Mobile Money and Financial Inclusion: An Analysis Report

Group 68

I. INTRODUCTION

This project aims to demonstrate how the application of a Business Intelligence (BI) tool, specifically Microsoft Power BI, can enable users to extract valuable insights from complex datasets and present them through data visualisations and interactive dashboards that support data-driven decision-making. In this project, we will apply Power BI to the World Bank's Global Findex Database, which contains a wide range of financial inclusion indicators throughout the world, in various countries over time.

This report has four main sections. The Background provides an overview of the dataset and introduces the key questions that will guide the analysis. The Methodology outlines the approach to cleaning, preparing, and analysing the data for solving the problems. The Solution describes the implementation steps, including how we develop the dashboard and what data we use, while the Discussion explains how these visualisations provide insights that address the problems. Finally, the Conclusion evaluates the result and reflects upon the challenges as well as ideas for future improvements.

II. BACKGROUND

The dataset used for this report is the Global Findex Database 2025 version which contains nationally representative survey data for the years 2011, 2014, 2017, 2021, and 2024, across the world (World Bank Group, 2025). This dataset provides insights into how adults interact with financial services throughout 141 different economies from 2011 to 2024 (World Bank Group, 2025). The aim of this database is to promote financial inclusion around the world and provide data to track the progress of the Sustainable Development Goals set by the United Nations (World Bank Group, 2025). In the 2025 Global Findex Report the primary focus of discussion surrounded how digital technology, through the use of mobile phones and the internet, were significantly increasing financial inclusion around the world, by providing more people around the world with digital financial service solutions (World Bank Group, 2025).

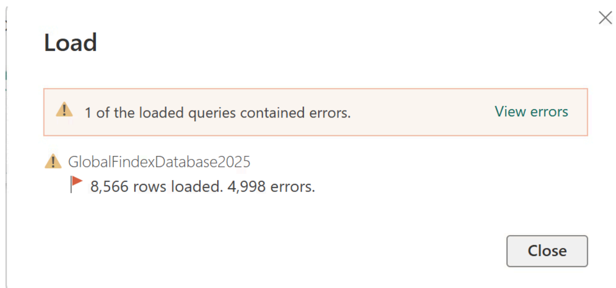
With this in mind, our group has decided to focus on exploring the impacts that mobile money accounts have had around the world. We aim to discover how mobile money is changing and/or increasing financial inclusion globally? As well as more specifically, how is the increase of digital financial services through mobile money accounts affecting low-income and middle-income countries?

The motivation and importance behind this question stem from the fact that financial inclusion is one of the most essential indicators in international development, and even in 2017 roughly 1.7 billion adults did not have a mobile money or financial institution account, classifying them as ‘unbanked’ (Duvendack & Mader, 2020). This staggering statistic of the number of ‘unbanked’ adults measured in 2017 comes after over 500 million adults opened an account and were no longer ‘unbanked’ from 2014 to 2017 (Duvendack & Mader, 2020).

III. METHODOLOGY

To effectively answer our research question, the *GlobalFindexDatabase2025.csv* dataset must first be properly loaded, inspected, cleaned, and transformed before being used for developing the visualisation. All data cleaning and transformation techniques applied in this project are based on the materials covered in Topic Seven: Your Power BI Task (T. Reed, online lecture, 15 September 2025).

Step 3.1: Data Loading and Initial Cleaning
We began our process by opening a new blank report in Power BI and importing the dataset. This was done by selecting Home -> Get Data -> Text/CSV, browsing to the dataset's location, ensuring that the delimiter is "Comma", and clicking Load. Once the data was imported, a quick inspection revealed that the raw dataset contained 8,566 rows but also 4,998 errors due to missing values.



When we clicked on the "View errors" warning, the Power Query Editor opened and showed that the dataset contained 438 columns in the left bottom corner. After examining the accompanying *GlobalFindex2025-glossary.xls* file, we decided to retain 35 key variables. These include descriptive columns, such as \`countrynewwb\` and \`incomegroupwb24\`, as well as the main indicators of financial inclusion, including \`account_t_d\`, \`fiaccount_t_d\`, and \`mobileaccount_t_d\`. In addition, we selected several variables that reflect mobile money usage, such as \`fin13aw\` to \`fin13an\`, \`fin13bw\` to \`fin13bn\`, \`fin13cw\` to \`fin13cn\`, and others potentially correlated with mobile money ownership, including \`internet\`, \`con9a\`, \`con10\`, and \`con30a\` to \`con30h\`. Under the "Choose Columns" option, we ticked all selected variables and removed the rest. In addition, we renamed our selected columns with meaningful names that reflect their description as follows:

Original Column Name	Renamed Column
countrynewwb	Country
codewb	Code
year	Year
pop_adult	AdultPopulation
regionwb24_hi	Region
incomegroupwb24	IncomeGroup
group	GroupType
group2	Group
account_t_d	AccountAccess
fiaccount_t_d	BankAccount
mobileaccount_t_d	MobileMoneyAccount
fin17b	SavedMobileMoney
fin13aw	DepositWeekly
fin13am	DepositMonthly

fin13alm	DepositLessMonthly
fin13an	NeverDeposit
fin13bw	SendWeekly
fin13bm	SendMonthly
fin13blm	SendLessMonthly
fin13bn	NeverSend
fin13cw	WithdrawWeekly
fin13cm	WithdrawMonthly
fin13clm	WithdrawLessMonthly
fin13cn	NeverWithdraw
con9a	Smartphone
con10	Whatsapp
internet	Internet
con30a	VoiceMsg
con30b	PhotoMsg
con30c	SocialMedia
con30d	ReadOnlineNews
con30e	OnlineLearning
con30f	OnlineEarning
con30g	OnlineGovService
con30h	OnlineJobSearch

Next, we inspected the `Country` column by clicking the arrow icon and discovered that it contained not only valid country names but also aggregate entries such as “world”, regional groupings like “South Asia” and “Europe & Central Asia (excluding high income)”, and categories based on income level such as “High income” or “Low income”. Since our analysis focuses on country level observations, these non-country rows were removed by clearing their checkboxes in the column filter. Moreover, we also inspected that `Year` column contained 2011, 2014, 2017, 2021, 2022, and 2024. Because entries from 2022 likely reflected late submission for the 2021 reporting period (World, we combined these observations with 2021 to maintain a regular 3-4 year interval. This recoding was performed via Transform -> Replace Values, entering “2022” in Value To Find and “2021” in Replace With input boxes.

