

# Explanatory Analysis of Gender Disparities in Digital Financial Access in Uganda

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## Abstract

Access to financial services is a recognized catalyst for economic development and poverty alleviation. In Uganda, digital financial services (DFS) have gained prominence through initiatives like mobile money, significantly reducing financial exclusion. However, gender disparities persist, with women facing social, economic, and cultural barriers to accessing DFS. Using the 2023 FinScope Survey, this study develops an explanatory model to explore the predictors of digital financial access among Ugandans, with a focus on gender disparities. We employed the Digital Financial Access Ratio (DFAR) as the dependent variable to measure engagement with DFS. Logistic regression models were developed for male, female, and combined datasets to assess adoption drivers. Key predictors included mobile money awareness, e-loan knowledge, and socio-economic factors like education, marital status, and occupational engagement. Results reveal that males exhibit higher DFS awareness and usage, while women face more pronounced barriers such as financial illiteracy and limited device access. Females' DFS adoption is strongly influenced by marital and financial decision-making dynamics, whereas males rely more on transactional behaviors and professional networks. The study underscores the need for gender-sensitive interventions, including awareness campaigns, improved access to digital tools, and targeted support for women in rural areas. By addressing these gaps, policymakers can create an inclusive financial ecosystem, enabling equitable access to DFS and fostering economic participation.

## Introduction

Access to financial services is pivotal to economic development and achieving the Sustainable Development Goals. Digital financial services (DFS), such as mobile banking and e-wallets, mitigate traditional barriers like high costs and limited infrastructure, empowering individuals and fostering economic participation. While Uganda has made significant progress in financial inclusion, gender disparities remain critical. Women face systemic barriers, including income inequality, low literacy, and cultural norms, restricting their access to DFS. This study aims to identify the key drivers of DFS adoption among Ugandans and to propose targeted interventions to bridge the gender gap.

## Background

Access to financial services is essential for economic development, poverty reduction, and achieving global sustainable development goals ([Finclusion, 2024](#)). Digital financial services, including mobile banking, online payments, and digital wallets, are increasingly offered by banks and non-bank entities to underserved populations, helping millions transition from cash-based transactions to formal financial services such as payments, savings, and credit ([World Bank, 2020](#)). Leveraging advances in mobile technology, cloud computing, and data analytics, digital finance mitigates barriers like physical distance, high costs, and limited infrastructure, ultimately empowering individuals and promoting economic participation ([Digital Frontiers Institute, 2024](#)). In Uganda, the National Financial Inclusion Strategy 2017–2022 aimed to reduce financial exclusion from 15% to 5%, and significant progress has been made, with 66% of Ugandan adults having access to mobile money accounts in 2022 ([Uganda Bankers NFIS, 2022](#); [FAO, 2023](#)).

Despite these advancements, women still face significant barriers to accessing digital financial services due to limited mobile phone ownership, lower financial literacy, and cultural norms ([Uganda Bankers NFIS II, 2023](#)). Women are 15% less likely to use mobile internet and 13% less likely to own a smartphone compared to men ([GSMA, 2023](#)). These disparities are even more pronounced in rural Uganda, where challenges like limited network connectivity and social barriers hinder financial inclusion for women ([Finscope Survey, 2022](#)). To address these issues, the Ugandan government and financial institutions have launched gender-targeted initiatives, such as the Women's Entrepreneurship Development Project to provide loans to women entrepreneurs ([World Bank Group, 2019](#)), as well as campaigns to increase women's digital financial literacy ([Ministry of Finance, 2022](#)).

## Research Objective

Our study aims to examine the relationship between variables such as income levels, mobile phone ownership, financial literacy, employment status, and urban-rural divide to better understand barriers to accessing digital financial services. This will help drive initiatives promoting gender-inclusive financial growth and develop targeted policies to bridge these gaps.

## Literature Review

Our study builds upon existing research examining digital financial inclusion and household financial vulnerability, with a focus on gender disparities.

The study "Digital Financial Inclusion and Household Financial Vulnerability: An Empirical Analysis of Rural and Urban Disparities in China" explores how digital finance impacts financial vulnerability using data from the 2019 China Household Finance Survey (CHFS) and the 2018 Digital Financial Inclusion Index (DFIIC). It identifies three key mechanisms for reducing vulnerability: enhancing financial literacy, increasing income from financial assets, and promoting commercial insurance adoption. These findings informed our study's model by incorporating variables like proximity to financial service points, financial knowledge, education, and marital status to explore their relationship with digital financial inclusion in Uganda, particularly for women.

"Advancing Women's Digital Financial Inclusion in Uganda," conducted by the Economic Policy Research Centre (EPRC), highlights a gender gap in digital financial services, with women being 30% less likely to use these services than men due to factors like limited digital literacy, access to devices, and socio-cultural norms. Our research builds on these insights by focusing on specific barriers that hinder women's access to digital finance, aiming to develop targeted interventions to promote equitable access.

### Literature Review References

1. Digital Financial Inclusion and Household Financial Vulnerability: An Empirical Analysis of Rural and Urban Disparities in China. Available at: <https://chfs.org.cn>.
2. Economic Policy Research Centre (EPRC). Advancing Women's Digital Financial Inclusion in Uganda. Available at: <https://eprcug.org>.

## Data and Methodology

### Data overview

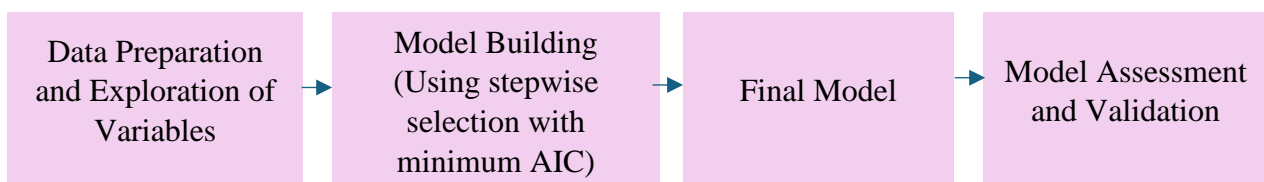
Our analysis is based on the **2023 FinScope Survey**.

The 2023 FinScope Survey the fifth edition since 2006, was conducted by the Bank of Uganda in collaboration with Financial Sector Deepening Uganda, the Uganda Bureau of Statistics, and other stakeholders. It provides a **national overview of financial inclusion among Ugandans aged 16 and above**, focusing on income sources, financial management, and use of both formal and informal financial services.

The survey offers insights into financial needs, behaviors, and perceptions regarding money management and financial products. **Its main objectives are to track trends in financial inclusion since 2018, offer policy and market-level insights for deepening financial inclusion, and describe the financial service needs of the adult population in Uganda.**

### Methodology

In this research study we utilized SAS Viya, powerful analytical tool, to uncover our explanatory model. The study involved data exploration, data preparation, variable selection, model building through **stepwise selection** of variables and model assessment in the following sequence.



The model was also built using a data partition of train, test, validation in the following proportions: 40%, 30%, 30% respectively. **This is essential for model validation which is further explained in Section 6.**

## Defining dependent variable

$$DFAR = \frac{\sum \text{Digital Financial Services Used}}{\sum \text{Digital Financial Services Offered}}$$

The Digital Financial Access Ratio (DFAR) measures an individual's engagement with digital financial services, calculated as the ratio of services used to the total available. It ranges from 0 to 1, where a higher value indicates greater digital financial inclusion. DFAR considers services like mobile banking, e-loans, online transfers, digital savings, and e-wallet payments, enabling comparison across demographics and regions to analyze disparities in digital financial adoption.

DFAR was chosen for this study due to its ability to capture the breadth and depth of digital finance usage in a single metric. Unlike binary indicators, DFAR aggregates multiple services, allowing comparison between demographic groups, such as men and women. It can also be transformed into a binary variable for logistic regression analysis, classifying individuals based on their adaptability to digital financial services, which helps identify key factors influencing digital inclusion.

## Variables of Interest

Our independent variable selection process involved verification of the variables of interest against the seven assumptions of multiple linear regression (Annex C). Subsequently, we considered the following **22 variables** for the development of our model, focusing on gender-based disparities in digital financial service adoption:

S.No.	Grouped Variables	Description	Reason for Selection
1	financial_satisfaction, money_control, financial_decision_bin, why_mm	Measures of financial satisfaction, control over finances, decision-making responsibilities, and reasons for using mobile money services.	These variables provide insights into individuals' perceptions, motivations, and autonomy regarding their finances, crucial for understanding financial behavior and disparity.
2	saving_comm_bank, has_savings, e_saving, has_borrowed, mm_borrowing	Savings and borrowing behavior.	These variables represent financial inclusion through saving and borrowing behaviors, helping analyze disparities in financial adaptability and credit access.
3	mm_barriers, mm_freq, mm_products_awareness, mm_products_use	Barriers to adoption, frequency of use, awareness, and actual usage of mobile money services.	Understanding obstacles, usage patterns, awareness levels, and adoption rates highlights key gaps in mobile money usage and digital financial inclusion.

