# Behavioural Biases in Financial Access and Usage Divide: The Kenyan Case

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# Abstract

The noticeable strides Kenya has made on digital financial services that anchor the positive narrative of financial inclusion is evidently leaning towards payment services. However, digital divide still exists due to behavioural heterogeneity. This paper explores the influence of behavioural biases in access and usage of mobile money services, the dominant digital financial services in Kenya. The 2021 FinAccess data anchors the empirical investigation on the extent to which behavioural biases are an obstacle to access and usage of mobile money. Deploying descriptive statistics on gender disaggregated data and a probit model to estimate marginal effects, we ascertain that behavioural biases contribute to the digital divide evident among men and women households in Kenya. These biases drive a wedge between access and enhanced usage of digital financial services in a manner that slows the sequential process of the former, leading to the latter. Beyond advancing literature in this area, this paper proffers arguments in favour of putting in place measures to enhance household incomes that have a gender lens, for they have the potential of ameliorating the gaps underlying financial exclusion of women and low-income earners in mobile money access and usage. It also argues for a policy position that discourages the consideration of basic digital financial services as a revenue mobilization platform through direct taxation as that could be counterintuitive.



**Keywords:** *Behavioural biases, Digital finance, Households, Kenya*

# 1. Introduction

The progress that Kenya has made in digital financial services (DFS) has received international acclaim, with the attendant desire to replicate it across other markets. The range of financial services that has attracted analytical attention by virtue of their delivery channels being digital, especially those backed by mobile devices, include payments, credit, insurance, and remittances (Agur, Peria and Rochon, 2020; Khera, Ng, Sumiko, and Sahay, 2021). The spotlight on Kenya's progress in this respect is underpinned by the reported strides in financial inclusion. According to the 2021 Financial Access Survey, both informal financial inclusion and financial exclusion has been on a declining trend as formal financial inclusion maintain a positive trajectory, rising to 83.7% in 2021 from a low base of 26.7% in 2006 and driven by increased mobile money and Internet-based banking services.

The motivation of this paper is the need for a deep dive into the distinction between mere access to DFS and their enhanced usage. That entails the recognition that there is an obvious sequencing that starts from the former but appreciating that there are behavioural biases that could impede the evolution from simple access to enhanced usage from a demand standpoint. Similarly, the supply side adjustment to the emerging technological developments could enable or impede the bridging of the gap between access and usage of DFS. The DFS in this context are seen under the broad umbrella of FinTech and therefore fall under the definition of being "technologically enabled financial innovation that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services" (CGFS and FSB, 2017).

At the core of our analysis is the recognition that the demand side of the DFS continues to grapple with consumer behavioural biases that are driving a wedge between access and enhanced usage. A fair amount of literature on financial behaviour is inconsistent with standard economic notions of rationality as could be inferred from the exhibition systematic biases and limitations (Karlan et al., 2016). An account of why the desired levels of financial inclusion and inclusive digital finance ecosystem utilization is not achieved can be looked at from the perspective of behavioural finance, a branch of finance that deals with human psychology. In every financial decision, there is a certain degree of risk and uncertainty (Hazarika and Bhowal, 2021).

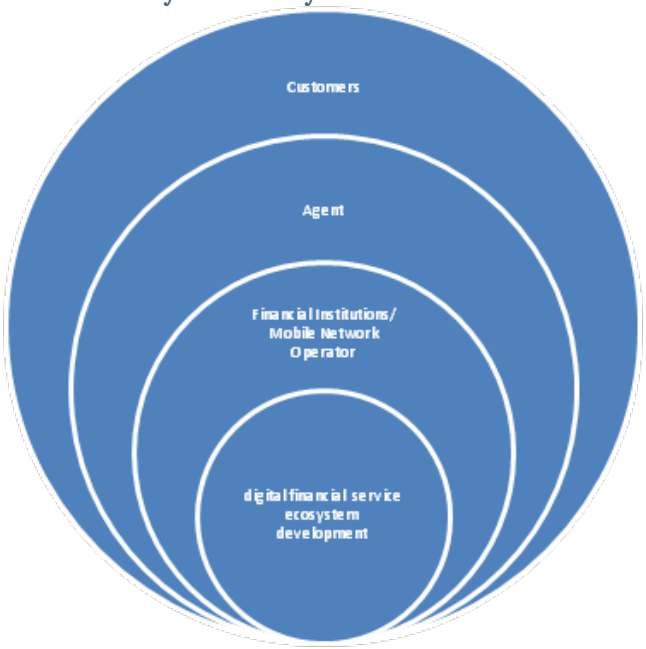
While the array of services that fit the DFS is broad (World Bank, 2020), mobile money dominates. The preference of mobile money is attributed to the fact that

Internet access is not a prerequisite for transactions on the channel and that even basic telephones are sufficient (Haas, Marilyn, Pamela and Abeba, 2013). With no attendant requisite for sophistication, mobile money is an enabler of e-money where value is stored virtually in an account associated with a Subscriber Identification Module (SIM) card and depositing (withdrawal) of cash into (from) a mobile account.

Mobile money has enabled access to financial services, albeit in a simple touchpoint sense that may be seen as necessary but not sufficient for impactful financial services. The next level that goes beyond mobile money is comprised of advanced DFS users, who utilize services that include mobile banking, digital health, digital education, e-government, e-commerce, digital information/news, content creation and other digital services that support livelihoods (Koyama et al., 2021). The new actors in the financial sector that are at the centre of DFS have shaped the basis of competition but, as some studies contend, are yet to materially change the competitive landscape (Navaretti, Calzolari and Pozzolo, 2017). Therefore, digital financial services are analyzed on the back of having facilitated the provision of services that traditional financial institutions do less efficiently, or not at all, and facilitated new users. At the same time, they have enhanced efficiency in the provision of the same old financial services.

While the new entrants may not be able to replace the dominant financial service provider, the emerging partnerships entail innovations that enable old things to done in a new way. The array of DFS in the ecosystem is therefore wide-ranging, with varying degrees of influence, market power, and product range, and compromised Mobile Network Operators (MNOs), banks, independent money transferring companies and large and boutique fintech operators (Figure 1).

**Figure 1: Digital financial system ecosystem**




Source: Adapted from European Investment Bank (2014)

One notable attribute of DFS is that the underlying technology helps reduce information market imperfections by way of lowering the extent of information asymmetry and transaction costs (World Bank, 2020). Consequently, technology is seen as an enabler of deepening the outreach of financial inclusion by reducing barriers to financial services access. On that account, financial inclusion is postulated to lead to welfare gains for individuals, households, and at the aggregate country level especially when anchored on savings and financial resilience (Sahay, Ogawa, Khera and Ng, 2021).

Even as progress in terms of financial inclusion is postulated to be evolving towards welfare enhancement, perception of progress based on first level interaction with financial services potentially masks the possibility that the arising benefits fall short of delivering deeper developmental benefits, being assessed as marginal (IFC, 2019). It could be argued that the gap between access to finance riding on the wave of DFS has not necessarily translated to enhanced usage. The argument is based on the acknowledgement that access and usage are sequential, the former being necessary but not sufficient for welfare enhancement unless it results in the latter. In that regard, behavioural biases potentially drive a wedge that slows their convergence. The objective of this paper is therefore:

- ***To assess whether behavioural biases drive a wedge between access and enhanced usage of DFS in Kenya.***

From the findings of the study, we draw policy recommendations towards supporting actors on the demand-side and supply-side of the DFS ecosystem so as to ameliorate the possible adverse effects of the behavioural biases.

This paper makes two key contributions. First, it questions the assumption that access automatically translates into usage. By providing insights on the drivers of the wedge between the two, we provide a motivation for future analysis on how the DFS access-usage divide can be bridged. Secondly, unlike other studies on the subject, it grounds its analysis on the effects of behavioural biases on financial access and usage. It is acknowledged that as households make financial decisions, there is a predisposition to those decisions leading to a less optimal welfare outcome, especially when such financial behaviour is linked to anxiety (Camilla et al., 2017).

Differences in financial decisions of individuals is explained by individual behavioural heterogeneity and self-exclusion attitude, with behavioural biases creating the wedge that inhibits the delivery of financial services (Karlan et al., 2016). Financial decisions are not always governed by logic, with emotions that encompass greed, fear, anxiety, and regret sometimes dominating the decision-making power (Hazarika and Bhowal, 2021). That makes behavioural biases not a preserve of low-income or the unbanked people (Arnold and Rhyne, 2016). Nonetheless, there is correlation between behavioural biases and financial inclusion (Liu et al., 2021). This implies that behavioural aspects of finance can influence some of the shortcomings in access and usage of DFS (Hazarika and Bhowel, 2021). A review of existing literature on financial inclusion points to a dearth of empirical work on the influence of behavioural biases on financial access and usage divide.

