Digital Credit for All? An Empirical Analysis of Mobile Loans for Financial Inclusion in Kenya

Digital credit, also known as mobile loan services, has shown considerable success in Kenya and is expected to provide opportunities for individuals who are excluded from formal loans because of their lower socioeconomic status. However, evidence supporting the greater positive impact of digital credit on financial inclusion than that of traditional loans is lacking. This study employs a multinomial logistic regression to investigate the impact of digital credit services, particularly mobile banking and FinTech loans (MBLs and FTLs, respectively), on financial inclusion in Kenya. The results highlight disparities in MBL and FTL usage. MBLs appear to be less accessible to vulnerable populations, such as women, low-educated groups, and casual workers, although both MBLs and FTLs are equally accessible to rural populations. In contrast, FTL services show no such constraints in terms of accessibility for women and low-income workers. This disparity indicates the relative inaccessibility of MBLs to vulnerable groups as compared to that of FTLs; however, note that greater loan access does not always benefit vulnerable groups.

Keywords: financial inclusion, digital credit, mobile loan, FinTech, mobile banking loan, FinTech loan, digital financial services, mobile money

1. Introduction

After the introduction of M-Pesa, a mobile phone-based money transfer service, in Kenya in 2007, the digital financial industry has grown to a level where 35 million customers in Kenya use digital financial services (Oluwole, 2022), accounting for 63% of the Kenyan population. Following the success of digital financial services such as M-Pesa, 75% of Kenyan adults have a formal account, which surpassed not only the worldwide average of 61% (Demirgüç-Kunt et al., 2015), but also that of several middle-income nations such as Chile, Brazil, India, Mexico, and Russia in 2014 (King

& Heyer, 2016). This was primarily cause by the spread of digital financial services in Kenya, which has achieved a significant increase, considering that in 2006, before the advent of M-PESA, only 18.5% of people had a formal account (Johnson & Nino-Zarazua, 2011). Kenya plays a significant role in driving the popularity of digital financial services in Sub-Saharan Africa and other low- and middle-income countries (LMICs)[1].

After a new loan service called 'M-Shwari' was introduced in 2012 as a form of digital credit, Kenyans can access a wider range of financial services. Digital credit refers to mobile loans that are rapidly disbursed and recovered, often within 30 days or less, and generally consist of loan amounts that are smaller than conventional loan amounts (Mwangi & Brown, 2015; Hwang, 2016). Advocates of digital credit expect it to be a transformative financial product contributing to improving financial inclusion by broadening access to financial services (Bazarbash & Beaton, 2020; Bharadwaj & Suri, 2020; Björkegren & Grissen, 2018), ultimately leading to economic development for disadvantaged and low-income segments of society (Demirgüç-Kunt & Klapper, 2012). They argue that the unique features of digital credit—low transactional and operational costs, simple process, and remote use (Chen & Mazer, 2016)—can contribute to its extensive use and the expansion of financial inclusion (Aron & Muellbauer, 2019; Bharadwaj & Suri, 2020; Björkegren & Grissen, 2018). As expected, digital credit has been a significant success in Kenya, with 35% of the adult population using digital credit as of 2017 (Gubbins & Totolo, 2018).

[1] Around one in eight adults in Sub-Saharan Africa possesses an account for digital financial services in 2015, and close to 50% of these account holders depend solely on digital services for their financial transactions. This prevalence is considerably greater than the worldwide average, where merely 2% of adults maintain a mobile money account (Villasenor et al., 2015).

However, as advocates of financial inclusion claim, has digital credit truly provided new opportunities for those previously excluded from financial services? The literature examining the impact of other digital financial services, such as digital remittances and transactions, on financial inclusion shows mixed results. Several studies have argued that low-income levels exclude people from both conventional and digital financial services (Alafeef et al., 2012; Ammar & Ahmed et al., 2016). Conversely, digital financial services appear to improve financial inclusion levels in rural areas (Batista & Vicente, 2013; Kikulwe et al., 2014; Munyegera & Matsumoto, 2016), and household economies can benefit from the use of mobile remittances (Batista & Vicente, 2013). A low education level is regarded as a major factor that impedes the diffusion of digital financial services in LMICs (Alafeef et al., 2012; Ammar & Ahmed, 2016; Dzogbenuku, 2013; Johnson & Arnold, 2012). Conversely, Hinson (2011) suggested a different perspective, arguing that digital financial services are a better option because they are easier to use than formal financial services. Regarding gender, a recent article by Johnen and Mußhoff (2023) mentions that digital credit has contributed to widening the gender disparity in financial inclusion; conversely, Johnson and Arnold (2012) suggest that, compared to traditional banking services, digital financial services provide women with greater access to funding because of the easier registration procedure and less-stringent verification requirements.

Although extensive research has been conducted on the influence of digital remittances and transactions on financial inclusion, a notable dearth of empirical data on the effects of digital credit has been observed. This gap is evident even in Kenya, which is renowned for its advanced digital credit sector with a well-studied digital financial services landscape, where a comprehensive analysis of the digital credit sector is still lacking. The analysis of digital credit is still at a nascent stage compared to research on digital remittances and transaction services. An evidence gap map presented by the MasterCard Foundation Partnership for Finance in a Digital Africa (Mastercard, 2019), which provides an overview of the literature on the impact of digital financial services, including digital credit, reveals that few studies have dealt with the theme of digital credit. While Johnen et al. (2021) conducted a study on the extent to which digital credit has reached vulnerable populations in Kenya, it was based only on a simple descriptive survey and does not rigorously examine the correlation between the characteristics of vulnerable populations and their use of digital credit. It also lacks evidence proving the effectiveness of digital credit on financial inclusion relative to other loans to determine whether digital credit has truly contributed to financial inclusion beyond traditional loans.

This study explores whether digital credit, as opposed to other traditional types of loans, has an impact on financial inclusion for the unbanked, despite their financially marginalised characteristics. We employed multinomial logistic regression analysis with data from the FinAccess Household Survey to address our core research questions.

Q-1. Does digital credit have an impact on financial inclusion for the unbanked despite their financially marginalised characteristics?

Q-2. Can the unbanked access digital credit despite their sociodemographic characteristics?

Q-3. Can the unbanked access digital credit despite their socioeconomic characteristics?