Our next step was to examine the data types of all variables to ensure that they matched their intended format. While the `Country` was correctly identified as text and `Year` as a whole number, many numerical variables from `AccountAccess (account_t_d)` to `OnlineJobSearch (con30h)` were still inappropriately stored as text. Since these columns represent proportions expressed in decimal values (e.g. 0.50 for 50%), we simultaneously highlighted them by holding the Ctrl key on the keyboard and applied Transform -> Data Type: Decimal Number.

After converting the data types, several errors appeared in cells containing NA values. To resolve this issue, we again selected these columns at once and used the Replace Values -> Replace Errors function. Under this option, we replaced each error value by filling “null” in the input box. Up until this step, we had ensured that subsequent analyses would not be affected by irrelevant rows and columns as well as data type conversion errors, resulting in a cleaned and consistent dataset.

Step 3.2: Both, Fiaccount_only, and Mobile_account_only Columns Creation

When examining the raw data, we observed that the sum of BankAccount (fiaccount_t_d) and MobileMoneyAccount (mobileaccount_t_d) does not equal AccountAccess (account_t_d). This suggests that most individuals who have a financial institution account may also have a mobile money account, resulting in some overlap between the two groups.

countryr	codewb	account	fiaccour	mobilea	BOTH	fiaccoun	mobile_
Afghanista	AFG	0.100	0.100	0.003	0.003	0.097	-
Argentina	ARG	0.502	0.502	0.004	0.004	0.498	0.000
Armenia	ARM	0.177	0.172	0.007	0.002	0.170	0.005
Banglades	BGD	0.310	0.291	0.027	0.008	0.283	0.019

To represent this relationship more clearly, we create three new columns to indicate:

1. Individuals who have both types of accounts,
2. Individuals who have a financial institution account only, and
3. Individuals who have a mobile money account only.

Create the three new columns by transforming data in a cleaned dataset with new name and related columns and observations, and then change to numeric data types.

```
= Table.AddColumn(#"Renamed Columns", "Both", each [BankAccount]+ [MobileMoneyAccount] -
```

g	1.2 OnlineEarning	1.2 OnlineGovService	1.2 OnlineJobSearch	ABC 123 Both

Both = BankAccount + MobileMoneyAccount − AccountAccess

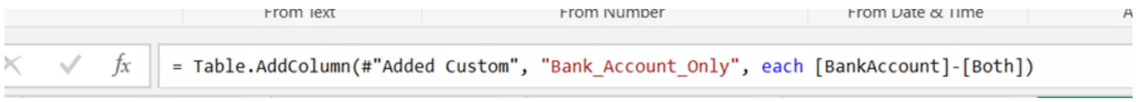
However, we found an interesting point here is in 2011, when mobile bank money accounts were not available yet so data for the variable are null or NA. Whenever we calculate NA the result will give NA. If it was the case the bank account will get NA even if it has data. To solve this problem, we apply the if-else function and it gives the correct output.

```
= Table.AddColumn(
        #"Added Custom",
   "Fiaccount_Only",
        each if [Both] = null then [BankAccount] else [BankAccount] - [Both]
)
```

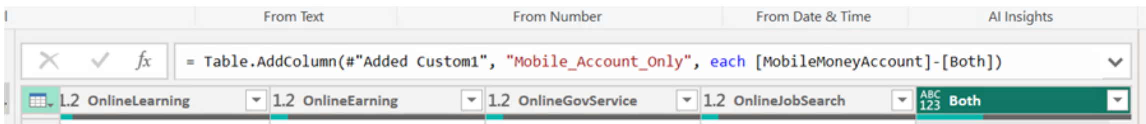
```
:om1", each ([Year] = 2011))
```

1.2 OnlineJobSearch	ABC 123 Both	ABC 123 Fiaccount_Only
null	null	0.090050121
null	null	0.282681244
null	null	0.332861125
null	null	0.392035423
null	null	0.33130217
null	null	0.174868727
null	null	0.990648467

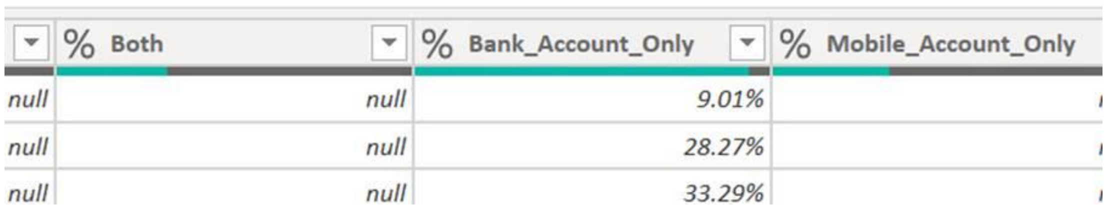
Column Bank_Account_Only = BankAccount – Both



Column Mobile_Account_Only = MobileMoneyAccount – Both



Next step we change the column names and suitable data.



Both	Bank_Account_Only	Mobile_Account_Only
null	null	9.01%
null	null	28.27%
null	null	33.29%

Step 3.3: Data Transformation for the Usage of Mobile Money

Firstly, a referenced query of the main dataset was created (Right-click → Reference), renamed as Usage, thereby maintaining the integrity of the original data while facilitating transformation in a separate query. Only the relevant variables were selected, including Country, IncomeGroup, Year, and twelve mobile money usage related columns (like NeverDeposit, DepositWeekly, etc). These columns were then renamed using a consistent pattern (like Deposit-Never, Deposit-Weekly) to facilitate later separation into distinct categorical variables.

Later, the twelve mobile money usage related columns were unpivoted (Transform → Unpivot Columns), converting the wide dataset into a long format. This operation produced two new columns, Attribute (e.g., *Deposit-Weekly*) and Value, suitable for tidy data principles and subsequent visual analysis. The Attribute column was split by the delimiter "–", producing two new variables: Usage (Deposit, Send, or Withdraw) and Frequency. To enhance readability, inconsistent frequency labels were standardised. Specifically, the value LessMonthly was replaced with the full phrase "Less than once a month".