Deploying probit models on a comprehensive dataset arising from the 2021 FinAccess Survey, we establish that an array of behavioural biases constrains the transitioning of access to usage. As such, the consumption of basic payments related mobile telephony enabled services dominates the enhanced usage in the form of services such as savings and credit. We observe that measures to enhance household incomes seen with a gender lens have the potential of ameliorating the gaps underlying financial exclusion of women and low-income earners in mobile money access and usage. Even as the need for increased infrastructure meant to further deepen financial inclusion remains compelling, the public policy that constrains households' incomes such as direct taxes on DFS could be counterintuitive.

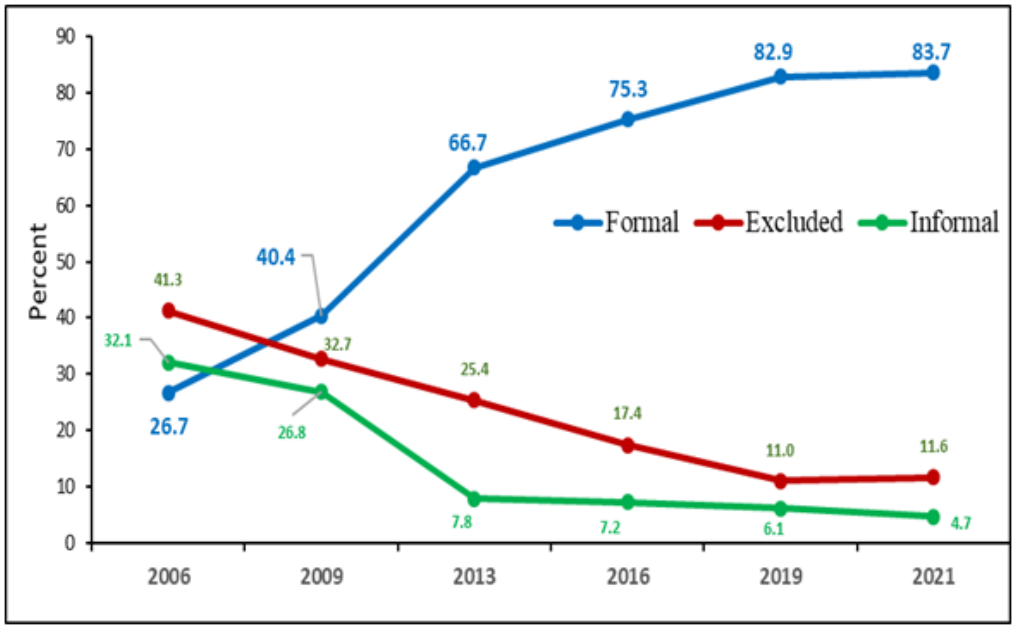
The rest of the paper is organized as follows: the next section presents some stylized facts that ground the paper's motivation. This is followed by literature review that contextualizes the theoretical and empirical aspects of the paper and preludes the methodology deployed pursuant to the outlined objectives. The findings and inferences arising thereto are then presented, upon which conclusions are drawn in the final section.

# 2. Overview of financial inclusion trends in Kenya – stylized facts

The evolution of DFS in Kenya reveals clear progress as far as financial inclusion is concerned, but does not go as far as illustrating how that progress translates to enhanced welfare through intense usage.

The first is associated with the amenability of mobile DFS, which has been described as the key driver of financial inclusion. Figure 2 depicts the evolution of formal financial inclusion that in 2006 was equivalent to 26.7% of the adult population and was below both the excluded and those relying on informal financial services. By 2021, the formal adult population accessing formal financial services had risen to 83.7%, a trend accompanied by a steady decline of both the share of those excluded and those depending on informal financial services steadily decline over the same time.

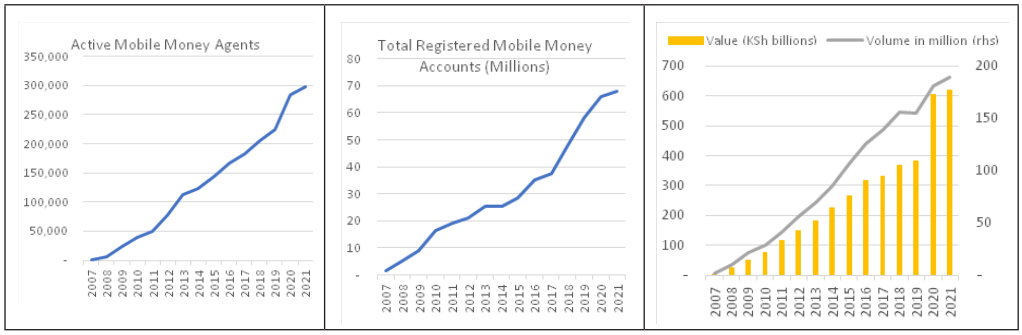
**Figure 2: Financial access trends, 2006 to 2021**




Source: FinAccess (2021)

The noticeable strides Kenya has made on DFS bolsters the positive narrative of financial inclusion leaning towards payment services. Since the advent of M-Pesa in 2007, mobile payments have registered sizeable growth both in number and value of transactions (Figure 3).

**Figure 3: Mobile money transactions**




Source: Central Bank of Kenya

The second is that as mobile payments entrench themselves, their initial complementary role to other DFS – mainly Automated Teller Machines (ATMs), Point-of-Sale (POS) machines, mobile and internet banking, and Unstructured Supplementary Service Data (USSD) provided in collaboration with mobile network operators (MNOs) – gradual substitution is emerging. The substitution effect is evident post-2015 as investment in new ATMs has stagnated and the rising trend in prepaid cards and charge cards has been in a declining trajectory. It is only POS machines that have maintained their growth trajectory.

The gradual substitution away from other DFS to mobile money in the recent past is attributed to reaction to the COVID-19 pandemic. The pandemic resulted in rapid adoption of financial innovation, with mobile payment services registering noticeable increase (Boot et al., 2020). The regulatory measures backing the entrenchment of mobile payments include the declaring of mobile money providers and agents essential service givers, waiving transaction fees, making Know Your Customer (KYC) and on-boarding requirements more flexible, maintaining liquidity for agents and enabling government social transfers to be disbursed directly to mobile money wallets (GSMA, 2021).

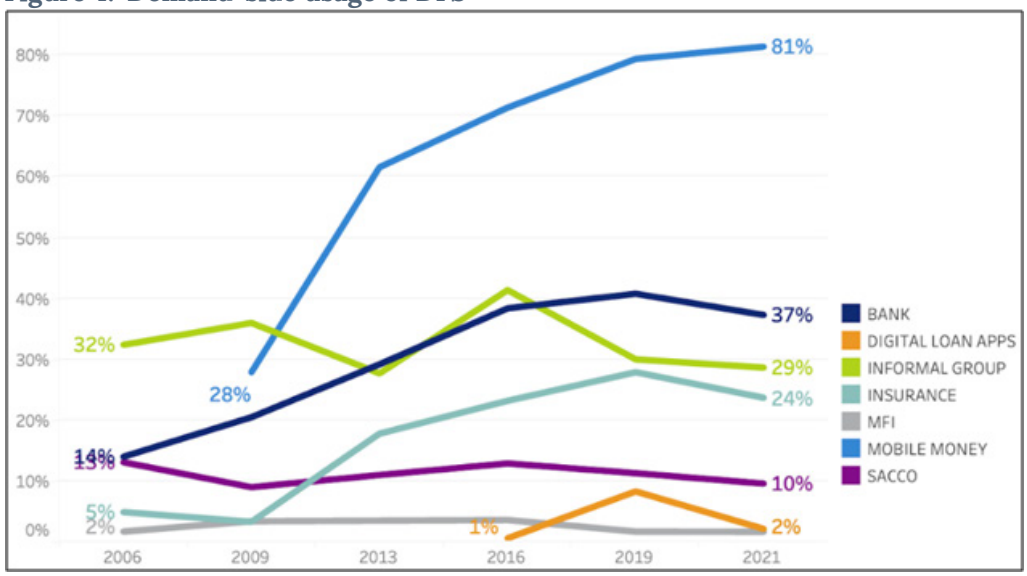
The third is that on the back of mobile money growth and the expansion of bank agent network and Internet penetration, consumption of banking services enabled by technology, especially mobile telephony, is gaining traction and is second to mobile money (Figure 4). While demand is central to the gains made in DFS, the supply-side response to emerging opportunities is instructive. The benefits of DFS that have been described as dividends (e.g., by the World Bank, 2016) are linked to the requisite investments meant to promote accessibility, affordability, and openness and safety that entails a divide between those that have optimized on the gains and those that have lagged. The interaction between the 'public good' and private motivation of the so-called divide and dividend necessitates the provision of digital finance to address investment needs that promote accessibility, affordability, and openness and safety.

