Spring 5-15-2022

Essays on Strategies for Increasing Repayment Rates of Digital Microloans

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Abstract

Access to credit can act as a highly effective tool for poverty reduction and economic growth. The ability to borrow increases the propensity of low-income people to start and maintain businesses, educate their children and withstand financial shocks. These factors, in turn, can help them to move out of poverty and lead to more sustainable economic development. However, traditional financial institutions have inherent limitations that have impeded their ability to serve the poor.

Digital lenders are able to leverage the widespread adoption of mobile phones and mobile money to extend credit quickly and conveniently to more people, especially in developing countries. However, due to a lack of credit bureaus and available financial histories of borrowers, digital lenders frequently need to amass vast amounts of data in order to screen borrowers and experiment to find the appropriate loan amount by gradually increasing credit limits based on past repayment. This can lead to high user default rates and over-indebtedness. The lack of collateral during loan applications also means that digital lenders have limited mechanisms for enforcing repayment of loans. Both of these challenges threaten to limit further adoption of digital credit.

Through three experimental studies conducted with an airtime lender, I explore theoretical and empirical mechanisms for reducing default rates of digital loans. In the first study, I demonstrate that limited mobile phone data contain enough signals for creating effective credit assessment methods that minimize privacy risks to borrowers.

In the second study, I find that increasing credit limits negatively impacts repayments and future borrowing, and offer recommendations for increasing credit limits while minimizing the drawbacks. In the final study, I draw on theories from psychology and consumer behavior to develop vivid repayment reminders. This study found that vivid reminders had limited effectiveness for increasing loan repayment and reducing loan duration. Taken together, these three studies propose new avenues for digital lenders to reduce default rates. The hope of this dissertation is that these proposed methods would lead to a reduction in interest rates, that would ultimately benefit the borrowers.

ESSAYS ON STRATEGIES FOR INCREASING REPAYMENT RATES OF DIGITAL MICROLOANS

by

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Dissertation
Submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Information Science and Technology.

Syracuse University
May 2022

Acknowledgments

To paraphrase the popular proverb, it took a village for me to complete this PhD. I would certainly not have completed this pursuit without the contributions of many people in my life.

First and foremost, I am deeply grateful to my parents who put their children's education above all else. Over the years, they made significant sacrifices and surmounted incredible challenges in order to give my siblings and me the best education that they could afford. Having grown through times of deep uncertainty, including wars, my parents believed that education, unlike material possessions, was the best investment that could not be taken away from us. Sadly, my father passed away a few months before my defense. However, he had an unwavering belief that I would complete my doctorate even when I could not envision a successful end myself. This dissertation is dedicated to him.

I owe an immense amount of gratitude to my dear wife. Throughout this journey, I have relied on her steady support. She has had to take on multiple roles, including providing for our family while raising our child, as I worked on my dissertation during the weekends. She has also been directly involved in my research as my sounding board and, more crucially, my patient editor. This dissertation is also dedicated to my son, whose arrival in our family has brought us immense happiness. Nathan has had to endure absent parents as his mother and I juggled different responsibilities to make room for my research.

I would like to express my sincere gratitude to my advisor, Martha Garcia-Murillo, for her guidance and support. Martha encouraged me to pursue my research interest from the beginning, introduced me to relevant research communities and generally made sure I was making progress towards completion of this dissertation. I am also thankful to my committee: Renée de Nevers (chair), Kira Kristal Reed (external examiner), Radhika Garg (internal examiner), Daniel Acuña, Joshua Blumenstock and Jeffrey Saltz for their insightful questions and feedback that greatly improved this document. I am particularly grateful to Joshua for his extensive feedback on my early research ideas and manuscript drafts; and to Daniel, who was a great joy to work alongside in Syracuse and hugely influential in shaping my approach to research. Indeed, many of the methods employed in this dissertation are directly attributable to my work with him.

I had the privilege of meeting and working alongside some truly remarkable people at the iSchool. Mahboobeh Harandi, Yaxing Yao, Yingya Li, Huichuan Xia, Natã Barbosa, Ivan Shamshurin and Erica Mitchell, thank you for the camaraderie and lifelong friendships. Becoming a remote student also meant that I had to rely on a lot of administrative support, particularly in terms of filing the right documents at the right time. And for this, I am grateful to Steve Sawyer, Jennifer Barclay and Bei Yu.

Finally, I am thankful for the research grant I received from the Digital Credit Observatory, a program of the Center for Effective Global Action (CEGA) with support from the Bill & Melinda Gates Foundation.

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Chapter 1 – Introduction

Access to finance, and particularly to credit, has been linked to poverty alleviation and economic development (Demirgüç-Kunt et al., 2008). Economists have shown that lack of access to credit (or financial market imperfections) impedes the ability of the poor to invest in their education despite the high marginal returns (Galor & Zeira, 1993) and significantly limits their occupational choices, pushing poorer people to choose to continue working for a wage over self-employment (Banerjee & Newman, 1993). Both of these effects can stunt countries' economic growth and increase income inequality. At the household level, access to credit can be an effective tool for poverty reduction by increasing the propensity to start income-generating activities, especially by marginalized groups (Khandker & Others, 1998); improving per capita expenditure on food and non-food items (Quach et al., 2005); and increasing the ability of the poor to educate their children (Ampah et al., 2017).

Despite this potential, however, traditional financial institutions in developing countries, such as banks, have limitations that make it hard for them to serve the poor. These limitations include sparse geographical coverage of the branch network, especially in the rural areas; the bureaucratic nature of banking services which have been proven to restrain the adoption of these services (for example, the deposit and withdrawal forms may impede uptake by people with low literacy levels; the requisite of collaterals for loans); and the lack of financial data about the poor which negatively impacts their creditworthiness in the eyes of banks (Hinson, 2011).

In the last decade, financial technology (fintech) has revolutionized the way people access credit, particularly in the developing world. By leveraging advances in machine learning and widespread adoption of mobile phones in developing countries, fintech companies have radically changed the microfinance infrastructure in these countries. Unlike traditional microfinance institutions, fintech firms are able to make use of the expansive infrastructure of mobile network operators (MNOs) as well as the vast amount of data routinely collected by MNOs to extend credit to significantly more people. In this manner, digital lenders are able to offer short-term loans that are instantaneous (loan approval is usually automated), convenient (borrowers request and receive loans through their mobile phones) and without the need for collateral.

Digital loans fall under two main categories: (1) a partnership between an MNO and a lender, in which the MNO usually avails data as well as its infrastructure in exchange for profit sharing (e.g., airtime lending); and (2) a sole enterprise of a lender with the MNO's infrastructure only used as a delivery channel (GSMA, 2019). Here, the lender is responsible for customer acquisition, credit risk assessment and loan recovery, and the MNO makes money by charging fees on the transactions occurring on the network. Examples include most lenders using smartphone applications (e.g., Tala[1]) and other companies using mobile money services to offer consumer products on credit (e.g., NOTS[2]).

[1] Digital lending through a mobile app and mobile money (https://tala.co)
[2] Home solar kits on loan, paid in installments (http://www.nots.nl)

This innovation in lending has led to a rapid growth in the number of digital loans, with some lenders seeing loan uptake by more than a third of qualified borrowers (Barriga-Cabanillas & Lybbert, 2020; Bharadwaj et al., 2019). In Kenya, for example, the percentage of digital loans has grown from 41.5% of total loans in 2014 to 91.2% in 2018, with 77% of all borrowers taking loans solely through digital means (CFI, 2019). Similarly, between 2016 and 2018, digital loans represented 86% of all consumer loans in Kenya (Mazer et al., 2020). In nearby Tanzania, a fifth of mobile phone owners took digital loans through their handset devices in 2018 (Kaffenberger, 2018).

The provision of quick and more easily accessible loans has provided a number of benefits to users. For low-income users, digital lending has helped increase households' resilience to financial shocks. These borrowers are able to maintain long-term expenses, such as paying for education, which tend to suffer cuts in favor of more immediate basic necessities such as food and medication when people face liquidity constraints (Ahmed & Cowan, 2019; Barriga-Cabanillas & Lybbert, 2020; Bharadwaj et al., 2019). For the less poor, digital lending also provides a convenient way to access certain products, such as mobile phone airtime (Barriga-Cabanillas & Lybbert, 2020). Finally, people with thin or non-existent credit histories (such as most people in developing countries) can use digital credits in order to create or improve their financial profile that could help them to secure loans from traditional lenders, such as banks (Balyuk, 2019).

However, this rapid adoption of digital lending has also been linked to unsustainable lending practices. In particular, the lack of collateral and limited ability of lenders to enforce repayment means that digital loans face especially high default rates when compared to traditional lending (Johnen et al., 2021). For example, close to a third of digital borrowers in Tanzania have defaulted on their loans, and more than half have missed their repayment schedule (Kaffenberger, 2018). In Kenya, 2.2 million borrowers (more than 6% of total population aged 15 and above[3]) had loans in default between 2016 and 2018, half of whom with balances less than $10 (CFI, 2019). This risk of default often becomes reflected in the high interest rates charged by digital lenders, which make their products less accessible for some consumers, such as entrepreneurs (Francis et al., 2017). In addition, certain lenders collect massive amounts of data (including call logs, text messages, contacts in phone books, and location histories) from the borrowers' mobile phones in order to improve their credit assessment system, which can have serious implications for users' privacy. A number of borrowers, on the other hand, have resorted to taking additional loans to settle those taken from a different lender (Wathome, 2020); while others borrow small amounts and repay them quickly in order to have their credit limit increased, a practice known as "spinning" (Oppong & Mattern, 2020) that can lead to increased indebtedness. Finally, a lack of enforcement mechanisms for loan repayment has pushed some lenders to resort to morally questionable and ineffective practices of shaming defaulters (Liao et al., 2020).

Mobile phone airtime was one of the first digital loan products offered by mobile network operators in developing countries. The vast majority (up to 95%) of mobile phone

[3] Statistics from the World Bank (https://data.worldbank.org)

subscribers in Sub-Saharan Africa are prepaid customers (GSMA, 2020), meaning that they have to load their mobile phone with “airtime” before they are able to make phone calls, send text messages or access the Internet. The word “prepaid” is in opposition to “postpaid” customers who are billed at the end of a usage period, usually a month. This prepaid strategy, that greatly helped in the expansion of mobile phone services in Africa[4], also poses a challenge to MNOs and their customers. Failure to access airtime in time of need means that customers are not able to communicate, while the MNO loses potential revenue. To address this issue, a number of MNOs created two services; (1) “Me2U” (me to you) which allows subscribers to share airtime; and (2) airtime lending services, which let subscribers quickly borrow airtime. This lending service is usually provided either as an in-house product or in partnership with third-party lenders.

Airtime can be seen to share some of the same characteristics as money, such as the ability to act as storage of value and an exchange mechanism of value (Madise, 2015). Consider the story below by Madise (2015), edited for brevity, that exemplifies this aspect of airtime:

> *In 2008, I went to Uganda (…) The Airtel phone however immediately provided a message, ‘Welcome to Airtel Uganda’ and informed me of the keys I had to use to access certain information. (...) But I soon ran out of airtime and was unable to go outside to buy more airtime credit. So I thought of using my mobile banking application, (...), running on the mobile phone platform, to procure more airtime*

[4] Mo Ibrahim, a Sudanese businessman who created Zain, one of the first and most successful mobile service provider, famously stated that “Mobile phones could not work in Africa without prepaid because it's a cash society” (https://www.economist.com/special-report/2009/09/26/eureka-moments)

credit using funds in my bank account in Malaŵi. (...) When I received the code, I used the same value entering system as I would in Malaŵi and voila credit topped up! I then realised that several people had also run out of airtime and were either sending people to procure airtime using Uganda Shillings or were just out of communication. I offered to exchange airtime with them for whatever of value they had which I could use. So I procured airtime from Malaŵi using my local account and gave the codes or used the M2U service to transfer the airtime credit to others. In return I received money, in various currencies or goods and services that I coveted.