Next, a custom column "FreqOrder" was added to preserve the logical order of frequency categories and prevent alphabetical sorting in Power BI visualisations (Add Column → Custom Column). The column was created using the following M-code:

```
if [Frequency] = "Never" then 1
else if [Frequency] = "Less than once a month" then 2
else if [Frequency] = "Monthly" then 3
else if [Frequency] = "Weekly" then 4
else null
```

The column type was defined as *Whole Number* to enable numerical sorting in subsequent stages.

Furthermore, we created a tiny helper UsageType table which contains the three usage categories, “Deposit”, “Send”, and “Withdraw”, so that the chart created in the Solution step always displays them in the X-axis even when a selected country or region has no rows. In the Model View, we navigated to Home -> Enter Data, added three rows representing the usage type, and renamed the column to “Usage”. Additionally, we created a New Measure that pulls value from the Usage table with the DAX:

```
Average of Value =
VAR selUsage = SELECTEDVALUE(UsageType[Usage])
RETURN
COALESCE(CALCULATE(AVERAGE(Usage[Value]), Usage[Usage] = selUsage), 0)
```

This measure recomputes the average value for each usage type in the Usage table. We wrapped this calculation in COALESCE(..., 0) so that if no rows match and the expression returns null, the visual shows 0 instead of disappearing (Microsoft, 2025).

Step 3.4: IncomeGroupOrder Table Creation

By default, Power BI sorts text alphabetically in either ascending or descending order. We created a new *IncomeGroupOrder* table to impose logical order instead of an alphabetical one, so that the Income Group slicer correctly displays High income -> Upper middle income -> Lower middle income -> Low income.

To create this table, we navigated to the Model View, selected New Table, and entered the DAX:

```
IncomeGroupOrder =
DATATABLE("incomegroup", STRING, "SortOrder", INTEGER,
  {
    {"High income", 1}, {"Upper middle income", 2}, {"Lower middle income", 3}, {"Low income", 4}
  })
```

This formula created a data table that has two columns, a string “incomegroup” and an integer “SortOrder”, and then mapped each income group label to a numeric rank of 1 to 4. Next, we dragged the IncomeGroupOrder[incomegroup] column and connected it with the “incomegroup” in both *GlobalFindexDatabase2025* and *Usage* tables to form one-to-many relationships. Finally, we navigated to the Table view, selected the *IncomeGroupOrder* table in the Data panel, highlighted the “incomegroup” column and sorted the order by “SortOrder” in the Column tools -> Sort by column menu.

SortOrder	incomegroup
1	High income
2	Upper middle income
3	Lower middle income
4	Low income

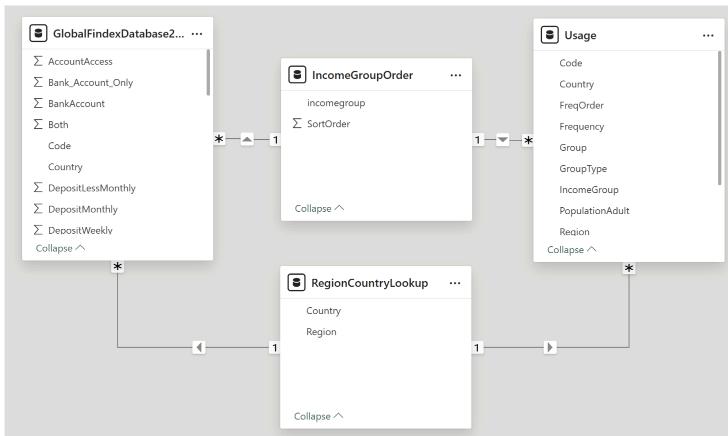
Step 3.5: RegionCountryLookup Table Creation

In order to make the Region+Country slicer reliably filter all visuals, especially those sourced from the newly created Usage table, we built a *RegionCountryLookup* table that connects *GlobalFindexDatabase2025* and *Usage* in the data model.

To create this lookup table, we navigated to the Model View, selected New Table, and entered the DAX:

```
RegionCountryLookup =
DISTINCT (UNION(
      SELECTCOLUMNS(GlobalFindexDatabase2025, "Region", [Region], "Country", [Country]),
      SELECTCOLUMNS(Usage, "Region", [Region], "Country", [Country])))
```

Using the SELECTCOLUMNS function, we first select only the Region and Country columns from each table, *GlobalFindexDatabase2025* and *Usage*, which also standardised the column names to "Region" and "Country". These two newly created columns are then stacked with UNION, before being filtered to produce only unique (Region, Country) combinations with DISTINCT function. Finally, we created one-to-many relationships from *RegionCountryLookup* to both *GlobalFindexDatabase2025* and *Usage* tables.

