income by Financial Inclusion",
       x = "monthly_income", y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
ggplotly(p)

```
Factors influencing financial inclusion and access to credit
==

Row {data-width=1000 .tabset}

Association between the factors and financial inclusion and credit access
```{r}

# Convert variables to factors
df$mobilephone_access <- factor(df$mobilephone_access, levels = c("No", "Yes"))
df$savings_mmoney_2 <- factor(df$savings_mmoney_2, levels = c("No", "Yes"))
#df$savings_formal <- factor(df$savings_formal, levels = c("Currently have", "Never had", "Used to
have"))
df$savings_mbanking_2 <- factor(df$savings_mbanking_2, levels = c("No", "Yes"))

library(gtsummary)
table2 <-
  tbl_summary(
    df,
    include = c(credit_Inst, Formal_digital_credit_only_users, savings_formal,mobile_money_access,
savings_mmoney_2, savings_mbanking_2, savings_formal),
    by = FinancialInclusion_modify, # split table by group
    missing = "no" # don't list missing data separately
  ) %>%
  add_n() %>% # add column with total number of non-missing observations
  add_p() %>% # test for a difference between groups
  modify_header(label = "**Variable**") %>% # update the column header
  bold_labels()

#table2
```
```{r}
mod1 <- glm(FinancialInclusion_modify ~ agegroup + Gender +
Residence+Marital_Status+education+Formal_digital_credit_only_users+credit_Inst+savings_formal
+savings_mmoney_2+savings_mbanking_2,data=df, family = binomial)

t1 <- tbl_regression(mod1, exponentiate = TRUE)

```

```{r}
# Assuming your logistic regression model is named 'mod2'
library(ggplot2)
library(broom)

# Convert model results to tidy format
tidy_results <- tidy(mod1)

# Plot coefficients
p<-ggplot(tidy_results, aes(x = term, y = estimate, color = term)) +
  geom_point() +
  geom_errorbar(aes(ymin = estimate - std.error, ymax = estimate + std.error), width = 0.2, position =
position_dodge(0.6)) +
  labs(title = "Logistic Regression Coefficients",
       x = "Variables",
       y = "Estimate") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

ggplotly(p)

```

Influence of technology adoption on financial inclusion

```{r}
mod2 <- glm(FinancialInclusion_modify~ATM+`Electronic payment`+mobilephone_access ,data=df,
family = binomial)



# Convert model results to tidy format
tidy_results <- tidy(mod2)

# Plot coefficients
p<-ggplot(tidy_results, aes(x = term, y = estimate, color = term)) +
  geom_point() +
  geom_errorbar(aes(ymin = estimate - std.error, ymax = estimate + std.error), width = 0.2, position =
position_dodge(0.6)) +
  labs(title = "Logistic Regression Coefficients",
       x = "Variables",
       y = "Estimate") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

ggplotly(p)

```

Informal financial services contribution to advancing financial inclusion and access to credit

```{r}
mod3 <-
glm(FinancialInclusion_modify~savings_informal+Informal_remittance_services+NotFormal_digital_
credit_only_users+`Shylock money lenders`+Informal_only_credit_users ,data=df, family = binomial)

# Convert model results to tidy format
tidy_results <- tidy(mod3)

# Plot coefficients
p<-ggplot(tidy_results, aes(x = term, y = estimate, color = term)) +
 geom_point() +
 geom_errorbar(aes(ymin = estimate - std.error, ymax = estimate + std.error), width = 0.2, position =
position_dodge(0.6)) +
 labs(title = "Logistic Regression Coefficients",
     x = "Variables",
     y = "Estimate") +
 theme_minimal() +
 theme(axis.text.x = element_text(angle = 45, hjust = 1))

ggplotly(p)

```
Potential barriers to financial inclusion and access to credit

```{r}

mod4 <- glm(FinancialInclusion_modify~monthly_income+financial_illiteracy +`Limited Access to
credit`,data=df, family = binomial)

# Convert model results to tidy format
tidy_results <- tidy(mod4)

# Plot coefficients
p<-ggplot(tidy_results, aes(x = term, y = estimate, color = term)) +
 geom_point() +
 geom_errorbar(aes(ymin = estimate - std.error, ymax = estimate + std.error), width = 0.2, position =
position_dodge(0.6)) +
 labs(title = "Logistic Regression Coefficients",
     x = "Variables",
     y = "Estimate") +
 theme_minimal() +
 theme(axis.text.x = element_text(angle = 45, hjust = 1))

ggplotly(p)

```

Appendix D: Python Code for Modelling

FinAccess_Logistic_Updated (1).ipynb
FinAccess_Logistic_Updated (1).ipynb_Notebook unstarred
All changes saved
[ ]

