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Digital financial services adoption: a retrospective time-to-event analysis approach

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Abstract

Expanding digital financial services (DFS) such as mobile money has become a key policy intervention for many developing and emerging countries as they seek to fast-track financial and economic inclusion. To date, adults in these markets have had more mobile money accounts than traditional bank accounts. Numerous studies have used binary approaches to understand the factors explaining DFS adoption. However, there is a dearth of studies, that investigate the time to DFS adoption and factors that predict time to adoption. To close this gap, this study used a time-to-event analysis approach to estimate the time to DFS adoption and investigate the factors that explain the variation in time to adoption. Using a sample of 1800 survey respondents from Zimbabwe, the study found that it took 4.4 and 8.5 years, respectively, for urban and rural residents to adopt DFS. Overall, the findings show that individuals who are significantly more likely to adopt DFS faster are those residing in urban areas, near mobile money agents, banked, with high levels of education and financial literacy, middle-aged, belonging to social groups, and self-employed. In addition, an expansionary macroeconomic environment was associated with greater DFS adoption intensities. The findings also show that gender and income level do not predict the time to DFS adoption in the studied market. This study provides policy and practitioner recommendations for possible actions to accelerate the adoption of DFS.

Keywords: Digital financial services, Mobile money, Time-to-event analysis, Survival analysis, Adoption factors

Introduction

Disruptive financial innovations, particularly digital financial services (DFS), have proliferated into developing and emerging markets (Manyika et al. 2016). To date, adults in these markets have had more mobile money accounts than commercial bank accounts (Bazarbash et al. 2020). It is estimated that sub-Saharan Africa alone had 548 million registered mobile money accounts, transacting US$ 490 billion, more than half of the world's mobile money transactions in 2020 (GSM Association 2021).

Evidence shows that DFS, such as mobile money, helps circumvent traditional financial market imperfections such as information asymmetries and transaction costs, which impede poor people from accessing formal financial services, thus denying them a chance to escape poverty (Demir et al. 2022). Expanding DFS has become a key policy intervention for many developing and emerging countries seeking to fast-track financial and economic inclusion (AFI 2022). Given the growing importance of DFS, policymakers and researchers are increasingly interested in understanding the drivers of DFS adoption to provide solutions to accelerate adoption. A review of the literature reveals a growing strand of research that uses innovation or technology acceptance frameworks and models to understand the latent factors that explain DFS adoption (Upadhyay and Jahanyan 2016; Shankar and Datta 2018; Gbongli et al. 2019; Murendo et al. 2018). Another strand of research explores the observable factors associated with DFS adoption (Akinyemi and Mushunje 2020; Senou et al. 2019; Afawubo et al. 2020).

Given that the adoption of DFS in many developing economies has advanced, reaching or exceeding 50% of the adult population,[1] I argue that much is known about who is likely to adopt DFS and what potentially explains their adoption. Numerous studies have taken a binary approach to understand the factors that explain the adoption of DFS (for instance, Senou et al. 2019; Osei-Assibey 2015; Murendo et al. 2018; Kodom et al. 2020; Lashitew et al. 2019). However, there is a dearth of studies that investigate the time to DFS adoption and factors that explain the variation in time to DFS adoption. Thus, instead of asking who adopts DFS and what factors drive their adoption, the novelty of this study is that it seeks answers on how long it takes for users to adopt such services and what factors explain the variation in time to adoption. Estimating the time-to-adoption of DFS helps businesses determine the resources required and the likely time needed before reaching the critical mass necessary to sustain the (line of) business and potentially catalyze the market. Insights from such analyses are key for entrepreneurs and businesses seeking to expand or introduce new DFS offerings, as they aim to target (first) consumers who matter the most to their businesses. Understanding the instantaneous potential by different population segments to adopt DFS can help service providers develop effective and targeted strategies. Policymakers are always interested in ensuring that marginalized population groups are not excluded from using such beneficial innovations. As such, understanding the time to adoption may help inform targeted policy initiatives to accelerate DFS adoption by unbanked and marginalized groups.

The objective of this study is to estimate the time to adoption of mobile money in Zimbabwe and understand the observable factors that predict its early adoption using a time-to-event or survival analysis approach. Therefore, the outcomes of interest are time-to-adoption and the adoption event. Modeling DFS adoption through survival models provides information that can help understand the observable characteristics of users likely to adopt a DFS innovation faster, and other factors that predict (time to) adoption. Survival models provide the opportunity to predict whether an event (DFS adoption) will occur and estimate when it will occur (Banasik et al. 1999; Chamboko and Bravo 2019a). Moreover, survival models can use censored observations in the analysis (Noh et al. 2005; Chamboko and Bravo 2019b). Thus, individuals who have not yet adopted mobile money are included in the analysis to estimate the time to adoption – a weakness of traditional regression approaches (e.g., ordinary least squares regression). In addition, survival models offer superiority in that they can forecast multiple periods (Tong et al. 2012), allowing the modeling of seasoning effects (Tong et al. 2012) and are

[1] E.g., in Tanzania 2017 [60%], Uganda 2018 [56%], Rwanda 2020 [61%], Zambia 2020 [58.5%], Kenya 2021 [81.4%], Zimbabwe 2022[63%].

dynamic, thus allowing the inclusion of time-dependent covariates (Bellotti and Crook, 2013; Chamboko and Bravo 2020, 2016).

This is most likely the first study to apply a time-to-event analysis approach to examine the adoption of mobile money. The findings of this study contribute to the literature a typical DFS adoption journey for a country, particularly showing the longitudinal trends in DFS adoption while revealing how the adoption propensity differs across population segments. For policymakers and service providers seeking to propel DFS adoption across developing countries, the findings provide insights into the key demographic, socioeconomic, geographic, structural, and behavioral predictors of early adoption of DFS.

The rest of the paper proceeds as follows. Section "Literature review" defines DFS and reviews its importance and the factors that affect adoption. Section "Data and empirical strategy" discusses this study's data and empirical methods, and Sect. "Results" presents the results. Section "Discussion" discusses the findings, and section "Conclusion and recommendations" concludes the study and provides recommendations.

Literature review

Definitions and theoretical underpinnings

Theory suggests that financial market imperfections, such as information asymmetries and transaction costs, hinder marginalized population segments from accessing formal financial services and hence lock them in poverty cycles (Demir et al. 2022). The rise of innovative digital financial services (DFS), such as mobile money, provides new opportunities for the marginalized to participate in the formal financial system, thereby accelerating financial inclusion (Ouma et al. 2017; Gosavi 2018; Demir et al. 2022). When responsibly provided, DFS benefits the unserved and underserved population segments, through products and services with better speed, convenience, accessibility, security, and reduced costs (Chamboko et al. 2021). These innovations lower operating costs, increase efficiency, and foster competitiveness (Manyika et al. 2016).

DFS refers to financial services (e.g., payments, credit, savings, and insurance) delivered through mobile phones, computers, cards, or the Internet (Manyika et al. 2016). Mobile money is a recent and novel financial technology that provides financial transaction services via mobile phones, including those for the globally unbanked poor (Aron 2018). Thus, mobile money is the most common type of DFS offered in developing and emerging economies and is used interchangeably with DFS in this study. In Africa, the Safaricon (M-PESA), which started in 2007 in Kenya was the first mobile money success story.

Growing evidence shows that mobile money contributes to increased financial inclusion for households and firms (Mbiti and Weil 2011; Ouma et al. 2017; Gosavi 2018). Demir et al. (2022) show that financial innovations such as mobile money are powerful tools that advance financial inclusion and reduce inequality. Several studies show that the use of mobile money services leads to an increase in the propensity to save, borrow, receive, and send remittances (Munyegera and Matsumoto 2018; Ky et al. 2018; Wieser et al. 2019). Mobile money also helps smooth consumption during financial and income shocks (Suri and Jack 2016) and allows rural households to maintain consumption levels despite rainfall shocks (Riley 2018; Afawubo et al. 2020). Sekabira and Qaim (2017) and

Suri and Jack (2016) show that mobile money services help poor rural women and smallholder farmers diversify their livelihoods.