This story illustrates how certain mobile subscribers have used airtime transfer services as a form of money transfer and a payment system for services and goods. Indeed, close to 10% of Tanzanian respondents to a survey by Comninos et al. (2009) mentioned that they used airtime to pay for goods or services. Furthermore, the above story also indicates that some users had adopted mobile airtime transfer as a channel for cross-border transactions. Exploiting this opportunity, a number of companies, such as SendAirTime.com[5], allow people abroad to purchase airtime for friends and families back in their home countries. The recipients can then sell this airtime for cash, thereby turning airtime into a form of remittance transfer service. At the country level, some mobile phone subscribers have used airtime transfer to help those in their communities facing a sudden, external shock, particularly in the context of underdeveloped financial structures. For example, people in Rwanda used airtime transfers to quickly send

[5] A service for sending airtime to people in Uganda from abroad (https://www.sendairtime.com)

financial assistance to those affected by a devastating earthquake that happened in the southwestern region of the country in 2008 (Blumenstock et al., 2016).

Economic theories suggest that to achieve efficiency in financial markets, a number of criteria must be fulfilled by participants (e.g., lenders and borrowers) such as, (1) symmetrical information flow between participants, (2) rational decision-making by participants, and (3) low transaction costs and entry barriers (Karlan et al., 2016). As previously discussed, digital lenders have drastically lowered transaction costs and barriers to entry by leveraging mobile phone technology and data generated by mobile phone use. In this dissertation, I explore avenues for tackling the first two criteria. Specifically, I partnered with an airtime lender to explore methods for reducing the high default rates observed in the digital lending industry by improving information flow to lenders and encouraging better decision-making by borrowers. This airtime lender operates in multiple countries across Sub-Saharan Africa, the Middle East and SouthEast Asia, serving tens of millions of customers. This dissertation analyzes and discusses three avenues for reducing default rates, both ex ante (credit scoring and setting of credit limits) and ex post (text reminders).

In the first study, I present the result of a credit scoring system that I designed and implemented in a central African country. Currently, digital lenders collect massive amounts of data, including text messages, contacts list, location and app usage history, from borrowers' mobile phones in order to build credit risk assessment systems, raising significant privacy concerns. This study found that an effective credit scoring system can be created using only recharge data that significantly reduces privacy risks to borrowers.

Currently, due to a lack of credit histories of borrowers, digital lenders often start by extending small loan amounts to large groups of people. The amount that a customer is able to borrow is then gradually increased based on their payment history. Research from the credit card industry shows that increasing credit limits can lead to increased indebtedness and spending. In this experimental study, I found that, similar to credit cardholders, digital borrowers respond to increases in their credit limits by increasing their borrowing and that this increased borrowing negatively affects their repayment rate and long-term usage of communication services. However, this study also identified key borrower characteristics which may reduce negative financial responses to increased credit limits. Based on the results of this study, I present key recommendations for digital micro-lenders to minimize the potential negative impacts of increasing credit limits.

Finally, the third study explores the use of vivid reminders to alter borrower behavior and increase repayment rates. Text reminders have shown mixed results when it comes to encouraging loan repayment. Research from consumer's decision-making indicates that to increase the effectiveness of reminders, it is necessary to make users care about the outcome of taking action (e.g., repaying a loan). Thus, in the last study, I designed text messages that make explicit the consequence of untimely payment to the "present self" or to the "future self". The results of this experimental study showed that vivid reminders, and reminders in general, had an insignificant impact on loan repayment and duration. Based on this product design (automated loan repayment) and use (mobile communication), I argue that this limited effect of reminders observed suggest that borrowers who failed to repay their loans may be facing other difficulties, such as financial hardship and / or lack of convenience for purchasing airtime.

Three Essays on Digital Microlending

Chapter 2 – Effective Credit Scoring Using Limited Mobile Phone Data[6]

2.1. INTRODUCTION

The number of digital micro-loans provided to people without credit history has recently surged. As of 2017, for example, it was estimated that there were over 11 million micro-loans provided to customers through mobile phones (Francis et al., 2017). This trend has been particularly noticeable in the developing world. Currently, for example, as many as a fifth of mobile phone owners in Tanzania have contracted a loan through their mobile phone (Kaffenberger, 2018). Likewise, in Kenya, there are now more borrowers using digital means to access credits than those using traditional financial institutions, such as banks or microfinance (Central Bank of Kenya, Kenya National Bureau of Statistics and FSD Kenya, 2016).

This surge has been fueled by a number of factors. Firstly, there is a growing market appetite for loans that are quick and relatively easy to obtain. Secondly, many customers face hurdles when securing loans from traditional lending institutions. For example, banks often demand significant collateral, especially when lending to risky borrowers. Finally, an increase in subscribers of mobile money platforms in the developing world has greatly facilitated the lending and repayment process.

[6] Material published as
Shema, A. (2019, January). Effective credit scoring using limited mobile phone data. In *Proceedings of the Tenth International Conference on Information and Communication Technologies and Development* (pp. 1-11).

From the perspective of lending institutions, digital credit provides new opportunities, such as reduced transaction costs, increased product customization, and improved credit scoring through the use of alternative data (Francis et al., 2017). At the same time, due to alternative lending approaches, digital financial lenders often face significantly higher customer default rates in comparison to traditional lending institutions. For example, a survey of digital borrowers in Tanzania found that close to a third defaulted on their loans, and more than half missed their repayment schedule (Kaffenberger, 2018). For this reason, digital lenders may benefit substantially from more effectively assessing the credit risks of their customers.

Currently, credit risk assessment in many developing countries is rendered difficult by the lack of effective credit bureaus (World Bank, 2016) and available credit data. This results in digital lenders increasingly relying on alternative data sources other than past financial data to estimate the creditworthiness of their potential borrowers, most of whom have limited or non-existent credit files. Examples of alternative data used in credit scoring include metadata of mobile phone communications, such as call detail records or CDR; data harnessed from social media platforms, such as “likes”, posts, and comments; and data collected directly from customers’ mobile handsets, with details such as application usage, call and SMS logs, SMS content, and handset model and manufacturer.

Despite the recentness of this change, a growing body of research has highlighted the potential of alternative data to create effective credit scoring models with predictive capabilities equivalent or even superior to those utilizing traditional credit models (Björkegren & Grissen, 2018; San Pedro et al., 2015). In particular, some research has highlighted the ability of alternative data sources to reduce default rates whilst increasing the number of issued loans (Speakman et al., 2017).

However, these massive datasets also pose considerable privacy risks for consumers. In particular, the vast quantities and extensive types of information collected can reveal details relating to consumers' private lives or other sensitive information that may be harmful. For example, patterns of phone application usage can identify a user's location or relationship status (Shema & Acuna, 2017). These risks may be especially problematic in developing countries, where there may exist weaker data regulations, knowledge gaps and unintended use of technology, etc. (Vashistha et al., 2018).

In this paper, we demonstrate that a reliable credit scoring system can be built using limited datasets with a smaller number of variables that focus only on a customer's airtime recharge history. This makes it possible to avoid more extensive, and possibly sensitive, datasets, such as phone and SMS logs. Using data obtained from a telecommunication provider and an airtime lending company, both operating in a central African country, we first built scoring systems that achieved high levels of accuracy by simply looking at subscribers' airtime recharges and past loans. Second, we report the results of an experiment conducted by extending loans to 125,000 randomly selected subscribers that were not previously qualified for loans. These results suggest our model is likely to generalize to the broader population of mobile phone users than those typically approved for loans by the lender. Third, we validate our proposed method in the real-world by using our models to assess the creditworthiness of 25% of the lender's customers, and compare our models to the lender's current system. We show that our models consistently outperform the lender's system across different customer segments. Finally, we discuss the implications of our results to the wider research area of digital credit scoring for micro-loans.

2.2. RELATED WORK

2.2.1. Credit Scoring Using Mobile Phone Data

The last decade has witnessed a surge in the number of start-ups and traditional financial institutions extending micro-loans to previously hard to reach and risky borrowers. These companies are increasingly gathering data either from telecommunication providers (Cook & McKay, 2015), social media platforms (Stewart, 2014), or directly siphoning data from mobile handsets with the use of mobile applications (Mandell et al., 2015). In response to this change, there is a small but growing body of research analyzing the reliability of mobile phone data in predicting consumers' creditworthiness. In particular, key studies have highlighted that the detailed patterns of real-time financial behavior revealed in mobile phone data may enhance understandings of consumer creditworthiness, thereby reducing consumer default rates whilst retaining or increasing the number of consumer loans.

Most research in this area combines data from traditional lending institutions with those collected by telecommunication companies to demonstrate the relationship between phone use, and credit use and repayment. A key example relates to a study of MobiScore, a credit scoring system created using mobile phone data as captured by a phone service provider in a Latin American country (San Pedro et al., 2015). By combining demographic data and call detail records (CDR) with credit card data from a financial institution in the same country, researchers demonstrated that mobile phone data could be used to create credit profiles that are as reliable as those issued by traditional credit bureaus.

Similarly, Björkegren and Grissen (2018) combined CDR data with loan data from a microfinance institution based in a Caribbean country. By using the mobile phone data in the CDR dataset, the authors were able to show that the microfinance institution could have reduced its default rate by as much as 41%, while retaining 75% of their borrowers. They determined that this would be achievable by analyzing metadata of consumers' phone calls, texts, Internet access and airtime top ups, in addition to key demographic data, such as age and gender.

Ruiz et al., (2017) also used mobile phone data, in addition to traditional data, to assess loans issued by a microfinance institution. The phone data used included call detail records (metadata of incoming and outgoing calls and texts, airtime balance and top-ups), as well as data gathered from customers' mobile handsets, such as applications installed, and device model and manufacturer. In addition, the authors gathered data used in traditional credit scoring systems, such as consumers' age, gender, and marital status, as well as loan characteristics; including loan amount, and length and reason of borrowing. The authors' most reliable model, based on support vector machines, almost halved the number of overdue loans while more than doubling the approval rate (Ruiz et al., 2017).

Despite the potential of mobile phone data to enhance the reliability of credit scoring, concerns have been raised regarding the privacy implications of the use of this data by lenders, discussed further in the following section. In addition, research in this field remains limited, and significant further work will be needed in order to better understand the use and value of different types of mobile phone data in developing reliable credit scoring models.

2.2.2. Privacy Risks of Mobile Phone Data

Mobile phones, with their increasing array of sensors, are now able to collect a large amount of information regarding their users (Shilton, 2009), and the significance of the privacy risks that this poses should not be underestimated. Many digital credit providers currently make use of a vast range of this digital data in order to assess user creditworthiness, and in particular may gather information from call detail records, users' social media data, and data collected directly from users' mobile phones. Each of these types of data carry a number of privacy risks that are discussed in more detail below.

A growing number of digital lenders now use call detail records to determine borrowers' creditworthiness. This growth can be linked to the increasing number of lending collaborations between telecommunication companies that provide data used for credit scoring, and financial institutions that loan capital (Francis et al., 2017). An example of this is M-Shwari, which was started as a partnership between a telecommunication company, Safaricom, and a commercial bank, Commercial Bank of Africa (CBA), to extend loans and savings products to M-Pesa users (Cook & McKay, 2015). Safaricom provides access to the M-Pesa platform, along with call detail records of potential borrowers; whilst CBA offers the savings accounts and extends the loans to users. Crucially, though the two companies have not disclosed the type of data they exchange, a similar anonymous product has shown extensive data exchange between the partner institutions, including network activity (such as airtime usage and active days), mobile money activity (such as amounts sent and received, and deposits and withdrawals), and key demographic information, including age and gender (Speakman et al., 2017).

The use of call detail records to determine creditworthiness in such situations raises concerns due to the type of personal information that can be revealed. Firstly, for example, CDR's can provide the locations of the cell towers of a caller and receiver. When coupled with the time of the communication, this information can be used to infer people's "significant places", such as their home and workplace (Yang et al., 2014). Likewise, the mobility pattern inferred from CDR data can reveal the user's mode of transportation (Wang et al., 2010), as well as the kind of activity a person is engaged in, such as travel (Sikder et al., 2016), in near real-time. In addition, the communication metadata contained in call detail records can also provide details about the user's social network, the people with whom they communicate, and the frequency and duration of these communications. Finally, in such an arrangement as described above, consumers may be unaware that personal information is able to be passed between their financial institution and telecommunication company or of the possible implications of this data exchange.

Björkegren and Grissen (2018) suggest it may be possible to mitigate some of the privacy risks associated with the use of CDR. Specifically, the study highlights the possible use of recharge data, which are less sensitive and do not contain a user's network structure of their contacts or their communication patterns.