```
#importing the dependencies
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

[ ]

```
#Loading the dataset
data = pd.read_csv("FinAccess data 3.csv")
```

[ ]

```
data = pd.DataFrame(data)
```

[ ]

```
#Dataset information
data.info()
```

[ ]

```
#Checking for missing values in each column
data.isnull().sum()
```

[ ]

```
# Replace the missing values with mode
data["Internet Access"].fillna(data["Internet Access"].mode().iloc[0], inplace=True)
data["ATM"].fillna(data["ATM"].mode().iloc[0], inplace=True)
data["Shylock money lenders"].fillna(data["Shylock money lenders"].mode().iloc[0], inplace=True)
```

[ ]

```
data.info()
```

[ ]

```
print(data.columns)
```

[ ]

```
#Recoding the varibles for regression
data.loc[data["Marital_Status"].isin(["Don't know    (DO NOT READ OUT)", "Refused to Answer(DO NOT READ OUT)", "Single/Never Married"]), "Marital_Status"] = "Single/Never Married"
data.loc[data['education'].isin(['Other', 'None']), 'education'] = 'None'
data.loc[data["Shylock money lenders"].isin(["missing", "Never used"]), "Shylock money lenders"] ="Never used"
data.loc[data["ATM"].isin(["-999999999", "No"]), "ATM"] = "No"
data.loc[data["Informal_remittance_services"].isin(["missing", "Never used"]), "Informal_remittance_services"] = "Never used"
data.loc[data["Internet Access"].isin(["Don't Know", "Refused to Answer", "missing", "No"]), "Internet Access"] = 'No'
data.loc[data["monthly_income"].isin(["Don't Know", "Refused to Answer"]), "monthly_income"] = "Don't Know"
data.loc[data["monthly_income"].isin(["KSh 0 - 100", "KSh 101 - 1500"]), "monthly_income"] = "KSh 0 - 1500"
data.loc[data["monthly_income"].isin(["KSh 70001 - 200000", "KSh 200001 - 400000"]), "monthly_income"] = "KSh 70001 - 400000"
```