4	pay_mob_internet, pay_mm_wallet, pay_mob_int_awareness, mm_wallet_awareness	Awareness and usage of digital financial services, including mobile-based payments and wallets.	These variables measure the extent of adoption and highlight gaps in awareness and usage of digital payment services.
5	e_loan_app, e_loan_dis, e_loan_payment, e_loan_awareness, e_transfer, e_recieve	Usage and awareness of electronic loans and transfers.	These represent engagement with digital financial services beyond basic transactions, reflecting deeper financial inclusion.
6	RTGS, EFT, mob_banking_usd, insurance_e_pay, insurance_e_recieve	Usage of advanced financial services such as real-time gross settlements, electronic fund transfers, and digital insurance transactions.	These variables capture adoption of more sophisticated financial tools, which are indicators of advanced financial inclusion.
7	age, age_range_lab, Rural_Urban, gender_lab, marital_status_lab, education_level_lab, occupation	Demographic and socioeconomic characteristics of respondents.	These are key control variables for analyzing disparities and identifying factors influencing adoption patterns.
8	mobile_access, internet_access, computer_access, smartphone_ownership, mobile_usage, internet_usage, computer_usage	Access to and usage of digital technologies.	These variables represent the infrastructure and digital readiness of respondents, which are foundational for digital financial adoption.
9	dfar	Digital Financial Access Ratio, measuring the proportion of digital financial services used by an individual.	DFAR is a composite measure of digital financial inclusion and the central variable for this study, enabling a holistic analysis of adoption levels.
10	avg_dist_fin	Average distance to financial institutions.	Proximity to financial institutions is a significant factor in financial inclusion, particularly in rural areas where accessibility is often a challenge.

# DATA EXPLORATION OF PREDICTORS WITH TARGET VARIABLE

This section analyzes the relationships between demographic, socioeconomic, and behavioral predictors with digital financial inclusion, focusing on gender disparities. Key patterns and insights are drawn from exploratory data analysis (EDA), with each graph referenced by its heading.

## Age, Gender, and Occupational Dynamics

- **Graphs:** Frequency of Age Range Grouped by Gender, Frequency of Gender, Frequency of Occupation Grouped by Gender
  - **Age and Gender:** Females dominate the 31–40 age range, followed by 25–30, highlighting their significant representation. Males show a more balanced distribution across age ranges.
  - **Occupational Patterns:** Females are predominantly engaged in "Looking after the home," while males dominate self-employment in production and services. This highlights occupational segregation affecting digital financial inclusion.

## Digital Financial Service Awareness and Usage

- **Graphs:** Frequency of e-Loan Application Grouped by Gender, Frequency of e-Transfer Grouped by Gender, Frequency of e-Saving Grouped by Gender, Frequency of Mobile Money Wallet Awareness Grouped by Gender, Frequency of e-Loan Awareness Grouped by Gender
  - **Awareness Disparities:** Males show higher awareness of e-loans and e-transfers, with a significant portion of both genders unaware of these services.
  - **Usage Patterns:** Males slightly outpace females in e-saving and e-loan applications, emphasizing the need for outreach programs targeting women.
  - **Mobile Wallets:** Awareness of mobile money wallets is low overall but slightly higher among males, reinforcing gender-based gaps in financial knowledge.

## Barriers to Financial Inclusion

- **Graphs:** Frequency of Mobile Money Barriers Grouped by Gender, Frequency of Mobile Money Reasons Grouped by Gender
  - **Barriers:** "Access and Usability" is the leading barrier for both genders, with females slightly more affected. Other issues, such as "Documentation" and "Cost," disproportionately impact females.

- **Usage Reasons:** Both genders primarily use mobile money for "Money Transfer," with females more influenced by external factors than males.

### Education and Marital Status Influences

- **Graphs:** Frequency of Marital Status Grouped by Gender, Frequency of Education Level Grouped by Gender
  - **Education:** Females are concentrated in primary and secondary education levels, while males more frequently achieve advanced education, contributing to differences in financial literacy.
  - **Marital Status:** Married individuals (monogamous) dominate across genders, with widowed females forming a notable subgroup. Marital status likely influences financial decision-making and autonomy.

### Geographic Accessibility and Financial Services

- **Graphs:** Frequency of Financial Service Distance
  - **Access:** Most individuals are within 2.5 km to 10 km of financial services, but some remain geographically isolated, disproportionately affecting females in rural areas.

### Digital Financial Activity Risk (DFAR)

- **Graphs:** Frequency of DFAR Grouped by Gender, DFAR by Gender and Marital Status
  - **Risk Profiles:** Females show lower DFAR values, indicating less risky financial behaviors, while males display greater variability.
  - **Marital Influence:** Married females exhibit lower DFAR values, while single and widowed individuals show higher financial risk variability.

### Summary and Implications

EDA reveals gender disparities in digital financial inclusion, with females lagging in awareness, usage, and education levels. Structural barriers, such as occupational segregation and geographic access, further restrict female participation. Tailored interventions—focusing on financial literacy, service accessibility, and user-friendly tools—are critical to promoting inclusive digital financial ecosystems.

### Explanatory Models



The final dataset was split into training (40%), validation (30%), and testing (30%) sets. Logistic Regression models were developed to analyze gender disparity in digital financial service adoption, with separate models for males, females, and the overall population. These models aimed to identify key factors and explain gender-based disparities. Model performance was evaluated using the Receiver Operating Characteristic (ROC) index and confusion matrix, with variable importance compared across the models.

## Logistic Regression

Logistic Regression models the non-linear relationship between a binary dependent variable (adoption of digital financial services) and categorical or continuous predictors. The logistic model outputs a probability of an event (digital service adoption) between 0 and 1, represented mathematically as:

$$\underbrace{\text{logit}(E[Y | X])}_{\text{expected value of Y given X}} = \underbrace{\text{logit}(p)}_{\text{probability of an event}} = \underbrace{\ln\left(\frac{p}{1-p}\right)}_{\text{a.k.a Log Odds}} = \underbrace{\beta_0}_{\text{intercept}} + \underbrace{\beta_1 X + \varepsilon}_{\substack{\text{change of Y} \\ \text{associated with} \\ \text{1-unit change in X}}} \quad \text{error term}$$

Figure 1 Logistic Regression Equation

Independent variables were selected using a stepwise method with Akaike Information Criterion (AIC) as the criterion, with Entrance and Stay significance levels set at 0.05. Variables with high collinearity (correlation > 0.7) were excluded to ensure robustness. The stepwise approach optimized the model by iteratively adding or removing variables based on AIC. Separate models for males, females, and the overall population identified gender-specific factors influencing digital financial service adoption, highlighting disparities and informing targeted interventions. Detailed findings are presented in the following sections.

## Model Results

### Overall Model

- **Training Dataset:** The overall logistic regression model demonstrated excellent fit with an AIC of 381 and a C Statistic of 0.989. The Max-rescaled R-Square was 0.9039, explaining a significant proportion of the variance. The model achieved a low misclassification rate of 4.88%.
- **Validation Dataset:** A high C Statistic (0.978) and Max-rescaled R-Square (0.9040) were observed, showcasing strong generalizability with a misclassification rate of 6.40%.
- **Testing Dataset:** The model maintained high performance, with a C Statistic of 0.982 and a misclassification rate of 6.82%.