**Table 1: Evolution of electronic payment cards in Kenya**

| Year | ATMs Machines | Cards | | | | POS Machines | Total Cards |
|---|---|---|---|---|---|---|---|
| | | Prepaid Cards | Charge Cards | Credit Cards | Debit Cards | | |
| 2009 | 1,717 | 16,749 | 1,682 | 108,456 | 3,700,646 | 15,871 | 3,827,533 |
| 2010 | 1,979 | 18,750 | 725 | 113,192 | 6,191,792 | 18,179 | 6,324,459 |
| 2011 | 2,130 | 22,405 | 1,339 | 122,212 | 8,548,390 | 16,604 | 8,694,346 |
| 2012 | 2,306 | 27,558 | 2,095 | 138,011 | 9,063,905 | 18,478 | 9,231,569 |
| 2013 | 2,417 | 73,395 | 750 | 158,612 | 9,543,204 | 21,089 | 9,775,961 |
| 2014 | 2,514 | 419,258 | 68 | 208,352 | 10,552,312 | 17,511 | 11,179,990 |
| 2015 | 2,579 | 2,047,340 | 873 | 252,178 | 10,673,090 | 22,230 | 12,973,481 |
| 2016 | 2,615 | 1,503,715 | 826 | 233,752 | 12,903,875 | 30,133 | 14,642,168 |
| 2017 | 2,564 | 1,357,372 | 700 | 236,392 | 13,616,645 | 35,466 | 15,211,109 |
| 2018 | 2,529 | 1,261,985 | 695 | 239,484 | 16,167,386 | 44,874 | 17,669,550 |
| 2019 | 2,459 | 635,039 | 541 | 263,255 | 10,597,465 | 42,846 | 11,496,300 |
| 2020 | 2,412 | 551,124 | 541 | 338,175 | 10,844,565 | 48,012 | 11,734,405 |
| 2021 | 2,366 | 599,959 | 638 | 322,104 | 10,950,498 | 48,968 | 11,873,199 |

Source: Central Bank of Kenya

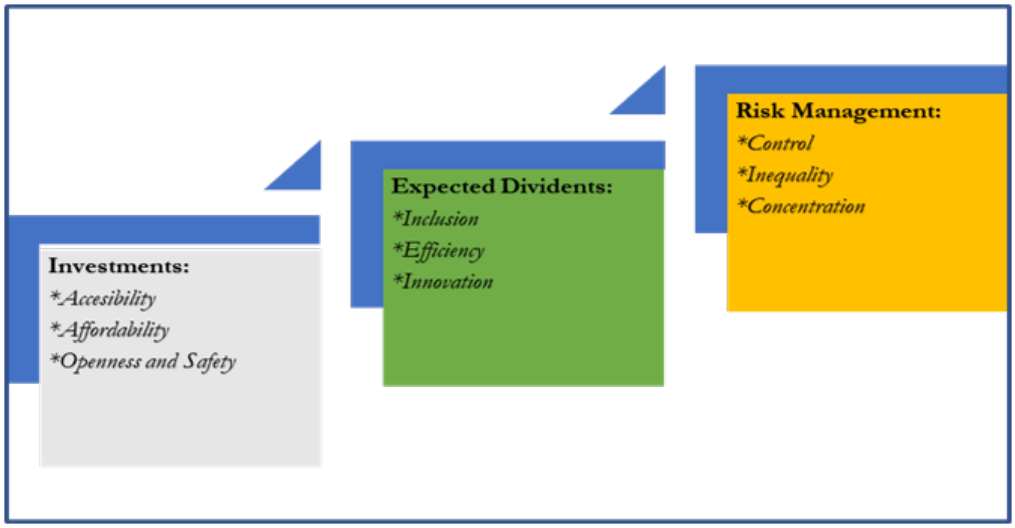
**Figure 4: Demand-side usage of DFS**




Source: FinAccess Survey trackers conducted between 2006 and 2021

For investments meant to enhance beneficial financial inclusion anchored on efficiency and innovation, the necessary risk management processes need to be anchored in public policy that leans towards promoting market competition devoid of concentration on service provision that could engender inequality and market-power induced control. Figure 5 illustrates the postulation that investments in DFS infrastructure guided by a coherent risk management framework will optimize the expected dividends.

**Figure 5: Digital financial services – The divide and dividends**

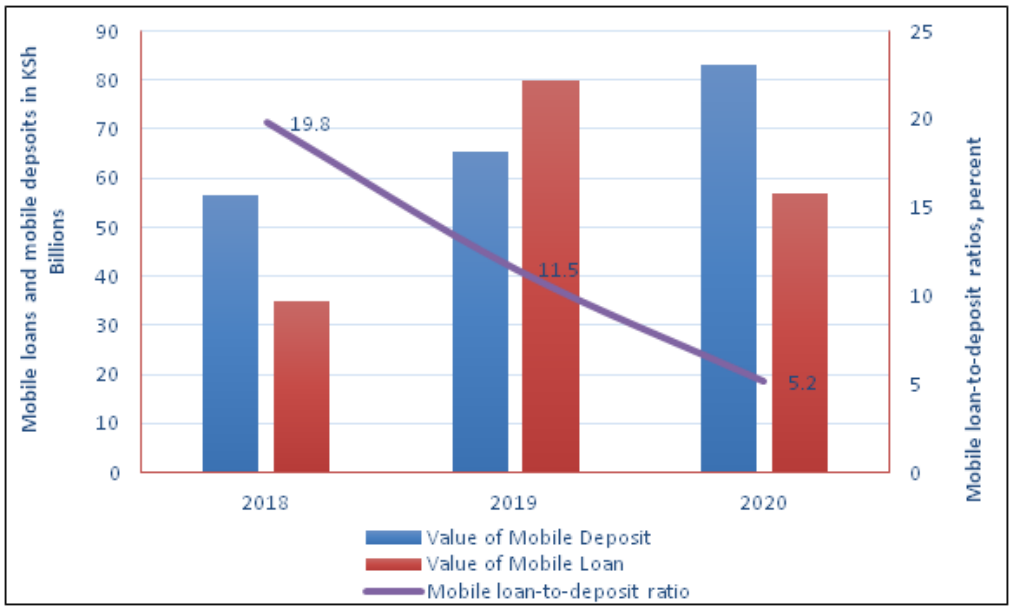



Source: Adapted from the World Bank (2016), World Development Report

A careful assessment of that ability to reap the dividends takes cognizance of the fact that even with broad array of actors, the supply-side of finance in Kenya is bank-dominated. The business models that banks determine to be ideal as they navigate the DFS space is critical, the three common ones being: (a) provision of digital products and channels alongside conventional products; (b) establishing digital subsidiaries; and (c) reorienting operations towards being digital banks, thereby making digital services business as usual. These strategies are not necessarily mutually exclusive in the sense that the pursuit of one does not preclude the simultaneous pursuit of another. On the demand-side, the acknowledgement of the heterogeneity of the consumers of DFS is critical. The role of demographics in influencing adoption of digital financial services is worth noting. So is the role of trust, as emerging literature reviewed in the next section indicates.

The fourth is that the supply-side digital financial ecosystem as it relates to banks mirrors demand-side figures. The supply-side perspective based on data from 13 banks that account for over 70% of the total market share reveals several insights insofar as DFS intermediation is concerned. First, the quantum of mobile deposits exceeded that of mobile loans between 2018 and 2020, a period from which the data is available. Second, the digital ecosystem's loan-to-deposit ratio, a structural measure of liquidity, has been trending downwards from 19.8% in 2018 to 5.2% in 2020. These aggregate trends, however, mask substantial heterogeneity across the different digital credit market players, and the digital products landscape evolution is presented in Figure 6. Furthermore, the intermediation process does not necessarily strive to match mobile deposits with mobile loans, as the latter could be provided through deposits mobilized though other means.

**Figure 6: Recent digital credit and deposit among Kenyan banks**




Source: Various Annual banks' integrated reports

The foregoing stylized facts provide context against which the paper's research questions are addressed. The behavioural biases underpin the demand-side modeling, with the analysis we infuse supply-side discussions that highlight market developments and regulatory interventions driving uptake of digital financial services while also bringing forth the challenges that remain unaddressed and critical in entrenching further financial inclusion.

# 3. Literature review

We review the relevant literature in two broad strands, one on studies that take stock of the dynamics in the DFS space and the other that focus on the behavioural biases as they influence uptake of DFS. The essence of understanding the transition from mere access to enhanced usage is backed by the argument that finance is a means to the end (Karlan et al., 2016) and that end is when enhanced DFS is perceived as an antidote for socio-economic development, poverty reduction, and improved livelihoods.