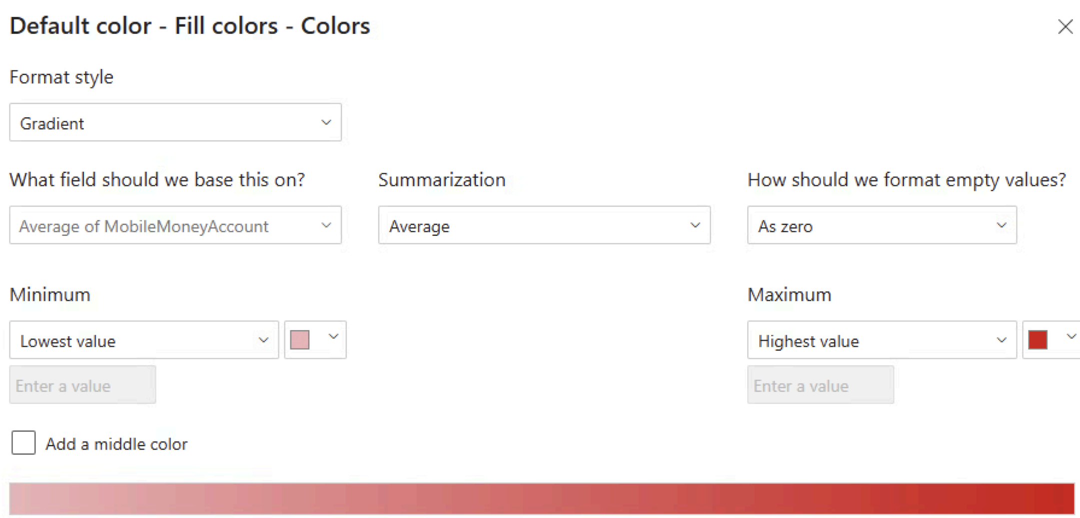


IV. SOLUTION

In this section, we describe how our Power BI dashboard was built and what data it used. To address our research question, we developed four main visuals and two slicers. First, a filled map shows the global distribution of mobile money adoption. Second, a stacked bar chart tracks the proportion of financial access, including traditional banking, mobile money, and both across years. Third, a clustered bar chart summarises the frequency of mobile money usage, such as deposit, send, and withdraw money. Finally, an R script correlation plot explores factors associated with mobile money adoption. To support drilling down and up through data, we introduced an Income Group and Region-Country slicers.

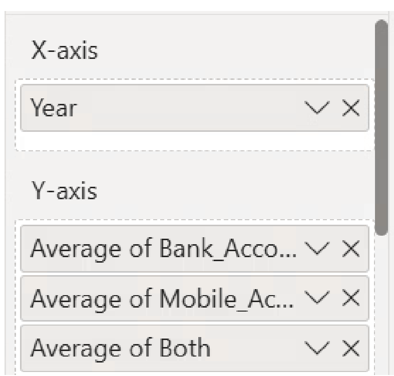
4.1. Filled Map

Different types of map visuals are available to use in Power BI. In **Topic Seven: History of BI Tools**, the lecture and lab both covered the usage of the map, which just shows data points on a map usually as circles or dots of differing size to explain the data. In **Topic Eight: Advanced Visuals and Coding,** the filled map was covered, which can be used to in our case to fill each country from our dataset with a different intensity, based on the colour scale, to give an overview of the average percentage of adults (15+) per country that have a mobile money account. For this visual the 'Location' is given by the 'Country' column and the 'Tooltips' is given by the average of the 'MobileMoneyAccount' column which gives the percentage of adults (15+) that have a mobile money account. In order to easily depict the difference to the viewer of the dashboard in average mobile money usage percentage for each country, the map was formatted by going to the 'Format visual' section, clicking on 'Fill colors', and the 'fx'. Here the ‘Format style’ was set to ‘Gradient’, the field was set to the average of ‘MobileMoneyAccount’ and the ‘Summarization’ was set to ‘Average’, instead of the default ‘Sum’. Lastly, the minimum value was set to a low intensity of the hue red, and the maximum was set to a high intensity of the hue red, each referencing the lowest and highest values respectively. This colour scale was used as it easily helps the viewer to differentiate between the countries that have low, moderate, and high average mobile money account usage. The countries on the map are white and the ocean (background) is blue so a colour that is easily identifiable against this must be used, which is why red was chosen. Additionally, using a colour scale based on different intensities of the same hue is much easier for the viewer to naturally understand than a colour scale based on two different colours or hues to represent the minimum and maximum values. This map also works alongside all the options presented to the user in the slicer in this dashboard.

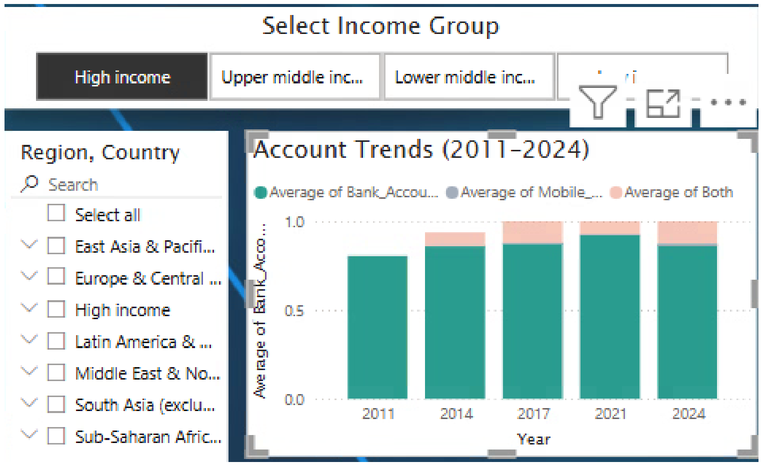


4.2. Stacked Column Chart

The bar plot was introduced in **Topic Seven: History of BI Tools,** section Creating the visuals (T. Reed, lecture,2025). To answer the question, we would like to use a stack bar chart to showcase the trend by X-axis with year variable, Y-axis with three types of account. In a single bar will capture differ type of account. This plot is built by following steps. On the visual panel we choose the stack bar chart, and choose the X-axis as year, Y-axis as three types of accounts in which we just created new columns. Then change the year visual from continuous to separate year for each bar. It gives us better visuals.



Subsequently, we add a region, country slicer and an income group slicer so when we click on a single region and income group type it gives us corresponding data. From this data, we can delve in the connection between mobile money accounts and differ areas and income levels.



4.3. Clustered Bar Chart

A bar chart was introduced in **Topic Seven: History of BI Tools,** section Creating the visuals (T. Reed, lecture, 2025). To answer the usage of mobile banking, we would like to imply a clustered bar chart to showcase the usage of mobile deposit, send, and transfer. It will capture different frequencies of usage: weekly, monthly, less than once a month, and never.

To explore behavioural differences in mobile money use across different income level countries, several steps need to be taken for Power BI visualisation using the transformed dataset: The Frequency field was configured to sort by the FreqOrder column (Column Tools → Sort by Column → FreqOrder). This ensured a logical ordering in visual outputs: *Never → Less than once a month → Monthly → Weekly*. A clustered bar chart was created with, drop UsageType[Usage] to the X-axis, UsageType[Average of Value] measure to the Y-axis and Usage[Frequency] for legend. This configuration allowed clear, side-by-side comparison of deposit, send, and withdrawal behaviours across frequency levels. Interactive slicers were incorporated to filter data dynamically by Country, and IncomeGroup. These were connected to the main table and an auxiliary table (incomeGroupOrder) to ensure consistent sorting and filtering behaviour across visuals.