Other lenders utilize data obtained directly from mobile devices, which raise alternative privacy concerns. For example, a combination of GPS traces and WiFi triangulation can be used to infer a person's home, workplace, and other places of interest (Christin et al., 2011). In addition, the sequence and timing of mobile application usage could reveal the location context (such as whether the user is at home or workplace) and relationship context (such as whether the user is with friends, relatives, colleagues) of the user (Shema & Acuna, 2017). Using location data collected from mobile phones, Eagle et al. (2009) demonstrated that one could infer highly personal aspects of users' lives, such as job satisfaction, from a range of mobile phone data. Finally, Christin et al. (2011) identified a number of privacy threats posed by data gathered from mobile phones, including those related to collecting pictures and videos, audio samples, and biometric data.

In addition, there now exist a growing number of lenders that use data from social media platforms to inform their lending decisions. For example, Lenddo[7] leverages data from borrower's social media and email accounts, including Facebook, Gmail, LinkedIn, Twitter and Yahoo, to create a credit score, the "LenddoScore" (Stewart, 2014). Crucially, besides affecting the credit score of consumers who sign up to the service, the default status of this application also propagates through borrowers' social network, impacting their contacts' credit scores as well (Hardeman, 2012).

Finally, a growing number of lenders are catering to smartphone users by providing them with micro-loans through mobile applications. In addition to acting as the interface for users to request loans, these mobile applications also collect massive amounts of data from the users' phones. A few examples include Branch[8], a popular lender, which indicates on its website that it collects "handset details, SMS logs, social network data, GPS data, call logs and contact lists". Another lender, Saida[9], states on its website that they "will check how you have been using your phone to make calls, SMS, data and how you use mobile money services such as M-Pesa". Other lenders, such as Tala[10] (formerly "InVenture"), do not disclose the kind of data they use. However, their Android application requests permission to access a variety of different sensors and sensitive

[7] Credit scoring using users' social media data (https://www.lenddo.com)
[8] Digital lending through a mobile app and mobile money (https://branch.co)
[9] Digital lending through a mobile app and mobile money (http://getsaida.com)
[10] Digital lending through a mobile app and mobile money (https://tala.co)

data on the user’s phone, such as running applications, web bookmarks, SMS contents, contacts list, and call logs (see figure 1).

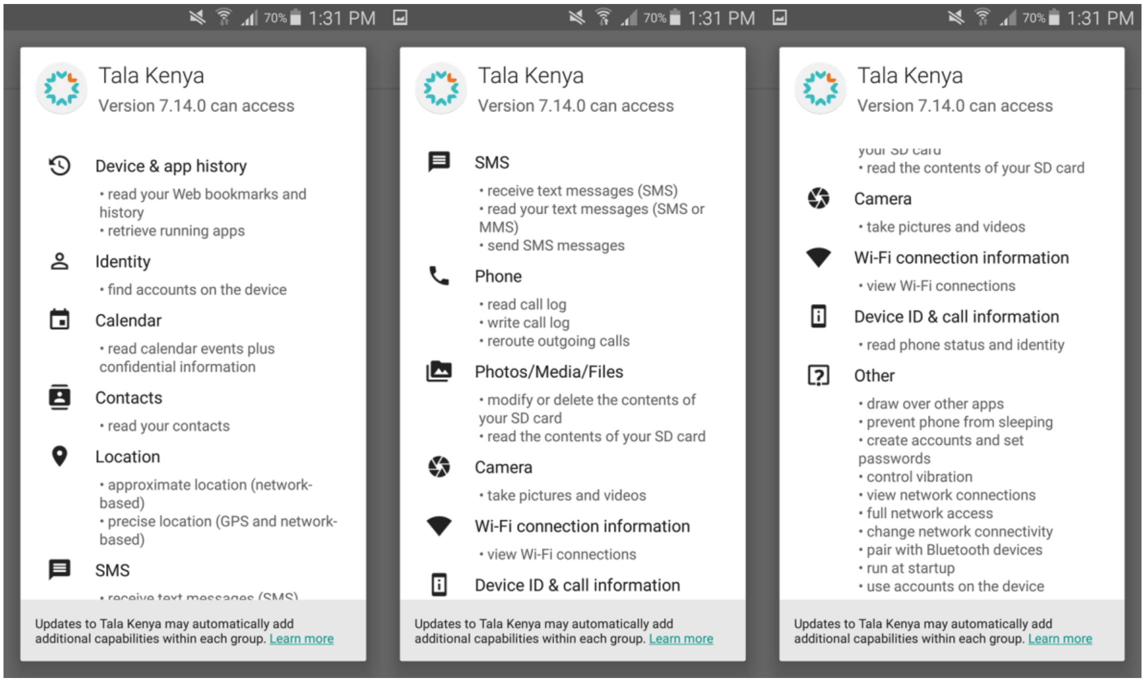

Figure 1: Tala app permissions request

These massive data collections and the privacy risks that they pose to borrowers show the need for creating effective credit scoring systems that utilize limited data to minimize privacy exposure for borrowers, but still provide lenders with a reliable mechanism for assessing credit risk. This paper makes such a contribution by demonstrating the effectiveness of using recharge data in predicting airtime loan outcomes.

2.3. DATA

For this study, we obtained data from a mobile network operator (MNO) and a lender that loans airtime credit to the customers of the aforementioned MNO. Both companies operate in a central African country. From the MNO, we obtained a dataset that contains details of airtime recharges by its customers; while the airtime lender gave us access to its lending data. Additionally, we conducted an experiment whereby we extended loans to randomly selected phone numbers and collected data on their repayment behavior. This section gives more details about each dataset.

Table 1: Data summaries. Amounts in USD

	Recharge Data	Loan Data	Experiment
Minimum	0.0018	0.18	0.18
Maximum	3,557.80	18.00	1.80
Average	0.96	0.76	0.42
Standard deviation	2.56	0.99	0.37

2.3.1. Recharge Dataset

As in many developing countries, the vast majority of our MNO's subscribers are prepaid customers. As such, they are required to have credit on their phone account before making calls or sending texts. If their account balance is too low, users have to credit their account by recharging airtime. This can be done through different means, such as airtime vouchers, digital credit purchased via mobile money, and airtime transfers. These transactions are captured by the MNO to keep track of customers' account balances. Each record in the database contains the following details; (1) an anonymized identifier for the mobile number receiving credit; (2) the date and time when the recharge occurred; (3) the amount of money being added to the account (or recharge amount); (4) the account's balance before the recharge happened; and (5) the user's new balance after the recharge.

For the purposes of this study, we obtained a subset of this data that comprises more than 150 million records, generated by close to three million unique mobile subscribers. The dataset covers a one year period from April 1st, 2017 to March 31st, 2018. The recharge amounts range from as little as the equivalent of $0.0018 to as much as $3,500 (see table 1 for a descriptive summary).

It is worth highlighting that the data used in this study only contained details of airtime recharges (also called “top-ups”) and did not include details regarding subscribers’ communication patterns or locations. In addition, the phone numbers were anonymized, such that we could not identify individual phone numbers. However, the anonymization process produces the same identifier as in the loan dataset. In this way, we could link individual subscriber’s recharge data and their loan data. From this recharge dataset, we created features that capture users’ recharge behavior which, we posit, can reveal people’s mobile phone usage and act as a reliable indicator of their creditworthiness.

2.3.2. Loan Data

Our second dataset was obtained from a mobile airtime lender that operates on the same MNO’s network. When the customers of the telecommunication company exhaust their airtime balance to make calls, they can borrow a small amount of credit from the lender through a USSD and/or an SMS application. The loan amounts are in fixed denominations from $0.18 up to $18.00. The borrower then has a period of seven days to repay the loan, with an addition of a 10% service fee. Therefore, if a customer has not yet fully repaid their loan after seven days, they are considered to be in default.

Before issuing loans to subscribers, the lender performs an in-house credit scoring to assess the risk of the borrower. Other checks are also performed, such as not issuing a second loan before the current loan has been fully repaid. For repayment, a customer simply has to recharge their account and the system automatically deducts any outstanding loan amount and service fee.

For this study, we obtained a subset of the lender's loan dataset. This subset contained details of loans issued between April 1st, 2017 and March 31st, 2018. During this one year period, there were close to 40 million loans issued to more than 1.7 million unique customers. The borrowers' phone numbers were anonymized in the same way as in the recharge dataset, such that we were able to link both datasets. Table 1 shows a descriptive summary of the loan data. The average default rate stood at 14.9%; i.e., 14.9% of loans had not been fully repaid by seven days. This dataset of loans gave us a benchmark to evaluate the performance of our proposed models vis-à-vis an existing credit scoring system, as well as the data for training ground truth.

2.3.3. Experiment Data

As mentioned above, the lender conducts its own credit risk assessment of subscribers before issuing loans. Therefore the dataset of loans contains information only about those customers that were qualified for loans. These customers are not representative of the MNO's subscribers as they have been pre-selected based on their ability to pay, as assessed by the lender's credit scoring system. To verify that our proposed models can be generalized to predict the creditworthiness of any of the MNO's subscribers, we conducted an experiment in collaboration with the lender in which we collected data from subscribers who were not previously qualified for loans.

For the experiment, we randomly selected 125,000 numbers from the pool of numbers that could not borrow under the current scoring system. To ensure that these numbers were still active on the network, we only selected numbers that had made at least one recharge in the six months prior to the experiment. We conducted this experiment in April 2018, with an additional one week to allow people who had borrowed in the last week of April to repay their loans.

To ensure that our experiment remained blind to our participants, we assigned the 125,000 numbers randomly into five groups of equal sizes, with each number having an equal probability of being assigned to any of the five groups. The groups were based on the different credit limits used by the lender. Our five groups could respectively borrow the equivalent of $0.18, $0.36, $0.54, $0.90 and $1.80. These amounts are discrete (i.e., the customers could only borrow one or another of these amounts), and individuals in groups with larger borrowing amounts were also allowed to borrow the smaller amounts, but not vice-versa. For example, a customer in the $0.54 group could borrow $0.54, $0.36 or $0.18, whereas a customer in the $0.18 group could only borrow $0.18. These groups and borrowing conditions represented normal lending procedures by our partner during their credit assessment, although with an addition of two extra groups with larger permitted borrowing amounts. Hence, the subscribers in our experiment could not tell that they were part of an ongoing experiment. Table 1 presents some descriptive statistics of our experiment data.

Since the participants in our experiment had never been judged creditworthy by the lender's system, we sent everyone an SMS informing them that they qualified for loans. This functionality is also used by the lender with other customers. Thus, we kept the experience of our participants exactly the same as with the other customers of the lender.

2.4. METHOD

In this study, we aimed to predict the probability of default using only data on past airtime recharges. Here, we use the lender's definition of default, which is that a customer does not successfully service all their loans within seven days of borrowing in a given month. For example, if a customer A borrows five times in a month, but fails to pay one of the loans within seven days of contracting it, they are considered to be in default. On the other hand, a customer B who only borrowed once and paid it back within the seven-day period would not be considered as a defaulter.

We employed a supervised learning approach, using a random forest classifier (Hastie et al., 2001) to predict the probability of default. We chose to use a random forest classifier as this algorithm has been shown to perform particularly well with imbalanced datasets, such as those used for credit scoring (i.e. these datasets usually have a low percentage of defaults) (Brown & Mues, 2012). Additionally, models based on a random forest algorithm are easier to interpret, with the ability to find the weight of each feature in the prediction, as well as more easily understand the various decision trees in the model. These two characteristics are particularly important in the lending industry, where managers may not want black-box tools, but rather models whose functionality they are able to understand and easily explain to users.

Using the random forest algorithm as implemented in the machine learning library of Apache Spark, we developed three models based on three different sets of features: those derived from the recharge dataset, the loan dataset and the combined features from both the recharge and loan datasets. We used this approach of different datasets for two main reasons. First, we wanted to use data that is available prior to the lender issuing a loan, i.e. the recharge data. This would help in assessing all customers, even those who have never been qualified for loans based on the lender’s current credit assessment method. Since the loans are used when a customer’s airtime balance is low, we posit that looking at their history of airtime recharge and usage could be a good indicator of whether a person would pay back their contracted loan, i.e. recharging their account after using their airtime loan. Second, we wanted to compare the predictive power of each dataset, such that we can estimate the number of defaults expected by using each dataset on its own, or in combination.