[ ]

```
data["Informal_remittance_services"].value_counts()
[ ]
data["ATM"].value_counts()
[ ]
data["Shylock money lenders"].value_counts()
[ ]
data["Marital_Status"].value_counts()
[ ]
data["education"].value_counts()
[ ]
data["Internet Access"].value_counts()
[ ]
data["monthly_income"].value_counts()
```
Converting the string variables to numeric

```
[ ]
# Converting string variables to numeric using mapping
data['Residence_new'] = data['Residence'].astype('category').cat.codes
data['Gender_new'] = data['Gender'].astype('category').cat.codes
data['agegroup_new'] = data['agegroup'].astype('category').cat.codes
data['education_new'] = data['education'].astype('category').cat.codes
data['Marital_Status_new'] = data['Marital_Status'].astype('category').cat.codes
data['wealth_quintile_new'] = data['wealth_quintile'].astype('category').cat.codes
data['InternetAccess_new'] = data['Internet Access'].astype('category').cat.codes
data['ATM_new'] = data['ATM'].astype('category').cat.codes
data['Electronicpayment_new'] = data['Electronic payment'].astype('category').cat.codes
data['savings_informal_new'] = data['savings_informal'].astype('category').cat.codes
data['savings_formal_new'] = data['savings_formal'].astype('category').cat.codes
data['mobile_money_access_new'] = data['mobile_money_access'].astype('category').cat.codes
data['financial_illiteracy_new'] = data['financial_illiteracy'].astype('category').cat.codes
data['monthly_income_new'] = data['monthly_income'].astype('category').cat.codes
data['Shylockmoneylenders_new'] = data['Shylock money lenders'].astype('category').cat.codes
data['Informal_remittance_services_new'] =
data['Informal_remittance_services'].astype('category').cat.codes
data['Informal_only_credit_users2_new'] =
data['Informal_only_credit_users2'].astype('category').cat.codes
data['credit_Inst_new'] = data['credit_Inst'].astype('category').cat.codes
data['mobilephone_access_new'] = data['mobilephone_access'].astype('category').cat.codes
data['savings_mbanking_2_new'] = data['savings_mbanking_2'].astype('category').cat.codes
data['savings_mmoney_2_new'] = data['savings_mmoney_2'].astype('category').cat.codes
data['Formal_digital_credit_new'] =
data['Formal_digital_credit_only_users'].astype('category').cat.codes
[ ]
import statsmodels.formula.api as smf

# Convert the variable to categorical with a reference category
data['Gender_new'] = data['Gender_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(Gender_new, Treatment(0))"
# Fit the model with the modified formula
```

```
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['InternetAccess_new'] = data['InternetAccess_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(InternetAccess_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()

[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['Residence_new'] = data['Residence_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(Residence_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['ATM_new'] = data['ATM_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(ATM, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
```

```
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['Marital_Status_new'] = data['Marital_Status_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(Marital_Status_new, Treatment(2))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['agegroup_new'] = data['agegroup_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(agegroup_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['Electronicpayment_new'] = data['Electronicpayment_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(Electronicpayment_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['mobilephone_access_new'] = data['mobilephone_access_new'].astype('category')
```

```
# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(mobilephone_access_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['Shylockmoneylenders_new'] = data['Shylockmoneylenders_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(Shylockmoneylenders_new, Treatment(1))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['Informal_only_credit_users2_new']                                                                    =
data['Informal_only_credit_users2_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(Informal_only_credit_users2_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['Formal_digital_credit_new'] = data['Formal_digital_credit_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(Formal_digital_credit_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
```

```
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['NotFormal_digital_credit_only_users']                                                    =
data['NotFormal_digital_credit_only_users'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(NotFormal_digital_credit_only_users, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['credit_Inst_new'] = data['credit_Inst_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(credit_Inst_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['savings_informal_new'] = data['savings_informal_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(savings_informal_new, Treatment(1))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
```

```
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['savings_formal_new'] = data['savings_formal_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(savings_formal_new, Treatment(1))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['mobile_money_access_new'] = data['mobile_money_access_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(mobile_money_access_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['Informal_remittance_services_new']                                                    =
data['Informal_remittance_services_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(Informal_remittance_services_new, Treatment(1))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['savings_mbanking_2_new'] = data['savings_mbanking_2_new'].astype('category')
```

```
# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(savings_mbanking_2_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['savings_mmoney_2_new'] = data['savings_mmoney_2_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(savings_mmoney_2_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# Convert the variable to categorical with a reference category
data['financial_illiteracy_new'] = data['financial_illiteracy_new'].astype('category')

# Specify the reference category using C() function
formula = "FinancialInclusion_modify ~ C(financial_illiteracy_new, Treatment(0))"

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
import statsmodels.formula.api as smf

formula = "FinancialInclusion_modify ~ agegroup_new + Gender_new + education_new +
Residence_new + Marital_Status_new + InternetAccess_new + ATM_new + Electronicpayment_new
+ mobilephone_access_new + Shylockmoneylenders_new + Informal_only_credit_users2_new +
Formal_digital_credit_new + NotFormal_digital_credit_only_users + credit_Inst_new +
savings_informal_new + savings_formal_new + mobile_money_access_new +
Informal_remittance_services_new + savings_mbanking_2_new + savings_mmoney_2_new"
```

```
# Check for correlation between variables
correlation_matrix = data[['agegroup_new', 'Gender_new', 'education_new', 'Residence_new', 'Marital_Status_new', 'InternetAccess_new', 'ATM_new', 'Electronicpayment_new', 'mobilephone_access_new', 'Shylockmoneylenders_new', 'Informal_only_credit_users2_new', 'Formal_digital_credit_new', 'NotFormal_digital_credit_only_users', 'credit_Inst_new', 'savings_informal_new', 'savings_formal_new', 'mobile_money_access_new', 'Informal_remittance_services_new', 'savings_mbanking_2_new', 'savings_mmoney_2_new', 'financial_illiteracy_new']].corr()

# Remove highly correlated variables
variables_to_remove = set()
for i in range(len(correlation_matrix.columns)):
    for j in range(i):
        if abs(correlation_matrix.iloc[i, j]) > 0.9:  # Adjust the correlation threshold as needed
            colname_i = correlation_matrix.columns[i]
            colname_j = correlation_matrix.columns[j]
            variables_to_remove.add(colname_i)
            variables_to_remove.add(colname_j)

# Remove the highly correlated variables from the formula
for variable in variables_to_remove:
    formula = formula.replace(f" + {variable}", "")
    formula = formula.replace(f" + {variable}:", ":")
    formula = formula.replace(f": {variable}", ":")

# Fit the model with the modified formula
model = smf.logit(formula=formula, data=data).fit()
[ ]
model.summary()
[ ]
conf  = model.conf_int()
conf["OR"] = model.params
conf.columns = ["2.5%", "97.5%", "OR"]
print(np.exp(conf))
[ ]
# List of column names to convert to numeric
columns_to_convert = data[["agegroup", "Gender", "education", "Residence", "Marital_Status", "wealth_quintile", "Electronic payment", "Internet Access", "ATM", "monthly_income",
           "Informal_only_credit_users2", "Formal_digital_credit_only_users", "mobile_money_access", "Shylock money lenders", "Informal_remittance_services",
           "NotFormal_digital_credit_only_users", "savings_informal", "savings_formal", "Limited Access to credit",
           "savings_mbanking_2", "savings_mmoney_2", "financial_illiteracy", "Informal_only_credit_users", "credit_Inst", "mobilephone_access"]]

# Custom conversion function
def custom_conversion(value):
    if isinstance(value, str):
        return hash(value) % (10 ** 8)  # Assign a unique numeric value based on the hash of the string
    else:
        return value
```

```
# Convert the specified columns from string to numeric using the custom conversion function
for column in columns_to_convert:
    data[column] = data[column].apply(custom_conversion)

# Check the converted DataFrame
data.info()
[ ]
#Separating the data for analysis
excluded = data[data.FinancialInclusion_modify == 0]
included = data[data.FinancialInclusion_modify == 1]
[ ]
print(included.shape)
print(excluded.shape)
Splitting the data into Features and Targets

[ ]
X = data.drop(columns="FinancialInclusion_modify",axis=1)
Y = data["FinancialInclusion_modify"]
Splitting the data into training and testing

[ ]
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.2, stratify=Y, random_state=2)
Model Training : Logistic Regression

[ ]
model = LogisticRegression()
[ ]
#Training the logistic regression model with training data
model.fit(X_train, Y_train)
Model Evaluation : Accuracy Score

[ ]
#Training data accuracy
X_train_pred = model.predict(X_train)
training_data_accuracy = accuracy_score(X_train_pred,Y_train)
[ ]
print("Accuracy on training data :", training_data_accuracy)
[ ]
#Accuracy on test data
X_test_pred = model.predict(X_test)
test_data_accuracy = accuracy_score(X_test_pred,Y_test)
[ ]
print("Accuracy on testing data :", test_data_accuracy)
[ ]
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Obtain predictions on the test data
X_test_pred = model.predict(X_test)

# Calculate accuracy
```

```
test_data_accuracy = accuracy_score(Y_test, X_test_pred)

# Calculate precision
precision = precision_score(Y_test, X_test_pred)
```