4.4. R Script Visual: Correlation Plot

The correlation plot was built using the R script visual in Power BI, as explained in Topic Eight: *Programming and BI* lecture material (T. Reed, online lecture, 22 September 2025). To enable this functionality, Power BI must first be connected to a valid R installation within UniApps by navigating to *File -> Options and settings -> Options -> R scripting* and selecting the R directory located at *C://Program Files/R/R-4.5.1*. Once the connection was established, we inserted an R script visual from the Visualizations pane and populated it with selected variables from the *GlobalFindexDatabase2025* table, including MobileMoneyAccount, Internet, Smartphone, Whatsapp, VoiceMsg, PhotoMsg, SocialMedia, ReadOnlineNews, OnlineLearning, OnlineEarning, OnlineGovService, and OnlineJobSeach.

Within the R script editor, we first cleared the default comments. The *corrplot* package (Wei & Simko, 2024) was then installed, and then commented out to prevent repeated execution. Finally, the package was loaded using the command library(corrplot).

Next, we built our initial correlation matrix using the following R code:

```
corr_matrix <- cor(dataset)
corrplot(corr_matrix)
```

The correlation matrix was then recalculated using the “pairwise.complete.obs” option to ensure that missing values are handled without discarding the entire rows (R Documentation, n.d.). We also specified Pearson method to compute correlation coefficients on a scale from -1 to 1. Moreover, we replaced any null values with zero to improve robustness of the analysis and ensure consistency across the dataset. The R code for this corr_matrix modification is:

```
corr_matrix <- cor(dataset, use = "pairwise.complete.obs", method = "pearson")
corr_matrix[is.na(corr_matrix)] <- 0
```

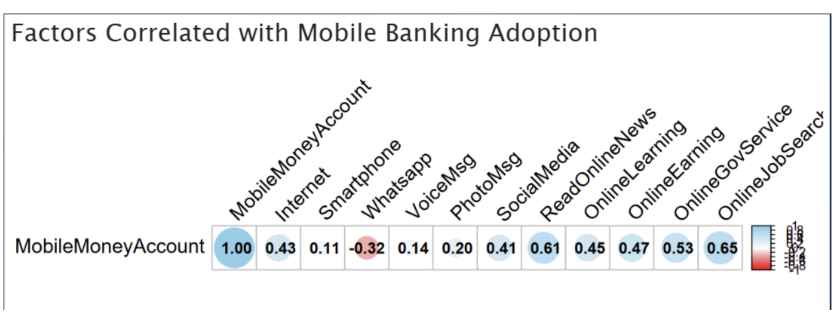
Since the focus of our analysis is mobile account adoption, we created a subset that displays only the correlations between mobile accounts and the remaining variables using the [ ] operator (Datacamp, n.d.). The R code for creating this subset is:

```
mobile_df <- corr_matrix["MobileMoneyAccount", , drop = FALSE]
```

Finally, we replaced the data from corr_matrix to the newly created subset mobile_df, added a title, and refined the correlation plot design by adjusting the parameters. Circles were used to represent correlation magnitude, where size indicates strength and color specifies direction. Labels were adjusted by increasing their size (tl.cex), rotating to 45 degree (tl.srt), and changing font colour (tl.col). The legend was scaled from -1 to 1 using col.lim, and correlation coefficients were displayed directly inside the circle using addCoef.col. In addition, we applied a custom colour palette that transitions from red (negative) through white (neutral) to sky blue (positive). The final R code that reflect these modifications is:

```
corrplot(mobile_df, method = "circle", is.corr = FALSE, tl.cex = 1.25, tl.srt = 45,
        tl.col = "black", col.lim = c(-1, 1), addCoef.col = "black",
        col = colorRampPalette(c("red", "white", "skyblue"))(200))
```

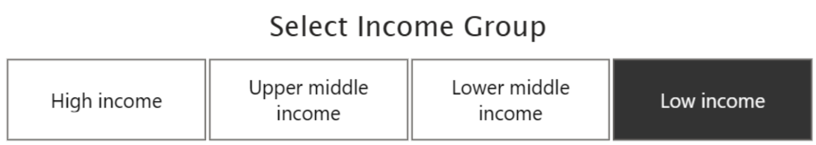
The final correlation plot is now presented as a single row, displaying only the correlation between Mobile Account and other variables with clear and readable labels. Moreover, the combination of circle size, color, and text to represent coefficients helps improve interpretability.



4.5. Income Group Tile Slicer

To allow users to interactively explore the visualisations by income group, we introduced a tile slicer. It was created by selecting the Slicer icon from the Visualizations pane and assigning the `incomegroup` field from the newly created *IncomeGroupOrder* table. Under *Slicer settings*, we changed the style to <u>Tile</u>, and the selection type was set to <u>Multi-select with CTRL</u>. The slicer header was then turned off to avoid redundancy.

Next, under *General -> Title*, we turned on the title and renamed it to "Select Income Group". Under the *Effects* tab, the shadow was enabled to improve presentation. At this stage, the slicer still contains a (Blank) value. To remove this, we apply advanced filtering in the Filters pane by setting the conditions to "is not blank" AND "is not empty" before clicking *Apply filter*. After these modifications, the slicer is fully interactive, visually polished, and displays the income groups in the correct logical order.