## Logistic Regression of dfar overall

Logistic Regression **dfar\_flagg\_category** Event: 1 ▾ Fit: **Test Misclassification Rate (Event)** 0.0682 ▾ Observations: 3.2K of 3.2K

< Fit Summary Odds Ratio Residual Assessment >

### Fit Summary

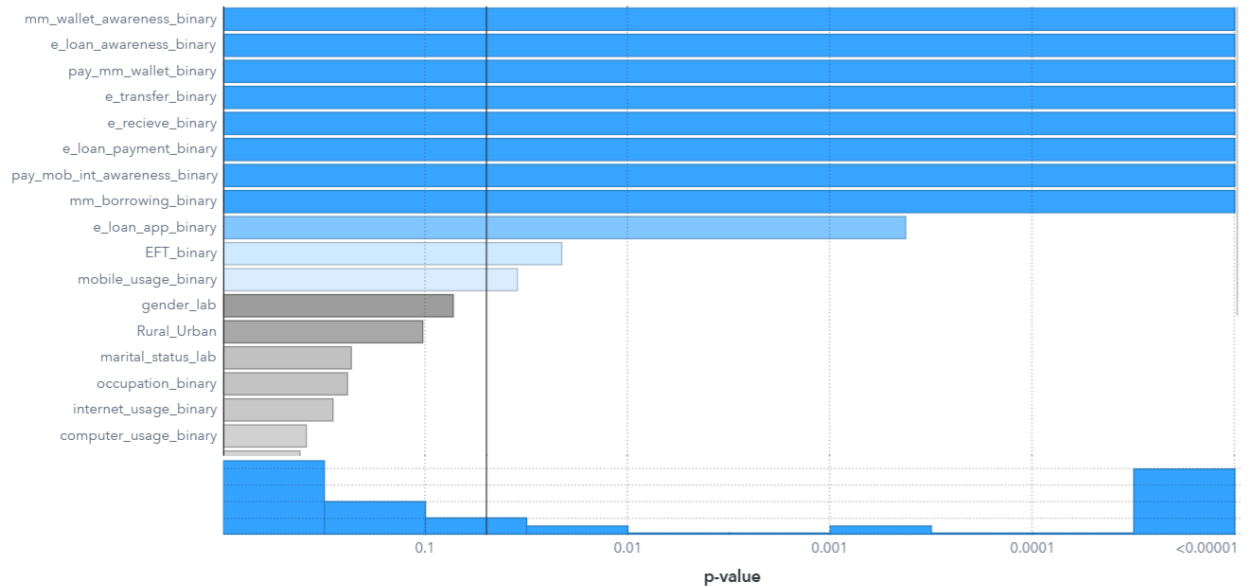


Figure 2 Overall Logistic Reg. Model Fit Summary

## Female Model

- **Training Dataset:** The model fit was strong, with an AIC of 172 and a C Statistic of 0.990. It explained 91.21% of variance (Max-rescaled R-Square) with a misclassification rate of 4.69%.
- **Validation Dataset:** Performance remained robust (C Statistic of 0.971, misclassification rate of 7.56%), indicating reliable predictions for unseen data.
- **Testing Dataset:** A high C Statistic (0.966) and a low misclassification rate (9.26%) confirmed the model's consistency.

## Logistic Regression of dfar females

Logistic Regression **dfar\_flagg\_category** Event: 1 ▾ Fit: Validation KS (Youden) 0.8595 ▾ Observations: 1.1K of 3.2K

< Fit Summary Odds Ratio Residual Assessment >

### Fit Summary

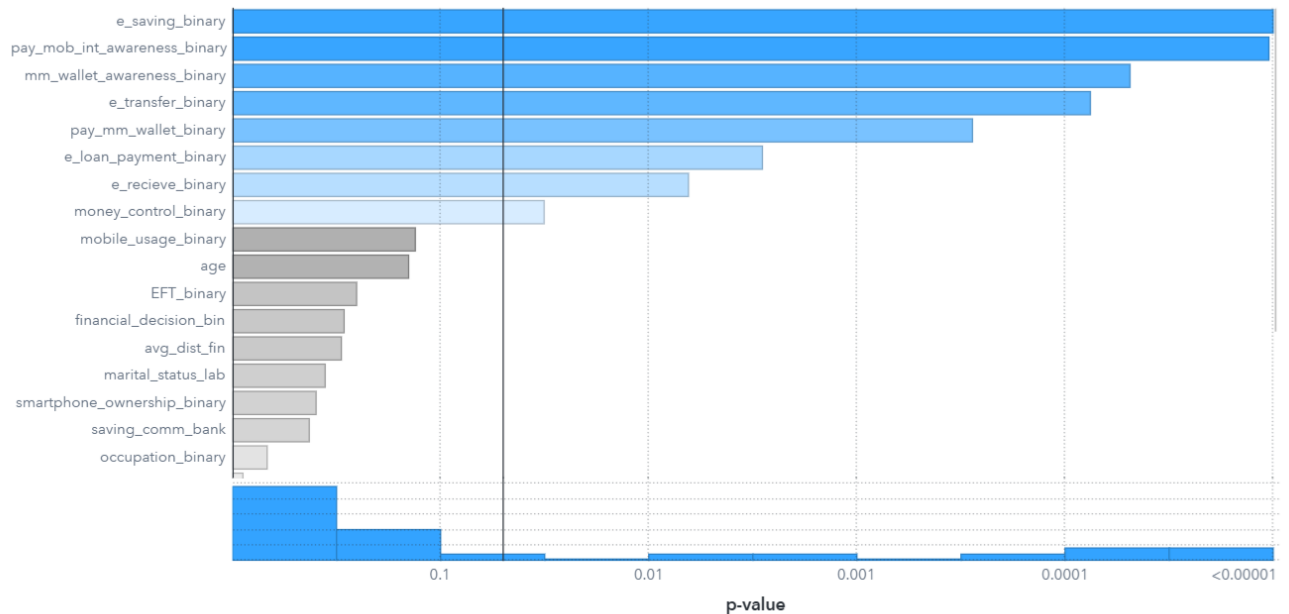


Figure 3 Female Logistic Reg. Model Fit Summary

## Male Model

- **Training Dataset:** The male-specific model showed a strong fit (AIC of 185, C Statistic of 0.991). Variance explanation was 92.81% (Max-rescaled R-Square) with a misclassification rate of 3.15%.
- **Validation Dataset:** A C Statistic of 0.977 and misclassification rate of 5.53% indicated reliable generalization to unseen data.
- **Testing Dataset:** The model demonstrated consistent performance, with a C Statistic of 0.983 and a misclassification rate of 3.66%.

## Logistic Regression of dfar Males

Logistic Regression dfar\_flagg\_category Event: 1 ▾ Fit: Test Misclassification Rate (Event) 0.0366 ▾ Observations: 1.4K of 3.2K

< Fit Summary Odds Ratio Residual Assessment >

### Fit Summary

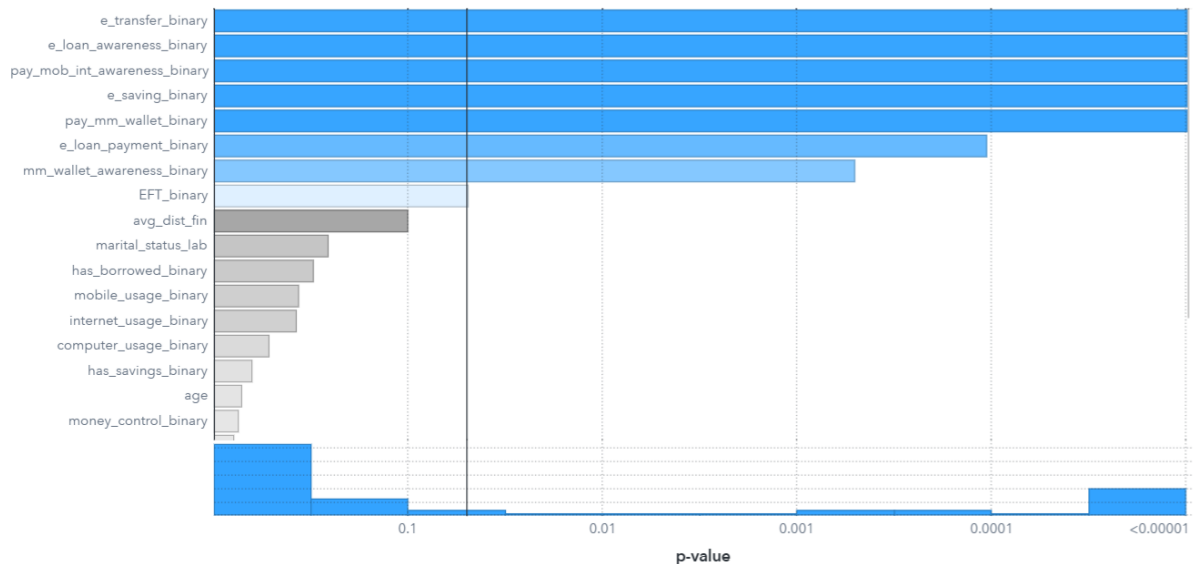


Figure 4 Male Logistic Reg. Model Fit Summary

## Model Interpretation

### Overall Model

Key predictors include mm\_wallet\_awareness\_binary, e\_loan\_awareness\_binary, and pay\_mm\_wallet\_binary, which had the lowest p-values ( $<0.00001$ ). Demographic variables like gender\_lab, Rural\_Urban, and marital\_status\_lab also showed moderate significance, reflecting their contextual importance.

### Female Model

For women, the most influential predictors were e\_saving\_binary, pay\_mob\_int\_awareness\_binary, and mm\_wallet\_awareness\_binary. Contextual factors like marital\_status\_lab and financial\_decision\_bin were more significant compared to men, indicating the impact of household dynamics on adoption.

### Male Model

The male-specific model identified e\_transfer\_binary, e\_loan\_awareness\_binary, and pay\_mob\_int\_awareness\_binary as the strongest predictors. Occupational variables and transactional behaviors, such as e\_transfer\_binary, were more impactful, highlighting men's professional engagement as a key factor.