The literature also reveals that using mobile money reduces long-term poverty levels by increasing per capita consumption levels (Munyegera and Matsumoto 2016; Suri and Jack 2016). Wieser et al. (2019) reported that mobile money reduces food insecurity among rural inhabitants. Polloni-Silva et al. (2021) showed that the adoption of financial technology and financial inclusion reduced the poverty headcount ratio and Gini index (i.e., inequality) among 13 Latin American countries.

The evidence also suggests that innovations in the financial sector, such as mobile money, significantly promote inclusive economic growth. Through a cross-section of 93 countries, Asongu and Nwachukwu (2018) studied the relationship between mobile banking and inclusive development (measured by the quality of growth, inequality, and poverty). They found that using mobile phones to perform financial transactions, such as bill payments and sending or receiving remittances, was significantly and negatively associated with income inequality, especially in upper-middle-income countries. Similarly, Asongu and Odhiambo (2018) find that mobile banking reduces income inequality and fosters women's economic empowerment. Zhang et al. (2020) used the digital financial inclusion index to show that fintech reduces the income gap between rural and urban China.

In addition, a growing body of literature shows that mobile money innovation promotes financial integration. This is largely because alternative data generated through mobile money transactions (by individuals and small firms), are being used by mobile money operators, fintech companies, and financial institutions to score users, thus increasing their access to finance. For firms, especially small and medium enterprises, emerging evidence suggests that adopting mobile money increases investments (firms purchasing more fixed assets). This is largely attributed to reduced transaction costs and increased creditworthiness (due to the increased digital footprint), which allow firms to access lines of credit or loans (Islam et al. 2018; Gosavi 2018).

Determinants of DFS adoption

Broadly, the factors that drive DFS adoption can be grouped into latent and observable factors. The observable factors include demographic, socioeconomic, geographic, structural, macroeconomic, and contextual factors. On the other hand, latent factors may include perceived ease of use, perceived usefulness, quality of systems, task-technology fit, discomfort, connectivity, perceived cost, trust, and self-efficacy.

At the country level, studies have attempted to understand why some countries have higher DFS adoption rates than others. Senou et al. (2019) investigate the factors that drive the adoption of mobile money using country-level data and find that country characteristics such as literacy rates, labor force participation, mobile infrastructure, and banking infrastructure are the main factors driving the adoption of mobile money. Similarly, Lashitew et al. (2019) adopted a cross-country approach to understanding the factors that explain the variation in mobile money adoption rates across countries and found that regulatory, institutional, and macroeconomic factors play a key role in the adoption and usage of mobile money services.

Mothobi and Grzybowski (2017) used survey data from 11 sub-Saharan African countries and analyzed how physical infrastructure availability (approximated by data on nighttime light intensity) influenced the adoption of mobile phones and the usage of mobile services. After controlling for certain factors, the study found that the adoption of mobile phones was highest in areas where the physical infrastructure was more developed. However, individuals residing in areas with poor infrastructure were more likely to rely on mobile phones for financial transactions. Suri (2017), Jack and Suri (2014), and Koomson et al. (2021) find that mobile money adoption is highest among people with greater physical proximity to mobile money agents. In Ghana, Kodom et al. (2020) found that network failures and service charges also play an important role in explaining adoption while erratic networks and high charges act as inhibitors.

Other studies have analyzed individual-level factors associated with adopting DFS in many countries. Afawubo et al. (2020) investigated the factors associated with mobile money adoption in Togo and found that affiliation with social, religious, or savings groups plays a key role. This study also established that having other financial products or being a bank or MFI client served as channels for mobile money adoption. This could be primarily due to the integration of mobile money services with core banking services, which has allowed bank users to link their banking services to mobile money accounts. Murendo et al. (2018) analyzed the effects of social networks on the adoption of mobile money in some rural parts of Uganda. This study finds that the size of a social network positively influences the adoption of mobile money, which is more pronounced among non-poor households. Chamboko et al. (2018) also established that women relied more on information from their social networks to make decisions about mobile money adoption. Bongomin et al. (2018) also showed the moderating effects of social networks on mobile money adoption and financial inclusion in rural Uganda.

Akinyemi and Mushunje (2020) investigated the determinants of mobile money adoption in rural areas of Africa and found that age, level of education, employment status, and having a bank account explained both the adoption of mobile money and the amount of money remitted through the mobile money channel. These findings corroborate those of Senou et al. (2019), who found that being young, male, educated, having a relatively higher socioeconomic status, and having a bank account increased the chances of adopting mobile money in the West African Economic and Monetary Union.

Several studies have used an information systems approach to investigate the latent factors affecting DFS adoption. Shareef et al. (2018) studied consumer attitudes and perceptions toward adopting mobile money as a service channel. The study found that perceived usefulness, ease of use, system quality, task-technology fit, discomfort, and connectivity significantly impacted the usage intention of mobile money services. Gbongli et al. (2019) found that the perceived ease of use mostly influenced the adoption of mobile-based money services in Togo. Similarly, Shankar and Datta (2018) investigated the factors affecting mobile payment (m-payment) adoption intention in India and found that perceived usefulness, perceived ease of use, trust, and self-efficacy have a significant positive impact on the intention to adopt m-payment. The issue of trust was echoed by Chamboko et al. (2021), who found that women are particularly concerned about trust, as they prefer to transact in a way that ensures that their financial position remains secret, especially when transacting with agents.

Abrahão et al. (2016) also studied the factors influencing Brazilian mobile phone consumers' intentions to adopt mobile payment services. Importantly, the researchers found that perceived cost was not statistically significant. This finding is consistent with the observations in Kenya, where mobile money has flourished more than anywhere else. It has been argued that the M-PESA money transfer service in Kenya has the highest transfer prices in the country, but because of its competitive position in the market, it is still widely used (Cook 2017). Dayour et al. (2020) investigate the factors that explain the continuous use of mobile money services among Ghana's small- and medium-sized tourism and hospitality enterprises. The researchers made an important finding suggesting significant differences between males and females in terms of effort expectancy and continuous use intention. Similarly, Chamboko et al. (2018) document numerous differences in how women and men in sub-Saharan Africa engage in DFS, such as mobile money. These differences include men being more likely to adopt DFS and use the services more frequently than women.

Implications of the literature

DFS, such as mobile money, has gained much traction in developing countries as it presents the opportunity to eradicate financial exclusion, especially among the marginalized. However, the literature shows that it is not the most marginalized people who are most likely to adopt such services. It is likely that those who adopt mobile money first are those who are well catered for by existing financial systems, that is, the banked, the most educated, in urban areas, and of higher income.

Data and empirical strategy

Data

This study used data from a nationally representative financial inclusion survey (FinScope) conducted in Zimbabwe. The survey comprised a sample of 3000 adults aged 16 and older from 10 provinces of Zimbabwe. The sample was drawn using a multistage sampling methodology based on probability proportional to size. The data were collected between April and May 2022.

Survival analysis

Outcome variables and sample determination

To implement the survival analysis approach, this study uses two outcome variables: event and time. The event is considered a single event without recurrence or repeated events, as it captures whether one had adopted mobile money by the time the survey was conducted, regardless of past inactivity spells. Given that some individuals experienced the event before the end of the observation period while others did not (mobile money adoption), the data were regarded as right-censored. The time variable refers to the time taken before adopting mobile money in years. The event or adoption variable was derived from the survey question, "Are you currently using mobile money?" The time variable derived from the survey question "For how long have you been using mobile money since?" shows the year in which mobile money was adopted. To ensure that the study only focused on adults (16 years and above) eligible to adopt mobile money when it was introduced in 2011, I truncated the data by age, which meant only retaining individuals who were 29 years and above by the time of the 2022 survey. I further truncated the data to retain respondents who answered questions on adoption dates, if they had adopted mobile money. After this two-stage truncation process, 1800 respondents were retained. The retained sample reflects the population characteristics of the country, given the rural and urban representation and gender distribution (see section "Univariate and descriptive analysis" for sample description). Given that mobile money was introduced in Zimbabwe in 2011, the follow-up period was 12 years.

Explanatory variables

Table 1 presents the explanatory variables used in this study. These include gender, education level, age, locality (rural or urban), income level, source of income, banking, proximity to a mobile money agent, belonging to social groups, and economic growth rate.