The behavioural biases that are critical in this analysis are bolstered by decision theory espoused by, for instance, Hansson (1994). According to the theory, a person's decision about something is the freedom they have and face some options that they have to choose and take one of those as consideration, which will lead to achieving a desired goal. Decision theory is related to behaviour directed to achieving a goal, with various options. Behaviour biases influence the decisions of individuals and households who face options to consider. There are two types of decision theory: descriptive theory, and normative decision theory.

Normative decision theory is a theory that explains how a decision must be made, and descriptive decision theory is about how decisions are actually made. People are normal but not rational decision makers as they exhibit systematic biases and limitations in making financial decisions. Individual behaviour is biased due to information overload and tends to follow descriptive decision theory in decision making (Liu et al., 2021; Karlan et al., 2016; Aren and Canikle, 2018), which can contribute to cognitive biases towards digital finance access and usage.

Access to credit, especially when digitally driven, improves levels of employment in society and supports mental health of individuals (Liu et al., 2021; Pazarbasioglu, 2021; Khera et al., 2021; Mukavaza et al., 2018). The opposite, which takes the form of exclusion from the DFS ecosystems, impairs resilience of households (Aziz and Naima, 2021; Sahay, Ogawa, Khera and Ng (2021). Even with the rise of DFS, many of the world's poor are still using cash as they are afflicted by multiple overlapping market failures that mute the benefits of a market intervention (Karlan et al., 2016).

In a broad sense, recent studies in Kenya confirm that there is a positive relationship between digital financial innovation and financial depth, with the strongest impact emanating from Internet usage and mobile financial services and the lowest impact from bank branches (Misati, Osoro, Odongo and Abdul, 2022). The significant positive impact of financial depth on economic growth, consistent with the supply-leading finance theory revealed in such studies align with the thesis that enablers of enhanced usage are key for welfare benefits of DFS. On that account, the case is made for increased investment in technology enabling infrastructure for DFS and having frameworks that obviate financial exclusion of low-income earners due to the unaffordability of digital devices, gender dimensions and financial and digital illiteracy.

Thus, government policies are critical in looping those outside the DFS ecosystem as they have been overlooked in the past for an inclusive digital finance and increase financial inclusion (Hazarika and Bhowal, 2021).

Investment in DFS enablers is a supply-side consideration that often takes cognizance of the fact that mobile financial services are the main drivers of financial inclusion. The case for Kenya and Tanzania as determined by Mazer and Rowan (2016) indicates the necessity of developing countries having a competitive ecosystem that facilitates entry into the market, the development of innovative products, and high-quality, value-for-money services. This will entail regulatory oversight on matters of competition taking a broad approach based on a market-wide jurisdiction facilitative of fair play across banks, mobile network operators (MNOs), and other provider types. In essence, with interoperability, addressing competition and efficiency concerns in a segment of the mobile financial services ecosystem is sub-optimal.

Take the case of the Kenyan banking sector which leads the financial system and, according to Kiemo and Kamau (2021), is characterized by monopolistic competition attributes albeit with an upward trend in efficiency. Through optimizing on scale of operations and continuous adoption of technology, the study contends that the sector has room to enhance competition, and that the case for continued adoption of policies that promote greater banking sector efficiency and competition remains strong. That, however, is not sufficient in enhancing usage of mobile financial services unless the same considerations are brought to bear on the MNOs.

As the supply-side is adapting to the fast-evolving demand-side dynamics as far as provision of DFS is concerned, the gains arising from utilization appear to be modest. A study in Kenya over a course of 8 years shows that an increase in mobile money, measured by increase in agent density, led 185,000 female-headed households to switch into business as their main occupation, decrease in farming participation by 3% and holding multiple occupations by 1% (Suri and Jack, 2016; BMGF, 2021). This is against the background of impressive access parameters such as mobile money account ownership at 73%, digital payment adoption at 79%, savings rate at 26.8%, digital account access at 72%, a digital literacy score of 9.01 out of 15 and 41% satisfied with their financial situation (Lyons et al., 2020).

In behavioural finance, two important concepts are bias and heuristic, whereby the former is a predisposition towards an error or deviations from certain norms and the latter is mental shortcuts or cognitive limitations, which facilitates decision making. People are normal but not rational decision makers (Aren and Canikle, 2018; Liu et al., 2021). Consumers may tend not to behave rationally while making financial decisions among different choices, and individual behaviour is biased when they decide to take financial services (Liu et al., 2021). The word bias refers to the tendency of an individual towards a conclusion or disposition. Biasness is a specific design the human mind uses to handle information overload and in decision making (Liu et al., 2021). Human biases tend to inhibit the ability to make good financial decisions, even resulting in decisions we know to be against our best interests (Arnold and Rhyne, 2016). In this study, we set out the demand side behavioural biases as outlined below:

(i) **Self-control bias** is the tendency of an individual that causes them to consume today at the expense of tomorrow. It is a lack of ability to balance between current and future expense, which affects savings and pension decisions (Aren and Canikle, 2018; Liu et al., 2021). The contrast is self-control, whereby there is the ability to control our current self (Camilla et al., 2017). Self-control and self-discipline are used interchangeably, and the lack thereof leads to self-centeredness, impulsivity, enjoying ease and being riskier (Liu et al., 2021).

(ii) **Status quo bias** refers to the idea that when people face various alternatives, the choice is to protect the current situation (Aren and Canikle, 2018).

(iii) **Confirmation bias** is the tendency to search and approve evidence to favour, support and confirm one's existing believe (Hazarika and Bhowal, 2021). Individuals exposed to this bias ignore information that conflicts with their decision and assume that they do not exist (Aren and Canikle, 2018).

(iv) **Endowment bias** is the tendency to continue to retain the things owned irrationally over those they do not own (Aren and Canikle, 2018).

(v) **Overconfidence bias** is the tendency to hold false and misleading assessment of one's own capability and skills to handle the various dimensions of a decision (Hazarika and Bhowal, 2021; Renu and Christie, 2019).

(vi) **Regret aversion** refers to the tendency of an individual to avoid distress and emotional pain arising from poor decisions (Hazarika and Bhowal, 2021; Renu and Christie, 2019).

While the paper delves into the six listed behavioural biases, we acknowledge that there are other biases in literature that we do not consider to be closely tied to the focus of this study. These biases can be summarized as follows:

- The availability bias is where individuals concentrate on information that they remember and attain easily (Renu and Christie, 2019).

- Framing bias is where decisions are influenced by how information is presented, rather than the information itself (Aren and Canikle, 2018; Renu and Christie, 2019). Under illusion of control bias, an individual over-estimates decision-making capability as they try to control the events that influence results without any objective basis.

- Loss aversion bias is the tendency to prefer avoiding losses to acquiring equivalent gains (Hazarika and Bhowal, 2021).

- Anchoring bias refers to subconscious use of irrelevant information as reference point or to anchor one's decision. A reference point can be a buying price, which is true at first but loses its trueness with time – high commitment to past decisions and low reaction to new information (Aren and Canikle, 2018; Hazarika and Bhowal, 2021).

- Representativeness bias influences an investor to look at the past prices of the stocks while making stock market decisions as the past price is assumed to be a representative of the future price (Renu and Christie, 2019).

On the back of the outlined biases is the consideration that socio-demographic characteristics specific to a household head such as gender, age, education level, marital status, household size, income, employment, and area of residence can shape financial services access and usage decisions (FAO, 2019; i2i, Aziz and Naima, 2021; GSMA, 2021; Ntwiga and Wafula, 2021; Cera et al., 2020; Kulkarni and Ghosh, 2021). Income has a positive effect on financial behaviour (Camilla et al., 2017), which influences access and usage of DFS. Renu and Christie (2019) observed that income is significant with anchoring bias, with high income earners being less prone to biases and low-income earners more prone to biases and are risk averse. In Pakistan, a predominant Islamic nation, people tend to shun the conventional financial services due to their religious beliefs and have strict behaviour towards interest rates in these products and services (Liu et al., 2021).

Negative attitudes towards the disabled in the community disempower individuals and leads to their social exclusion and isolation (Babik and Gardner, 2021) in all life's activities, including access and usage of DFS. Religion is an anchoring bias individuals grow up with in society. Self-control positively influences financial behaviour and tends to influence a savings culture where individuals feel less anxious and more secure in their current and future financial matters (Camilla et al., 2017). Regret aversion is observed more in men than women and individuals who have regret aversion, status quo and confirmation bias display more risk aversion behaviour (Aren and Canikle, 2018).