This study deepens the understanding of financial inclusion via digital credit in LMICs. In the following section, we present a literature review that explores the concepts and impacts of financial inclusion and exclusion, as well as the rise of digital credit in

Kenya. Section 3 outlines the conceptual framework of the theory of change that guided this research. Section 4 offers an in-depth description of the data used, specifically the FinAccess Household Survey, and discusses the methodology of the multinomial logistic regression. The analysis results are then presented, followed by a discussion section that suggests the deeper implications of the impact of digital credit on financial inclusion in Kenya. Finally, Section 7 summarises the paper and raises questions for further studies.

2. Literature Review

2.1. Financial inclusion

Access to financial services is a critical driver of economic development (Demirgüç-Kunt & Klapper, 2012). However, according to the Global Findex data (Demirgüç-Kunt et al., 2021), approximately one-third of population worldwide, that is, 1.7 billion people, were still unbanked in 2017. Particularly, a significant portion of the unbanked population consists of women, individuals from low-income backgrounds, rural residents, and the unemployed (World Bank, 2022). These groups experience difficulty in accessing formal financial services because of their lack of adequate assets or a level of income that is required to access such services or because they reside in remote areas where financial services are not provided. Consequently, these groups tend to rely more on alternative loan services than on formal financial institutions such as banks. Microfinance has emerged as a service specifically designed to offer financial services to those who cannot access formal financial channels (Yunus, 2004; Christen et al., 2004; Hulme & Mosley, 1996). Its primary goal is to alleviate poverty, empower women, and promote self-sufficiency in vulnerable households (Yunus, 2004). Microfinance for the poor has grown rapidly since the 1990s; the total number of customers rose to 211 million in 2013, including 114 million among the poverty-stricken population (Reed et al., 2015).

Despite its success in reaching the poor in LMICs, microfinance has been criticised for its overall impact on poor and vulnerable groups. Critics (Duvendack & Mader, 2020; Stewart et al., 2010) argue that microfinance has not brought transformative improvements to the poor in LMICs and has even been accused of leading customers into a debt trap. A report by the Consultative Group to Assist the Poor (CGAP), which reviewed a diverse body of evidence on microfinance with a year-long survey of the financial diaries of 400 active borrowers in rural southern India, identified that approximately 21% of households had suffered from high levels of over-indebtedness and financial distress (Prathap & Khaitan, 2016). This was primarily due to the imprudent delivery of loan services to the poor who lack the capacity to repay.

As the debate on microfinance has continued, many experts are turning to a broader notion, ‘financial inclusion’, which brings microfinance together with efforts to provide various financial services to underserved communities (Cull & Morduch, 2017). Financial inclusion, as defined by the World Bank, refers to efforts to responsibly and sustainably deliver affordable financial services to those excluded from formal financial systems. It includes a range of services such as transactions, payments, savings, credit, insurance, and other innovative financial services aimed at the previously unbanked population. Mobile devices have become an important tool for promoting the financial inclusion of the previously unbanked population in LMICs (Kanobe et al., 2017). The Universal Financial Access 2020 initiative of the World Bank also highlights the importance of mobile devices for financial inclusion (World Bank, 2018). According to a report by the International Monetary Fund, a majority of the 52 emerging markets and developing economies experienced advancements in financial inclusion from 2014 to

2017 owing to digital financial services. This progress was particularly notable in nations across Africa, Asia, and the Pacific region (Khera et al., 2021), indicating that digital financial services have the potential to expand financial inclusion.

2.2. Rise of digital credit – the case of Kenya

Various digital financial services, such as digital remittances, transactions, savings, credit, and insurance, are already being provided in LMICs (Lauer, 2015). Digital credit, which provides quick and small loans via digital channels, particularly mobile devices, has garnered attention as an alternative to formal finance or microfinance services, especially in LMICs (Dupas et al., 2022). Consequently, it enables the unbanked, who cannot access formal loans, to use loan services (Gachuhi et al., 2023), and contributes to enhancing financial inclusion (Aron & Muellbauer, 2019; Bharadwaj & Suri, 2020; Björkegren & Grissen, 2018; Khera et al., 2021). Kenya, with its well-rooted digital financial industry, has witnessed a rapid increase in digital credit usage. After its first launch in 2012, 35% of adults were using these services by 2017 (Gubbins & Totolo, 2018).

Early digital credit services such as M-Shwari and M-Pesa, offered by Safaricom, were built through a collaboration between Mobile Network Operators (MNOs) and formal financial institutions, including banks. These services are based on the ‘mobile banking loan (MBL)’ model (Francis et al., 2017; MicroSave Consulting, 2019), where MNOs serve as channels for disbursing and collecting the loans via electronic wallet and agent networks. Financial institutions provide the lending capital, assess customer creditworthiness, manage customer accounts, and take responsibility for high-risk lending (Hwang & Tellez, 2016). The growth of the MBL model attracted profit-seeking private companies, leading to the emergence of a new digital credit model in Kenya—‘FinTech loans (FTLs)’ (Hwang & Tellez, 2016). Unlike the MBL model, the FTL model operates independent of the banking system. In this model, FinTech firms supply financial products, devise credit scoring systems, and distribute services via their own platforms, without partnering with banks or financial institutions (Francis et al., 2017). Tala and Branch are two examples of FinTech-based digital credit products in Kenya (MicroSave Consulting, 2019). Table 1 presents a brief comparison between MBL and FTL.

Table 1. Description of various types of digital credit in Kenya

	Product	**Start Year**	**Providers**	**Head Office**	**Loan Size**	**Fee**	**Maturity**	**Platform**
Bank-based loan (MBL)	M-Shwari	2012	- Safaricom (MNO) - Commercial Bank of Kenya	Kenya	Ksh 100 – 100,000	7.50%	1 month	Sim toolkit
	KCB M-Pesa	2015	- Safaricom - Commercial Bank of Kenya	Kenya	Ksh 50 – 1,000,000	3.66%	1 month	Sim toolkit
	Equitel Eazzy loan	2015	Equity Bank Group	Kenya	Up to Ksh 3,000,000	3.66%	1 month	Sim toolkit
FinTech-based loan (FTL)	Tala	2014	Tala (FinTech company invested in by PayPal)	United States	Ksh 500 – 50,000	15.00%	1 month	Android App
	Branch	2015	Branch (FinTech company, invested in by VISA)	United States	Ksh 270 – 70,000	1.00-14.00%	1 month	Android App

Digital credit services vary depending on the supplier type. MBLs operate through feature phones, indicating that people do not need to own a smartphone to access digital credit services. MBLs are based on the SMS protocol and do not require 3G networks. In contrast, FTL services typically require smartphones (Francis et al., 2017; MicroSave Consulting, 2019). Lenders ask borrowers to install an application and provide their social media accounts (Blumenstock, 2018; Francis et al., 2017). The application monitors mobile phone and mobile money usage, as well as social media activities. For example, Tala Kenya demands full permission for accessing information related to GPS, SMS, photo/media/files, camera, device ID, and calls when installing its application (Tala, 2023). This procedure allows the collection of data related to the income, bank balance, savings, and even educational level of the borrower from social networking information. The collected data are used to determine the creditworthiness of the borrower.