## Model Assessment

### Overall Model

- **Fit Summary:** Top predictors were related to digital awareness and transactional behaviors. Moderate significance was observed for demographic variables.
- **Odds Ratios:** Awareness-related variables had the highest odds, emphasizing their critical role in adoption.
- **Residual Analysis:** Minimal deviations in residuals confirmed reliable predictions.
- **Confusion Matrix:** The model accurately classified adopters and non-adopters with consistent performance across datasets.

### Female Model

- **Fit Summary:** Awareness-related predictors had the highest influence, with marital\_status\_lab playing a more prominent role.
- **Odds Ratios:** Higher odds for awareness variables indicated their importance for women.
- **Residual Analysis:** Predictions aligned well with actual outcomes, as reflected by minimal deviations in residuals.
- **Confusion Matrix:** Strong performance in classifying adopters and non-adopters, with slightly higher misclassification rates in the test dataset.

### Male Model

- **Fit Summary:** Transactional predictors like e\_transfer\_binary and occupational variables had higher significance.
- **Odds Ratios:** Awareness and access variables had the highest odds, underscoring their importance.
- **Residual Analysis:** Predictions showed minimal deviations, confirming model robustness.
- **Confusion Matrix:** High accuracy across datasets, with the lowest misclassification rate in the training partition.

## Conclusion and Policy Insights

The models highlight shared and unique drivers of digital financial service adoption across genders. Awareness variables like mm\_wallet\_awareness\_binary and pay\_mob\_int\_awareness\_binary are universally critical. However, socio-economic dynamics, represented by variables like marital\_status\_lab and financial\_decision\_bin, are more influential for women, whereas professional engagement and transactional behaviors, such as e\_transfer\_binary, hold greater significance for men.

To bridge gender disparities, targeted strategies are necessary:

1. **For Women:** Awareness campaigns should focus on household dynamics and financial decision-making roles, coupled with improved access to digital tools.
2. **For Men:** Promoting transactional digital tools and leveraging professional networks could enhance adoption.

By addressing these gender-specific barriers, policymakers and financial institutions can foster an inclusive digital financial ecosystem.

## Future Work

These additional variables would help you:

- Better understand the socio-economic context that impacts mobile money adoption.
- Analyze how employment, income, and education affect differences between men and women in adopting digital financial services.
- Determine if geographical barriers influence usage patterns differently for men and women.

## References

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#### 4. Data Sources and Methodology

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#### 5. Additional Studies on Digital Finance and Vulnerability

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- Women's Entrepreneurship Development Project (WEDP). World Bank Group (2019). Available at: <https://www.worldbank.org>.

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## Annex

### Annex A: Variables Selected for the Study

S.No.	Variable Name	Description	Reason for Selection
1	financial_satisfaction	Measures of financial satisfaction and control over finances.	Crucial for understanding financial autonomy and behavior.
2	e_saving	Usage of digital savings services.	Reflects deeper financial inclusion.
3	mm_barriers	Barriers to mobile money adoption.	Identifies obstacles for increasing DFS adoption.
4	gender_lab	Respondent's gender.	Key demographic variable for studying gender disparities.
5	avg_dist_fin	Average distance to financial institutions.	Indicates accessibility issues, especially for rural populations.
6	dfar	Digital Financial Access Ratio.	Measures the extent of DFS adoption and serves as the dependent variable.

## Annex B: Methodology and Logistic Regression Equations

### 1. Model Equation

$$\underbrace{\text{logit}(E[Y|X])}_{\text{expected value of Y given X}} = \underbrace{\text{logit}(p)}_{\text{probability of an event}} = \underbrace{\ln\left(\frac{p}{1-p}\right)}_{\text{a.k.a Log Odds}} = \underbrace{\beta_0}_{\text{intercept}} + \underbrace{\beta_1 X + \varepsilon}_{\substack{\text{error term} \\ \text{change of Y} \\ \text{associated with} \\ \text{1-unit change in X}}}$$

### 2. Data Partitioning

- **Training Set:** 40% of the data.
- **Validation Set:** 30% of the data.
- **Testing Set:** 30% of the data.

## Annex C: Acronyms

Acronym	Full Form
DFS	Digital Financial Services
DFAR	Digital Financial Access Ratio
GSMA	Global System for Mobile Communications
NFIS	National Financial Inclusion Strategy

## Annex D: Graphs and Plots



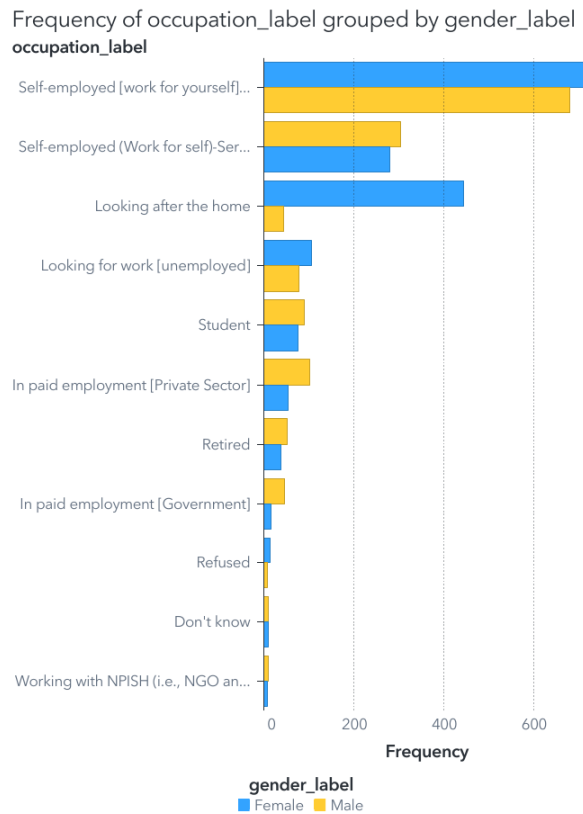
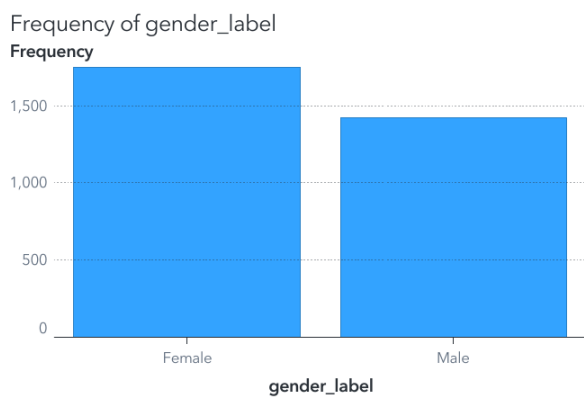
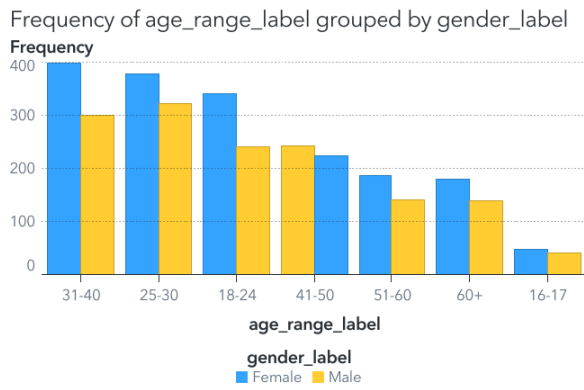