Savings accounts with features that help people overcome behavioural biases fortify their willpower and memory, and this enables them to improve their welfare (Karlan et al., 2016). Herding behaviour contributes to low financial inclusion as individuals may herd the irrational choices of others in Pakistan (Liu et al., 2021). An automated teller machine (ATM) stimulator in Mexico reduced fear of ATMs, confidence barriers to financial exclusion among poor women and increased confidence around technology (Arnold and Rhyne, 2016). Marketing practices by supply-side that exploit behaviour biases lead consumers to making impulsive decisions to take up loan that they do not need or larger than necessary (Arnold and Rhyne, 2016).

The supply-side is adapting to the provision of DFS to the fast-evolving demand-side dynamics, but the gains in usage appear to be modest. One plausible explanation is that human biases tend to inhibit the ability to make good financial decisions, even resulting in decisions we know to be against our best interests. The paper probes into FinAccess Survey data as a proxy for estimation biases and considers endowment, confirmation, status quo, self-control, overconfidence and regret aversion biases and how they influence financial access and usage.

# 4. Empirical strategy, estimation framework and findings

## Data sources

The 2021 FinAccess Survey data is used in this study. The survey is a demand-side dataset based on a multi stage stratified cluster sampling with three sets of units, namely, Enumeration Areas (EAs), households, and an eligible individual within the households being sampled. The survey targeted individuals aged 16 years. A total of 22,024 out of the eligible 25,724 households were interviewed, resulting in an overall household response rate of 85.6%. This is an equivalent of 71.8% of the total Kenya Household Master Sample Frame (K-HMSF) sample size. In terms of geographical distribution, 88.6% were from rural households compared to 80.5% for urban households. Based on gender, 48.7% of the sample were male and 51.3% were female.

The 2021 FinAccess Survey is suitable for demand-side analysis of digital financial services given that it is designed to examine financial inclusion in detail compared to other existing nationally representative datasets such as the Kenya Integrated Household budget Survey (KIHBS) or the Kenya Demographic Health Survey (KDHS). Further, the 2021 FinAccess Survey is relevant as it was conducted during a period within which adoption of digital financial services was high, exacerbated by the pandemic shock and therefore better suited to analyze the dynamics of digital financial services adoption. Similarly, the survey collects demographic information at an individual and household level and therefore allows for examination of possible heterogeneities among different segments of the population.

Table 2 highlights the household shortcomings, variables adopted, and the respective cognitive bias that forms a basis for the behavioural biases upon which the demand-side assessment is undertaken.

**Table 2: Behavioural biases exhibited by households**

| Household shortcoming | Study variable | Cognitive bias | Base Group |
|---|---|---|---|
| Low income | Income | Confirmation | 0-100 |
| Voluntary exclusion | Religion | Endowment | Islam |
| Disruptive innovation | Mobile ownership | Status quo | No |
| No budgeting | Spending plan | Self-control | Disagree |
| Withdrawal of savings (No savings) | Draw on savings | Overconfidence | Yes |
| Lack of trust of financial systems | Trust | Regret aversion | Bank |

The control variables (socio-demographic characteristics), moderating variable (gender), behavioural biases variables, the dummy variables and description of the variables used in the analysis are highlighted in Table 3.

### Table 3: Description of the variables used in the analysis

| Variable | Description | Dummy variables | Definition |
|---|---|---|---|
| **Dependent variables** | | | |
| Mobile money usage<br>- Currently have<br>- Used to have<br>- Never had | Currently =1, otherwise = 0<br>Reference: Used to have/ Never had | Mobile: Usage | Mobile money usage (Current have, used to have, never had) |
| Mobile money access<br>- Used to have<br>- Currently have<br>- Never had | Used to have = 1<br>Currently have = 1<br>Reference: Never had | Mobile: Access | Mobile money usage (Current have, used to have, never had) |
| **Moderator variable** | | | |
| Gender<br>- Male and Female | Female = 1, otherwise = 0<br>Reference: Male | Gender: Female | Sex of the respondent |
| **Socio-demographic characteristics (Control variables)** | | | |
| Age<br>- 16 - 17<br>- 18 - 25<br>- 26 – 35<br>- 36 – 45<br>- 46 – 55<br>- >55 years | 18 – 25 = 1, otherwise = 0<br>26 – 35 = 1, otherwise = 0<br>36 – 45 = 1, otherwise = 0<br>46 – 55 = 1, otherwise = 0<br>>55 = 1, otherwise = 0<br>Reference: 16-17 years | Age :18-25<br>Age :26-35<br>Age :36-45<br>Age :46-55<br>Age :>55 | 16-17, 18-25, 26-35, 36-45, 46-55, >55 (years) |
| Marital status<br>- Single/Never<br>- married<br>- Married/Partner<br>- Widowed<br>- Divorced/Separated | Single = 1, otherwise = 0<br>Married/partner = 1, otherwise = 0<br>Widowed = 1, otherwise = 0<br>Reference: Divorced | Marital: Single<br>Marital: Married<br>Marital: Widowed | Single/never married, Divorced/separated, widowed, married/ living with partner) |
| Education<br>- None<br>- Primary<br>- Secondary<br>- Tertiary | Primary = 1, otherwise = 0<br>Secondary = 1, otherwise = 0<br>Tertiary = 1, otherwise = 0<br>Reference: None | Education: Primary<br>Education: Secondary<br>Education: Tertiary | None, Primary, Secondary, Tertiary and Other |
| **Confirmation bias** | | | |
| Income<br>- 0 – 1500<br>- 1501 – 3000<br>- 3001 - 7500<br>- 7501 – 15000<br>- 15001-30000<br>- >30000 | 1501 – 3000 = 1, otherwise = 0<br>3001 – 7500 = 1, otherwise = 0<br>7501 – 15000 = 1, otherwise = 0<br>15001-30000 = 1, otherwise = 0<br>>30000 = 1, otherwise = 0<br>Reference: 0-1500 | Income: 1500<br>Income: 3000<br>Income: 7500<br>Income: 15000<br>Income:>30000 | Ksh (0-100, 101-1500, 1501-3K, 3001-7.5K, 7501-15K, 15001-30K, 30001-70K, 70001-200K, 200001-400K, 400001-1M, > 1M) |

*continued next page*

**Table 3 Continued**

| Variable | Description | Dummy variables | Definition |
|---|---|---|---|
| **Endowment bias** | | | |
| Religion<br>- Islam<br>- Christianity | Christianity = 1, otherwise = 0<br>Reference: Islam | Religion: Christianity | Religion (Christianity, Islam, Traditional African and Hindu) |
| **Overconfidence bias** | | | |
| Draw savings<br>- Yes and No | No = 1, Yes = 0<br>Reference: Yes | Savings: No | Draw on the savings? (Yes/No) |
| **Self-control bias** | | | |
| Spending plan<br>- Agree<br>- Disagree<br>- Neither agree nor<br>- disagree (NAnD) | Agree = 1, otherwise = 0<br>NAnD = 1, otherwise = 0<br>Reference: Disagree | Spending: Agree<br>Spending: NAnD | Spending plan (Disagree, agree, Neither agree nor disagree) |
| **Regret aversion bias** | | | |
| Trust<br>- Bank<br>- Digital<br>- Group/chama<br>- Sacco<br>- Auxiliary institutions (AI) | Digital = 1, otherwise = 0<br>Group/chama=1, otherwise = 0<br>Sacco = 1, otherwise = 0<br>AI = 1, otherwise = 0<br>Reference: Bank | Trust: Digital<br>Trust: Group<br>Trust: Sacco<br>Trust: AI | Bank, Sacco, mobile money provider and banking, group/ chama, insurance company and broker, pensions, digital credit app, CDS, shylocks, etc |
| **Status quo bias** | | | |
| Mobile ownership<br>- Yes and No | Yes = 1, otherwise = 0<br>Reference: No | Mobile: yes | Mobile phone ownership (Yes/No) |

## Descriptive analysis

From the total respondents in the survey data used in this paper, males represent 43.5% and females represent 56.5%. For the individual variable percentage, we map men and women to the attributes of AU (Access and Usage), ANU (Access and no usage) and NANU (No access, no usage). Percentages for men and women are then calculated based on the groups of AU, ANU and NANU. Any value above 43.50% in aggregate variable for men shows a gender gap in favour of men. Any value above 56.50% in aggregate variable for women shows a gender gap in favour of women. Based on that, we observe a mixed picture of the gaps, depending on the underlying behavioural biases.

The extent of those gaps and whether they are male- or female-leaning is given in Appendix Table 1A. The table shows the disaggregated data based on gender and with access and usage, access and no usage, and no access and no usage. Further, Appendix Table 1A provides the descriptive statistics and Chi-square test results for the respective categorical variables and gender. Overall, gender differences in all the

domains considered are evident, notably in the level of education, income, mobile phone ownership, savings and spending, and trust in financial service providers. While mobile ownership by women is higher than that of men, the gender gaps in mobile money access and usage are in favour of males, with the differences being statistically significant.