Estimation strategy

I used survival analysis to estimate the time to mobile money adoption and characterize the predictors of early adoption. Two important concepts in survival analysis are the survivor function, denoted by $S(t)$ and the hazard function, denoted by $h(t)$. The survival function $S(t)$ is defined as the probability that the survival time will be greater than or equal to t and is expressed as follows:

$$S(t) = P(T \geq t) = 1 - F(t). \tag{1}$$

In this study, this is interpreted as the probability of not having adopted mobile money (surviving) from the time mobile money was introduced to time beyond t, while the hazard function $h(t)$ measures the instantaneous potential of adopting mobile money per unit time given that one has not adopted mobile money until time t. The hazard function $h(t)$ is also known as the hazard rate, or, in this case, the adoption intensity. Mathematically, this is formulated as follows:

$$h(t) = \lim_{\delta t \to 0} \left\{ \frac{P(t \leq T < t + \delta t | T \geq t)}{\delta t} \right\}. \tag{2}$$

In the Cox proportional hazards (PH) model, the covariates affect the hazard multiplicatively as follows:

$$h(t, X) = h_o(t) \exp \left[\sum_{i=1}^{p} \beta_i X_i \right] \tag{3}$$

The model expresses the hazard at time t for an individual i by using a set of specified explanatory variables X_i. Thus, the model is a product of the baseline hazard function $h_0(t)$ and the exponential expression, e to the linear sum of $\beta_i X_i$, where X_i are the explanatory variables and parameters, β_i are the model coefficients that can be estimated through the maximum likelihood approximation. To incorporate time-dependent covariates into the analysis, I used an extended Cox proportional hazards model (see Kleinbaum and Klein 2011). The extended Cox proportional hazards model can be mathematically expressed as follows:

$$h(t, X(t)) = h_0(t) \exp \left[\sum_{i=1}^{p_1} \beta_i X_i + \sum_{j=1}^{p_2} \delta_j X_j(t) \right] \tag{4}$$

where the value of $X_j(t)$ determines the hazard at any given time t and δ_j represents the coefficients of $X_j(t)$.

Logistic regression

To validate the results of the survival model, additional analysis was performed using a different approach to assess the robustness of the results. To achieve this, I extracted a part of the sample of users who adopted mobile money in the first year of the 12 years of follow-up and assigned them one (1) and the rest as zero (0). I also selected those who adopted the service in the first two years and assigned them one (1) and the rest zeros (0). Using these binary outcomes, I fit the logistic regression models as follows:

$$logit(\pi_i) = log\frac{\pi_i}{1 - \pi_i} = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k + \varepsilon_i \tag{5}$$

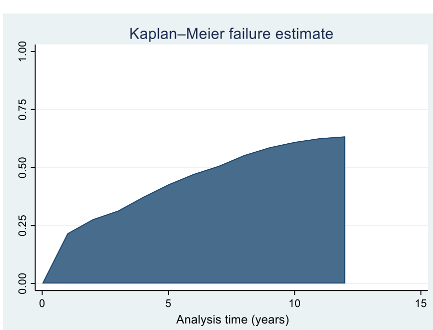
where $X_1 \ldots X_k$ are the covariates in "Explanatory variables" above and $\beta_1 \ldots \beta_k$ is the vector of regression coefficients and ε_i is an error term.

Results

Univariate and descriptive analysis

This section presents the sample characteristics of the respondents and mobile money adoption trends across population segments. Given that the sample mirrors the population across gender and rural–urban composition, the results were inferred at the population level. The results in this section indicate the population subgroups that adopted the mobile money service faster than other groups without controlling for other factors.

Figure 1 shows the failure estimates that reflect the mobile money adoption trend at the population level for the 12-year study period (2011–2022). By the end of the first year, 21.6% of the population had adopted mobile money, and the proportion of users grew steadily to 27.7% in the second year. Seven years after the service was introduced, half (50.7%) of the population adopted it. By the end of the study observation period (12th year), 64.2% of the population had adopted mobile money. The proportion of the



Interval		Beg. total	Deaths	Lost	Survival	Cummulative Failure	Hazard
1	2	1800	389	0	0.7839	0.2161	0.2423
2	3	1411	109	0	0.7233	0.2767	0.0804
3	4	1302	67	0	0.6861	0.3139	0.0528
4	5	1235	107	1	0.6266	0.3734	0.0906
5	6	1127	97	0	0.5727	0.4273	0.0899
6	7	1030	81	1	0.5276	0.4724	0.0819
7	8	948	63	0	0.4926	0.5074	0.0687
8	9	885	83	0	0.4464	0.5536	0.0984
9	10	802	60	0	0.413	0.587	0.0777
10	11	742	42	0	0.3896	0.6104	0.0583
11	12	700	29	2	0.3734	0.6266	0.0424
12	13	669	14	655	0.3581	0.6419	0.0419

Fig. 1 Mobile money adoption over time [failure (adoption) estimates]

Table 1 Mobile money adoption over time

Variable	Sample	Median Adoption time	Year 1 Adoption	Year 2 Adoption	Year 4 Adoption	Year 6 Adoption	Year 8 Adoption	Year 10 Adoption	Year 12 Adoption
All	100	7.035633	0.2161	0.2767	0.3734	0.4273	0.5536	0.6104	0.6419
Urban	36.8	4.445619	0.3489	0.4366	0.5891	0.7372	0.8323	0.8912	0.9253
Rural	63.2	8.543091	0.1388	0.1837	0.2478	0.3182	0.3913	0.4468	0.4758
Male	45.3	6.55762	0.2586	0.3162	0.4203	0.5246	0.6020	0.6462	0.6719
Female	54.7	7.43212	0.1809	0.2439	0.3344	0.4290	0.5135	0.5807	0.6169
29–36	23.9	7.095349	0.1884	0.2558	0.3465	0.4558	0.5674	0.6372	0.6806
36–65	62.3	6.589993	0.2451	0.3075	0.4162	0.5205	0.5964	0.6500	0.6802
66 +	13.8	8.951803	0.1331	0.1734	0.2259	0.2826	0.3353	0.3839	0.4001
Primary or less	38.3	9.29026	0.1030	0.1379	0.1858	0.2498	0.3007	0.3646	0.3979
Secondary Education	49.2	6.262751	0.2316	0.3028	0.4249	0.5447	0.6568	0.7168	0.7526
Tertiary	12.5	3.190266	0.5000	0.5973	0.7434	0.8673	0.9204	0.9425	0.9513
< 200	65.8	7.477423	0.1816	0.2449	0.3277	0.4284	0.5097	0.5757	0.6093
201–500	12.6	5.096916	0.3568	0.4053	0.5374	0.6784	0.7621	0.7930	0.8060
501 +	21.6	6.822622	0.2391	0.2982	0.4165	0.4859	0.5656	0.6093	0.6451
Formally Employed in Private or Government	19.2	4.062069	0.4000	0.4793	0.6690	0.7793	0.8448	0.9000	0.9103
Informally Employed in Private or Government	7.2	6.747626	0.2661	0.2844	0.3853	0.4684	0.5990	0.6736	0.7300
Unem-ployed/Student/Stay at Home	43.4	8.167085	0.1631	0.2104	0.2759	0.3569	0.4363	0.4791	0.5066
Self-Employed Formally	2.7	4.756098	0.3659	0.4634	0.5610	0.7317	0.7805	0.8049	0.8049
Self-Employed Informally	27.5	6.129496	0.2254	0.3118	0.4341	0.5659	0.6619	0.7386	0.7667
Time to the nearest mobile money outlet/agent									
Less than 30 min	36.1	4.835131	0.3405	0.4222	0.5609	0.6872	0.7889	0.8413	0.8766
Between 30 and 60 min	14.8	7.02658	0.1798	0.2697	0.3785	0.4952	0.5555	0.6271	0.6497
More than 60 min/no infra-structure	49.1	8.654185	0.1357	0.1719	0.2342	0.3077	0.3802	0.4357	0.4662
Financial planning									
Plan or Budget accu-rately	36.9	6.049624	0.2556	0.3368	0.4571	0.5774	0.6662	0.7143	0.7412
Niether plan/budget accurate nor inac-curate	17.7	6.912708	0.1975	0.2665	0.3824	0.5080	0.5774	0.6152	0.6560
Plan or Budget inaccu-rately	29.1	7.143626	0.2309	0.2824	0.3665	0.4469	0.5292	0.6076	0.6361