Figure 5 EDA Age, occupation , gender

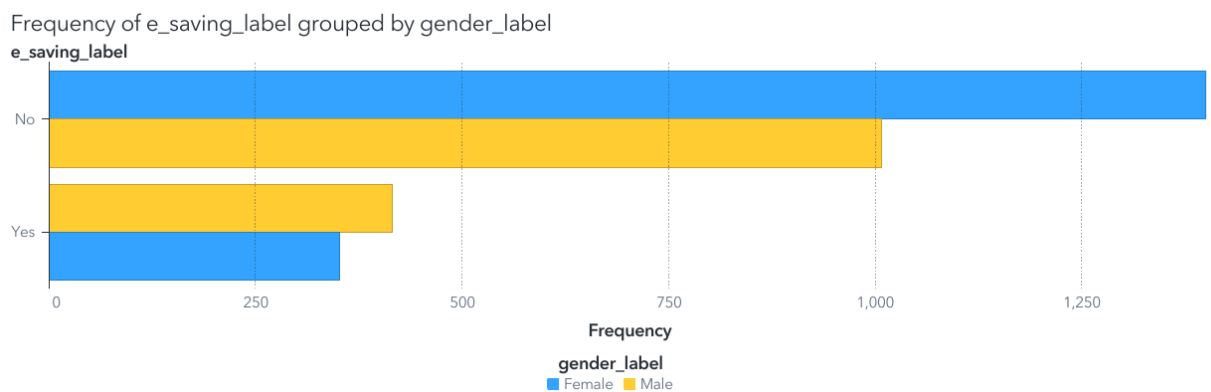
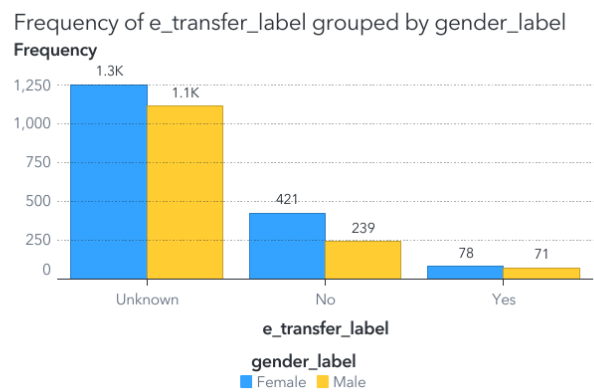
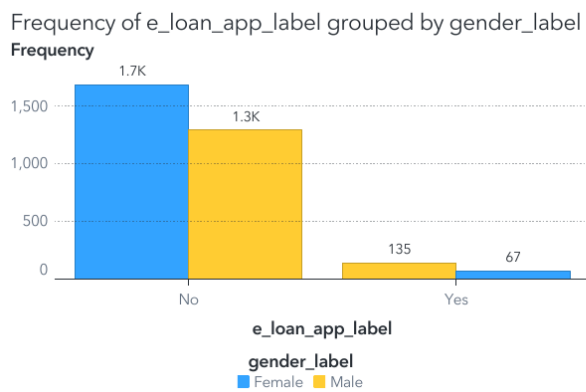
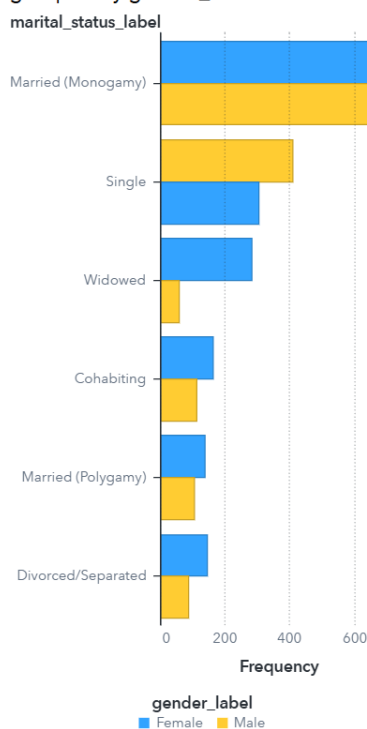
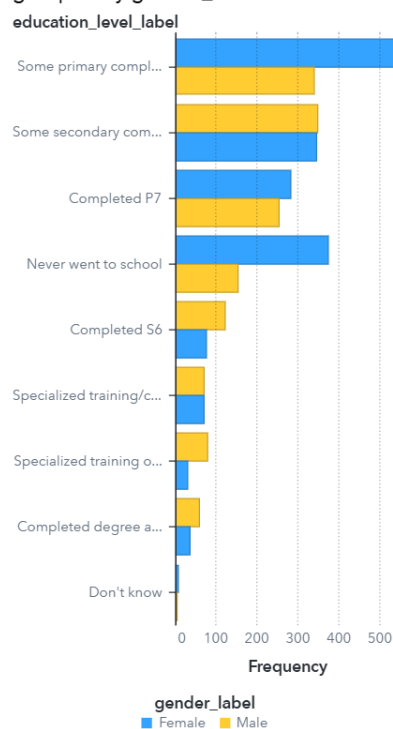


Figure 6 EDA e-loan, e-transfer, e-saving

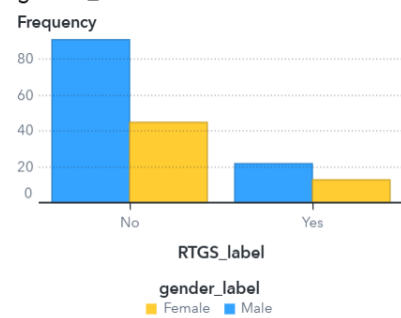
Frequency of marital\_status\_label grouped by gender\_label



Frequency of education\_level\_label grouped by gender\_label



Frequency of RTGS\_label grouped by gender\_label



Frequency of EFT\_label grouped by gender\_label

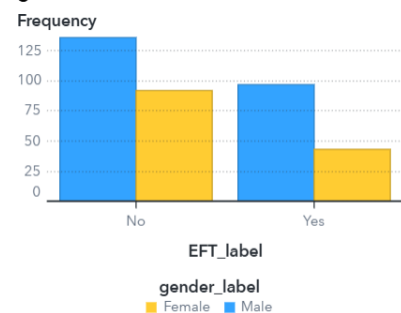
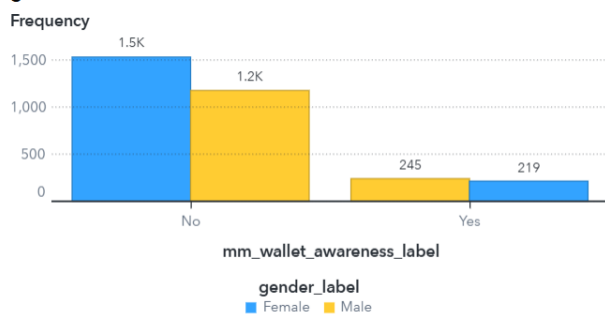
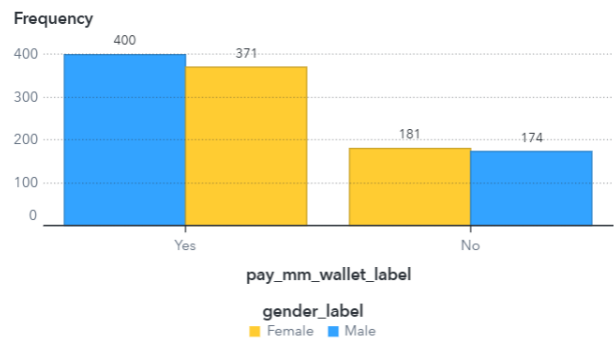