## Model specification

Two equations are implemented to establish how, and to what extent, behavioural biases are a significant obstacle to the utilization/access and usage of DFS with the control variables and gender as a moderating variable.

$$MM_i = \gamma_0 + \gamma_1 BB_i + \gamma_2 Gender_i + \gamma_3 Controls_i + \gamma_4 Gender_i * BB_i \quad (1)$$

$MM_i$ represents mobile money access and usage of the $i^{th}$ individual with three categorical measures, namely 'currently have', 'used to have', and 'never had'. To create two response variables, 'currently have' is treated as mobile money usage while 'currently have' and 'used to have' are treated as mobile money access.

In equation (1), $BB_i$ is a proxy of the vector for behavioural biases that are deemed to influence the adoption and usage of DFS, and they include: confirmation, endowment, overconfidence, self-control, regret aversion and status quo bias as indicated in Table 1. In addition, we also include a vector of $Controls_i$, namely age, marital status, and education level. Gender is the moderating variable on the relationship between DFS adoption and usage and the behavioural biases. Income is a variable that influences the proportions spent on savings, investments, and other expenses. The term, $Gender_i * BB_i$ is the interaction between gender and behavioural biases. We treat income as a confirmation bias in line with Renu and Christie (2019) as it influences households' options and financial decisions. Behavioural biases are selected based on the household shortcoming, and the control variables are crucial in assisting to establish the true effects on behavioural biases and gender as a moderator.

The behavioural biases with gender are estimated from Probit model and marginal effects calculated for the differences on biases based on gender. The Probit model is used as it employs a Probit link function, and the model is often estimated using the standard maximum likelihood procedure. Probit analysis is based on the cumulative normal probability distribution. Probit regression model response variable is mobile money usage and mobile money access – a binary response. The Probit regression of mobile money access and usage with each of behavioural biases are computed and the partial derivatives estimated to obtain the marginal effects based on gender. R statistical software performs all the analysis in the study.

## Diagnostic test for probit model

We test the diagnostic power of the Probit model by comparing the null model and the model with predictors. Table 4 reports the diagnostic assessment using the R-squared and Chi-square test based on the null model and a model with the predictors, upon which we reject the null hypothesis that the model without predictors is as good as the model with the predictors. That indicates that the two models are significantly different. The models prediction power based on R-square ranges from the minimum of 28.09% to a high of 62.83%. The introduction of the controls increases the explanatory power of the models compared to models with the moderating variable (gender) only. We therefore report the study findings based on the estimation of equation 1.

# 5. Results

**Table 4: Probit models diagnostic test using R-squared and Chi-square tests**

| | CoxSnell (%) | Nagelkerke (%) | McFadden (%) | Chi-square | Df | P-value |
|---|---|---|---|---|---|---|
| MM access – Gender | 28.09 | 52.32 | 42.84 | 5443.1 | 16732 | 0.001 |
| MM access – Control | 31.53 | 58.73 | 48.25 | 6371 | 16732 | 0.001 |
| MM usage – Gender | 34.59 | 59.11 | 48.25 | 7035.1 | 16732 | 0.001 |
| MM usage - Control | 36.77 | 62.83 | 52.09 | 7677.8 | 16732 | 0.001 |

In Table 5, the marginal effects are estimated from the Probit regression equation (equation 2) by finding the partial derivative of mobile money access and mobile money usage with respect to each of the six explanatories (behavioural biases), moderating (gender) and control variables (marital status, education level and age). The results are interpreted as a percentage in change of explanatory variable to the response variable.

We deduce that men have higher access and usage of mobile money than women when moderating for gender. For incomes above Ksh 30,000, the gender gap favours women with percentage of access (15.2%) compared to men (14.4%) and percentage of usage among women (16.4%) and men (12.6%). Men earning above Ksh 30,000 had higher usage (0.1%) than access with similar observations for women earning above Ksh 30,000 with higher usage (1.2%) than access. A plausible explanation is that they borrowed family/friends' mobile phones to utilize mobile money services.

Males (females) earning above Ksh 30,000, access and usage increases by 14.4% (15.2%) and 12.6% (16.4%) compared to Ksh 0-1500 earners. Controlling for marital status, age and education level decrease access and usage of mobile money. Men earning above Ksh 30,000 had the highest decrease of 7% when usage (with moderator) is compared to usage (with controls). Evidently, age, education and marital status have a profound influence in usage of mobile money among households led by men earning above Ksh 30,000. An increase in income increases mobile money access and usage but decreases when controlling for age, education, and marital status. Behavioural biases can be mitigated by education, marital status, and the age of the respondent. These characteristics influence a household head's decision-making by shifting their life's goals and aspirations. At high income levels, women have lower confirmation bias compared to men, but shifts at low-income levels. When men and women are put on the same pedestal (controlling for age, marital status, and education), they have lower confirmation bias at any income levels with an increase in access and usage of mobile money services.

**Table 5: Marginal effect of response variables with gender and control variables**

| Variable | Gen | Access – Gen | | Usage – Gender | | Access – Control | | Usage-Control | |
|---|---|---|---|---|---|---|---|---|---|
| | | Estimate | std. err | Estimate | std. Err | Estimate | std. err | Estimate | std. err |
| Income:1500 | F | 0.047** | 0.007 | 0.038** | 0.007 | 0.029** | 0.007 | 0.025** | 0.007 |
| Income:1500 | M | 0.065** | 0.008 | 0.056** | 0.009 | 0.038** | 0.008 | 0.034** | 0.008 |
| Income:3000 | F | 0.071** | 0.009 | 0.068** | 0.009 | 0.044** | 0.009 | 0.045** | 0.009 |
| Income:3000 | M | 0.108** | 0.009 | 0.094** | 0.009 | 0.062** | 0.008 | 0.055** | 0.009 |
| Income:7500 | F | 0.063** | 0.007 | 0.053** | 0.007 | 0.041** | 0.007 | 0.036** | 0.007 |
| Income:7500 | M | 0.097** | 0.008 | 0.085** | 0.008 | 0.056** | 0.007 | 0.051** | 0.008 |
| Income:15000 | F | 0.080** | 0.014 | 0.073** | 0.014 | 0.044** | 0.014 | 0.041** | 0.013 |
| Income:15000 | M | 0.109** | 0.012 | 0.110** | 0.012 | 0.048** | 0.011 | 0.058** | 0.012 |
| Income:>30000 | F | 0.152** | 0.038 | 0.164** | 0.040 | 0.095** | 0.040 | 0.113** | 0.042 |
| Income:>30000 | M | 0.144** | 0.022 | 0.126** | 0.019 | 0.059** | 0.020 | 0.050** | 0.019 |
| Religion: Christianity | F | 0.012 | 0.009 | 0.016* | 0.009 | -0.024** | 0.009 | -0.016* | 0.009 |
| Religion: Christianity | M | 0.024** | 0.008 | 0.025** | 0.008 | -0.006 | 0.008 | 0.001 | 0.008 |
| Savings: no | F | 0.004 | 0.008 | 0.007 | 0.008 | -0.015* | 0.008 | -0.004 | 0.008 |
| Savings: no | M | 0.006 | 0.007 | -0.004 | 0.007 | -0.011 | 0.007 | -0.017** | 0.007 |
| Spending: agree | F | 0.021** | 0.006 | 0.033** | 0.006 | 0.010** | 0.005 | 0.024** | 0.005 |
| Spending: agree | M | 0.019** | 0.006 | 0.025** | 0.006 | 0.006 | 0.005 | 0.014** | 0.005 |
| Spending: nand | F | 0.010 | 0.021 | 0.010 | 0.020 | 0.013 | 0.020 | 0.014 | 0.020 |
| Spending: nand | M | 0.019 | 0.018 | 0.021 | 0.018 | 0.016 | 0.018 | 0.019 | 0.018 |
| Mobile: yes | F | 0.263** | 0.005 | 0.315** | 0.006 | 0.213** | 0.004 | 0.272** | 0.005 |
| Mobile: yes | M | 0.216** | 0.005 | 0.271** | 0.007 | 0.175** | 0.005 | 0.234** | 0.006 |
| Trust: group | F | -0.005 | 0.008 | -0.018** | 0.008 | -0.024** | 0.008 | -0.031** | 0.008 |