With each of the datasets above, we created features that capture the usage of airtime, either from recharge or loans, in the six months prior to taking a loan. Therefore, to predict the probability of default for a particular subscriber in a specific month, we use their recharge data and/or loan data in the preceding six months. For example, to predict the loan outcome of March 2018, we use the recharge and/or loan data collected from the subscriber from September 2017 to February 2018. We decided to use a six-month period because the MNO deactivates a number from the network after six months of inactivity.

- Recharge features:
  - Total number of recharges in a month
  - Minimum, maximum, average and standard deviation of recharge amounts in a month.
  - Minimum, maximum, average and standard deviation of balances before recharges in a month
- Loan features:
  - Total number of loans in the past 30, 90 and 180 days
  - Average number of days since activation of the phone number at the time of borrowings
  - Minimum, maximum, average and standard deviation of the number of days between borrowings and repayments in a month (or age of the loan)
  - Average number of days between two consecutive borrowings
  - Minimum, maximum, average and standard deviation of the loan amounts in a month

Using these features of six months of data prior to loans, we constructed the training dataset with recharge and loan data of all subscribers from April 1st, 2017 to March 31st, 2018. For each subscriber's loan outcome, we built features from the data of six months prior to the loan. Table 2 shows in detail the mapping between features and target, or prediction outcome. Similarly, to construct our testing dataset, we used data from November 1st, 2017 to March 31st, 2018 for the features and April 2018 for the target outcome.

Table 2: Map of features and prediction target for the training dataset

Features Period	**Target Period**
April 1st, 2017 to September 30th, 2017	October 2017
May 1st, 2017 to October 31st, 2017	November 2017
June 1st, 2017 to November 30th, 2017	December 2017
July 1st, 2017 to December 31st, 2017	January 2018
August 1st, 2017 to January 31st, 2018	February 2018
September 1st, 2017 to February 28th, 2018	March 2018

In training our models, we used grid-search with ten-fold cross validation to tune our models' parameters. In the following section, we report the results of the study.

2.5. RESULTS AND ANALYSIS

In this section, we report the results of our study. We start with a descriptive analysis of our lending experiment. Thereafter, we report the results of our prediction models and discuss the importance of each feature in our comprehensive model. Lastly, we report the results of using our method in a real-world setting and compare its results with that of the lender’s current system.

2.5.1. Experiment Results

Of the 125,000 phone numbers randomly selected for our experiment, 33,379 unique numbers, or 26.7%, made a borrowing. This lending rate is about the same currently achieved by the lender. Our experiment participants took a total of 56,286 loans, with an average loan amount of $0.42. Figure 2 shows the total number of borrowings for each group and the corresponding default rates. The average default rate of our experiment group was 35.88%. This is more than double the 14.9% average default rate under the lender’s scoring system during the same period. This result indicates that the lender’s credit risk assessment had removed borrowers with double the default risk as compared to those who qualify for loans.

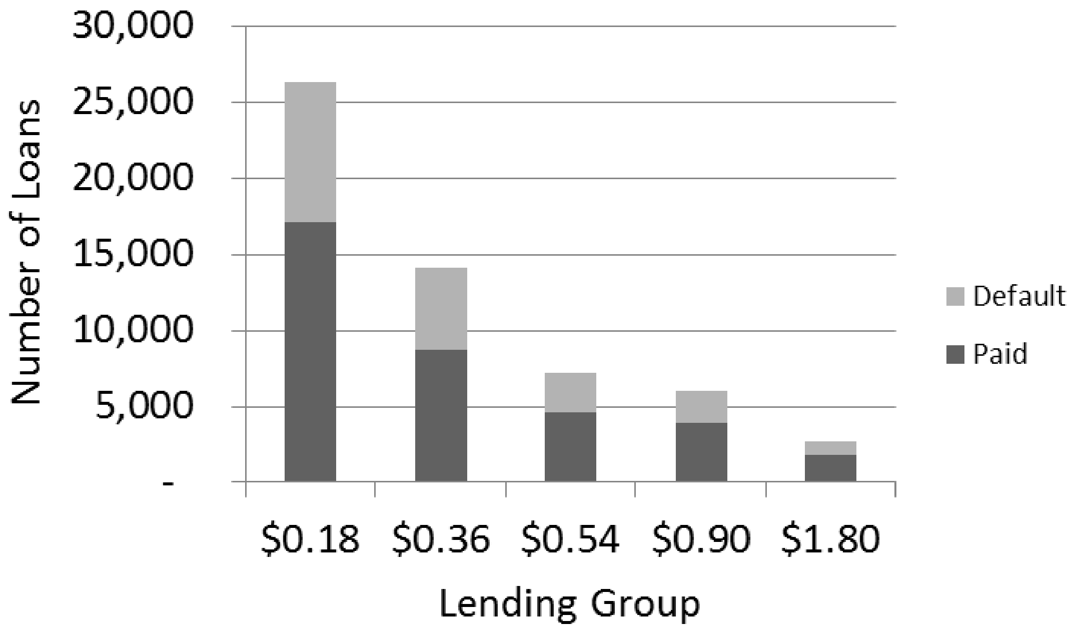

Figure 2: Borrowing during the experiment – Number of loans

The data shows that our participants' borrowing strongly reflected their recharge patterns. Figure 3 depicts the percentages of total borrowings and recharges made by subscribers by hour of day. Most borrowings and recharges are made in the peak hours of morning and evening. The curve of loans almost perfectly mirrors that of the recharges throughout an average day. This could suggest that subscribers view borrowing as another way of recharging their phone account, instead of using this as an emergency recharge, as the product was originally intended by the lender. Instead, borrowers adapted the service to their need, i.e., as a convenient way to recharge their airtime accounts. Thus, it seems that the airtime lending service supplements other channels of airtime recharge. A spatial analysis of borrowing and recharges, looking at the locations where subscribers borrow airtime or recharge their account through other means, might help confirm whether the airtime lending service is used as another means of recharge.

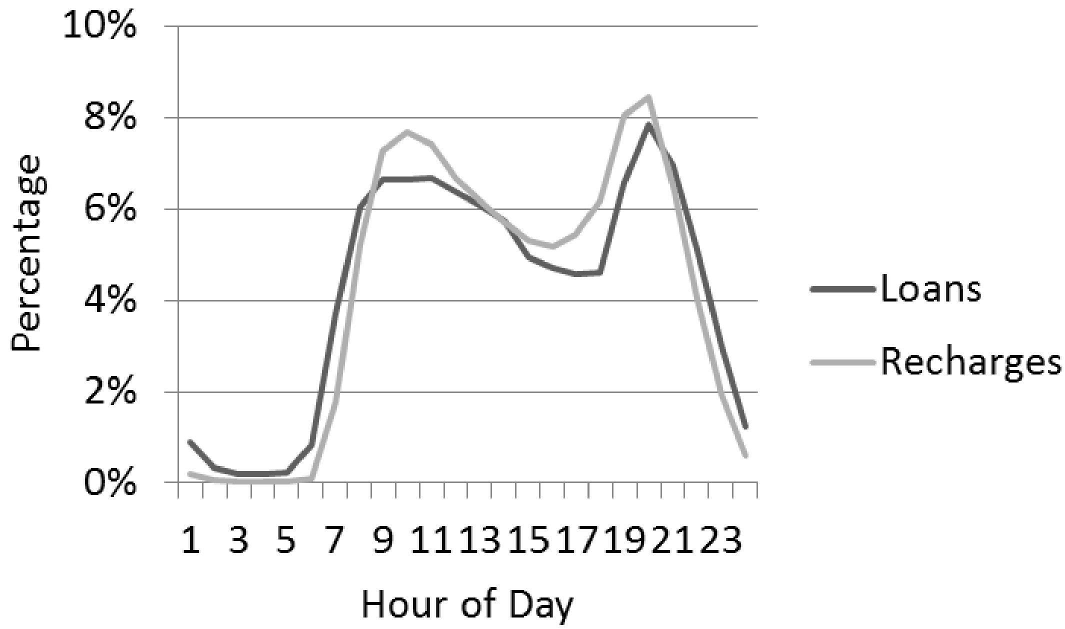

Figure 3: Borrowing during the experiment – Loan by hour of day

2.5.2. Predictions

We trained three random forest models using each set of features, i.e., features from the recharge dataset, the loan dataset and the combined recharge and loan features. The prediction target in our test dataset was obtained from the experiment we ran in April 2018 by extending loans to randomly selected phone numbers that were judged not creditworthy by the lender. We also used the data on loans issued by the lender during the same period. To compare the prediction accuracy of our models, we tested them on the data of all loans issued in April 2018 (see Table 3), and also specifically on the loans issued during the experiment (see Table 4). In this manner, we were able to compare how models trained on past loans could perform with consumers that were never granted loans previously, i.e., those in the experiment. This approach is particularly important for a credit scoring system as it would allow lenders to estimate the risk of lending to new customers on whom the models were not trained.

Since our dataset is imbalanced, we used the sensitivity, precision and the area under the receiver operating characteristic (AUROC) curve to evaluate and compare the performance of the three models. The sensitivity of a model predicting a binary output, also known as the true positive rate, indicates the proportion of all the actual true values (i.e., not default) that were correctly identified by the model; whereas its precision, or positive predictive value, refers to the proportion of actual true values among all the values predicted as true by the model. Thus, the sensitivity of a model predicting loan default refers to the model's ability to correctly identify all the customers that are creditworthy, while its precision looks at defaulters that the model misclassified as creditworthy. The AUROC, on the other hand, plots the sensitivity of a model as a function of its false positive rate (or specificity) and, in one metric, represents the overall performance of a model. A model with random prediction would have an AUROC of 0.5, while a perfect model would achieve an AUROC of 1. The area under the receiver operating characteristic is a metric generally used in research to evaluate the performance of credit scoring models (Wang et al., 2011).

Table 3: All loans issued in April

Features	Sensitivity	Precision	AUROC
Recharge	**62.62%**	73.99%	0.79
Loan	24.19%	**81.63%**	0.67
Recharge + Loan	60.77%	76.22%	**0.80**

Table 3 presents the results when our models predict the loan outcomes for all the users who borrowed in April. The model that used only features from the recharge dataset performed better than the alternative two models in identifying the highest number of users that did not default (highest sensitivity). However, in selecting these users, the model also included a high number of borrowers who defaulted (lowest precision). The model using only features from the dataset of past loans, on the other hand, achieved the lowest default rate (high precision), but picked up only a small proportion of non-defaulters (low sensitivity). Thus, the model trained on the recharge dataset was more effective at finding the highest number of subscribers who did not default, but also misclassified more defaulters, while the model trained on past loans was better at classifying defaulters. This can be explained by the fact that the model trained on past loans learned from these loans the characteristics of bad loans. Interestingly, the combination of both recharge and loan features yielded the best overall model (highest AUROC), with an acceptable compromise between sensitivity and precision.

Table 4: Loans issued during the experiment

Features	Sensitivity	Precision	AUROC
Recharge	**64.31%**	74.09%	0.82
Loan	37.70%	**80.30%**	0.72
Recharge + Loan	63.78%	75.68%	**0.83**

Table 4 shows the results of models prediction of default outcomes for users that would not have been granted loans under the current credit scoring system. These results are interesting to analyze, since the models were essentially making predictions on a different set of subscribers than those on which the models were trained. Overall, all the models performed slightly better than when predicting default status for all the users (in

Table 3). Surprisingly, the sensitivity of the model trained only on loan features improved by 13 percentage points, meaning that the model became much better at finding users who did not default, with a slightly decreased precision. This indicates the performance improvement of our approach when compared to the lender's current credit risk assessment system. Our models were better at finding the characteristics predictive of loan outcome beyond those used by the current system.

2.5.3. Feature Importance

In this section, we present and discuss the importance of the features in the model that combined data from recharge and past loans. Table 5 provides details of each feature and its weight in the predictions made by the model.