Another difference is that the interest rates of MBLs are lower than those of FTLs (Francis et al., 2017). Although MBLs have higher interest rates than other formal loans, the interest rates of FTLs are significantly higher. As listed in Table 1, the monthly rate of an FTL with hovers around 15% (MicroSave Consulting, 2019), which is equivalent to 180% when annualised (Faux, 2020). Such high interest rates are uncommon for traditional lending services. However, digital credit has gained steady popularity in Kenya despite such high interest rates.

Finally, MBLs supplied through a bank-based model are regulated by the Central Bank of Kenya (CBK), whereas FinTech firms are not (Greenacre, 2020). Consequently, FinTech companies operate with more freedom than lenders within the bank-based model. Although FTL providers can distribute services more conveniently, they offer less legal protection to customers. The hypothesis that this lenient regulatory milieu might have engendered conditions for FinTech lending services to levy more substantial interest rates, given their exclusion from interest rate cap regulations, warrants exploration. Moreover, the numerous ancillary consequences of such a regulatory environment must also not be overlooked.

2.3. Concern about financial exclusion from digital financial services

The high popularity of digital credit is linked to its potential to improve financial inclusion, similar to other digital financial services, such as digital remittances and transactions that were introduced in 2007. However, the results on the impact of digital remittances and transaction services on financial inclusion are mixed. Several studies have demonstrated that digital remittances and transaction services can expand the access of low-income groups to financial inclusion in emerging nations (Hinson, 2011; Maurer, 2012). These services effectively address infrastructural constraints and foster financial inclusion (Allen et al., 2014; Hinson, 2011; Maurer, 2012).

In contrast, Evans and Pirchio (2014) assert that efforts to increase the use of digital financial services to enhance financial inclusion in LMICs have largely failed, except for a few instances in Pakistan, the Philippines, and Kenya. Mishra and Bisht (2013) also identified that only 8 of the 22 nations adopting digital financial services managed to build a viable digital financial industry; three countries exhibited slow and restricted growth, and in the remaining eight countries, the digital financial industries failed to grow. Critics argue that several vulnerable groups are still excluded from digital financial services (Kim et al., 2018). According to Van Hove and Dubus (2019), uneducated individuals, poor individuals, and women do not benefit from digital financial services. Furthermore, the rural population, which is considerably larger than the urban population in emerging nations, has mostly been excluded from the benefits of the digital financial industry.

Several studies (Alafeef et al., 2012; Ammar & Ahmed, 2016; Johnson & Arnold, 2012) contend that low income and unstable employment prevent people from accessing digital financial services. People who are insecurely employed are usually excluded from formal financial services; moreover, they do not feel the need to use digital financial services because they usually cannot expect a steady income stream to facilitate repayment. Furthermore, insufficient education, including financial literacy, is a key impediment to the spread of digital financial services in LMICs (Alafeef et al., 2012; Ammar & Ahmed, 2016; Johnson & Arnold, 2012). According to Sarfo et al. (2023), financial literacy positively and significantly influences the knowledge farmers have on digital credit, thereby affecting their use of digital credit. Illiteracy limits the ability of people to use these services, and potential users must at least understand how to use mobile phones and applications.

In terms of gender, whether gender discrimination limits the ability of women to access digital financial services is debatable, as is the case with other formal financial services. According to certain studies (Alafeef et al., 2012; Ammar & Ahmed, 2016; Potnis, 2014), gender discrimination leads to inequitable financial behaviour, inhibiting women from accessing both informal and formal financial services and even digital financial services. Conversely, Johnson and Arnold (2012) contend that digital financial services provide women with superior access to credit compared to traditional banking services, given that the registration procedure is simplified and does not necessitate complex documentation.

Research on the effects of financial inclusion on digital remittances and transaction services has yielded mixed results. However, only a few studies specifically examine the utilisation of digital credit among financially underserved populations in comparison with traditional loan services. Therefore, this study attempted to delve into the research question of whether digital credit, which refers to lending facilitated through mobile platforms, has a discernible influence on the financial inclusion of financially marginalised Kenyans.

3. Conceptual Framework

To investigate the impact of digital credit at the household level, a conceptual framework is required to appropriately assess the impact of digital credit on households. Consequently, an innovative framework that delineates the development pathway of digital credit was constructed by amalgamating elements from three distinct theories of change (Duvendack & Mader, 2020; Heeks & Alemayehu, 2009; Kim et al., 2018), as illustrated in Figure 1. It incorporates various elements of digital credit development, including supply and demand elements and the influences of sociodemographic and economic factors, in conjunction with regulations and policies that have influenced its trajectory.