*continued next page*

**Table 5 Continued**

| Variable | Gen | Access – Gen | | Usage – Gender | | Access – Control | | Usage-Control | |
|---|---|---|---|---|---|---|---|---|---|
| | | Estimate | std. err | Estimate | std. Err | Estimate | std. err | Estimate | std. err |
| Trust: group | M | 0.015 | 0.014 | 0.002 | 0.014 | -0.004 | 0.012 | -0.009 | 0.012 |
| Trust: digital | F | 0.019** | 0.006 | 0.013** | 0.006 | 0.018** | 0.006 | 0.013** | 0.006 |
| Trust: digital | M | 0.023** | 0.006 | 0.013** | 0.006 | 0.022** | 0.005 | 0.015** | 0.006 |
| Trust: others | F | 0.012 | 0.028 | -0.006 | 0.027 | -0.001 | 0.026 | -0.015 | 0.026 |
| Trust: others | M | 0.022 | 0.032 | -0.031 | 0.029 | 0.004 | 0.029 | -0.041 | 0.026 |
| Trust: sacco | F | 0.027** | 0.013 | 0.027** | 0.013 | 0.007 | 0.012 | 0.012 | 0.012 |
| Trust: sacco | M | 0.051** | 0.014 | 0.051** | 0.014 | 0.026** | 0.012 | 0.031** | 0.012 |
| Marital: single | F | | | | | -0.045** | 0.010 | -0.017* | 0.009 |
| Marital: single | M | | | | | -0.035** | 0.008 | -0.014* | 0.007 |
| Marital: widowed | F | | | | | -0.019* | 0.011 | 0.005 | 0.010 |
| Marital: widowed | M | | | | | -0.015* | 0.008 | 0.004 | 0.008 |
| Marital: married | F | | | | | -0.016* | 0.009 | 0.016** | 0.008 |
| Marital: married | M | | | | | -0.013* | 0.007 | 0.012* | 0.006 |
| Education: primary | F | | | | | -0.060** | 0.006 | -0.049** | 0.006 |
| Education: primary | M | | | | | -0.047** | 0.005 | -0.039** | 0.005 |
| Education: secondary | F | | | | | 0.004 | 0.005 | 0.011** | 0.005 |
| Education: secondary | M | | | | | 0.003 | 0.004 | 0.009** | 0.004 |
| Education: tertiary | F | | | | | 0.059** | 0.010 | 0.067** | 0.010 |
| Education: tertiary | M | | | | | 0.046** | 0.008 | 0.053** | 0.008 |
| Age:2635 | F | | | | | 0.179** | 0.011 | 0.157** | 0.012 |
| Age:2635 | M | | | | | 0.139** | 0.009 | 0.125** | 0.010 |

*continued next page*

**Table 5 Continued**

| Variable | Gen | Access – Gen | | Usage – Gender | | Access – Control | | Usage-Control | |
|---|---|---|---|---|---|---|---|---|---|
| | | Estimate | std. err | Estimate | std. Err | Estimate | std. err | Estimate | std. err |
| Age:1625 | F | | | | | 0.098** | 0.009 | 0.093** | 0.011 |
| Age:1625 | M | | | | | 0.076** | 0.007 | 0.074** | 0.008 |
| Age:3645 | F | | | | | 0.190** | 0.011 | 0.170** | 0.012 |
| Age:3645 | M | | | | | 0.147** | 0.009 | 0.135** | 0.010 |
| Age:4655 | F | | | | | 0.184** | 0.012 | 0.171** | 0.013 |
| Age:4655 | M | | | | | 0.143** | 0.010 | 0.136** | 0.011 |
| Age:56 | F | | | | | 0.166** | 0.012 | 0.150** | 0.013 |
| Age:56 | M | | | | | 0.129** | 0.009 | 0.119** | 0.010 |
| | | | | | | | | | |

Key: ** p<0.05; * p<0.10; nand-Neither agree nor disagree; religion_christ– religion_christianity; education_pry – education_primary; Gen – Gender

A unit increase in mobile phone ownership increases usage (access) among women by 26.3% (31.5%) and men by 21.6% (27.1%). In controlling for age, education and marital status, a women led household has 21.3% (27.2%) chance of access (usage). For men, access (usage) is at 17.5% (23.4%). Women mobile phone ownership increases their chances of access and usage of mobile money to higher levels than that of men. The advantage men have in education, which can have a bearing on their marital status, lowers the status quo bias compared to women.

A unit increase in spending plan increases usage (access). An increase in planning of spending boosts access (usage) by 2.1% (3.3%) among women, with corresponding increases access (usage) by 1.9% (2.5%) among men. In controlling for age, marital status and education, women access (usage) increases by 1.0% (2.4%), while among the men, access (usage) increases by 0.6% (1.4%). Budgeting among women compared to men increases their access and usage of mobile money. Women have elevated self-control bias, and this increases their chances of having a budget as opposed to men. Self-control bias is good in the sense that women are able to save for the rainy season and be financially resilient.

On savings, lack of, or having a savings plan did not influence access and usage of mobile money. On religion, a Christian compared to a Muslim had higher access (women, 1.2% and men, 2.4%), and usage (women, 1.6% and men, 2.5%) when moderating gender. Men are more likely than women not to have a savings plan due to higher levels of overconfidence exhibited by men. For controls, access and usage for Christian women is 2.4% less and 1.6% less compared to the Muslim counterparts. The effects of age, education level and marital status increases the chances of Muslim women to have higher access and usage compared to Christian women. Muslim women have received much less schooling than Christian women due to the endowment bias. Thus, endowment bias lowers access and usage of mobile money services.

Trust of digital services increases access and usage of mobile money. Women have 1.9% chance of usage, men 2.3% chance and in access, women, 1.3% and men, 1.3%. In the controls, women have 1.8% chance of access and men with 2.2%; with usage of women, 1.3% and men, 1.5%. Moderating for gender and controlling for age, education and marital status does not change the probability of access and usage. Women who trust groups/chama have lower chances of mobile money access and usage. Trust of a savings and credit cooperative organization (SACCO) increased the chances of mobile money access and usage among both men and women. Regret aversion bias is lower in men than it is in women as women are more disadvantaged economically compared to men.

Owning a mobile phone, trusting digital services, having a budget, trusting SACCO and increase in income increases the chance of the household having access to and usage of mobile money. Gender gap in favour of men in access and usage is due to income, religious beliefs, trust of digital services and trust of SACCO. Gender gap in favour of women in access and usage is due to mobile phone ownership and budgeting skills of women. Thus, women have higher status quo bias, regret aversion bias and self-control bias compared to men in access and usage of mobile money services. Men tend to exhibit higher overconfidence bias compared to women. On income, women have lower confirmation bias at high income levels than men. This shifts at low income where confirmation bias is high among women compared to men.

# 6. Conclusions and policy implications

We highlight the key findings from the study and the policy implications arising from the behavioural biases driving the wedge between access and usage of mobile money. It is evident that behavioural biases influence access and usage of mobile money, the most prominent among the DFS as highlighted in the following key findings:

- Households with higher income are less prone to confirmation biases compared to households with lower monthly income. Households that face this bias tend to ignore information that conflicts with their mobile money access and usage decisions and assume that they do not exist. Women exhibit higher confirmation bias compared to men in mobile money access and usage but the trend reverses at higher income levels.

- While Muslims are perceived to exclude themselves from financial products and services, no evidence of exclusion is found in the access and usage of mobile money among Christians and Muslims, for both men- and women-headed households. But Muslim men and women are more likely to exhibit endowment bias due to their religious beliefs. As markets develop digital credit products, the issue of exclusion will likely be prominent if issues such as sharia compliance are not embedded. Women with access are more likely to save than their male counterparts with increase in savings decreasing overconfidence bias. Women are risk averse, making them more cautious in their financial decision and consequently better savers than men who suffer from overconfidence bias.

- Women exhibited higher self-discipline as observed in budgeting, which in turn increased access and usage compared to men. Budgeting means that women have lower self-control bias. As women seek to enhance the welfare of their lot, they are keen to promote mobile phone ownership, even though that does not automatically translate into improved access and usage. They nonetheless have lower status quo bias than men.

- On regret aversion due to lack of trust of financial providers, women are more likely to have lower mobile money access and usage compared to men. Women's financial decision-making and their cautious nature can explain this gender gap. Being a member of a SACCO reduced regret aversion with being member of groups/chama increasing risk aversion as they probably prefer cash transactions due to other barriers evident in access and usage of financial services such as documentation, digital skills, and general lack of trust.

Based on the foregoing, in can be inferred that gender-sensitive approaches are essential in enhancing the decision-making that promotes enhanced usage of DFS. At the core of these approaches is the need for policies meant to address the binding behavioural biases mitigating against access and usage of DFS. Measures to enhance household incomes that have a gender lens have the potential of ameliorating the gaps underlying financial exclusion of women and low-income earners in mobile money access and usage. In the same vein, measures to engender a competitive environment in the DFS are essential in supporting enhanced uptake on the back of good pricing.