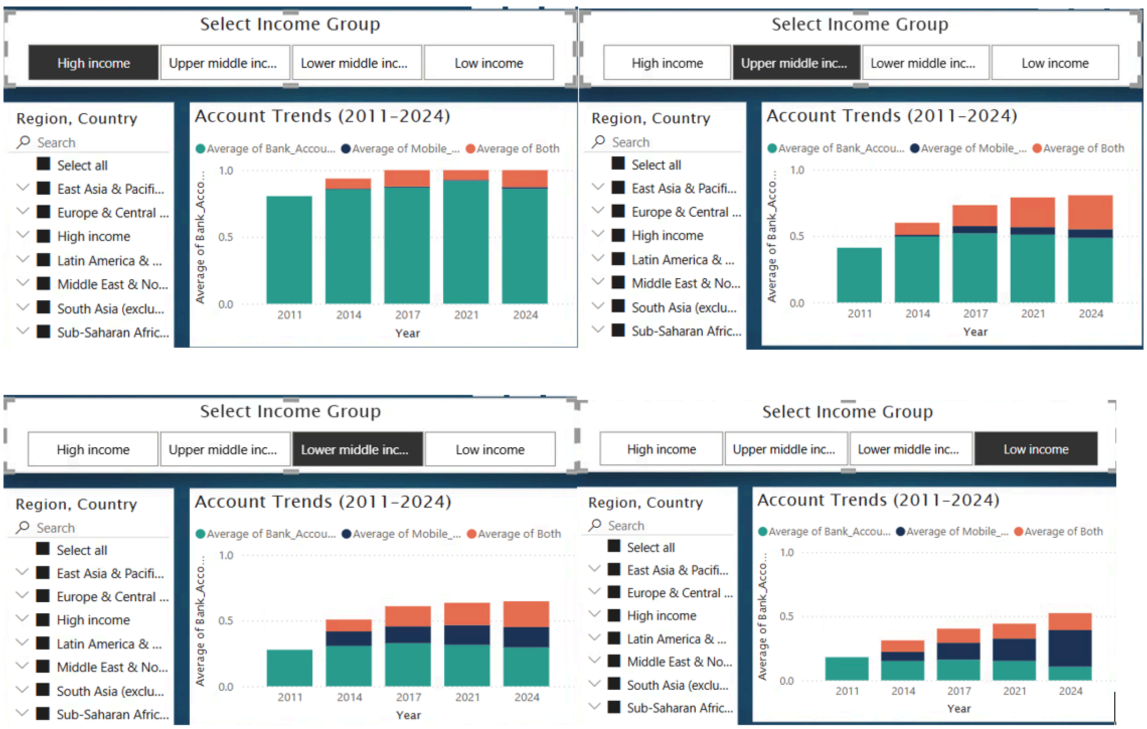
4.6. Region + Country Vertical List Slicer

To allow users to further drill down the focus of the analysis in a region or country level, we introduced a region + country vertical list slicer. The process began by selecting the Slicer icon from the Visualizations pane and assigning `Region` and `Country` from the *RegionCountryLookup* table. Under the *Slicer setting*, we set the style as <u>Vertical list</u> and the selection type as <u>Multi-select with CRTL</u>. Finally, we enabled the search box by clicking on the … (More options) -> Search.

V. DISCUSSION

5.1. Bank Accounts and Mobile Money Account

In general, the use of mobile bank accounts has an upward trend between income groups and regions.

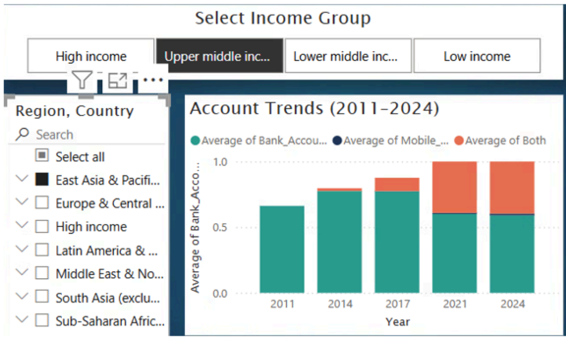


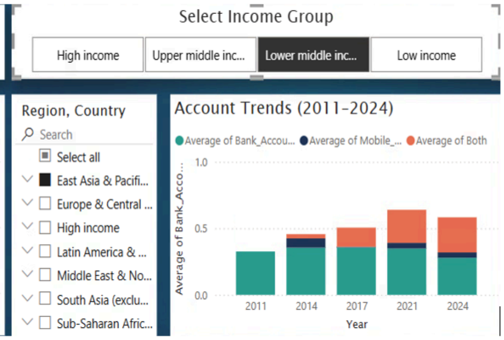
The stacked bar chart shows financial account ownership has grown from 2011 to 2024 across all income groups. High-income groups remain dominated by traditional bank accounts, while mobile money is increasingly important in lower-income groups. In this group, mobile money use is minimal because almost everyone already has bank accounts. It plays only a small supplementary role, showing little change over time.

In the upper middle-income group, mobile money appears from 2014 onwards and gradually rises. It supports inclusion but is still secondary compared to banks.

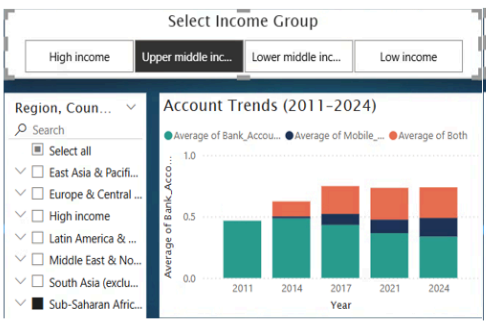
In the lower middle-income group, mobile money adoption is stronger and continues to expand steadily and it combines with bank accounts to form a significant share of overall financial access.

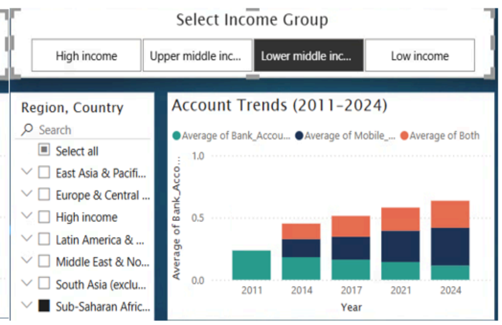
We would like to take the East Asia and Pacific region and Sub-Saharan Africa as examples to answer our main question in more detail.