Table 1 (continued)

Variable	Sample	Median Adoption time	Year 1 Adoption	Year 2 Adoption	Year 4 Adoption	Year 6 Adoption	Year 8 Adoption	Year 10 Adoption	Year 12 Adoption
Do not plan/budget	16.2	9.222603	0.1199	0.1404	0.1849	0.2397	0.3151	0.3733	0.4106
Banked	50.8	4.802195	0.3435	0.4300	0.5722	0.6970	0.7805	0.8419	0.8701
Unbanked	49.2	9.339534	0.0847	0.1185	0.1682	0.2405	0.3196	0.3716	0.4064
Sample	1800	1800	1800	1800	1800	1800	1800	1800	1800

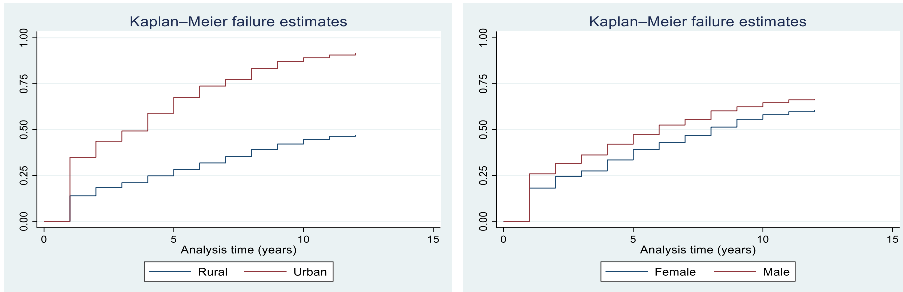
Column 2 presents the description of the sample composition across explanatory variables. Column 3 shows the median adoption time whilst columns 4–10 shows the adoption rates for the specified year

population who adopted the service in the first year was very high compared to that in subsequent periods, which was also reflected by the higher hazard estimates for the same period.

Table 1 presents the sample composition and proportion of different population subgroups that adopted mobile money during different periods. Column 2 of Table 1 shows the sample distribution across categorical explanatory variables. Table 4 (Appendix) presents descriptive statistics for continuous variables. About 36.8% of the respondents were urban residents, with the remaining 63.2% residing in rural areas. The adoption results show that 34.9% of urban dwellers, compared to 13.9% of rural inhabitants, adopted mobile money during the first year of its introduction. By the end of the observation period, 92.5% of those residing in urban areas had adopted the service, compared to 47.6% in rural areas. Figure 2 also shows the gap in adoption trends between rural and urban residents during the study period. Based on the log-rank test, this difference was statistically significant (chi-square = 477.92, $p < 0.01$). For those who had adopted mobile money by the end of the study observation period, it took urban residents 4.4 years and rural residents 8.5 years to adopt the service (Table 1).

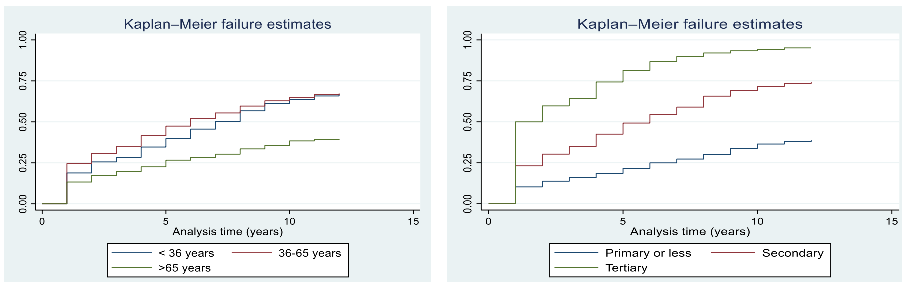
In terms of gender, Table 1 also shows that the sample was comprised of 44.3% males and 54.7% females. During the first year after the introduction of mobile money, 25.5% of males and 18.1% of females adopted it. By the end of 12 years, 67.2% of males and 61.7% of females had adopted the service. It took females 7.4 years, compared to 6.6 years for males, to adopt mobile money. It is also evident from Fig. 2 that, at any given time, slightly more males adopted mobile money than females. The persistent adoption gap between males and females over the observation period suggests that males adopted mobile money slightly faster than females, and this difference was statistically significant (chi-square = 11.71; $p < 0.01$).

Table 1 shows that the sample was dominated by those aged between 36 and 65 (62.3%), whereas those aged less than 35 and > 65 years comprised 23.9% and 13.8% of the sample, respectively. It took 7.1 years, 6.6 years and nine years for those aged less than 36, 36–65, and over 65 years, respectively, to adopt mobile money. As also shown in Fig. 3, those aged above 65 years persistently lagged in adopting the service, and this difference was statistically significant (chi-square = 58.9; $p < 0.01$). With respect to the level of education, Table 1 shows that the greatest proportion of the sample (49.2%) had a secondary education, 38.3% had a primary education or less, and the remaining 12.5% had a tertiary education. Regarding the adoption of mobile money,



Log-rank test: Chi2(1) = 477.92, Pr>chi2 = 0.0000 Log-rank test: Chi2(1) = 11.71, Pr>chi2 = 0.0006

Fig. 2 Mobile money adoption by locality and gender

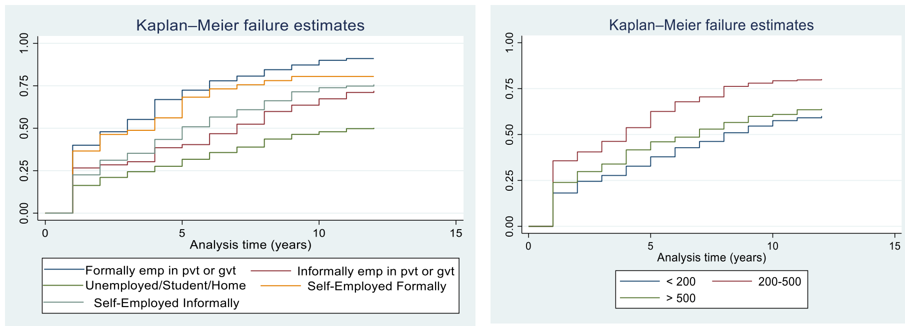


Log-rank test: chi2(2) = 58.9, Pr>chi2 = 0.0000 Log-rank test: chi2(2) = 450.92 , Pr>chi2 = 0.0000

Fig. 3 Mobile money adoption by age group and level of education

50% of those with tertiary education, compared with 23.2% and 10.3% of those with secondary and primary education, respectively, adopted the service during the first year it was introduced into the market. It took 9.3 years to adopt mobile money for those with primary education or less, 6.3 years for those with secondary education, and 3.2 years for those with tertiary education. The adoption gap was statistically significant (Chi-square = 450.92; $p < 0.01$) and persisted over the study observation period (also see Fig. 3). By the end of the observation period, 95.1% of those with tertiary education, 75.3% of those with secondary education, and 39.8% of those with primary education had adopted the service.

Regarding income sources, Table 1 shows that most respondents were either unemployed, dependent, or stayed at home (43.4%), followed by self-employed informally (27.5%), formally employed in the private sector or government (19.2%), and informally employed in the private sector or government (7.2%). The smallest group comprised those who were formally self-employed (2.7%). Consistently over time and statistically different (chi-square = 229.28; $p < 0.01$), the way individuals earned their income was reflected in their mobile money adoption, with those formally employed in the government or private sector having higher adoption rates over the 12 years (Fig. 4). Being the fastest, it took those formally employed in the private sector or government 4.1 years compared to 8.2 years for those who were unemployed or dependent.