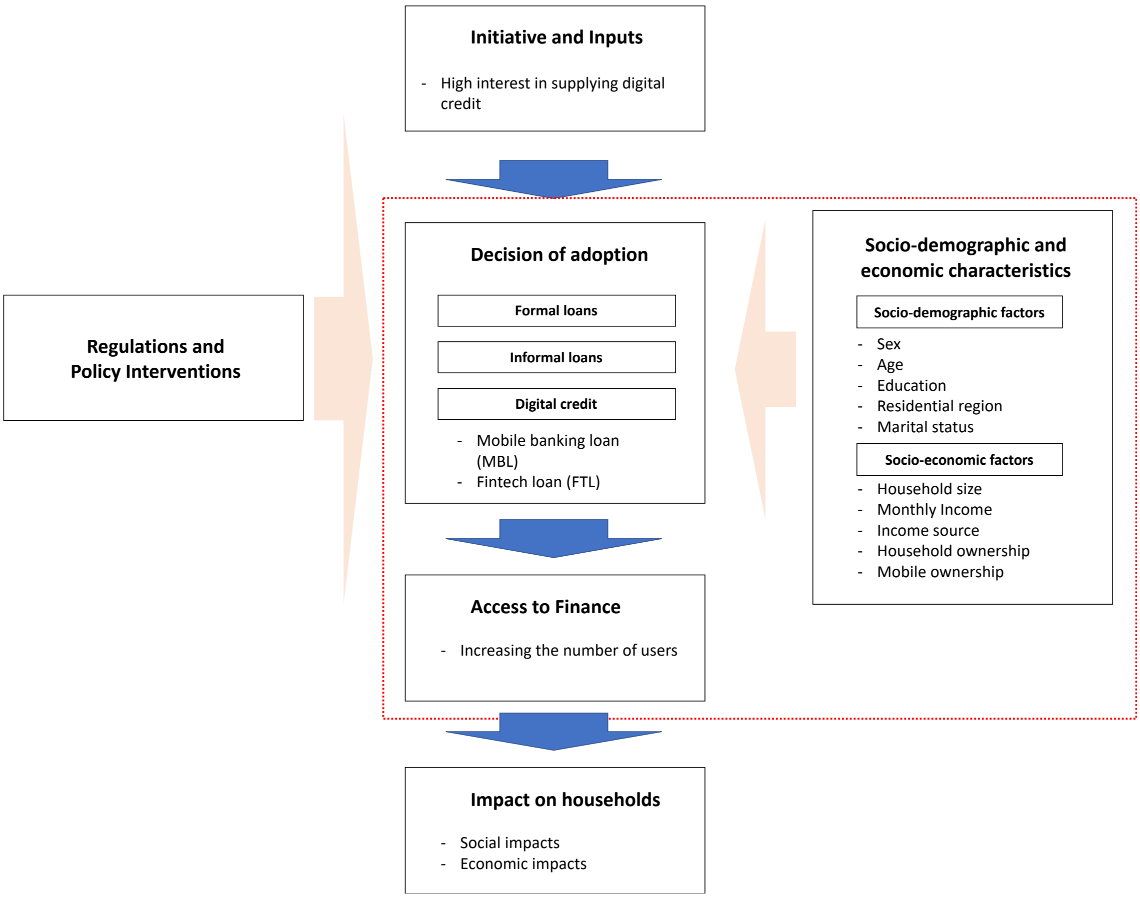

Figure 1. Theory of change for digital credit

'Initiatives and Inputs' are essential for supplying digital credit services, encompassing crucial resources such as capital, infrastructure, technologies for operating digital credit services, and motivation of suppliers to supply products (Duvendack & Mader, 2020; Heeks & Alemayehu, 2009). With sufficient initiatives and inputs, a diverse array of lenders can supply loan services in Kenya, which are categorised as formal or informal loans based on whether the service is legally regulated. Formal loans operate within the regulated financial market under the supervision of the CBK, whereas informal loans, which are not subject to regulation, remain beyond the purview of official financial markets. Similarly, digital credit services can be categorised as formal (MBL) or informal (FTL), contingent upon the lending entity.

Given the supply of digital credit services, households can make a ‘Decision of Adoption’ to determine whether to adopt a loan service, and which types best align with their preferences. Households can choose single or multiple loan services from formal and/or informal sources, including digital credit. Alternatively, they may decide not to borrow.

The decision to adopt a loan service is influenced by external factors, such as sociodemographic characteristics, socioeconomic circumstances, and financial regulations (Kim et al., 2018). The level of regulation plays a crucial role in determining whether the digital credit industry thrives. Certain studies contend that strict regulations must be maintained to mitigate potential risks and protect the security and stability of financial systems (Makulilo, 2015). In contrast, others argue that excessive restrictions lead to a rigid business environment (Evans & Pirchio, 2014). Thus, the expansion of digital credit access is likely to depend on regulation levels.

Sociodemographic and socioeconomic factors also significantly influence the development pathway of digital credit (Figure 1), which is the focal point of this study. Thus, understanding the influence of these factors on loan adoption and choice is imperative. For instance, individuals with certain sociodemographic attributes, such as gender or education, or those with a lower socioeconomic status, such as low-income or temporary workers, tend to be less engaged in formal financial services. This trend is supported by several studies (Alafeef et al., 2012; Ammar & Ahmed, 2016; Johnson & Arnold, 2012; Potnis, 2014), suggesting that these individuals might opt for informal borrowing methods. Loan adoption varies depending on the sociodemographic and socioeconomic characteristics of the borrowers, which can impact the level of financial inclusion. Once a decision to utilise a loan service is made, households gain 'access to finance', followed by considering the 'impact on households', including social and economic impacts within the framework.

In summary, the conceptual framework outlined provides a comprehensive understanding of the factors that influence the adoption and impact of digital credit on financial inclusion. This framework offers a valuable tool for researchers and practitioners to dissect the development pathway of digital credit by considering supply and demand elements, sociodemographic and economic factors, and the impacts of regulations and policies. Amid various ambiguities in the academic sphere regarding the developmental pathway of digital credit, this study aims to address a gap in knowledge by examining whether digital credit, in contrast to traditional lending, influences financial access for financially marginalised groups, despite their vulnerable sociodemographic and socioeconomic characteristics. This will enable a deeper understanding of the financial inclusion of excluded populations concerning access to digital credit services compared to other loan services.

4. Data and Methodology

4.1. Data sources

This study used data from the FinAccess Household Survey 2019 (Kenya National Bureau of Statistics, 2021), conducted by the Financial Sector Deepening Kenya, CBK, CGAP, and the Kenya National Bureau of Statistics (KNBS). The survey was designed to measure and track access to financial services among Kenyans from the demand side, including a wide range of information on household economic activity, financial service utilisation, and household demographic characteristics. As per the KNBS, the survey was conducted based on the household population, specifically targeting individuals aged 16 years and above. Its design aimed to yield estimates at the national, regional, and residential levels (rural and urban areas). The survey utilised the fifth National Sample Survey and Evaluation Programme household sampling frame, which comprised 5,360 clusters. These clusters were then stratified into urban and rural areas within each of the 47 counties, resulting in 92 sampled strata[2]. The collected data were weighted back to the population to provide estimates at the national and regional levels. The survey included 8,669 households across Kenya. Table 2 presents a descriptive summary of the demographics of the sample.

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[2] The survey employed a two-stage stratified cluster sampling design to ensure the generation of valid and reliable estimates at various levels. In the first stage, 1000 clusters were selected from the fifth National Sample Survey and Evaluation Programme. The second stage involved the random selection of a uniform sample of 11 households (434 in urban and 566 in rural areas) in each cluster, using a systematic random sampling method. In the third stage, individuals at the household level were selected using a Computer Aided Personal Interview Kish grid, ensuring the inclusion of one eligible individual (16+ years) from a roster of all eligible individuals in the household. All selections were conducted without replacement.