Table 5: Feature importance for the model using features from both the recharge and the loan datasets

No	Feature	Weight
1	Number of Recharges in a month	0.520709
2	Maximum balance before recharge in a month	0.147356
3	Number of received loans in the past 30 days	0.120838
4	Average balance before recharge in a month	0.049052
5	Number of received loans in the past 90 days	0.038900
6	Minimum balance before recharge in a month	0.035913
7	Maximum recharge amount in a month	0.027765
8	Number of loans in the past 180 days	0.021142
9	Maximum loan amount in a month	0.011381
10	Average loan amount in a month	0.010507

11	Average recharge amount in a month	0.007539
12	Minimum recharge amount in a month	0.005983
13	Minimum loan amount in a month	0.002522
14	Average number of days since activation	0.000393
15	Average number of days between loans	0.000000
16	Average number of days before repayment	0.000000
17	Standard deviation of loan amount	0.000000
18	Standard deviation of balance before recharge	0.000000
19	Standard deviation of recharge amount	0.000000
20	Minimum number of days before repayment	0.000000
21	Maximum number of days before repayment	0.000000
22	Standard deviation of number of days before repayment	0.000000

The most important feature in the model is the average number of monthly recharges per subscriber, accounting for more than half of the weight in the prediction of loan outcomes. This indicates that subscribers who regularly recharge their accounts are more likely to pay back their loans. In fact, our data shows that the non-defaulters make on average 14.9 recharges per month, which is more than double the 6.4 average number of recharges made by defaulters in a month. Since repayments are made through recharges, the model picked up that subscribers who regularly recharge their accounts are better borrowers. Surprisingly, however, the amount of money recharged on users' accounts is much less important. The minimum, average and maximum amounts that a subscriber recharged in a month (number 12, 11 and 7, respectively) are only marginally important compared to the number of recharges.

The second most important feature is the maximum balance that subscribers had before recharging their account. In fact, the average and minimum that a subscriber has on their account before they recharge their account follow closely in order of importance at number 4 and 6, respectively. These features indicate that subscribers who recharge their accounts before their balance is too low often do not default on their loans, since these are subscribers who want to have the ability to make calls at any time.

The frequency of borrowing is also indicative of ability and willingness to service a loan. Indeed, people who fully repaid their loans had contracted on average 5.7, 16.1 and 26.4 loans in the 30, 90 and 180 days prior to the current loan, consistently more than the 3.3, 10.6 and 17.9 loans that defaulters had received during the same number of days prior to their default. Interestingly, the features related to the loan amount, such as the maximum, average and minimum loan amount (number 9, 10 and 13), are less important than those indicating the frequency of borrowing.

The number of days a phone number has been active on the network is the last significantly important feature in our model (number 14 on the table). Though still an important feature in the loan outcome decision by the model, it is surprising that the age of a subscriber on the network does not carry more weight. Since loan defaulters are deactivated from the network after 90 days if they do not fully service their loan, one could have expected people who have been longer on the network to be better borrowers as they may wish to remain on the network and keep their long-held mobile number.

The standard deviation features that are meant to capture any change in a user’s recharge and borrowing patterns do not seem to be significantly important in our model. In adding these features, we had expected that any such changes could signal potential financial distress. However, these less significant weights could indicate that subscribers rarely change their communication patterns in meaningful ways over time. This fact could contribute to the robustness of our credit models as people seem to be consistent in their recharge behavior. Also, any change in recharging could be expensive for users and may thus deter people from trying to cheat the scoring model.

Overall, our model indicates that frequency in borrowing and recharging are more indicative of good customers, rather than the amount of money borrowed or recharged.

2.5.4. Model External Validity

To test the external validity of our proposed method, we deployed it in the market and compared the results with the lender’s current credit scoring system. In collaboration with the lender, we split the entire subscriber base in the country in two random sets of 25% and 75%. In August 2018, we deployed our model to assess the creditworthiness of 25% of borrowers in real-time, while the lender’s current system was used on the remaining 75% of the market.

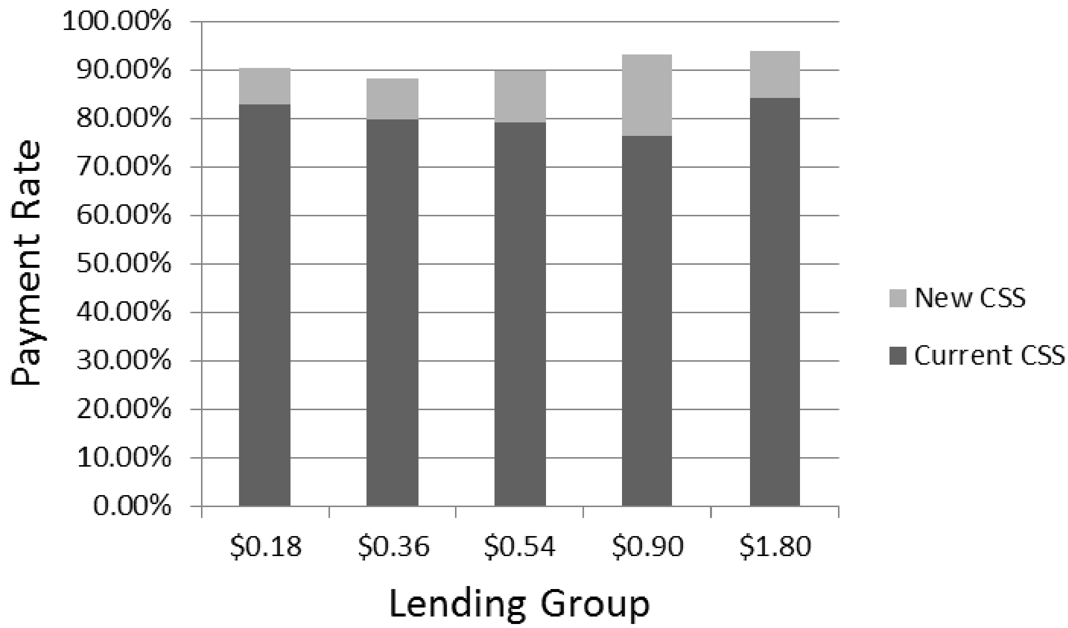

Figure 4: Payment rates with the lender's current system vs our method

Figure 4 shows the payment rates achieved by both the lender's current credit scoring system (current CSS) and our proposed model, or new credit scoring system (new CSS). Our method consistently outperformed the lender's current credit scoring system, achieving a payment rate of 91.11% of the total loan amount issued to customers assigned to our method, a difference of close to 11 percentage points compared to the 80.27% total payment rate reached by the lender's current system.

However, if our method had been deployed in the entire market, it would have disqualified 24.9% of customers who are currently eligible to borrow, and would have issued 80% of the total loan amount lent under the current system. Since the loan volume is an important aspect of the system to the lender, we are currently exploring a number of ways of fine-tuning our system before deploying it in the entire market. The first possibility of dealing with borrowers judged non-creditworthy by our system is to put them in the lowest lending group (i.e., only able to borrow $0.18) and gradually move them to lending groups with higher credit limit depending on their payment behavior.

Second, we are investigating the possibility of lowering the threshold for subscribers to qualify for loans. Since our scores indicate the ability of a borrower to pay all their loans within seven days of contracting them in a month, we could build scores that use this probability with the addition of a credit limit to allow subscribers with low probability of payment to borrow fewer times than those with higher scores. Indeed, during our pilot with 25% of the market, people with higher probability of payment tended to be better borrowers than those with lower probabilities. The non-defaulters had an average probability of 0.59, compared to 0.57 for borrowers in default.

Since the lending methodology assigns people in groups with varying credit limits, we were able to look into the effect that increasing and decreasing credit limit had on borrowers' payment pattern. During our pilot with a quarter of the market, 26.92% of the total number of loans was issued to customers who had seen their credit limit increased, whereas the rest either stayed with the same credit limit, or had it decreased. However, customers with increased credit limits borrowed 39.45% of the total loan amount. This indicates that borrowers with increased credit limits had individual loans that were 38.22% bigger than the average loan extended to the other borrowers. This increased debt amount also led to an increased default rate, with customers with an increased credit limit only able to pay 85.23% of their loan amount, compared to 94.94% for customers who had the same or decreased credit limit.

Therefore, increasing credit limits leads people to borrow more, while lowering their ability to pay back their debt. For lenders intending to increase the credit limits of their customers, we would suggest completing this gradually, while monitoring the increased loan issued and the payment rate so as to avoid over-indebtedness for their borrowers, which would lead to increasing default rates.

This study presents a few avenues for future research and a number of limitations that we discuss in the next section.

2.6. LIMITATIONS

This work focused on predicting default on a specific type of digital loan, airtime borrowing, by analyzing airtime usage patterns. More research needs to be done to validate the use of airtime usage as a predictor for other types of loans (such as cash or electricity). We are currently working with a company that issues solar kits on loans that are paid in installments. We will use the airtime consumption of borrowers to assess their ability to pay, and thereby investigate the predictive power of airtime usage for people making relatively larger payments over longer periods of time.

The airtime loans analyzed in this paper also present another difference to other types of digital loans, in that payments are made through automatic deduction of airtime from the borrower’s account once they make a recharge. Therefore, there is a need to explore whether there would be a difference between this type of passive payment, where money is automatically deducted from borrowers’ accounts, to active payment, where borrowers have to make the payment themselves. Our future study with the solar kits will help answer this question.

Finally, the airtime loans analyzed in this study attracted a fixed 10% commission fee, regardless of a borrower’s creditworthiness. In addition, this fee was not cumulative over time. This is different from other types of loans that may attract different interest rates, and that are sometimes cumulative. A possible avenue for future work would be to investigate the effect of interest rates on payment. For example, it may be worthwhile to consider whether lowering the interest rate charged to good customers would encourage repayments.

2.7. CONCLUSION

In this paper, we explored the effectiveness of credit scoring models built on limited data. Such models have the potential to lower the privacy risks to borrowers of micro-loans dispensed through digital media. We used massive, real-world datasets of airtime recharge and loans from a telecommunication provider and an airtime lender. We validated our proposed method by using our models to assess the creditworthiness of customers in the real-world, and compared our results with that of the lender's current credit scoring system. In addition, we conducted an experiment by lending airtime to randomly selected phone numbers that were not qualified to borrow previously.

We built three different credit scoring models that use (1) airtime recharge dataset; (2) a dataset with past loans; and (3) a combination of both the recharge and loan datasets. The model that was trained on the recharge data was best at finding the highest number of borrowers that did not default, with the highest true positive rate or sensitivity among the three models. However, the model trained on data of past loans had the lowest default rate, or precision, of the three models. By combining both datasets on recharge and past loans, our third model achieved the highest overall performance as measured by the area under the receiver operating characteristic (AUROC) curve.

Additionally, we tested our three models on the experiment data. Since this data comes from phone users who were not previously able to borrow, we demonstrated that our approach is able to generalize to new borrowers who were not part of the training datasets. In fact, our models maintained and even improved their prediction accuracy on such new borrowers.

Finally, we validated our proposed method by using it to assess the credit risk of customers in the real-world. By comparing our models' results with that of the lender's current credit scoring system, we demonstrated that our models consistently performed better than the lender's. However, in reducing the default rate, our method also reduced the total loan amount issued. To increase this amount, we have suggested a few avenues for improving and fine-tuning our system.

This study was conducted on a specific type of lending, i.e., airtime lending. In future work, we intend to research whether our approach can be used with other types of lending. For example, we would like to explore airtime recharge as a predictive signal for payment of other types of loans, such as relatively larger loans paid in installment over longer periods of time. In addition, since we used data from one central African country, a possible avenue for future research is to see how these types of models generalize to other countries that may have different socioeconomic aspects.

Overall, this study has demonstrated that we can build credit scoring models for digital lenders with high levels of accuracy by using limited data that may not compromise people's privacy.

Chapter 3 – Effects of Increasing Credit Change in Digital Microlending[11,12]

3.1. INTRODUCTION

The recent decade has witnessed a rapid growth in the number of microloans provided through digital channels, particularly using mobile money platforms, in a number of developing countries. For example, the percentage of digital loans in Kenya has grown from 41.5% of total loans in 2014 to 91.2% in 2018, with 77% of all borrowers taking loans solely through digital means (CFI, 2019). Similarly, Tanzania in 2018 had as much as a fifth of its mobile owners borrowing through digital channels (Kaffenberger, 2018).

Since 2012, when the first digital microloans were disbursed on M-Pesa (Suri & Gubbins, 2018), the popular Kenyan mobile money platform, product offerings have diversified from pure cash loans. Newer and more innovative companies now use mobile phones to provide a variety of products, such as Okoa Stima[13], which lets M-Pesa customers buy electricity on credit, and solar kits payable in installments (examples include NOTS[14], Mobisol[15] and M-Kopa[16]). In addition, Twiga[17], a Kenyan

[11] Results of this study published as
Shema, A. (2021). Effects of increasing credit limit in digital microlending: A study of airtime lending in East Africa. *The Electronic Journal of Information Systems in Developing Countries*, e12199. https://doi.org/10.1002/isd2.12199

[12] The work presented in this chapter was made possible in part by the Digital Credit Observatory (DCO), a program of the Center for Effective Global Action (CEGA), with support from the Bill & Melinda Gates Foundation.