Log-rank test: chi2(4) = 229.28, Pr>chi2 = 0.0000 Log-rank test: chi2(2) = 55.02, Pr>chi2 = 0.0000

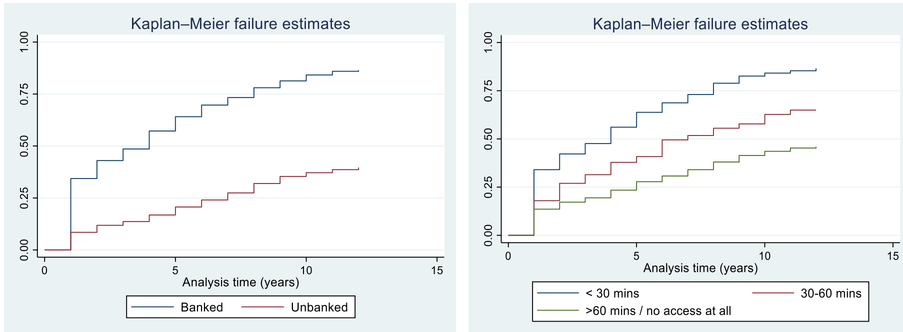
Fig. 4 Mobile money adoption by level of income source and level of income

Figure 4 also shows that middle-income individuals adopted mobile money services faster than those with lower or higher incomes, and this difference is statistically significant (chi-square = 55.02; $p < 0.01$). As shown in Table 1, those who earned less than US$ 200 took about 7.5 years to adopt mobile money, while those who earned between US$ 200 and US$ 500 and above US$ 500 took 5.1 years and 6.8 years, respectively, to adopt the service.

Regarding access to banking services, Table 1 shows that 50.8% of the respondents were banked, whereas the remaining 49.2% were unbanked. Figure 5 shows that the banked adopted mobile money much faster than the unbanked this difference was statistically significant (chi-square = 524.31; $p < 0.01$). As shown in Table 1, it took less than four years for half of the bank respondents to adopt mobile money, yet for the unbanked, not even half of them adopted the service by the end of the observation period. Overall, it took a banked individual 4.8 years to adopt mobile money compared to 9.3 years for an unbanked individual.

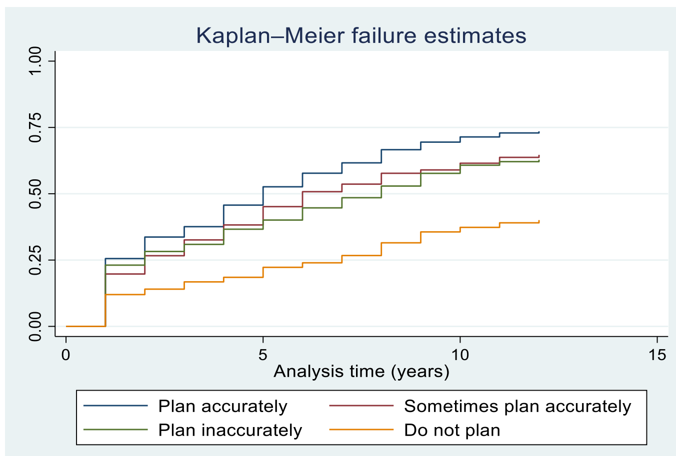
With respect to the distance to mobile money agents or outlets, Table 1 shows that 49.1% of the respondents lived one hour or more away from a mobile money outlet or did not have access to such at all. Approximately 36.1% lived between 30 and 60 min away from a mobile money outlet, whereas 14.8% lived less than 30 min away. The log-rank test results suggest that adoption rates significantly differed with distance to mobile money outlets (chi-square = 332.83; $p < 0.01$). Those who resided near mobile money outlets consistently adopted mobile money faster than those who stayed far away or without access (Fig. 5). Specifically, Table 1 shows that 34.1% of those who lived less than 30 min away from an outlet, 18% of those who stayed 30–60 min away, and 13.6% of those who stayed more than an hour away from an outlet adopted mobile money in the first year. Consistent with the above pattern, by the end of the observation period, 87.7% of those who lived less than 30 min away from an outlet, compared to 65% and 46.6% of those who stayed 30 to 60 min and those who stayed more than an hour away from an outlet, respectively, had adopted mobile money. Overall, it took those living within 30 min of an agent 4.8 years to adopt mobile money compared to 7 years and 8.6 years for those staying 30–60 min and > 60 min (or no access), respectively.

Figure 6 shows that individuals who reported carrying out accurate financial planning adopted mobile faster than those who planned somewhat accurately and those who did not plan, and this difference was statistically significant (Chi-square = 98.25, $p < 0.01$).



Log-rank test: chi2(1) = 524.31, Pr>chi2 = 0.0000 Log-rank test: chi2(2) = 332.83, Pr>chi2 = 0.0000

Fig. 5 Mobile money adoption by bank account ownership and access to mobile money outlet or agent



Log-rank test: chi2(3) = 98.25, Pr>chi2 = 0.0000

Fig. 6 Mobile money adoption by financial planning

For instance, by the end of the study observation period, 74.1% of those who planned accurately, compared to 41.1% of those who did not plan, had adopted mobile money. As shown in Table 1, it took 6 years for those who planned accurately to adopt mobile money compared to 9.2 years for those who did not plan or budget.

Predictors of time to mobile money adoption

Multivariate analysis

The level of dependence between the explanatory variables was assessed prior to conducting multivariate analysis. The results in the correlation matrix in the Appendix (Table 5) show no concern regarding the level of dependence or potential multicollinearity. The highest correlation coefficient was between the location of mobile money outlets and locality (urban/rural) at 0.367. This is further confirmed by the results in Table 6 (Appendix section), with the highest Variance Inflation Factor (VIF) value of 1.58 on the locality (urban/rural) variable, showing that none of the variables are significantly correlated with the other explanatory variables.

Table 2 Predictors of time to mobile money adoption (survival analysis)

Variable	Survival model (1)		Survival model: Rural (2)		Survival model: Urban (3)	
	Hazard ratio	**Standard error**	**Hazard ratio**	**Standard error**	**Hazard ratio**	**Standard error**
Urban	1.70482***	0.146464	–	–	–	–
Male	1.022543	0.066106	1.049657	0.099884	1.03052	0.093024
Age group. Ref = 29–36 years						
36–65 years	1.248937***	0.094524	1.440998***	0.184692	1.134404	0.110057
66+ years	1.079563	0.148393	1.198668	0.23396	1.083009	0.223095
Level of education. Ref = Primary education						
Secondary education	1.448753***	0.132215	1.422884***	0.161305	1.315541*	0.2046
Tertiary education	1.923563***	0.227359	2.132726***	0.417369	1.670237***	0.294863
Financial planning. Ref = did not plan/budget						
Planned/budgeted accurately	1.312065**	0.154796	1.539646**	0.27018	1.160544	0.18767
Neither planned/budgeted accurately nor inaccurately	1.265196**	0.162948	1.246362	0.246744	1.256165	0.217595
Planned/budgeted inaccurately	1.202008	0.145944	1.270531	0.22703	1.093548	0.185466
Source of income. Ref = Unemployed/Student/Stay at home						
Formally Employed in Private or Government	1.207832*	0.117733	1.299332	0.222283	1.083844	0.140384
Informally Employed in Private or Government	1.016836	0.133193	1.039514	0.235698	0.927633	0.155367
Self-Employed Formally	1.552653**	0.293236	1.668576**	0.434886	1.537139*	0.425544
Self-Employed Informally	1.365155***	0.11274	1.406277***	0.161838	1.267368*	0.150534
Income Ref: < 200						
201–500	1.037944	0.096152	0.8478	0.14024	1.165659	0.132983
501-max	0.930242	0.074323	0.8911	0.102661	0.958077	0.109121
Banked	2.257794***	0.181409	2.769107	0.29733	1.773297	0.20974
Mobile money outlet. Ref = > 60 min/ No infrastructure						
Less than 30 min	1.409451***	0.124571	1.553012***	0.198528	1.293536*	0.163601
Between 31 and 60 min	1.257682**	0.12404	1.249658*	0.148006	1.232339	0.227997
Belong to informal group (savings, burial society etc.)	1.169142*	0.096090	1.105287	0.142432	1.231263*	0.134100
Real GDP Growth	1.346615***	0.021378	1.373313***	0.033093	1.331103***	0.028653

Table 2 (continued)

Variable	Survival model (1)		Survival model: Rural (2)		Survival model: Urban (3)	
	Hazard ratio	Standard error	Hazard ratio	Standard error	Hazard ratio	Standard error
Harrell's C concordance statistic	0.7539		0.7364		0.6434	
AUC	0.8711		0.8479		0.8489	
Sample (n)	1800		1138		662	

For results presented in Table 2, the survival model considers adoption of mobile money as the event and time to adoption as the time variable. Columns 2 and 3 show the hazard ratios and standard errors from the main survival model with both and rural respondents. Columns 4 and 5 show the hazard ratios and standard errors from the survival model with only rural respondents whilst columns 6 and 7 present the same estimates for urban respondents. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Ref = reference category

Table 2 presents the multivariate analysis results from the Cox proportional hazard models for the factors that predict the time to mobile money adoption (controlling for other factors). Model 1 is the main model, while Models 2 and 3 fit the same model after separating rural and urban residents. The hazard ratio (HR) represents the hazard or risk of failure, for which failure in this study was interpreted as a mobile money adoption event. Thus, an HR above one indicates that a population group has an increased (hazard) chance of adopting mobile money more quickly. An HR below one means that the population group has a lower chance of adopting mobile money faster (see Spruance et al. (2004) for a careful interpretation of hazard ratios).