Table 2. Demographic information of the samples collected in the FinAccess Household Survey 2019

Demographic information	Percent
Age	
16-17 y	7.5
18-25 y	18.9
26-35 y	26.9
36-45 y	18.3
46-55 y	11.3
>55 y	17.7
Sex	
Female	51
Male	49
Rural/Urban	
Rural	60
Urban	40
Education	
None	11.6
Primary	42.8
Secondary	32.4
Tertiary	13
Other	0.3

4.2. Multinomial logistic regression

This study used multinomial logit regression to dissect the influence of sociodemographic and socioeconomic characteristics on the decisions of vulnerable households to use digital credit services. The multinomial logit model was selected because it is suitable for classifying respondents into one of several types of loan service usage, which are inherently unordered and include MBL, FTL, and other formal and informal loans. This model is particularly suitable for our research because it accommodates the categorical nature of our dependent variable (Greene, 2012)—loan service choice—which cannot be sensibly ranked but is instead distinct and non-sequentially dispersed (Cameron & Trivedi, 2005; Gujarati, 2003). The reference category for this analysis is the absence of loan service usage, which allows a comparative evaluation of the utilisation of different loan types.

Moreover, we recognised the limitations and assumptions inherent in the multinomial logit framework. These include the independence of irrelevant alternatives, which posits that the relative odds of choosing a selection from any two options are unaffected by the presence of additional choices (Cheng & Long, 2007), and the requirement for a sufficiently large sample size to ensure reliable parameter estimations (Pate et al., 2023). We also accounted for the potential for multicollinearity among the independent variables. Despite these considerations, the multinomial logit model remains a robust analytical tool for examining multivariate influences on household loan service selection in Kenya because it effectively captures the probabilistic nature of loan selection across multiple outcomes.

The loan choice, denoted by Y, is a dependent variable, whereas the sociodemographic and socioeconomic variables are independent variables, denoted by X_{i1}, X_{i2},., X_{ip}, where *i* denotes the observation of a household and *p* the number of independent variables. We assumed that $Y_i = \left(Y_{i1}, Y_{i2}, \dots, Y_{ir)}\right)^T$ has a multinomial distribution with index, $n_i = \sum_{j=1}^{r} Y_{ij}$ and parameter $\left(\Pi_{i1}, \Pi_{i2}, \dots, \Pi_{ir)}\right)^T$. *R* indicates response categories of the dependent variable, that is, the number of loan choices. When the response categories 1, 2, … *r* are unordered, Π_i is related to the independent variables through a set of *r*-1 baseline category logits. Taking j^* as the baseline category, the model can be expressed as follows:

$$\ln\left(\frac{\Pi_{ij}}{\Pi_{ij^*}}\right) = X_i^T \beta_j + e_{ij}, \qquad j \neq j^*. \qquad (1)$$

Here, X_i^T is the transpose of the independent variable vector X_i, β_j is a vector for the j-th level of the response variable, and e_{ij} is a random error term. Four generalised logits are defined based on this analysis because the five categories of the response variables in this analysis have no inherent ordering. Π_{ij} can be calculated from β as follows:

$$\Pi_{ij} = \frac{\exp\left(X_i^T \beta_j\right)}{1 + \sum_{k \neq j^*} \exp(X_i^T \beta_k)}. \qquad (2)$$

The probability of Π_{ij} equals the probability of loan choice of j. The k^{th} element of β_j can be regarded as the increase in log-odds of falling into category j versus category j^*, resulting from a one-unit increase in the k-th independent variable, holding the other independent variables constant. The details of the vector of the independent variable X_i are presented in Appendix 1. This model allowed us to examine the hypothesis of whether the sociodemographic and economic characteristics of households that have been excluded from financial services are associated with loan choices, particularly digital credit.

5. Results

5.1. Descriptive results

The data in Table 3 show that numerous respondents currently use digital credit, MBL, and FTL services. Digital credit services rank third and fourth in terms of usage, following loans from friends/neighbours and Chama[3]. MBL and FTL are used by 25 and 21.7% of the borrowers, respectively. This indicated that digital credit has become more popular than other formal loan services that are obtained from banks and microfinance services within a short period since its launch in 2012. However, whether the increase in the use of digital credit is due to an influx of people who were previously

[3] Chama (Swahili:, "come together") refers to locally organized groups that meet regularly. Typically, members contribute money to the group, which is then distributed among members (Chidziwisano et al., 2020).

excluded from loan services or a diversification of loan portfolios by those who have already used loan services is unclear.

Table 3. Description of various types of digital credit in Kenya

	(1) **			(2) **		
	Current borrowers*	Percentage of total borrowers	Percentage of respondents	Current borrowers	Percentage of total borrowers	Percentage of respondents
MBL	643	25.0	7.4	643	25.0	7.4
FTL	559	21.7	6.5	559	21.7	6.5
Bank	259	10.1	3.0			
SACCO	326	12.7	3.8			
Microfinance	72	2.8	0.8			
Government	89	3.5	1.0			
Informal lender	39	1.5	0.5			
Chama	665	25.8	7.7			
Employer	90	3.5	1.0			
Friend/ neighbour	790	30.7	9.1			
Shopkeeper	158	6.1	1.8			
Buyer	74	2.9	0.9			
Formal loan				1,139	44.2	13.1
Informal loan				1,909	74.1	22.0

* Current borrowers indicate the number of borrowers who answered that they are currently using a particular loan. In the survey, respondents could tick/check multiple loan services that they were currently using (e.g., if a household respondent was using various loan services sourced from mobile banking, Savings and Credit Cooperative Organisation (SACCO), and buyer, they selected three different choices).

** Model (1) shows a comparison between each loan service and Model (2) represents a comparison between digital credit services and formal and informal loans.

Moreover, digital credit borrowers use loan services more frequently than other borrowers (Table 4). The data in Table 4 show the frequency of loan service usage by a household in the previous 12 months. The borrowers of MBL used the services 3.24 times per year on average, whereas borrowers using other formal loan services, including banks, SACCO, microfinance, and the government, only used these services 1.25 times. Surprisingly, FTL borrowers used FTL services 26.8 times per year, which is significantly higher than any other borrowing source, including informal loans, with an average frequency of 2.5 times. The primary drivers of the higher frequency of digital credit service usage are simplicity and ease of use (Chen & Mazer, 2016). Borrowers can access digital credit services quickly and efficiently, which encourages frequent use.