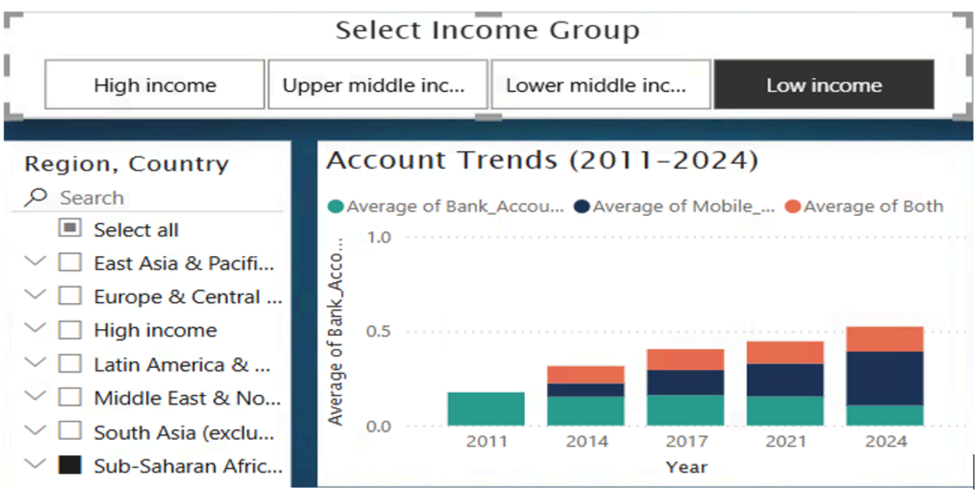




In the East Asia and Pacific region, the charts show that in **low-income**, bank account ownership stays relatively low, but mobile money and combined use of both steadily rise from 2011 to 2024. This indicates that mobile money is filling the gap where traditional banking access is limited, expanding financial access for more people.







In Sub-Saharan Africa, the chart shows financial inclusion has evolved across income groups, highlighting the growing role of mobile money from 2011 to 2024.

Upper middle-income: Mobile money appears alongside bank accounts and steadily increases, showing it supports but does not replace traditional banking.
Lower middle-income: Mobile money grows more strongly, becoming a major contributor to inclusion as

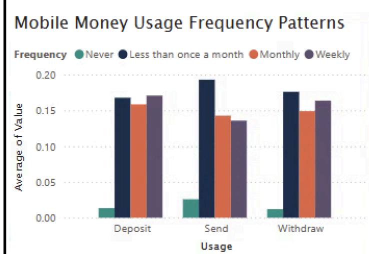
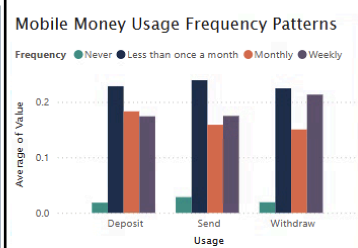
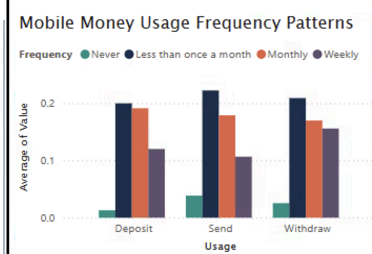
bank access remains limited.

Low-income: Mobile money dominates growth, surpassing bank accounts and emerging as the main channel of financial access in low-income Sub-Saharan Africa.

5.2. Mobile Money Usage and Frequency

With the development of technology, mobile money bridges the gap of financial inclusion in different countries by providing under-served citizens with secure, affordable transactions and a private, reliable means to store their funds (Aron, 2018). Since mobile money is still a relatively new concept, and most available data on mobile money usage is concentrated in Sub-Saharan Africa, the current analysis primarily focuses on that region, based on the 2024 dataset collected.

Cross-Group Comparison in Usage and Frequency Pattern

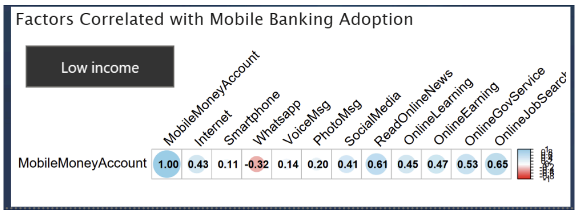
Income Group	Low Income 	Lower-Middle Income 	Upper-Middle Income 
Most Frequent Use	Less than once a month	Less than once a month, weekly use rising	Less than once a month / Monthly
Overall Usage Pattern	Irregular, low usage	Gradual growth	Balanced & frequent
Maturity Level	Early adoption	Developing stage	Mature usage

Mobile money is used widely across all income levels, helping more people join the financial system. People use mobile money more often as their income increases. Sending money is the most common activity for everyone, while very few people never use mobile money, showing that most people, even those with low income, know about it and have access to it. The small number of "never users" suggests that even poorer communities are now connected to digital finance.

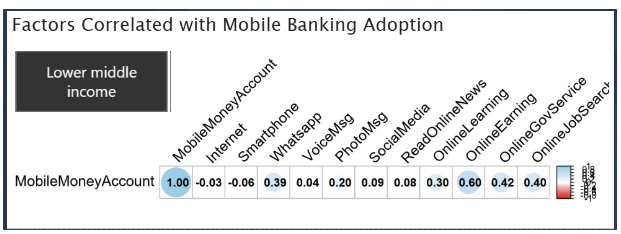
However, people with lower incomes tend to use it less often, the possible challenges may be related to low literacy or irregular income. Middle-income users are starting to use mobile money more regularly as they build trust in it. For higher-income users, mobile money has become part of their everyday money management, showing that as economies grow, people move from simply having access to actively managing their finances digitally.

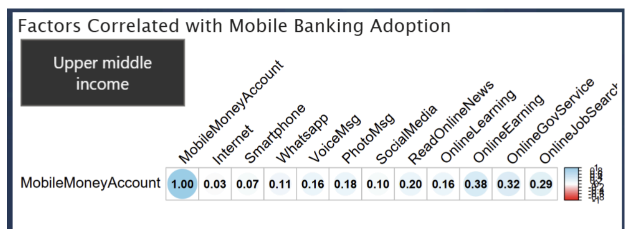
5.3. Factors Correlated with Mobile Money Adoption

Next, we discuss the correlation plot findings as a supplement to our research question. It adds valuable context and serves as a diagnostic tool that helps researchers and policymakers prioritise variables for further analysis or modelling, which are beyond this project scope. Most importantly, here we only measure relationship strength between mobile money adoption and other factors, as correlation does not imply causation (Australian Bureau of Statistics, n.d.).