The Model 1 results show that urban residents were significantly more likely to adopt mobile money faster than rural ones (HR = 1.705, $p < 0.01$). However, the results show that gender is not a significant predictor of the time to mobile money adoption. With respect to age, the results suggest that those aged between 36 and 65 years were significantly more likely to adopt mobile money faster than the youth (HR = 1.249, $p < 0.01$). Those older than 65 years were not statistically different from the youth. The results further show that the effect of age was more pronounced in rural areas and insignificant in urban areas. The results showed that higher levels of education were associated with faster service adoption. Those with secondary (HR = 1.449, $p < 0.01$) and tertiary education (HR = 1.924, $p < 0.01$) were significantly more likely to adopt mobile money faster than those with primary education or less.

The results show that income level is not a significant predictor of the time to mobile adoption. Instead, what matters is how individuals generate income. Compared to dependents, students, the unemployed, and those staying at home, those who were formally self-employed (HR = 1.553, $p < 0.05$) and informally self-employed (HR = 1.365, $p < 0.01$), and those who were employed in the private sector or government (HR = 1.207832, $p < 0.1$) were significantly more likely to adopt mobile money faster.

Regarding access to banking services and financial infrastructure, the results showed that individuals with bank accounts were significantly more likely to adopt mobile money faster than those without (HR = 2.258, $p < 0.01$). Similarly, shorter distances to mobile money agents were associated with faster service adoption. The results show that those who stayed 30 min or less (HR = 1.409, $p < 0.001$) and those who stayed between

30 min and an hour (HR = 1.258, $p < 0.05$) from a mobile money outlet were significantly more likely to adopt the service faster than those who stayed more than an hour away from an outlet or those who had no access to an outlet.

This study also included financial planning or budgeting as a proxy measure of financial literacy or capability. The results show that higher levels of financial planning are associated with early service adoption. Individuals who reported planning or budgeting accurately (HR = 1.312, $p < 0.05$) and those who sometimes planned accurately (HR = 1.265, $p < 0.05$) were significantly more likely to adopt mobile money faster than those who did not. Those who planned inaccurately were not significantly different from those those who did not plan at all. The results also show that financial planning does not affect the time to mobile money adoption for those living in urban areas.

Regarding the role of social groups, the study showed that those belonging to social groups were significantly more likely to adopt mobile money than those who did not (HR = 1.169, $p < 0.1$). The results further showed that the effect of social groups was only significant in urban areas. The results also indicate that the macroeconomic environment is important in mobile money adoption. High gross domestic product (GDP) growth rates were associated with a higher intensity of mobile money adoption (HR = 1.346, $p < 0.001$).

Robustness checks

In this section, I conduct additional analysis to validate the empirical findings of the survival analysis presented in the previous section. The results from Models 4 and 5 in Table 3 collaborate with those from Model 1, with slight variations in the strength of the association between covariates and the outcome variable. Models 4 and 5 consider the adoption of mobile money in the first and first two years, respectively, as the outcome. The models used logistic regression to determine the predictors of mobile money adoption during the specified periods. In contrast to Models 1 to 3, Model 5 results show that beyond gender and income level, source of income and belonging to social groups were insignificant predictors of mobile money adoption. Model 4 added financial planning to the insignificant predictors identified in Model 5.

Model assessment

As shown in Tables 2 and 3, models 1 (AUC = 0.8711), 2 (AUC = 0.8479), 3 (AUC = 0.8489), 5 (AUC = 0.8453), and 6 (AUC = 0.8593) showed good discriminant ability, with an AUROC curve above the commonly acceptable discriminant ability threshold of 0.7 (Hosmer et al. 2013; Chamboko and Bravo 2016; Kou et al. 2021). Figure 7 graphically shows the performance of these models using ROC curves. Given that the models have different time horizons (Models 1–3 = 12 years, Model 5 = 1 year, and Model 6 = 2 years), they are not comparable.

Given the limitations of binary models for dealing with censored individuals, survival analysis is the ideal methodology for modeling the time to DFS (such as mobile money) adoption and the predictors for early adoption. I now consider additional model assessment approaches for survival models. Table 2 shows the concordance probabilities,

Table 3 Predictors of time to mobile money adoption (logit models)

Variable	Logit model: 1 = First year (5)		Logit model:1 = First 2 years (6)	
	Odds ratio	Standard Error	Odds ratio	Standard Error
Urban	1.654027***	0.289995	1.689582***	0.277129
Male	1.200942	0.177761	1.192877	0.153274
Age group. Ref = 29–36 years				
36–65 years	1.810187***	0.304626	1.688651***	0.263172
66+ years	1.614212*	0.460444	1.506504	0.396968
Level of education. Ref = Primary education				
Secondary education	1.366478*	0.258112	1.428403**	0.245464
Tertiary education	2.800618***	0.665069	3.069573***	0.698948
Financial planning. Ref = did not plan/budget				
Planned/budgeted accurately	1.141271	0.282025	1.500678*	0.351119
Neither planned/budgeted accurately nor inaccurately	0.820023	0.226542	1.185935	0.306308
Planned/budgeted inaccurately	1.243034	0.313698	1.455843	0.34857
Source of income. Ref = Unemployed/Student/Stay at home				
Formally Employed in Private or Government	0.978434	0.197598	0.964026	0.186247
Informally Employed in Private or Government	1.123575	0.30321	0.86308	0.225593
Self-Employed Formally	1.565945	0.618707	1.838837	0.702637
Self-Employed Informally	0.98497	0.175167	1.138236	0.184824
Income Ref: < 200				
201–500	1.388613	0.261827	1.107509	0.203957
501-max	1.036669	0.173436	0.9357151	0.148135
Banked	3.071106***	0.530262	2.987422***	0.459438
Mobile money outlet. Ref = More than 60 min/ No infrastructure				
Less than 30 min	1.533187**	0.275763	1.695163***	0.286199
Between 31 and 60 min	0.92388	0.197816	1.297991	0.246875
Belong to an informal group (savings, burial society etc.)	1.188104	0.205196	1.143771	0.187051
Real GDP Growth	1.461446***	0.035614	1.443245***	0.043671
AUC	0.8453		0.8593	
Pseudo R Squared	0.1559		0.1636	
Sample (n)	1800		1800	

Table 3 presents results from the logit models. Columns 1 and 2 presents the odds ratios and standard errors with the outcome variable as binary (have adopted mobile in the first year of introduction = 1; did not adopt mobile money during the first year of introduction = 0). Columns 3 and 4 presents the odds ratios and standard errors from the logit model with the outcome variable as binary (have adopted mobile in the first two years of mobile money introduction = 1; did not adopt mobile money during the first two years of introduction = 0). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Ref = reference category

interpreted as the probabilities of concordant outcomes and predictions. A value of 0.5 of Harrell's C (Harrell et al. 1982, 1996) suggests that a model has no predictive ability (Cleves et al. 2010). The concordance statistic for the main model (Model 1) was 0.7539, and those for Models 2 and 3 were 0.7364 and 0.6434, respectively. Figure 8 illustrates the concordance between rural and urban respondents' observed and predicted survival probabilities. In this case, survival is the opposite of failure (adoption). Thus, individuals who have survived to any given time have not adopted mobile money services until that time.