Table 4. Size and frequency of loan services

	(1) **		(2) **	
	Loan frequency*	**Borrowed amount (Ksh)**	**Loan frequency***	**Borrowed amount (Ksh)**
MBL	3.24	6,245	3.24	6,245
FTL	26.79	1,836	26.79	1,836
Bank	1.16	660,987		
SACCO	1.24	183,867		
Microfinance	1.54	110,882		
Government	1.34	96,066		
Informal lender	2.29	24,610		
Chama	1.96	16,424		
Employer	2.18	38,810		
Friend/ neighbour	2.74	5,937		
Shopkeeper	3.42	2,604		
Buyer	-	3,738		
Formal loan* **			1.25	330,239
Informal loan****			2.50	12,221
Total (Average)	5.97	70,846	5.97	70,846

* Loan Frequency indicates how often a household has used a particular loan service in the past 12 months.

** Model (1) shows the comparison between each loan service and Model (2) represents the comparison between digital credit service and formal and informal loans.

*** Formal loan covers all formal loan services, including bank, SACCO, microfinance, and government sources.

**** Informal loan covers all informal loan services, including informal money lender, Chama, employer, friend/ neighbour, shopkeeper, buyer.

Despite these two findings regarding digital credit use (the increasing number of households using digital credit and high frequency of digital credit use), these results provide insufficient evidence to prove the expansion of financial inclusion. Consequently, this study aimed to determine whether digital credit has been embraced by individuals who were previously excluded from formal loan services. To achieve this objective, this study employed a multinomial logit regression analysis, drawing on the obtained results.

5.2. Results of the regression model

Tables 5 and 6 show how sociodemographic and economic factors are correlated with the decision to use loan services, using the choice of not using loan services as the reference category for comparison with various types of loan services. Appendices 2 and 3 show the results of the multinomial logistic regression analyses, respectively, where the choice of ‘MBL’ or ‘FTL’ is the reference group. The results shown in the appendices demonstrate the extent to which the borrowers of MBL and FTL services vary as reference groups. In Tables 5 and 6, Model 0 shows the relationship between the independent variables (sociodemographic and economic factors) and dependent variable of the possibility of not using loans; Model 1 is for using MBL, Model 2 is for using FTL, Model 3 is for using formal loans, and Model 4 is for using informal loans.

Sociodemographic Factors

According to Table 5, digital credit appears to be adopted by certain groups who were marginalised from formal financial services to a certain extent. First, we examined the results of sociodemographic factors in the rural population. This finding suggests that no link exists between the residential region and the use of digital credit ($p > 0.1$), implying that the use of both digital credit services is not associated with the residential location of the borrowers. Rural residents often struggle to use loan services because of limited access to financial services stemming from physical limitations, such as a lack of financial infrastructure (Chick et al., 2010). Nonetheless, digital credit services enable rural populations to access financial services anytime and anywhere. Thus, the region-related variable does not have a meaningful effect on access to either type of digital credit service, mirroring findings from other digital financial services (Batista & Vicente, 2013; Kikulwe, 2014; Munyegera & Matsumoto, 2016).

Table 5. Multinomial logistic regression: sociodemographic determinants of the use of loans

	(0)	(1)	(2)	(3)	(4)
VARIABLES	**None***	**Mobile Banking**	**Mobile App-based**	**Other formal loans**	**Other informal loans**
Gender (Male)					
Gender (Female)		**−0.288**** (0.1247)	0.016 (0.1338)	**−0.167*** (0.0998)	**0.255***** (0.0693)
Age (18-24 years)					
Age (25-39 years)		**0.563***** (0.1902)	−0.058 (0.1815)	0.242 (0.1738)	**0.426***** (0.1071)
Age (40-54 years)		0.126 (0.2312)	−0.155 (0.2226)	**0.676***** (0.1895)	**0.339***** (0.1218)
Age (55-64 years)		−0.124 (0.3286)	−0.136 (0.2995)	**0.661***** (0.2275)	**0.344**** (0.1491)
Age (≥ 65 years)		−0.095 (0.4025)	**−1.138**** (0.4699)	**0.491*** (0.2598)	−0.037 (0.1667)
Education (None)					
Education (Primary)		**2.242***** (0.7203)	**1.180***** (0.3749)	**1.290***** (0.2879)	**0.593***** (0.1099)
Education (Secondary)		**3.074***** (0.7195)	**1.277***** (0.3829)	**1.778***** (0.2926)	**0.652***** (0.1212)
Education (Tertiary)		**3.337***** (0.7269)	**1.469***** (0.4067)	**2.635***** (0.2998)	**0.460***** (0.1574)
Region (Rural)					
Region (Urban)		0.207 (0.1473)	0.037 (0.1514)	**−0.310***** (0.1140)	0.029 (0.0764)
Marital status (Single)					
Marital status		0.077	0.018	**0.301****	0.128

(Married)		(0.1546)	(0.1654)	(0.1390)	(0.0932)
Marital status (Divorced)		−0.194 (0.3140)	−0.218 (0.3089)	−0.003 (0.2631)	−0.027 (0.1549)
Marital status (Widowed)		0.054 (0.3534)	−0.672 (0.3953)	0.397 (0.2332)	0.054 (0.1473)
Observations	8,393	8,393	8,393	8,393	8,393

* 'None' is the reference category to compare with other loan services.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Second, we can note that gender plays a significant role in the use of formal and informal loan services. Formal loan services are more likely to be used by men than by women, in comparison with non-borrowers (baseline) because the coefficient value of gender on the use of formal loans is (−)0.167 ($p<0.1$). However, women typically appear to use informal loan services, as indicated by the positive coefficient value for females relative to that of males (+0.255, $p<0.01$). Arguably, this result can be explained by specific informal loan services such as Chama, which predominantly target women customers. However, as only a few informal services are exclusively designed for women, this argument is limited in scope. A more plausible explanation is that women are excluded from the formal loan market, leading to a higher dependency on informal loan services. Numerous studies indicate that gender inequalities or discrimination can lead to differences in financial behaviour and access, limiting the access of women access to formal financial services (Alafeef et al., 2012; Ammar & Ahmed, 2016; Johnson & Arnold, 2012; Potnis, 2014). Similarly, the coefficient value for females relative to males was 0.288 units less in terms of the preference for the use of MBL ($p<0.05$), indicating that women are less likely to opt for MBL services than men, similar to the case of formal loan services. In contrast, no significant correlation exists between FTL borrowers and gender ($p > 0.1$), suggesting that FTL services are utilised by people regardless of their gender. These findings suggest a gender bias in MBL and other formal credit services, whereas FTL services display gender inclusivity.