[13] Electricity on loan (https://www.safaricom.co.ke/personal/m-pesa/do-more-with-m-pesa/okoa-stima)
[14] Solar kits on loan (http://www.nots.nl)

start-up that links farmers and food vendors, partnered with IBM to assign credit scores to owners of small shops (Gebre, 2018) enabling the vendors to borrow from a number of digital lenders when they need to buy produce (Reagan, 2020). Other companies, such as Channel VAS[18] and Comza[19], work with mobile network operators to provide airtime loans to phone subscribers. For a number of digital borrowers, these loans are the first they have obtained from formal financial lenders (Goslar, 2016).

Due to a lack of credit histories and limited data from credit bureaus in many of the countries of operation (World Bank, 2016), microlenders are often required to provide small loans to many applicants with the understanding that a number of these consumers will default. Reports indicate that up to 35% of first loans are never repaid; whereas this rate is halved by the third loan (Izaguirre et al., 2018). This permissive approach on first loans is adopted in order to collect as much data as possible to help create and refine the lenders' credit risk assessment models (Izaguirre et al., 2018). The amount that a consumer is subsequently able to borrow (their credit limit) is then changed based on their payment patterns.

Extensive research from the credit card industry has shown that increases in credit limits tend to lead people to increase their spending (Lin et al., 2019; Soman & Cheema, 2002) and become "over-indebted" (Bertaut & Haliassos, 2006). In developing countries where a large number of people are taking on their first formal loans through digital

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[15] Solar kits and household's appliances on loan (https://www.mobisol.rw/)
[16] Pay-as-you-go solar kits and household's appliances (http://www.m-kopa.com)
[17] Food distribution from farmers to retail shops (https://twiga.com)
[18] Mobile phones and airtime on loan (https://www.channelvas.com)
[19] Airtime on loan (http://www.comzafrica.com)

channels, over-indebtedness can negatively impact borrowers' nascent credit histories and limit their prospect for future borrowing.

Digital lending presents a number of similarities with borrowing through credit cards: (1) loan decisions are mostly automated; (2) loans are disbursed both instantaneously and remotely; and (3) borrowers are able to spend the loan either in digital form or via a cash withdrawal (Chen & Mazer, 2016). However, research on microlending has yet to consider the effect of changing credit limits on borrowers' behavior, whether in traditional microfinance or digital lending. Understanding this potential effect could help reduce default rate and minimize the consequences of defaulting, such as over-indebtedness. This chapter proposes to fill this gap in the literature.

3.2. RELATED WORK

3.2.1. Impact of Credit Limit Changes within the Credit Card Industry

Within the credit card industry, multiple existing studies have shown that raising credit limits tends to lead to increased borrowing and indebtedness (Lin et al., 2019; Soman & Cheema, 2002). Through a series of five studies, Soman and Cheema (2002) found that consumers tended to respond to credit limit increases by increasing their borrowing. The studies included three scenario-based experiments conducted at a US-based university, one survey collected from patrons of a science museum, and an analysis of the Survey of Consumer Finances of 1998. Similarly, Lin et al. (2019) revealed that Chinese credit cardholders tended to increase their spending and debt level in response to increases in credit limit. Investigating the relationship between multiple determinants grouped under (i) socioeconomic characteristics; (ii) attitude towards money of cardholders; and (iii) credit card features, existing spending patterns, and debt levels, the study showed that a 1% increase in credit limit led to a 0.44% increase in monthly spending as well as a 0.20% increase in debt. Other alternative factors related to credit limits, such as the number of credit cards held by borrowers, have been proven to be correlated with increased debt as they are associated with higher credit limits (Abdul-Muhmin & Umar, 2007; Baek & Hong, 2004).

Research suggests that higher credit limits can result in increased borrowing as consumers may perceive their credit limit to be reflective of their current or future income. For example, the studies by Soman and Cheema (2002) revealed that consumers are often unable to correctly estimate their future earnings and rely instead on alternative indicators, such as their credit limit, in order to approximate their future income. Thus, they concluded, borrowers with larger available credit tend to spend more than those with less available credit on their credit cards. Likewise, Lin et al. (2019) attributed the increase in borrowing observed in their study to “income illusion”, a term used by Wang et al., (2014) to describe increased borrowing patterns observed in credit card users in China.

Other research has found that consumers’ existing credit utilization patterns may better explain the link between raised credit limits and increased borrowing levels. Using a sample of the Surveys of Consumer Finances conducted between 1983 and 2001, Bertaut and Haliassos (2006) noticed that households tended to maintain the same utilization rate after a credit limit increase initiated by the lender. Thus, consumers increased their borrowing proportionately to the increase in credit limit and would respond to changes to credit limits in order to keep this utilization rate similar throughout their borrowing time. Interestingly, Bertaut and Haliassos (2006) also found that households tended to strategically default on their credit card debts, especially those with high interest rates; i.e., they would choose not to repay their loans even though they had low interest bearing assets.

On the other hand, Gross et al. (2000) argued that consumers might also have “conventional precautionary motives” which can act to limit changes in borrowing in response to credit limit increases. In their data, collected from a number of credit card issuers in the US, the authors found that after an initial increase in borrowing following a raised credit limit, consumers tended to restore their previous utilization rates within five months. The authors attributed this to a behavioral pattern in which consumers aim to maintain a certain amount of available credit in case of future financial shocks or need.

Research has also identified that individual borrowers may respond differently to changes in credit limit (Bearden & Haws, 2012; Soman & Cheema, 2002). There are a number of possible reasons for these variations. Firstly, Soman and Cheema (2002), describe a moderating effect which they refer to as the consumers’ “credibility” of the perceived link between credit limits and earnings. Consumers who believe their credit limit to be highly reflective of their future earning tend to spend more in response to increases in credit limit. On the other hand, when the consumer's credibility is lower, the effect of credit limit on spending tends to be attenuated. Interestingly, the authors identify older and/or more experienced borrowers as those with generally lower levels of credit credibility; meaning that these borrowers may respond moderately to increases of their credit limits.

Secondly, variations in consumer response to an increase in credit limit may be linked to the effect of borrowers' different attitudes to spending. Bearden and Haws (2012), for example, discovered that people with low levels of "Consumer Spending Self-Control" (CSSC) respond most strongly to credit limit increases. For such types of borrowers, a higher credit limit resulted in an increased willingness to pay higher prices for goods and higher credit card premiums. On the other hand, a higher credit limit had practically no influence on the willingness of people with high CSSC to pay premium prices for goods.

Finally, individual variations in response to an increased credit limit may also relate to previous credit utilization rates. Gross and Souleles (2002) for example, observed that consumers with low initial utilization rates tended to respond less strongly to an increase in credit card limit and revert more quickly back to previous utilization patterns. Those with high utilization rates (above 90%) responded most strongly to increases in their credit card limit, increasing their debt by almost 50% of the credit limit increase. Overall, these variations suggest that whilst increased credit limits tend to result in increased borrowing, the actual impact on individual borrowing levels may also be strongly influenced by a range of existing borrower characteristics and behavioral patterns.

The generalized borrowing patterns described above can also be seen to be reflected in some lenders' behaviors. Gan et al. (2016), for example, found that some credit card issuers in China were issuing higher credit limits as a way to entice applicants and increase credit card uptake, particularly amongst high spending demographics, such as married people with children or those living with extended families, who have been shown to have high expenditures on their credit cards (Chien & Devaney, 2001; Kinsey, 1981; Steidle, 1994). As a result, some consumer advocacy groups now recommend to regulators that credit card issuers be restricted in increasing their customers' credit limits to mitigate over-indebtedness (Citizens Advice, 2017).

3.2.2. Borrowing and Repayment in the Microfinance Industry

Currently, there is very little work which considers the impact of credit limit changes on loan repayment. Relevant studies considering the impact of loan size on repayment patterns have proven inconclusive, with larger loan sizes found to be both a positive (Roslan & Karim, 2009) and a negative (Sharma & Zeller, 1997) predictor of loan repayment. For example, Roslan and Karim (2009) found that larger loans had a better repayment rate since the lender, a microfinance institution working with farmers in Malaysia, was more careful in evaluating the creditworthiness of borrowers of larger amounts. In addition, borrowers of smaller amounts blamed the default rate on the fact that these loans were insufficient and negatively affected the cash flow of their projects. On the other hand, analyzing the loan performance of group based lending in Bangladesh, Sharma and Zeller (1997) noted that larger loan sizes increased the risk of default due to “limited investment capacities and the limited risk-bearing abilities of the rural poor” (Sharma and Zeller, 1997, p. 1741). Thus, it would seem that the impact of loan size on repayment within microfinance may be dependent on context-specific factors.

Most existing studies have tended to focus on alternative factors which may impact loan repayment patterns. Key elements identified by this body of work include:

- group vs individual loans: group lending has a better repayment rate than lending to individual customers (Brehanu & Fufa, 2008);
- gender: female borrowers tend to be better at repaying loans than their male counterparts (Abdullah & Quayes, 2016; D’Espallier et al., 2011);
- age: loans to older borrowers tend to outperform those to younger borrowers (Mokhtar, 2011);
- business productivity: people engaged in more productive activities are able to make timely repayments (Brehanu & Fufa, 2008; Haile, 2015); and
- repayment installment: shorter repayment period (for example, weekly vs monthly) and higher installments amount were linked to poor repayment (Haile, 2015; Mokhtar, 2011).

Schicks (2010) provides an extensive literature review on the causes of over-indebtedness of microfinance customers, such as external shocks, lender behavior like offering unsuitable products and borrowers’ unstable income.

The reason for this current lack of research may be attributed to the perceived economic behaviors and attributes of microfinance customers. Specifically, this group of consumers have been considered to be credit constrained (Diagne, 2002; Diagne et al., 1998, 2000; Hazarika & Alwang, 2003; Kedir, 2003) and this may have limited the number of studies able to analyze credit limit changes. This study contributes to the literature by analyzing the effects that increasing credit limits have on borrowing patterns and loan repayments of airtime borrowers.

3.3. METHOD

3.3.1. Study Background

For this study, we partnered with an airtime lender that works with a mobile phone operator (MNO) to provide micro airtime loans. Both the lender and the MNO are based in a small East African country that is classified in the “low income” category (i.e., countries whose gross national income per capita is less than $1,036 per year) by the World Bank. This MNO is the second largest mobile service provider in the country, commanding about 46% of the total national subscriber base in July 2019, at the start of this study. Due to the sensitivity of the commercial data disclosed in this article, we were not authorized to reveal the identities of the lender, the MNO and the country.

Similar to many developing countries, the vast majority of mobile phone subscribers in that country are prepaid customers; i.e., they have to load (or recharge) airtime on their phone account before they can make phone calls, send text messages or access the

Internet. Customers running out of airtime when they are unable to recharge their accounts means that the MNO is losing potential revenue, while the customers are inconvenienced in their phone usage. In this situation, the lender provides a means of borrowing airtime that the customer can repay later, with the addition of a service fee. This independent lender underwrites the entire loan amount, guaranteeing the MNO payment in case of customer default, in exchange for a share of the service fee. Therefore, the lender has two ways of maximizing profits: (1) increasing the lent amount, while (2) reducing the loan default rate.

About 73% of the MNO's active subscribers were qualified to borrow in July, with 45% of qualified customers taking loans. Airtime loans represent ≈ 27% of the airtime spent on the network, with a number of customers borrowing up to 40% of their monthly airtime usage. The median borrower is in the bottom third of spenders on the network, suggesting that most of the lender's customers were predominantly low-income people with limited spending capability.

Unlike her neighbors in the wider East Africa region, such as Kenya and Tanzania, digital lending in our country of study is not yet widespread. The consumer digital credit landscape remains dominated by banks that extend this facility solely to their existing customers. With only a quarter of the population having bank accounts, airtime lending is currently the most used form of digital borrowing in this country, especially among the poor and unbanked people who have access to mobile phones.