[ ]

Colab paid products - Cancel contracts here

Appendix E: Ethical Clearance Exemption

Strathmore UNIVERSITY

27th March 2024

Chebet Tanui
Student Number: 051687
chebet.tanui@strathmore.edu
MSc. DSA

Dear Chebet,

RE: Predicting Financial Inclusion and Access to Credit in Kenya

This is to inform you that the Office of Graduate Studies received your request for exemption from ethical clearance. This is based on the fact that your study cannot be reviewed by the Strathmore University Institutional Scientific Ethics Review Committee (SU-ISERC) since you have already collected data and written the Dissertation. The ethics approval process is ONLY done before any collection of primary or secondary data. Additionally, ethical clearance is mandatory for all studies including desktop research.

The office notes that: On the grounds of not having completed the ethical clearance process, with reason of ethical clearance not having been communicated to you by your supervisor and the Research Centre, and henceforth having already proceeded to data collection and written your Dissertation before ethical clearance. This is a letter for you to proceed with the next steps of your academic requirements.

Please be advised, that in future, all research proposals should be submitted to the SU-SIERC through the RHInnO Ethics platform: https://strathmoreuniversity.rhinno.net/login

Disclaimer: *1) This is not in any way an ethical approval letter. 2) Should there be any legal implications/actions emanating from the research in terms of any ethical violations, you will be personally liable.*

Yours sincerely,

Dr. Bernard Shibwabo
Director of Graduate Studies

Ole Sangale Rd, Madaraka Estate. PO Box 59857-00200, Nairobi, Kenya. Tel +254 (0)703 034000
Email admissions@strathmore.edu www.strathmore.edu

Appendix F: Turnitin Report