Figure 7 EDA marital status , education level , rtgs , eft

Frequency of mm\_wallet\_awareness\_label grouped by gender\_label



Frequency of pay\_mm\_wallet\_label grouped by gender\_label



Frequency of e\_loan\_awareness\_label grouped by gender\_label

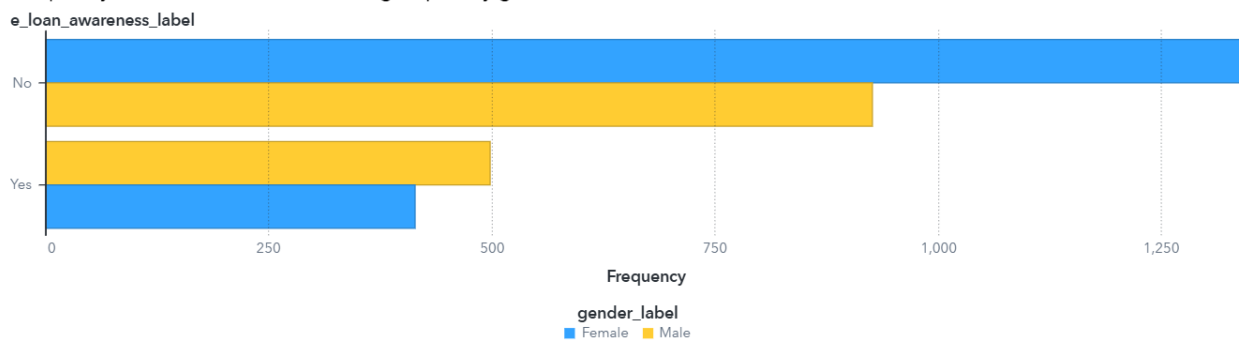


Figure 8 mobile money awareness, pay and e-loan awareness

Frequency of fin\_service\_dist

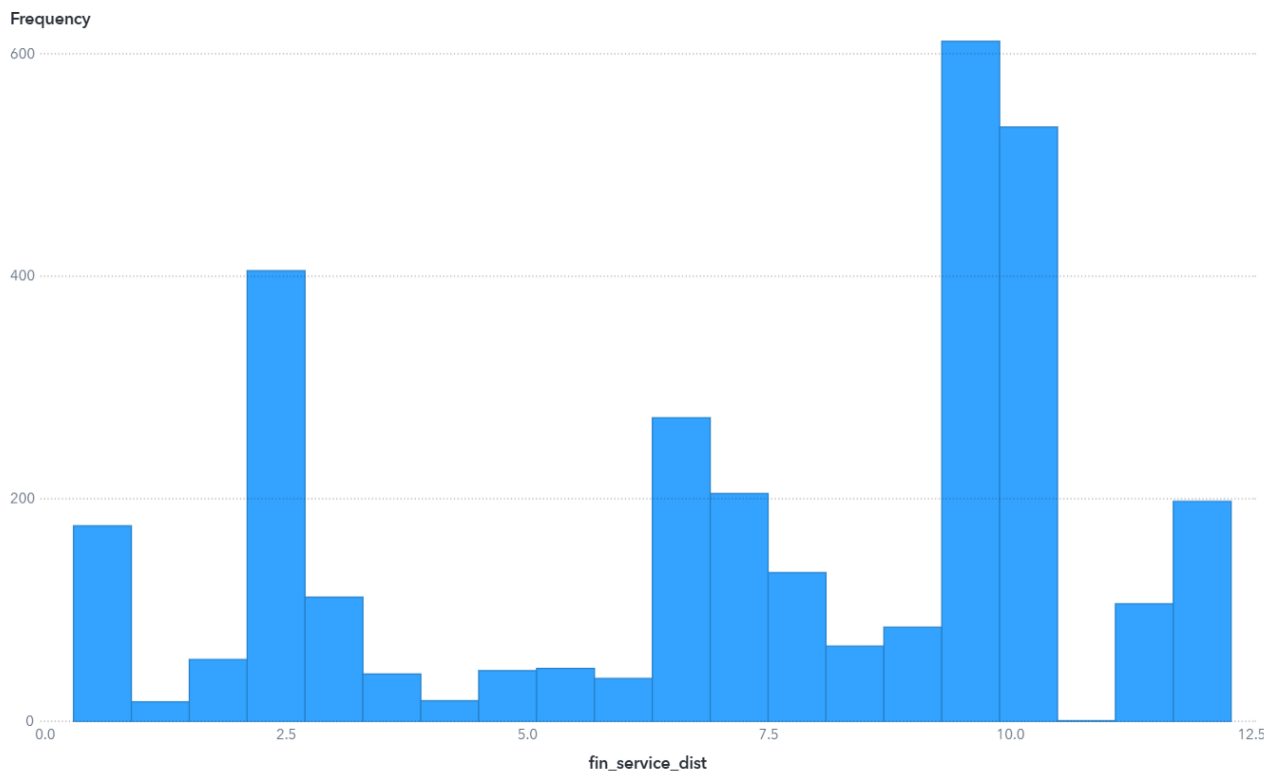
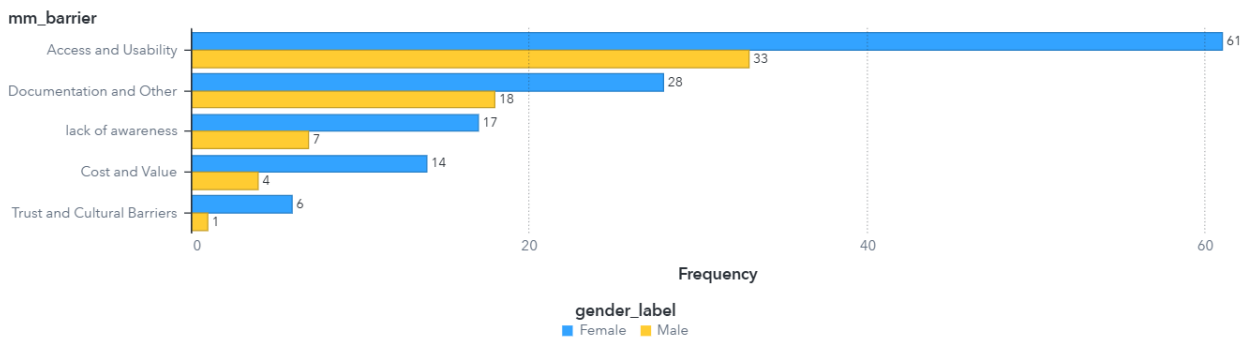


Figure 9 Distance from financial services

Frequency of mm\_barrier grouped by gender\_label



Frequency of mm\_reason grouped by gender\_label

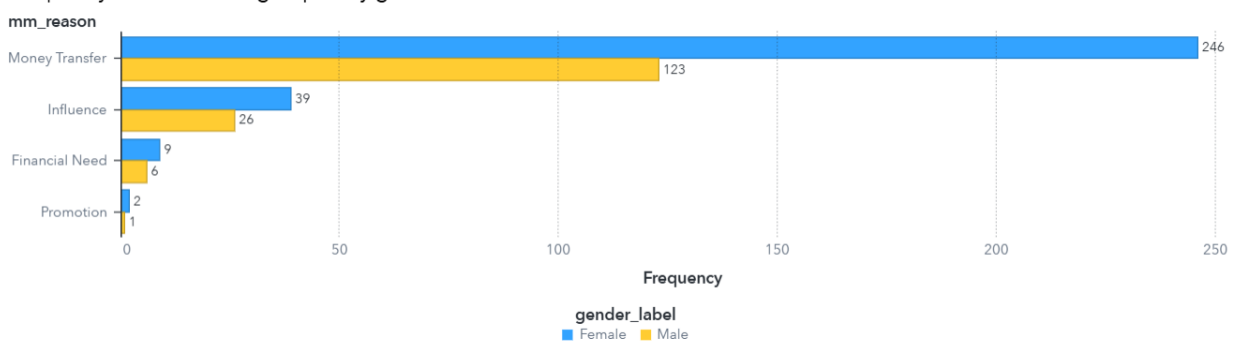


Figure 10 mobile money barriers to use and reasons to use

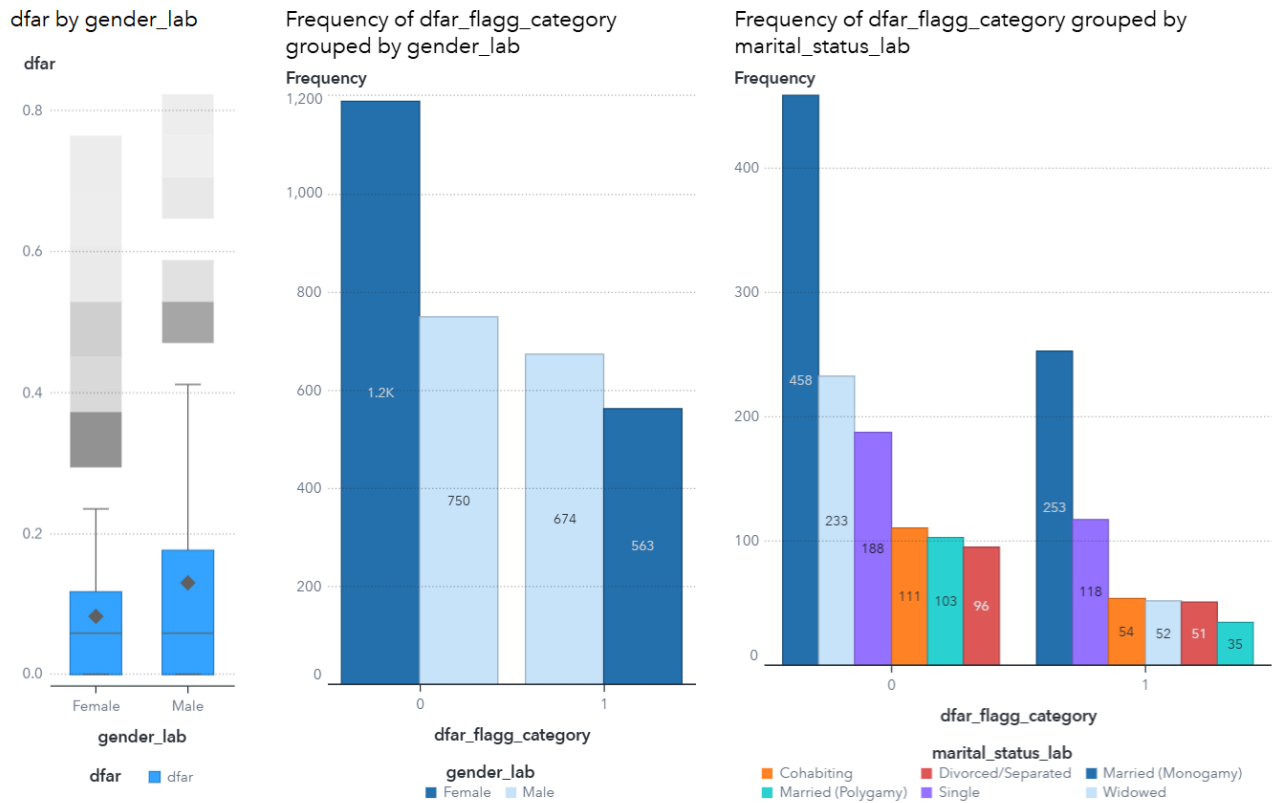


Figure 11 DFR and DFAR flagged

## Logistic Regression of dfar overall

Logistic Regression dfar\_flagg\_category Event: 1 Fit: Test Misclassification Rate (Event) 0.0682 Observations: 3.2K of 3.2K