Education level was another significant factor closely related to both MBL and FTL usage. The results in Table 5 show that education has the greatest coefficient value among the variables influencing loan access and uptake. Higher education correlates positively with an increased possibility of utilising loan services. In all education segments, a greater likelihood of using all types of loan services has been exhibited than that exhibited by the non-educated population (reference group). When examining the educational level variable in Table 5 for each model, a universal trend becomes evident: the probability of using a loan increases with the level of education. Particularly, education predominantly affects the use of both digital credit services, among other sociodemographic and socioeconomic variables. FTL usage exhibits a stronger correlation with the level of education than other informal loan services. However, the impact of education on FTL usage is less significant than its influence on formal loans and MBL usage. Notably, the connection between education and MBL usage is even stronger when considering the coefficient values compared to other loans, indirectly indicating that lower education levels increase the difficulty in accessing MBLs when compared to that of formal loans.

Existing studies also suggest that a low level of education could be an obstacle to adopting mobile financial services (Alafeef et al., 2012; Ammar & Ahmed, 2016; Dzogbenuku, 2013; Johnson & Arnold, 2012), and the results in Table 5 support this assertion. Challenges such as ‘financial illiteracy’ related to education levels pose significant impediments to utilising loan services. Less-educated individuals often lack essential financial knowledge, such as understanding the importance of financial services and their proper usage. In LMICs such as Kenya, financial education programmes are often deficient; therefore, people are usually excluded from formal financial services, preventing them from gaining experience or learning about financial services (Berger et al., 2013). Moreover, ‘digital illiteracy’ can compound the difficulty for less-educated individuals to access digital credit services. Several studies have indicated that educational level is the most relevant factor related to differences in learning digital skills (Hargittai, 2001; van Deursen and van Dijk, 2009). Studies have highlighted the correlation between education level and the ability to acquire digital skills (Hargittai, 2001; van Deursen and van Dijk, 2009). Thus, a higher educational level equips individuals with better proficiency in using digital devices or software programs, making it easier for them to access digital credit services.

When considering age as a determinant of digital credit service usage, the oldest group exhibits apparent limitations in using FTL services. Table 5 shows that the influence of age on the use of both types of digital credit service differs. For MBL, the coefficient for the age group of 25-39 years as compared to the reference age group is (+)0.563 units ($p<0.01$), indicating that this group uses the services more actively. No significant effects can be observed for other age groups ($p > 0.1$), suggesting that younger, working-age individuals use MBLs more than older groups when compared to non-borrowers (baseline). In the case of FTL, the older group encounters difficulties in accessing the use of FTLs, as the coefficient for the oldest group (≥65 years) relative to the youngest group (18 to 24 years) was (−)1.138 units for using FTL services ($p < 0.05$). The technology-centric nature of FTLs may be challenging and unfamiliar to older adults. Neither the use of formal nor informal loans showed meaningful results for the oldest group, ≥65 years (Models 3 and 4 in Table 5). This reveals that FTL is the only loan that older individuals struggle to use, whereas younger individuals demonstrate a preference for digital credit. Both formal and informal loans also appear to be influenced by age; however, people aged 44–64 years are the most active in using both formal and informal loans, unlike digital credit, which is predominantly used by the youngest group.

Socioeconomic Factors

In terms of socioeconomic factors of households, income level does not appear to significantly affect FTL usage, whereas a positive association is observed between income level and MBL usage, as is the case for other formal loan services. Reviewing the income variables of Models 1 and 3 in Table 6, as income level increases, the likelihood of using MBLs and formal loans gradually increases. In contrast, informal loan and FTL services do not exhibit correlations with monthly income ($p > 0.1$). The results demonstrate no significant effect of income level on the possibility of using FTL or informal loan services. The lack of a significant effect of income level on the possibility of using FTL or informal loan services suggests that lower-income individuals, while struggling to access MBLs and formal loan services, face fewer barriers when attempting to access FTL and informal loans. This phenomenon may be attributed to the exclusion of lower-income groups from the screening system of formal loan lenders. Formal financial loans are governed by interest rate cap regulations, which prohibit charging interest rates above the established ceiling. This legislative constraint often leads to hesitation among financial institutions in extending credit to borrowers with a certain degree of risk[4]. Similar to formal loans, MBLs offered by banks may present challenges for lower-income individuals in terms of access to loans (Hwang & Tellez, 2016; MicroSave Consulting, 2019). Conversely, informal lenders may also attract customers with lower credit scores. FTL suppliers can provide services with high

4 The interest rate cap was imposed by the CBK in September 2016; however, it was removed in November 2019 and re-implemented in 2020 (African business, 2020).

interest rates regardless of regulations, even when a potential borrower has a risky credit rating owing to low income. Furthermore, the absence of a stringent screening system by informal and FTL lenders, who often lack access to credit information systems and comprehensive information about the borrowing activities of applicants, may increase the risk of over-indebtedness and default (Agarwal et al., 2019).

Table 6. Multinomial logistic regression: socioeconomic determinants of the use of loans

	(0)	(1)	(2)	(3)	(4)
VARIABLES	**None***	**Mobile banking**	**Mobile app-based**	**Other formal loan**	**Other informal loan**
Household size		**-0.056****	**-0.126*****	**-0.088*****	**-0.033****
		(0.0328)	(0.0348)	(0.0255)	(0.0158)
Income (Ksh 0-2250)					
Income (Ksh 2251-5000)		0.318	-0.211	**0.446****	**-0.172***
		(0.2444)	(0.1954)	(0.2031)	(0.0891)
Income (Ksh 5001-10000)		**0.517****	0.091	**0.693*****	-0.007
		(0.2390)	(0.1928)	(0.2005)	(0.0933)
Income (Ksh 10001-)		**1.027*****	0.065	**1.472*****	-0.055
		(0.2368)	(0.2154)	(0.1953)	(0.1076)
Income source (Farming)					
Income source (Employed)		0.120	**1.194*****	**0.813*****	**0.417*****
		(0.2276)	(0.2719)	(0.1529)	(0.1306)
Income source (Casual worker)		0.074	**0.991*****	**-0.968*****	0.091
		(0.2094)	(0.2334)	(0.1957)	(0.0927)
Income source (Own business)		**0.588*****	**1.027*****	0.280	**0.348*****
		(0.2017)	(0.2497)	(0.1485)	(0.1030)
Income source (Supported)		-0.141	**1.011*****	-0.262	-0.078
		(0.2594)	(0.2557)	(0.1931)	(0.1077)
Income source (Rent/ pension)		0.277	0.732	-0.402	-0.008
		(0.5697)	(0.7663)	(0.4429)	(0.3772)
Income source (Others)		-0.691	0.309	0.169	-0.386
		(0.7541)	(0.7540)	(0.4205)	(0.3605)
House ownership (No)					
House ownership (Yes)		-0.185	**0.336****	0.174	**0.183****
		(0.1562)	(0.1636)	(0.1284)	(0.0861)
Mobile ownership (No)					
Mobile ownership		**3.567*****	**1.734*****	**1.694*****	**0.494*****