The MNO’s subscribers are offered seven possible discrete loan amounts (denominations), which range from ≈ $0.021 to ≈ $0.316. Though seemingly low in absolute value, the $0.316 airtime loan gives a phone user up to 200 minutes of voice calls as well as 20 text messages.

The service fee charged is a fixed, non-compounding fee, whose amount depends on the loan amount. It ranges from 15% for the highest denomination to 75% for the lowest denomination. The lender uses the past recharge amounts of the MNO’s subscribers, among other factors, to assign customers various available credit limits from the seven different denominations. Therefore, a subscriber with a relatively large past recharge amount who fulfills the lender’s other criteria (such as the time since their phone number was activated) will be offered the highest credit limit (i.e., the highest denomination of $0.316). This subscriber is then able to borrow different amounts multiple times until they have exhausted their credit, at which time they have to make some payment before they can borrow again. Thus, this system can be considered akin to credit card lending, if customers had to borrow in specific discrete amounts.

When a subscriber borrows airtime successfully, they are informed of the commission fee, the total amount they will have to pay, as well as the loan due date which is seven days from the time of borrowing. In reality, unpaid loans remain due until the subscriber churns from the network. To repay the loan, the borrower simply needs to recharge their phone and the loan amount and commission fee are automatically deducted from their account.

3.3.2. Study Set-up

In this experimental work, we first started by randomly selecting 50,000 potential participants from the over 2.6 million mobile phone subscribers active on the network. We computed their new credit limits based upon their existing borrowing and repayment pattern, reflecting the practices of microlenders in the real-world, as noted in the previous section (Bharadwaj et al., 2019). To create the new credit limit for each borrower, we first computed the probability that the borrower would repay all their loans. This approach was based on the method described in the previous chapter (Shema, 2019), which provides an effective way of computing the probability that an airtime borrower would repay within seven days each loan borrowed in a month. This method, based on the random forest algorithm, uses data on recharges and past loans to compute this probability. However, in this study we increased the expected repayment period from seven to thirty days. The new credit limit for each borrower was then obtained by multiplying this probability by the total loan amount used by the borrower in the month prior to the start of the experiment; i.e., July 2019. We reasoned that if a customer is able to repay all their loans within thirty days, then they would be eligible to borrow up to the total amount they used in the previous month before they were required to make repayments in order to borrow further. Since the probability of repayment ranged from 0 to 1, the highest credit limit would be the total amount borrowed by a customer in July.

Using the above method to compute the new credit limit, 29,985 (or 64.44%) of our participants saw their credit limit increased compared to the July level. 2,521 (or 5.42%) had theirs decreased, mostly due to low borrowing in July. The remaining participants, 14,025 (or 30.14%), maintained the same credit limits. Since the focus of this study is on the effect that increasing credit limits has on borrowers of microloans, our treatment group comprised the 29,985 participants with increased credit limit.

We did not actively recruit the participants and did not inform them of the ongoing study. This was in order to minimize any potential influence on their borrowing behavior. Our participants instead learned about their new credit after the first borrowing, when they received a message regarding the remaining amount from their credit limit that they could still borrow. Thus, the change of credit limit was initiated by the researchers through the lender, with no input from the borrowers, besides their borrowing habit. We conducted this experiment for 8 months, from August 2, 2019 to March 31, 2020.

Figure 5 shows the distribution of the ratio in credit limit increase. The study participants with the median credit limit increase saw their credit limit doubled, some from ≈ \$0.16 to

≈ \$0.32, while the highest from ≈ \$0.47 to ≈ \$0.94. The highest credit increase was 209.15% for a participant with a large borrowing in July, but whose credit limit had been ≈ \$0.02.

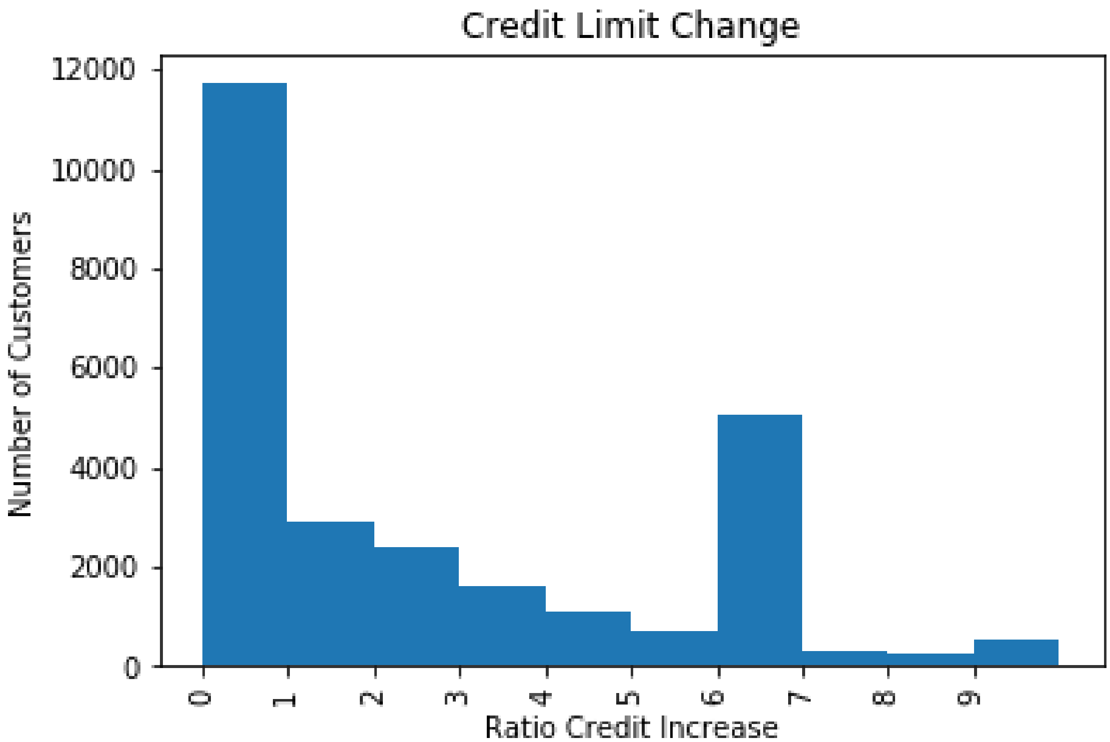


Figure 5: Ratio of Credit Limit Changes for Experiment

To isolate the effect of increasing credit limit on borrowing and repayment, we had to control for two major factors. First, the study participants had their credit limit increased based on their previous borrowing and repayment behavior. Thus, our participants had borrowed larger amounts in July and/or had been making timely repayments compared to the average airtime borrowers. To control for these two factors, we randomly selected another 29,985 group of borrowers who could have had their credit limits increased, but had not been selected as treatment participants. These borrowers had continued to be evaluated by the lender’s current system.

Second, the lender re-evaluates credit limits on a daily basis. Thus, borrowers can have their credit limits changed any day based on their repayment behavior as well as other criteria used by the lender for credit risk assessment. However, during the experiment, in addition to increasing the credit limits of our participants, we also froze these throughout the study period to allow for a longer evaluation period. To control for this factor, our second control group is made of the 14,025 participants who had their credit limit kept the same during the study period.

3.3.3. Data

Working with the lender, we obtained data from three sources: the MNO’s subscribers’ recharges, airtime usage, and their airtime borrowings. These three datasets cover a nine-month period from July 1, 2019 to March 31, 2020.

The recharge dataset contains daily summaries of airtime recharges. Thus, each record has (1) an anonymized identifier of the phone number whose account is credited; (2) the date of the recharges; (3) the number of recharges; and (4) the total amount recharged on that day. We do not have specifics of each individual recharge, such as the time of a recharge or the amount recharged at once, and these records are only summations conducted on a daily basis by the MNO. Also excluded from these daily summaries are phone numbers that did not make any recharge at all. In total, our recharge dataset has more than 75 million records generated by more than 3 million unique subscribers. The second dataset contains daily summaries of airtime usage. The MNO considers "usage" any activity that generates revenue for its business, such as voice calls, texting, Internet surfing, bundle purchases, or airtime loan repayment. Recharging of phone accounts does not necessarily result in revenue for the MNO, as people could keep the airtime without spending it. Airtime transfers between two mobile subscribers are also not considered as usage until the airtime is spent by the recipient. Each record in the usage dataset represents the total amount spent by a subscriber on a particular day. Thus, each record has the following fields: (1) an anonymized identifier of the phone number incurring the expense; (2) the date of the usage; and (3) the total airtime amount spent by the subscriber on that day. It is worth mentioning that we do not have details of how the airtime was spent or which activity the subscriber conducted to spend the airtime. The dataset only shows the total airtime amount spent by a subscriber on any particular day. This dataset has more than 165 million records of daily airtime usage from more than 3 million MNO's subscribers.

Our last dataset contains details of airtime loans disbursed by the lender. For each loan issued, the lender records details of the loan such as, (1) an anonymized identifier of the borrower; (2) the exact date and time when the loan was disbursed; (3) the amount borrowed; (4) the service fee (interest) associated with the loan; and (5) a flag indicating whether the loan has been fully or partially paid. In addition, details for each payment are also captured by the lender, including, (1) the date and time the payment was made, and (2) the amount paid. Though the lender saves the details for each partial payment, we only have the details of the last payment as well as the total amount paid for each loan. Therefore, we are unable to identify the amounts paid in multiple payments, although we have the total number of payments for each loan. Between July 1st, 2019 and March 31st, 2020, the lender had disbursed close to 40 million microloans. The median loan amount was $0.105, which attracts a 30% service fee. On average, the loans were paid in approximately 1.43 installments.

3.4. RESULTS

In this section we first report the effects that increasing credit limits has on borrowers' behavior, such as the borrowing patterns, airtime recharges and mobile service usage, and loan repayment rates. Second, we report the results of a regression analysis that shows factors that influence debt repayment when credit limits are manipulated.

3.4.1. Effects of Increasing Credit Limits

To better understand the effects that increasing credit limit has on these indicators, we divided the experimental group into two subgroups, (1) those with increased credit limit (credit increase); and (2) those whose credit limit was not changed from its level prior to the experiment. This second group helps in controlling for the effect that freezing the credit limit might have had on the outcomes of interest. In addition to these two groups, we also have two control groups of similar sizes to the corresponding experimental groups, (1) those who could have had their credit limit increased; and (2) those whose credit limit would not have changed. These control groups help isolate possible effects that previous repayment patterns and loan volumes of the experimental groups might have had on borrowing and repayment outcomes. The credit limit of these control groups continued to be assessed by the lender's current system.

Therefore, in this section, we compare the outcomes of the two treatment groups with their corresponding control groups. Unless otherwise stated, the lines in the following graphs represent the difference between the experiment groups and their control groups. We will use these differences to also compare the participants who saw their credit limits increased to those whose credits were maintained the same throughout the study period.

3.4.1.1 Impact on borrowing

Figure 6 shows the total loan amount borrowed by each treatment group as a percentage of the total loan amount borrowed by their corresponding control groups. The participants with increased credit limits responded to the change by immediately increasing their borrowing by about 10.73% compared to their control group. However, this increase in borrowing almost completely disappears the following month and becomes smaller than that of the control group, reaching a low of 91.05% of the total amount borrowed by the control group in February. The group with the frozen credit limit experienced a more gradual reduction of the total amount borrowed, before stabilizing at about 95% of the amount borrowed by its control group. Therefore, the drastic reduction in loan amount experienced by the group with increased credit limits does not appear to be due to the frozen credit limit, since it happened faster than that of people whose credit limits were not changed. This suggests that increasing credit limits can lead to a dramatic increase in borrowing followed by a similarly quick reduction to levels comparable to those with frozen credit limits.