The glaring behavioural biases are confronted with the supply side dynamics characterized by the pursuit of the necessary sophistication not accompanied by increased usage. While the focus seems to be on the continued need for increased infrastructure meant to further deepen financial inclusion, the public policy of seeing basic DFS as a platform for realization of government revenue needs through direct taxation could well be counterintuitive. Even as the case for the development of customer-centric products and services to increase access and usage can be made, the demand-side behavioural biases are worth addressing as a way of bridging access and usage divide.

Even as these inferences are made, we are alive to some limitations of the study. Given that the survey that forms the bedrock of this analysis was conducted during the COVID-19 pandemic, responses may differ from the pre-pandemic norms, thus the possibility of having biases. Furthermore, the proxy used to measure the behavioural biases from the households as evident from the household shortcoming has limitations in the following sense:

- First, a shortcoming from the household perspective cannot be fully attributed to behavioural biases; a myriad of other factors not captured in the study contributes to the household shortcoming.

- Second, the questionnaire approach to gather the FinAccess data might have resulted in common method bias, and thus not reflect the true household behaviour.

- Third, the six selected cognitive biases for the study might not be the most commonly exhibited ones among the households in Kenya. Selection is guided by the availability of the variables in the FinAccess Survey data.

- Finally, this research does not consider longitudinal data but cross-sectional data, which does not permit considering long-haul changes in behavioural biases of the households based on study variables.

To mitigate these study limitations, future FinAccess and other surveys can collect behavioural biases data using tools that enable the capturing of psychological aspects. The personality tests and behavioural observation tests can be customized to collect behavioural biases data. We see a multi-disciplinary approach to improved data collection being useful in retooling the data collection. Behavioural economists can collaborate with psychologists and other researchers to develop tools to collect behavioural bias data in surveys.

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# Appendix

**Table 1A: Study variables disaggregated by gender and mobile money access/usage**

| Variable | | Aggregate Variable | | | | | | Household Variable | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Women | | Men | | Frequencies | | Women (%) | | | Men (%) | | |
| | Categories | Freq. | % | Freq. | % | Chi-sq. test | | AU | ANU | NANU | AU | ANU | NANU |
| **Gender** | | 9479 | 56.52 | 7292 | 43.48 | | | 83.02 | 3.2 | 13.78 | 85.58 | 2.94 | 11.48 |
| **Age (years)** | 16-25 | 2311 | 57.75 | 1691 | 42.25 | | | 76.3 | 2.77 | 20.93 | 77.2 | 2.15 | 20.65 |
| | 26-35 | 2924 | 58.96 | 2035 | 41.04 | $\chi^2$ | 45.9** | 90.01 | 3.35 | 6.64 | 93.02 | 2.7 | 4.28 |
| | 36-45 | 1736 | 52.4 | 1577 | 47.6 | df | 4 | 91.52 | 2.54 | 5.94 | 92.58 | 3.68 | 3.74 |
| | 46-55 | 981 | 53.34 | 858 | 46.66 | | | 90.62 | 2.14 | 7.23 | 92.77 | 2.8 | 4.43 |
| | >55 | 1527 | 57.45 | 1131 | 42.55 | | | 76.67 | 5.05 | 18.28 | 85.59 | 3.98 | 10.43 |
| **Marital Status** | Divorced | 742 | 60 | 495 | 40 | $\chi^2$ | 731.1** | 88.66 | 4.45 | 6.88 | 83.81 | 9.31 | 6.88 |
| | Married | 5122 | 53.57 | 4439 | 46.43 | df | 3 | 87.54 | 2.85 | 9.61 | 93.2 | 2.14 | 4.66 |
| | Single | 2130 | 50.21 | 2148 | 49.79 | | | 73.17 | 2.63 | 24.2 | 71.09 | 2.74 | 26.17 |
| | Widowed | 1467 | 86.55 | 228 | 13.45 | | | 78.79 | 4.64 | 16.58 | 75.44 | 7.02 | 17.54 |
| **Education Level** | None | 1547 | 69.34 | 684 | 30.66 | $\chi^2$ | 210.2** | 69.71 | 5.37 | 24.92 | 77.92 | 3.95 | 18.13 |
| | Primary | 3936 | 57.18 | 2947 | 42.82 | df | 3 | 84.1 | 3.95 | 11.95 | 83.78 | 4.66 | 11.56 |
| | Secondary | 2856 | 52.59 | 2575 | 47.41 | | | 83.1 | 1.97 | 1.93 | 84.19 | 1.91 | 13.9 |
| | Tertiary | 1140 | 51.21 | 1086 | 48.79 | | | 97.28 | 0.79 | 1.93 | 98.53 | 0.18 | 1.29 |
| **Monthly income (KES)** | 0-1500 | 1720 | 69.3 | 762 | 30.7 | $\chi^2$ | 668.2** | 65.98 | 4.19 | 29.83 | 53.61 | 3.88 | 42.51 |
| | 1501-3000 | 2383 | 65.83 | 1237 | 34.17 | df | 4 | 79.52 | 4.32 | 16.16 | 78.25 | 4.77 | 16.98 |
| | 3001-7500 | 2824 | 57.33 | 2102 | 42.67 | | | 87.08 | 3.26 | 9.67 | 87.63 | 3.81 | 8.56 |
| | 7501-15000 | 1706 | 47.34 | 1898 | 52.66 | | | 92.09 | 1.64 | 6.27 | 92.89 | 2.16 | 4.95 |
| | >15000 | 846 | 39.55 | 1293 | 60.45 | | | 99.11 | 0 | 0.89 | 98.21 | 0.77 | 1.02 |

*continued next page*

**Table 1A Continued**

| Variable | | Aggregate Variable | | | | | | Household Variable | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Women | | Men | | Frequencies | | Women (%) | | | Men (%) | | |
| | Categories | Freq. | % | Freq. | % | Chi-sq. test | | AU | ANU | NANU | AU | ANU | NANU |
| **Mobile Ownership** | No | 1404 | 61.12 | 893 | 38.88 | $\chi^2$ | 22.73** | 2.57 | 2.1 | 9.98 | 1.84 | 2.01 | 8.29 |
| | Yes | 8075 | 55.79 | 6399 | 44.21 | df | 1 | 80.46 | 1.1 | 3.78 | 83.73 | 0.95 | 3.19 |
| **Religion** | Christianity | 8464 | 57.15 | 6346 | 42.85 | $\chi^2$ | 20.26** | 74.12 | 2.79 | 12.6 | 74.35 | 2.58 | 10.09 |
| | Islam | 1015 | 51.76 | 946 | 48.24 | df | 1 | 8.92 | 0.41 | 1.4 | 11.23 | 0.37 | 1.39 |
| **Draw savings** | No | 8111 | 57.84 | 5913 | 42.16 | $\chi^2$ | 60.1** | 70.52 | 2.83 | 12.22 | 68.69 | 2.71 | 9.69 |
| | Yes | 1368 | 49.8 | 1379 | 50.2 | df | 1 | 12.51 | 0.37 | 1.54 | 16.89 | 0.25 | 1.79 |
| **Spend Plan** | Agree | 6187 | 56.5 | 4764 | 43.5 | $\chi^2$ | 9.1** | 56.78 | 1.51 | 7.07 | 58.81 | 1.42 | 5.17 |
| | Disagree | 3136 | 57.04 | 2362 | 42.96 | df | 2 | 1.37 | 0.06 | 0.21 | 1.94 | 0.08 | 0.26 |
| | NAnD | 156 | 48.45 | 166 | 51.55 | | | 24.88 | 1.63 | 6.48 | 24.83 | 1.46 | 6.05 |
| **Trust financial systems** | Bank | 3731 | 51.84 | 3466 | 48.16 | | | 82.88 | 2.69 | 14.44 | 84.7 | 3.58 | 12.9 |
| | Digital | 3925 | 57.43 | 2909 | 42.57 | $\chi^2$ | 387.5** | 84.08 | 3.4 | 12.52 | 85.45 | 3.58 | 10.97 |
| | Group/Chama | 1086 | 80.09 | 270 | 19.91 | df | 4 | 75.21 | 5.16 | 19.63 | 81.34 | 4.85 | 13.81 |
| | Sacco | 647 | 63.83 | 596 | 36.17 | | | 91.19 | 1.55 | 7.26 | 93.95 | 1.68 | 4.4 |

Key: AU: Access and Usage; ANU: Access No Usage, NANU: No Access, No Usage, MPO: Mobile phone ownership; Single/NM – Single/Never Married; NAnD – Neither agree nor disagree; Values above 43.50% (56.50%) for men (women) show a gender gap in favour of men (women)

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