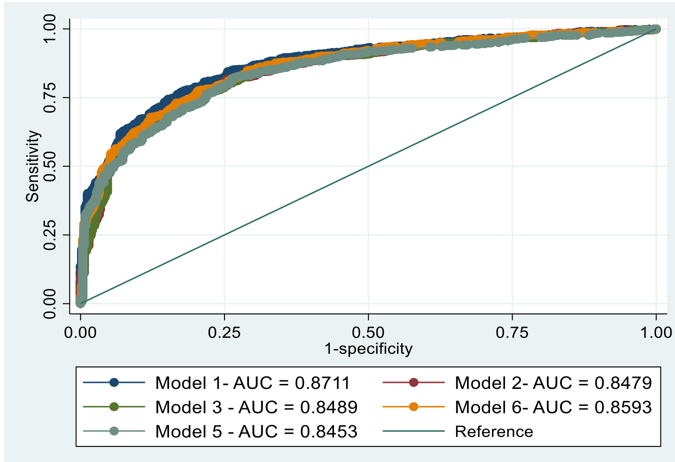


Fig. 7 Area under the ROC curves

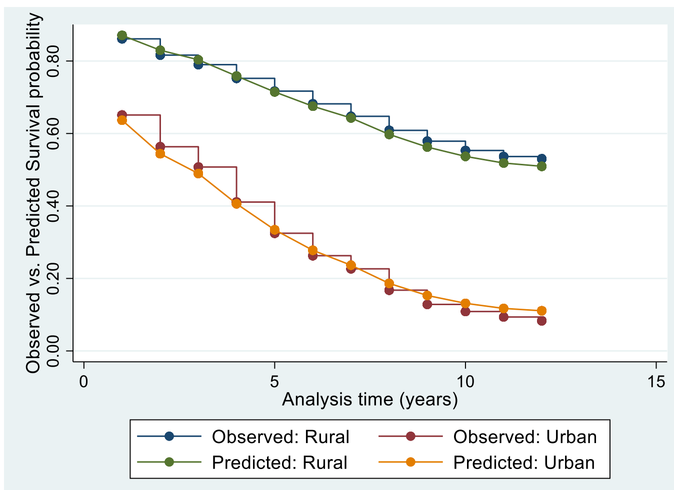


Fig. 8 Observed and predicted survival probabilities

Discussion

Overall, the findings show that it took Zimbabweans living in urban areas 4.4 years vs. 8.5 years for those living in rural areas to adopt mobile money. Given the absence of comparisons due to a lack of studies that took a similar approach, I am unable to compare the time-to-adoption in any country or previous studies. However, references are made to other studies on mobile money adoption predictors, given the availability of literature on this topic.

With respect to the macroeconomic environment, the results consistently and robustly across the models show that the macroeconomic environment is an important predictor of time-to-mobile money adoption. The findings reveal that higher economic growth rates are significantly correlated with higher intensities of mobile money services adoption. Thus, when the economy is booming, people have the resources to access the gadgets needed to use DFS. This result is supported by Lashitew et al. (2019), who found, through a cross-country analysis, that macroeconomic factors play a key role in adopting mobile money services.

In terms of gender, the results clearly show that despite men having adopted mobile money slightly faster than women, after controlling for other factors, gender was not a significant predictor of time to mobile money adoption. These results were consistent across urban and rural areas and were robust when the first year, first two years, or the entire 12 years observation period was considered. Thus, the role of gender in mobile money adoption in Zimbabwe does not conform to the vast literature that suggests that males are more adventurous, risk-receptive, and innovative than females and are, therefore, more inclined to be significantly early adopters of financial innovations (Wan et al. 2005; Jambulingam 2013; Demirci and Ersoy 2008; Dayour et al. 2020). Again, results from Zimbabwe (rural and urban) refute that women tend to be more anxious and cautious about adopting and using new technologies, particularly in the early stages (Lee et al. 2011). This finding confirms the recent evidence by Chamboko (2022) that gender is not a significant predictor of DFS usage in Zimbabwe. These findings also agree with Abdinoor and Mbamba (2017), Munyegera and Matsumoto (2016), Murendo et al. (2018), and Batista and Vicente (2020), who show that gender does not significantly predict mobile money adoption. This finding is important, as it suggests that policy actions to promote and accelerate DFS adoption and use in Zimbabwe should focus on factors other than gender.

The findings reveal that age significantly predicts the time spent on mobile money adoption. Those aged between 36 and 65 adopted mobile money faster than the youth, while those over 65 years were not significantly different. The effect of age was only significant in rural areas. This finding on age deviates from observations from other African markets, such as Rwanda (Donner, 2005) and Burkina Faso (Hahn and Kibora, 2008), where the adoption of mobile phone-based financial applications was found to be higher among youth who are perceived to be more risk receptive and have a higher interest in exploring new technologies (Dayour et al. 2020). This finding is supported by the literature, which shows that young people continue to be financially excluded, mostly because of their precarious financial circumstances and unemployment (OECD, 2020). Evidence from Mexico and Nigeria shows that young people do not need an account and lack the income or money, thus opt out of financial services (OECD, 2020; National Banking and Securities Commission 2018). These observations from Nigeria and Mexico plausibly fit the context of Zimbabwe, especially given the macroeconomic environment and limited employment opportunities the country offers young people (Maulani and Agwanda 2020). Economic inclusion is arguably an important ingredient in accelerating digital financial inclusion among the youth (less than 36 years old) in Zimbabwe. Thus, policy initiatives that seek to create employment or income-generating opportunities for the youth are essential.

Regarding banking services, this study shows that those with bank accounts are significantly more likely to adopt mobile money faster than those without. First, given the seamless integration of mobile money and banking services, it is not surprising that banked individuals were the earliest to adopt mobile money services because this integration allows them to move money between bank accounts and mobile money wallets. Second, the findings suggest that mobile money services compete with the banking sector, as the same individuals with bank accounts are mostly those who adopted mobile money earlier, possibly taking advantage of any cost, convenience, speed, and efficiency advantages brought about by mobile money innovations. These findings are in line with those of Akinyemi and Mushunje (2020), Afawubo et al. (2020), Batista and Vincente (2020), and Senou et al. (2019), who also found that being banked was significantly associated with higher adoption of mobile money services. From a policymaker's perspective, the findings provide insight into the important reality that those excluded from the banking system do not adopt mobile money services first. Ideally, it would be desirable for the unbanked to adopt the service the most and earlier as this would allow this population segment to participate in the formal financial system.

With respect to financial infrastructure, specifically the distance to a mobile money agent, the findings reveal that greater accessibility of mobile money agents, as reflected by the shorter distance between households and outlets, was associated with faster adoption of mobile money services. This finding is logical and supported by numerous studies, as agents are the interface for mobile money services in communities; thus, when they are located closely, individuals can easily open accounts and conveniently perform cash-in and cash-out transactions, among other services (see Jack and Suri 2014; Koomson et al. 2021). This finding is also consistent with Asravor et al. (2021), Tabetando and Matsumoto (2020), and Jack and Suri (2014), who found that the distance to agents is an important contributor to total mobile money transaction costs and, hence, a significant predictor of mobile money adoption. Importantly, proximity to a mobile money outlet or agent relates to transactions (including transport) and opportunity costs, as individuals have to forego other activities and travel to an agent or outlet to open an account or perform cash-in or cash-out transactions (Suri 2017). In addition, the distance to an agent also determines information (search) costs, as users may have to travel to the agents to acquire the requisite information needed to adopt and learn about using the service.