< Fit Summary Odds Ratio Residual Assessment >

## Odds Ratio Plot

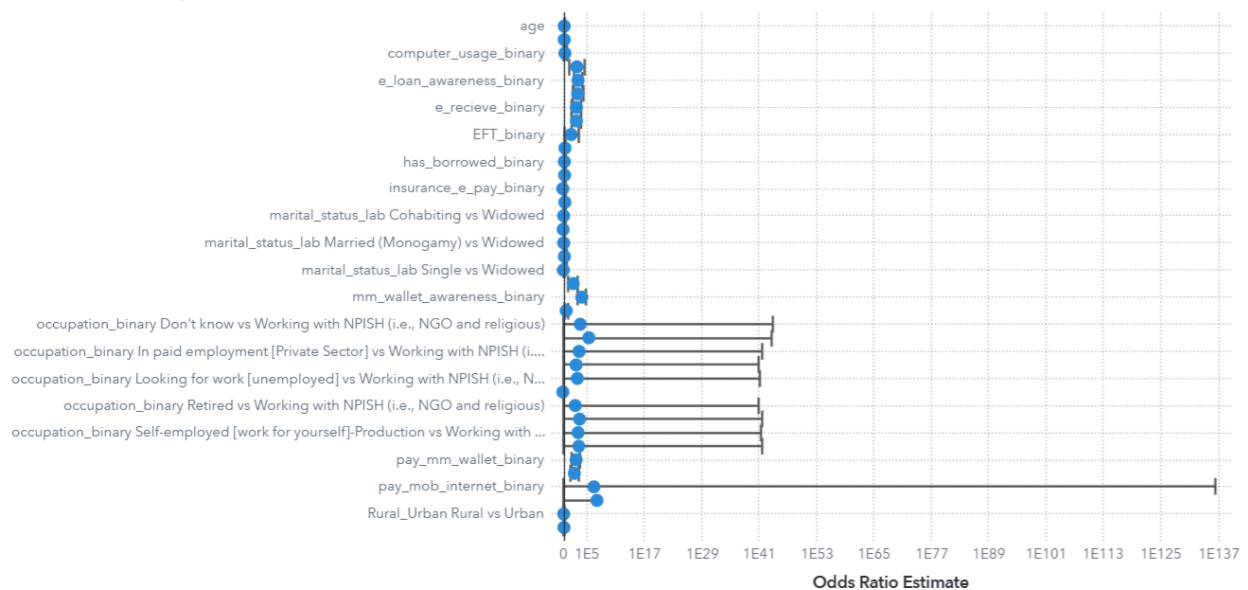


Figure 12 Overall Odds Ratio

Logistic Regression of dfar overall

Logistic Regression dfar\_flagg\_category Event: 1 Fit: Test Misclassification Rate (Event) 0.0682 Observations: 3.2K of 3.2K



Figure 13 Overall Residual Plot

Logistic Regression of dfar overall

Logistic Regression dfar\_flagg\_category Event: 1 Fit: Test Misclassification Rate (Event) 0.0682 Observations: 3.2K of 3.2K



Figure 14 Overall Confusion Matrix

## Logistic Regression of dfar females

Logistic Regression **dfar\_flagg\_category** Event: 1 ▾ Fit: Validation KS (Youden) 0.8595 ▾ Observations: 1.1K of 3.2K

< Fit Summary Odds Ratio Residual Assessment >

### Odds Ratio Plot

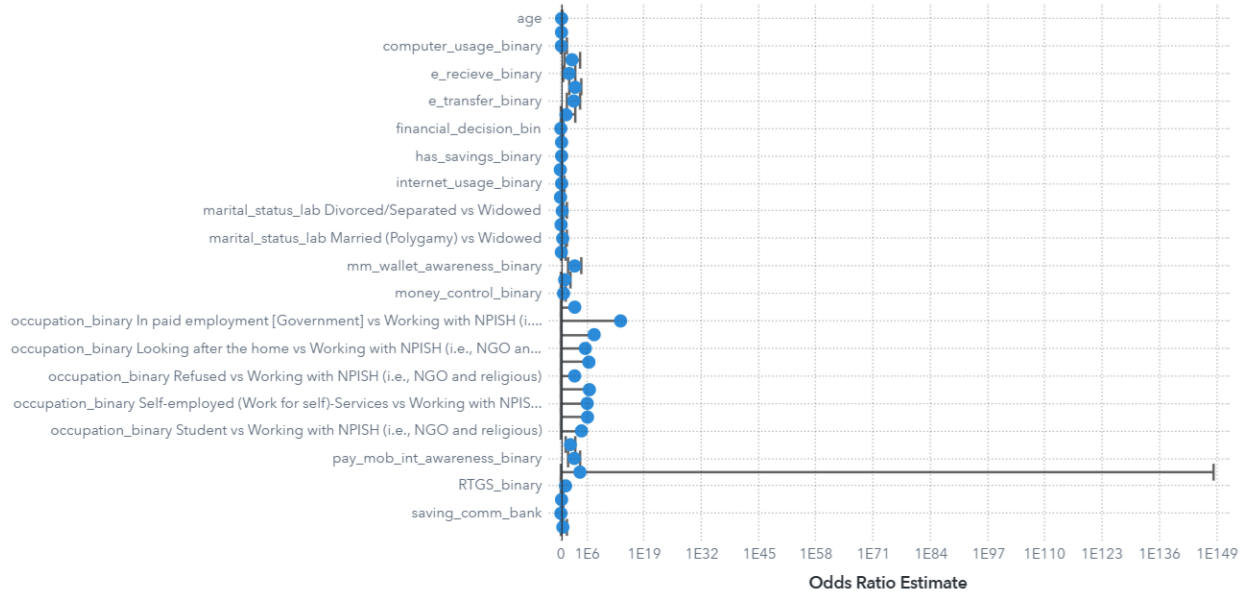


Figure 15 Female Odds Raio

## Logistic Regression of dfar females

Logistic Regression **dfar\_flagg\_category** Event: 1 ▾ Fit: Validation KS (Youden) 0.8595 ▾ Observations: 1.1K of 3.2K

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### Residual Plot

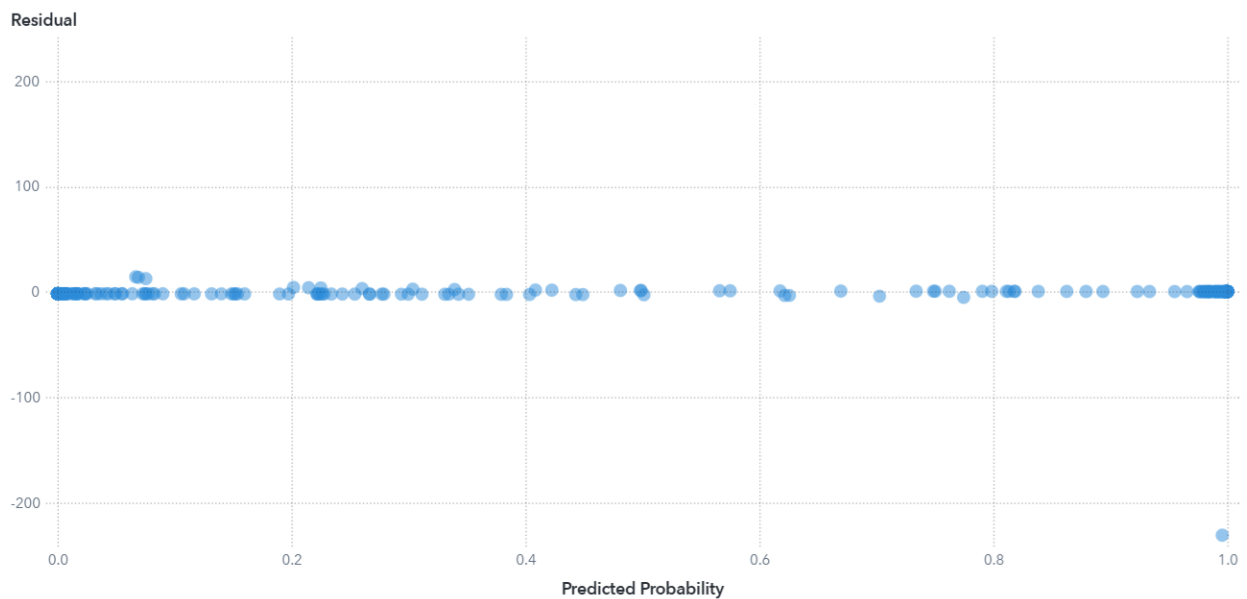


Figure 16 Female Residual Plot

## Logistic Regression of dfar females

Logistic Regression **dfar\_flagg\_category** Event: 1 ▾ Fit: **Validation KS (Youden) 0.8595** ▾ Observations: 1.1K of 3.2K