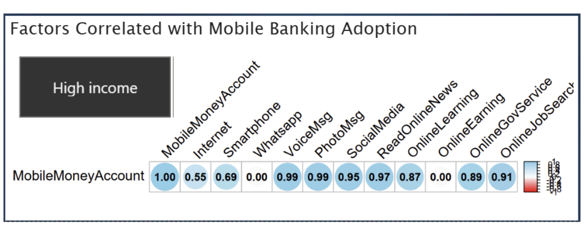


In low income countries, mobile money adoption correlates most with digital service and work-related activities rather than basic communication or chat. The strongest associations are with online job search (0.65), reading online news (0.61), and online government service (0.53), while factors related to personal communication, such as whatsapp, voice message, and photo message show weak or almost no correlation. This pattern suggests that where people use the internet for information, service, or economic opportunity, mobile money tends to be more prevalent, while basic messaging alone does not align with higher adoption.





In middle income countries, both lower and upper middle income groups exhibit a similar behavioural pattern. The adoption of mobile money correlated more with economic activities such as earning, governmental service, and job search. The main difference is that lower middle income countries showed a stronger online earning association and a distinct Whatsapp correlation. This finding suggests that messaging apps may be more integrated into payments at this income tier.



In high income countries, the relationship between mobile money adoption and other factors contrasts sharply with that in low and middle income countries. The strongest correlation came from digital communication activities, such as voice message (0.99), photo message (0.99), and social media (0.95). Moreover, educational activities such as online news reading and online learning, as well as economic activities such as government service and job search, also correlated strongly with mobile money adoption. However, Whatsapp and online earning were 0 because of limited data availability.

VI. CONCLUSION

To conclude, while we see that the adoption of mobile money is significantly increasing the level of financial inclusion, especially in lower, and middle income countries, it is important to note the nuances and negative effects that this can cause, specifically in countries of these income groups. A journal article from The Annual Review of Financial Economics found that five key issues were present in lower and middle income countries due to the rapid adoption of digital financial solutions. These include fraud, discrimination, overindebtedness, high and/or hidden prices, and contract exploitation (Garz et al., 2021). The authors note that consumers in countries and these income groups do not have the experience required in financial services, and even less so in digital financial services when compared to higher income countries, where even experienced consumers still face harm due to these services (Garz et al., 2021). While the scope of this project is limited to financial inclusion, rather than the overall net impact of consumers on financial inclusion, it is important to understand that the increase in financial and digital financial inclusion, with a focus on lower and middle income countries, is not strictly positive, and further research and analysis could be performed with the goal of understanding the deeper impact of financial and mobile money inclusion, instead of just identifying if country populations have an increased exposure to these services.

Furthermore, one of the biggest difficulties our group faced was the lack of simultaneous collaboration due to the functionality of Microsoft Power BI. Using this software for the complete implementation of our project meant that we were not able to all work together on one single file. Instead, each time someone worked on the project, the file had to be updated and re-sent to each group member, and in addition, the data source had to be updated every time it was opened. Not only did this make it hard to foster a collaborative environment but it also led to group members working on the wrong files, due to multiple people working on the project and updating different files at the same time. The best way we managed to overcome this was to all meet in person at the same time and contribute collectively to one device. If we were to do this project again we would definitely arrange more meetings to work on the visualisations together in person to not only increase efficiency but also maximise collaboration.

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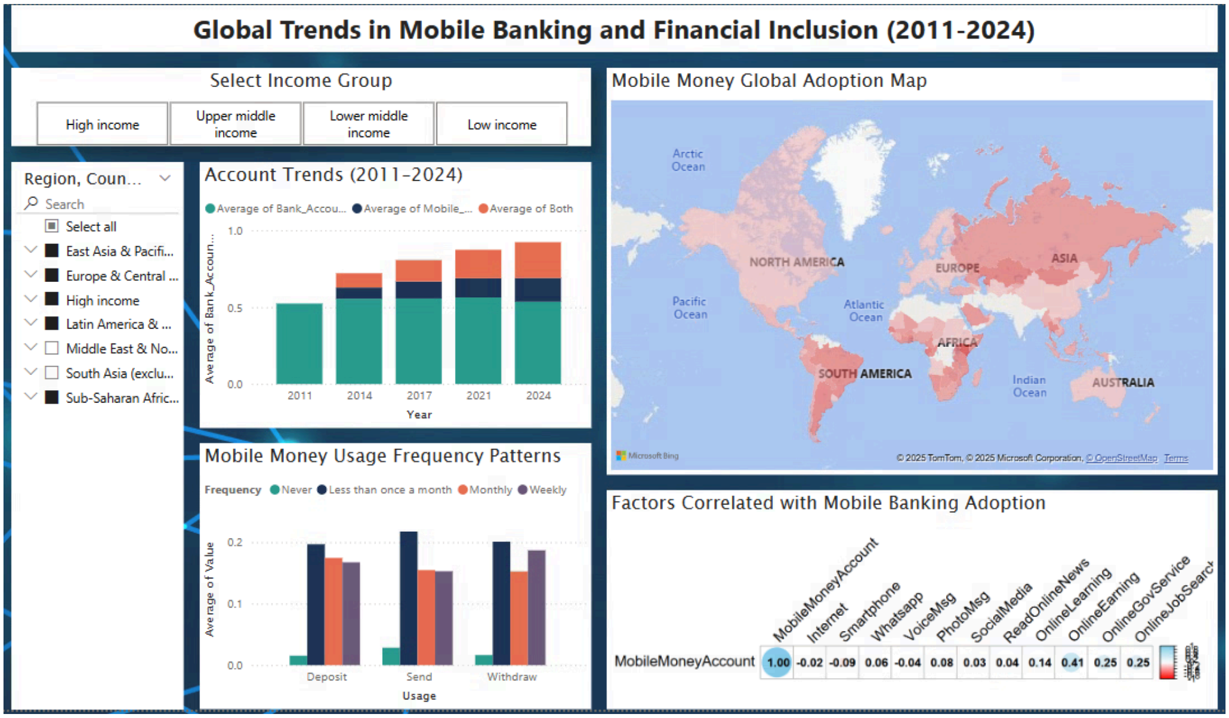
APPENDIX

Appendix 1. Global Trends in Mobile Banking and Financial Inclusion (2011-2024)



Appendix 2. Mobile Money Adoption Varies Widely Around the World