(Yes)		(1.0067)	(0.3110)	(0.3172)	(0.0955)
Constant		**-9.554*** **	**-6.145*** **	**-6.463*** **	**-2.997*** **
		(1.2623)	(0.5632)	(0.4752)	(0.2005)
Observations	8,393	8,393	8,393	8,393	8,393

* ‘None’ is the reference category to compare with other loan services.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

The income source-related variable also yielded interesting results. Farmers constitute a demographic group that is less active in using FTLs. According to the income source variables listed in Table 6, most household income sources do not affect the use of MBL, with the exception of households that operate their own businesses, which predominantly use MBLs. However, households with income sources other than farming, such as people with salaried jobs or who are self-employed, are more likely to use FTL. Surprisingly, even casual workers and individuals supported by government or non-governmental organisations (NGOs) demonstrated a higher likelihood of using FTLs than farmers. This finding is unexpected, as it indicates that FTLs are less likely to be used by farmers compared to temporary workers or unemployed individuals receiving NGO support. This suggests that individuals with highly unstable employment conditions can access FTL more readily than farmers.

6. Discussion

This study attempted to bridge an existing knowledge gap by analysing whether digital credit can improve the financial inclusion of marginalised individuals in Kenya who cannot access traditional loan services. The analysis identified that, to a certain extent, digital credit has widened financial accessibility for economically vulnerable demographics, albeit unevenly, across different regions. Notably, the traditional impediment of rural residency for financial access does not restrict access to either type of digital credit service, MBL or FTL, suggesting that rural populations can use these new financial services, similar to the urban population. This shifts the conventional conception that people living in rural areas struggle to access financial services (Klus et al., 2021).

In the case of FTL, financial access is relatively less correlated with the sociodemographic and economic status of borrowers. Although education level has some linkage with the use of both digital credit services to a certain extent, similar to other financial services, the study shows no major links between the use of FTL and other variables such as gender and income level. This disputes prior assertions that women and those with lower incomes face disproportionate exclusion from digital financial services (Alafeef et al., 2012; Ammar & Ahmed, 2016; Johnson & Arnold, 2012; Nan and Markus, 2018; Potnis, 2014). These findings reveal that women and low-income earners, who were previously considered financially vulnerable groups, can use FTLs without constraints, or at least with no more constraints than other groups.

However, the findings related to MBL demonstrate that it is used relatively less by vulnerable demographic groups that are often victims of financial exclusion. Households with particular sociodemographic and economic constraints exhibit lower utilisation of this form of digital credit, similar to their use of formal loans. The use of MBL is less prevalent among large families, women, individuals with low educational levels, low-income individuals, and casual workers. Notably, individuals with low education levels and a lack of mobile devices encounter more difficulties accessing MBL than conventional formal loan services, which are known to be the most challenging to access. These findings suggest that MBL services may not be adequately reaching vulnerable groups, whereas FTL services are more accessible for these groups.

Then, we must evaluate whether an FTL loan genuinely engenders a transformative, positive impact on the alleged financially excluded demographics. Undeniably, loan services can alleviate liquidity issues during emergencies or disasters (Bharadwaj et al., 2019; Suri et al., 2021), and enable households to plan and invest more effectively by offering resources for potential investment in education or small business ventures (Vidal & Barbon, 2018). However, note that the suppliers can distribute the loan services without an interest cap (Mitheu, 2018), leading to significant financial burdens for borrowers. FTL has a higher interest rate than other loan services and even MBL, making this credit service quite costly (MicroSave Consulting, 2019). Furthermore, the easier and faster process of obtaining loan services from FinTech companies, coupled with more lenient lending eligibility, could cause overborrowing, thereby exacerbating the economic status of households. The characteristics of FTLs have led to more frequent borrowing by vulnerable people. The descriptive summary elucidates that borrowers have used FTL approximately 27 times within a year, potentially increasing their risk of over-indebtedness.

Furthermore, the challenges in accessing FTLs for certain demographic groups should not be ignored. The findings showed that the elderly population and farmers were excluded from using FTLs. This phenomenon aligns with the notion of the 'digital divide'. FTL transactions require a smartphone, necessitating customers to download and operate an application from an application store, which can be a burdensome task for those who are unfamiliar with digital devices. Consequently, the older population group and farmers, who lack the knowledge to use technological devices such as mobile phones, may face difficulties in using digital credit. Therefore, to enhance the inclusiveness of digital credit, measures to alleviate the digital divide must be contemplated.

7. Conclusion

Digital credit has grown rapidly in Kenya over a relatively short period, which is attributed to its unique features. This success has fostered hope that digital credit can offer new opportunities to those previously excluded from conventional loan services. However, the findings of this study indicate that digital credit services do not universally improve financial inclusion as expected. The MBL usage among vulnerable groups paralleled that of traditional loan services, showing low usage rates. In contrast, FTL usage has penetrated the women-centric and unstable-income-group markets, although access is still limited for those with lower levels of education.

This raises a crucial question: does financial engagement with FTL services directly improve the quality of life of these vulnerable groups? We speculated whether financial inclusion is an indispensable condition for improving the quality of life and facilitating economic development at the household level. Financial inclusion through digital credit services has a clear advantage as it provides economic opportunities to those who were previously excluded from the financial sector. Securing liquidity in funds can provide immediate relief to those facing food insecurity or create new educational opportunities for those who were previously denied such access owing to financial constraints. However, offering loans to consumers who cannot afford to repay them may result in worse outcomes.

Given the current situation, we cannot definitively state whether digital credit has a net positive impact on households. Therefore, further research is warranted to ascertain whether digital credit has generated more positive impacts through 'financial inclusion' than negative effects by fostering 'a vicious circle of debt and poverty under an unregulated credit environment'.

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