< Fit Summary Odds Ratio Residual Assessment >

### Confusion Matrix ①

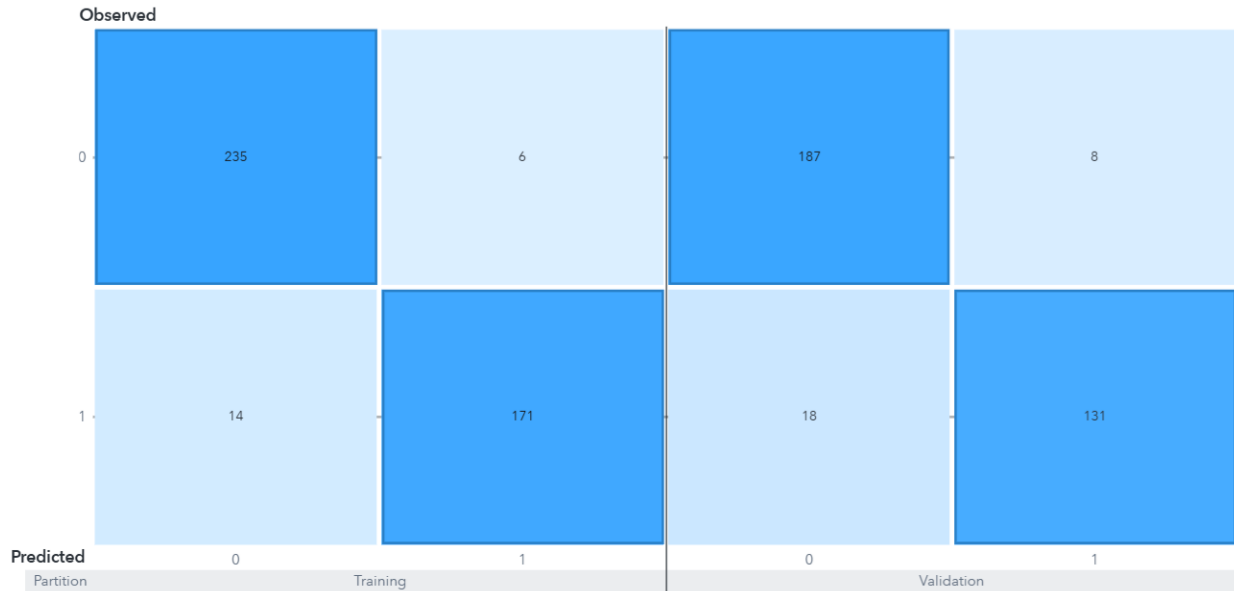


Figure 17 Female confusion matrix

## Logistic Regression of dfar Males

Logistic Regression **dfar\_flagg\_category** Event: 1 ▾ Fit: **Test Misclassification Rate (Event) 0.0366** ▾ Observations: 1.4K of 3.2K

< Fit Summary Odds Ratio Residual Assessment >

### Odds Ratio Plot ①

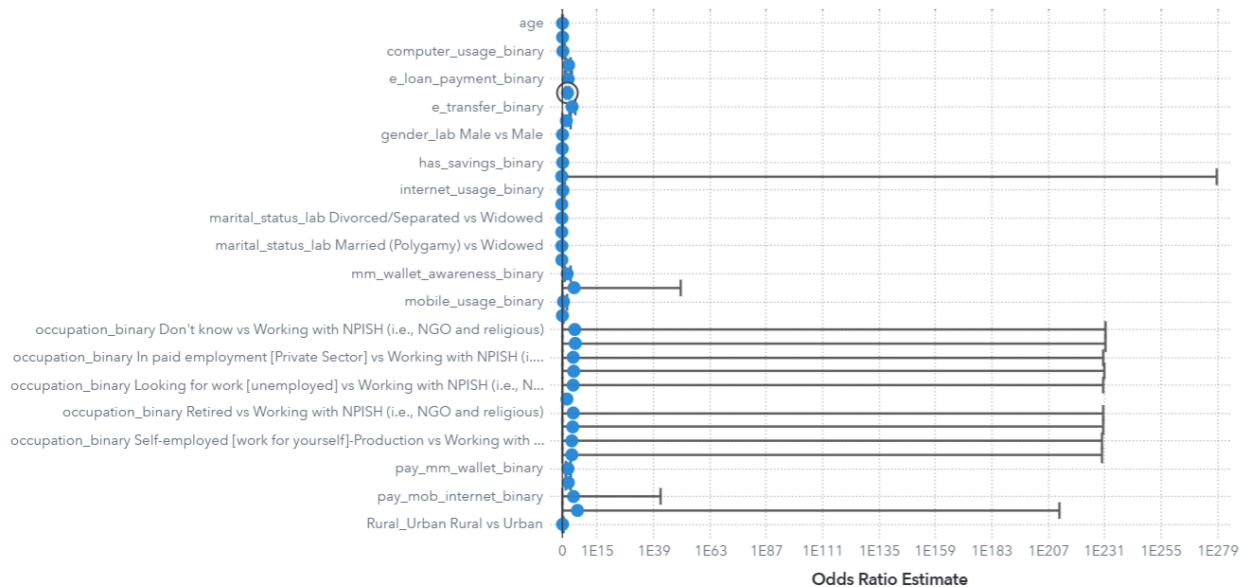


Figure 18 Male Odds ratio



Logistic Regression of dfar Males

Logistic Regression dfar\_flagg\_category Event: 1 Fit: Test Misclassification Rate (Event) 0.0366 Observations: 1.4K of 3.2K

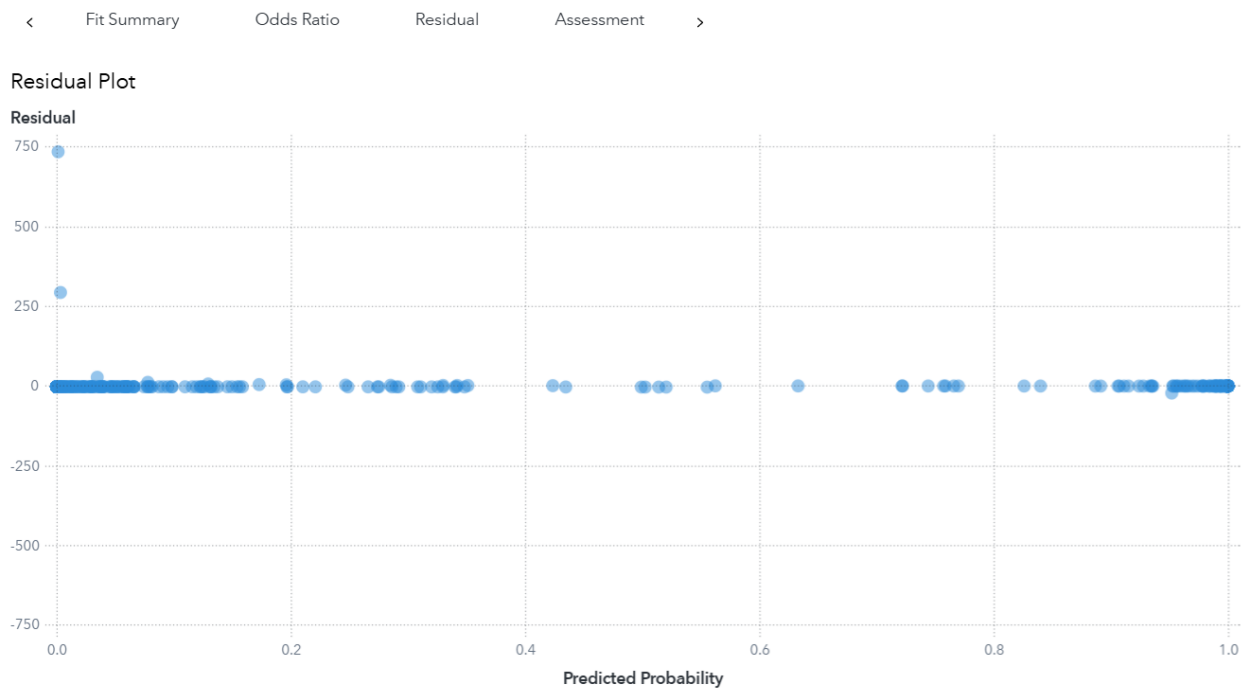


Figure 19 Male Residual Plot

Logistic Regression of dfar Males

Logistic Regression dfar\_flagg\_category Event: 1 Fit: Test Misclassification Rate (Event) 0.0366 Observations: 1.4K of 3.2K



Figure 20 Male Confusion Matrix

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