This study finds that income level does not predict the time to mobile money adoption in Zimbabwe. This is contrary to many studies showing that high wealth or income levels are significantly associated with mobile money adoption (Johnen et al. 2022; Munyegera and Matsumoto 2016). Instead, what matters in the Zimbabwean context is how educated individuals are, their financial planning, and how they earn income. Higher levels of education and good financial planning are associated with the faster adoption of mobile money services. This effect was the strongest in rural areas. Long-standing evidence which dates from Rogers' (1995) innovation diffusion model, show that higher levels of education are a key driver of early adoption. This is because individuals with higher levels of education are more likely to have better knowledge and confidence in using technology (Igbaria et al. 1995; Riddell and Song 2017). Studies on mobile money adoption in Nigeria and Ghana show that higher levels of education are associated with a higher chance of adopting MoMo mobile money services (Onyia and Tagg 2011; Dzokoto and Appiah 2014; Osei-Assibey 2015). Similarly, overwhelming evidence suggests that high levels of financial literacy and capability (proxied by financial planning in this study) lead to better financial behaviors and are strong predictors of financial access, including mobile money (Shibia and Kieyah 2016; Clark et al. 2012; Carpena et al. 2011).

Interestingly, after controlling for other factors, individuals who earned income through self-employment (formally or informally) were significantly more likely to adopt mobile money at the fastest rate. In the Zimbabwean context, this finding makes sense given that these individuals mostly operate in the informal sector (Chamboko and Guvuriro 2022) and require a means other than banks to be paid for their work, goods, and services (Chamboko 2022). Those who worked formally in the private sector and government also adopted mobile money relatively faster (but less than the self-employed). Those who were unemployed, students, and dependents were the slowest to adopt mobile money, which could be attributed to the absence of need, given that some of them hardly receive income, and when they do so, they receive it and transact in cash.

Importantly, the findings also show that those residing in urban areas are significantly more likely to adopt mobile money faster than those living in rural areas. This finding is supported by McKay and Kaffenberger (2013) and Balan et al. (2009), who also find that people residing in urban areas are significantly more likely to adopt mobile money than those residing in rural areas. The authors attribute the low adoption of services in rural areas to structural and technical barriers, including limited network coverage, a fundamental requirement for service adoption. Other important factors could drive this result in rural areas, including low education and financial literacy levels, limited technological appropriation and employment opportunities, limited access to financial infrastructure, such as mobile money agents, and erratic network connectivity. This finding has crucial policy implications given that people living in rural areas are the most excluded from other financial services, including banking. To alleviate this compounded jeopardy, service providers and policymakers should prioritize providing financial and digital education and reducing the distance to financial infrastructure by increasing the availability and accessibility of active mobile money agents and improving network coverage in rural communities. The results also suggest that belonging to a social group significantly increases the chances of adopting mobile money faster. A large body of evidence documents the positive effects of belonging to social networks (Bongomin et al. 2018; Afawubo et al. 2020) and network size (Murendo et al. 2018) on mobile money adoption in various countries.

Conclusion and recommendations

To inform DFS expansion and acceleration strategies, this study employed a time-to-event analysis approach to estimate the time to DFS adoption and to determine the factors that explain the variation in time to adoption. Using a sample of 1800 survey respondents from Zimbabwe, the study found that it took 4.4 and 8.5 years, respectively, for urban and rural residents to adopt mobile money. Overall, the findings show that individuals who are significantly more likely to adopt mobile money faster are those residing in urban areas, near mobile money agents, banked, have high levels of education and financial literacy, are middle-aged, belong to social groups, and are self-employed. In addition, an expansionary macroeconomic environment proxied by high GDP growth rates promotes greater mobile money adoption. The findings also show that gender and income levels do not predict the time to mobile money adoption in Zimbabwe.

This study offers the following policy, practitioner, and research recommendations on possible actions to accelerate DFS adoption:

1. Financial inclusion research houses and researchers responsible for data collection should consider including a standard question of when the DFS was first used to permit time-to-event (adoption) analysis. In addition to understanding the variation in time to adoption, this variable provides opportunities to conveniently investigate the effects of market or policy interventions or changes on DFS adoption intensities.
2. DFS providers should strengthen the teaching and educational components of the agents' roles in building the population's financial and technological appropriation

skills. Such interventions can help to boost confidence in adopting technology and its usage.

3. Service providers should consider product innovations that mimic the value proposition of social groups, such as savings clubs, to encourage and accelerate the adoption of DFS.
4. For policymakers, efforts to create and promote a favorable macroeconomic environment remain a priority, as this has implications for employment and income-generating opportunities, which affect the ability of individuals to acquire the requisite technology needed to adopt DFS and to have money to transact on.
5. Policy initiatives that seek to create income generation or employment opportunities for the youth are essential for accelerating the adoption of DFS, thus enhancing financial inclusion.
6. Service providers should continue strengthening the bank and mobile money integration to advance use cases, even for banked populations. This enhances the efficiency of services, including increasing speed and convenience, while reducing user costs.
7. With respect to rural areas, the following recommendations are made:

    a. Service providers should consider increasing the availability and accessibility of active mobile money agents, especially in rural areas, to reduce the distance, time, and costs of reaching outlets where users can perform various transactions and learn about the services.
    b. Policymakers should prioritize providing financial education to improve financial literacy and digital skills, especially in rural areas, to promote and accelerate the adoption and use of mobile technology and DFS.
    c. Policymakers and mobile money service providers (mostly mobile network providers) should consider bolstering the requisite infrastructure needed to improve network coverage in rural communities to provide reliable connectivity, which promotes the adoption and use of DFS through mobile phones.

A limitation of the study is that one must truncate the sample to retain only adults eligible to adopt mobile money when it was introduced. Removing these participants from the dataset may significantly reduce the sample size and affect its representativeness. More studies using the same approach are needed to generate sufficient research to allow comparisons of the time-to-adoption across countries.

Appendix

See Tables 4, 5 and 6.

Table 4 Descriptive statistics for continuous variables

Variable	Observations (n)	Minimum	Mean	Median	Standard deviation	Maximum	Skewness	Kurtosis
Age	1800	29	47.688	44	11.916	79	0.965	3.391
Real GDP growth	1800	− 6.2	7.302	4.8	7.180	16.7	-0.221	1.795

Table 4 presents descriptive statistics for the GDP growth and age. Only Real GDP growth was used as a continuous variable whereas age was binned

Table 5 Correlation matrix

	URBAN	EDUFIN ~ F	FINCAP	LIVELI ~ D	INCFINAL	GENDER ~ F	AGE_FF	BANKED_F	MM_OUT ~ F	GDP_GR ~ H
URBAN	1									
EDUFINAL_FF	0.289	1								
FINCAP	− 0.052	− 0.089	1							
LIVELIHOOD	− 0.051	− 0.249	0.033	1						
INCFINAL	0.014	0.203	-0.089	− 0.126	1					
GENDER_FF	0.024	0.121	0.024	− 0.168	0.001	1				
AGE_FF	− 0.175	− 0.198	0.049	0.047	− 0.023	− 0.015	1			
BANKED_F	− 0.150	− 0.282	0.165	0.264	− 0.206	− 0.095	− 0.021	1		
MM_OUTLET_F	− 0.367	− 0.230	− 0.012	0.032	− 0.032	− 0.017	0.074	0.130	1	
GDP_GROWTH	0.108	0.190	− 0.068	− 0.063	0.075	0.059	0.038	− 0.157	− 0.139	1

The correlation coefficients between the explanatory variables. The highest coefficient was 0.367 between location of mobile money outlets and locality (urban/rural). All other coefficients have lower values and thus, there was no concern about significant dependency between explanatory variables

Table 6 Variance Inflation Factor

VARIABLE	VIF	1/VIF
URBAN	1.58	0.632549
MM_OUTLET_F	1.51	0.663273
EDUFINAL_FF	1.32	0.760137
BANKED_F	1.22	0.82147
LIVELIHOOD	1.14	0.87644
INCFINAL	1.08	0.92299
AGE_FF	1.08	0.92806
GDP_GROWTH	1.07	0.934801
GENDER_FF	1.06	0.944325
FINCAP	1.05	0.954912
MEAN VIF	1.19	

The highest VIF value is 1.58 on the locality (urban) variable showing that none of variables are significantly correlated with the other explanatory variables

Abbreviations

AFI	Alliance for financial inclusion
DFS	Digital financial services
AUC	Area under the curve
GDP	Gross domestic product
OECD	Organisation for Economic Co-operation and Development
ROC curve	Receiver operating characteristic curve
AUROC	Area under the ROC curve

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Disclaimer
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Author contributions
RC conducted the research from conception to completion. The author has read and approved the final manuscript.

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Declarations

Competing interests
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