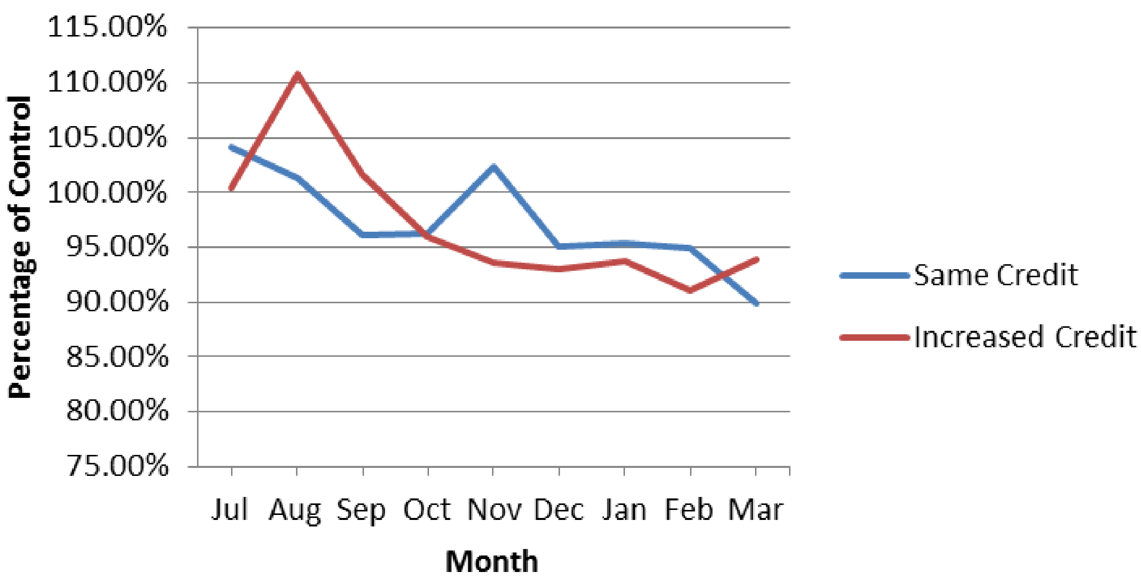


Figure 6: Total loan amount

3.4.1.2 Impact on airtime usage and recharge

The sudden increase in borrowing described above could have been an indication of unmet communication needs. That is, perhaps people want to use the MNO's services more, but are constrained by a lack of means to afford them. If this is the case, we would expect to see a corresponding spike in the amount spent on various MNO's services.

However, figure 7 shows that, whereas the increase in loan amount observed in August correlates with an increase in the amount spent on communication, the magnitude of these increases greatly differ (about 1.06% increase in the amount spent on communication services compared to the 10.73% increase in borrowing). This suggests that people viewed the ability to borrow more airtime as an alternative, instead of a complement, to buying it.

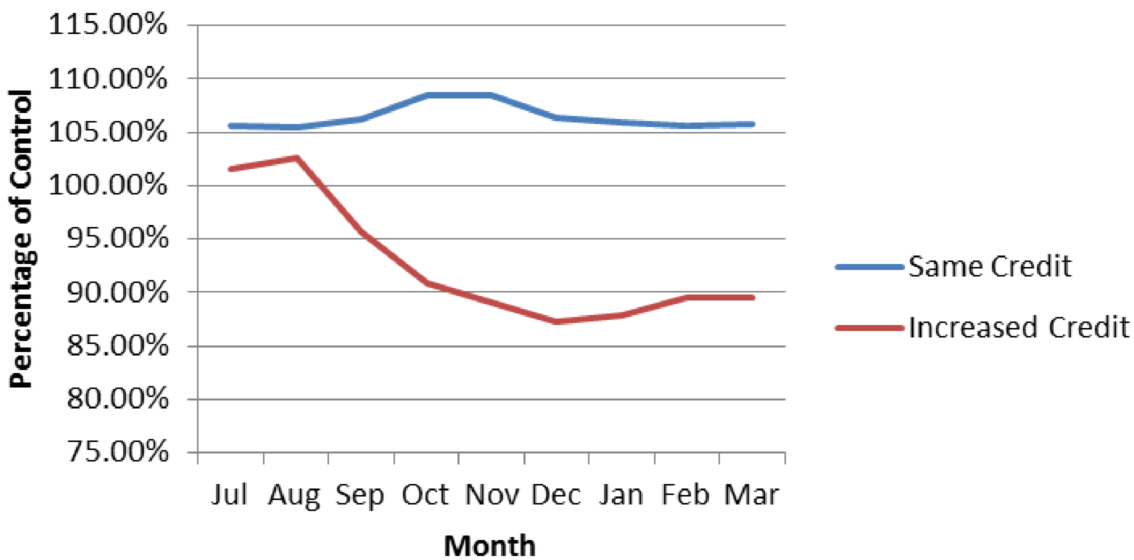


Figure 7: Total usage amount compared to control groups

Indeed, figure 8 shows a drastic reduction in airtime purchases (recharges) that correspond to the observed increase in airtime borrowing. Perhaps more worrying is the fact that neither airtime usage, nor recharge ever recovered from this effect during the study period. Increasing credit limit for airtime borrowers seems to reduce the amount of airtime usage and recharge by about 15% and 25%, respectively, once we control for borrowers' preexisting characteristics as well as the fact that their credit limit was not changed throughout the experiment period.

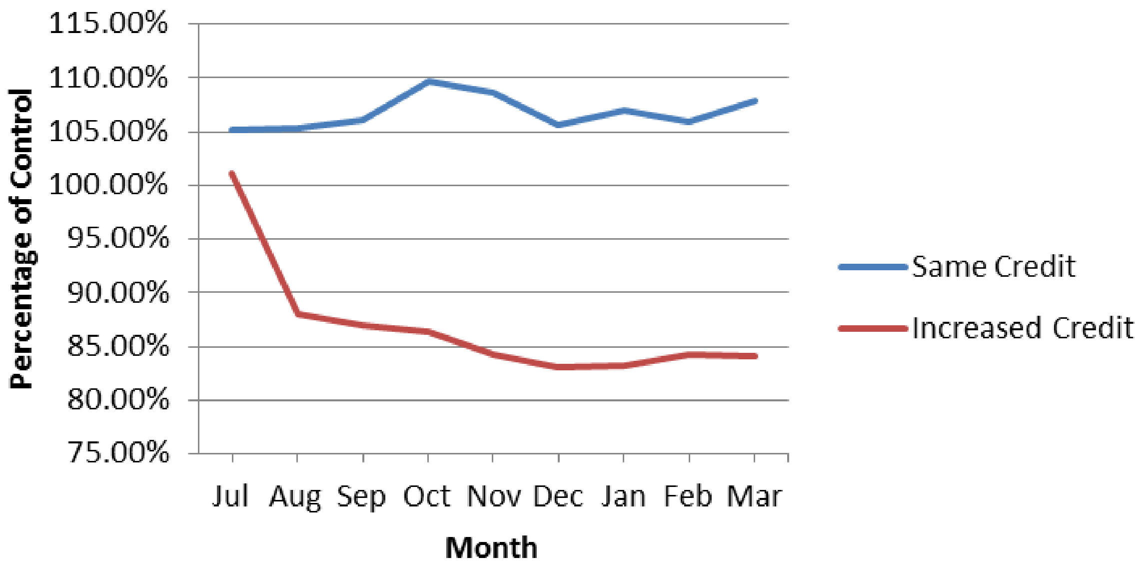


Figure 8: Total recharge amount compared to control groups

3.4.1.3 Impact on loan repayments

Unsurprisingly, this reduction in recharges coupled with an increase in borrowing led to a drastic reduction in repayment rates by the group that had a credit limit increase. Figure 9 shows the difference in repayment rates between the two experimental groups (those with increased credit limits and those with frozen credit limits) and their corresponding control groups. Loan repayment rate is here defined as the percentage of loans paid within thirty days of borrowing. In July, prior to the start of the experiment, the thirty-days repayment rates for both groups were similar to their control groups.

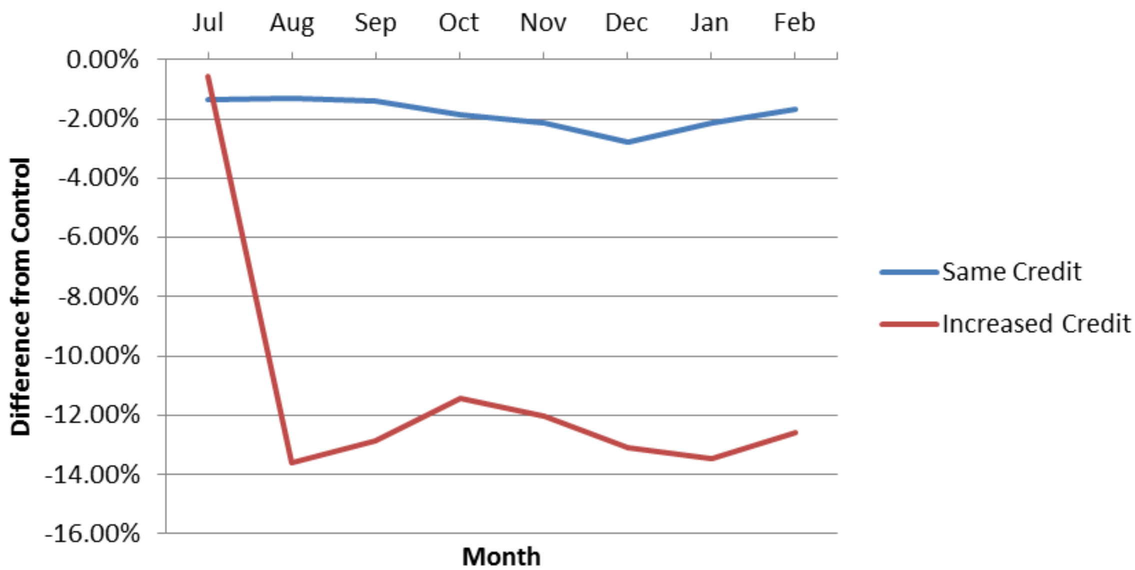


Figure 9: Difference in repayment rates between the experimental and the control groups

Freezing credit limit appears to have minimal impact on repayment rate, as the "same credit" group reduced theirs only slightly and gradually when compared to the average repayment rate of their corresponding control group. The largest reduction in repayment rate attributable to the freezing credit limit was observed in December, five months after the start of the experiment, when it was 2.78 percentage points lower than that of the control group.

On the other hand, the people with increased credit limit had the sharpest decrease in repayment rate at the very start of the experiment, by 13.62 percentage points compared to people who could have had their credit increased but had not been selected. This loan repayment rate stayed low throughout the study period and never recovered. Figure 9 shows that increasing credit limits was responsible for roughly a 10 percentage points decrease in repayment rate.

In summary, airtime borrowers seem to respond by taking on more loans when their credit limits are increased. However, this increase in borrowing is only temporary and quickly dissipates, with the borrowing amount returning to previous levels. On the other hand, their usage of communication services suffers a fast and long lasting reduction after a small initial increase. Similarly, our participants decreased their purchases of airtime even long after the initial credit limit increase, impacting their repayment rates. However, increasing credit limits seemed to impact people differently. Some people completely stopped using the services of MNO and may have left the network; while others continued to make timely repayments. Therefore, in the next section we explore possible factors that might affect how people respond to credit limit increases.

3.4.2. Factors Influencing Debt Repayment

In order to understand how various factors affect the airtime loan repayment rates when credit limits are increased, we ran two separate linear regression models for the group with increased credit limits and those whose credit limits were not changed, who act as a control group. The regression independent variables were partially inspired by the body of literature on the effect of increasing credit limit on borrowing and repayment. Here, the dependent variable is the percentage of loans paid within 30 days (repayment rate) in the month after the independent variables were observed. For example, to predict the 30 days repayment rate of March, we computed the independent variables as they occurred in and up to February. This was in order to observe how a customer would respond to changes in their credit limit before these changes are effected.

Table 6 reports the coefficients of the two linear regression models. For these models, we used the data from the participants, collected during the experiment period from August 2019 to March 2020. However, since the experiment ended in March 2020, we used only the dependent variable, the 30 days repayment rate, from this month's data. The independent variables computed for February are used to predict the 30 days repayment rate of March. We cannot use the independent variables from March since our data does not have the 30 days repayment rate for April.

Table 6: Regression Coefficients

Features	**Description of Features**	**Increased Credit Limit**	**Same Credit Limit**
New credit limit	assigned credit limit at the start of the experiment (in USD)	(0.030)†	(0.040)*
Percentage of credit limit change	ratio of new credit limit to July credit limit	(0.009)†	0.000
Probability of payment	computed probability that borrower will repay all loans within 30 days (ranges from 0 to 1), see Shema (2019)	0.242†	0.336†
Average loan duration	average number of days before loan repayment	(0.001)†	(0.001)†
30 days payment rate	percentage of loans paid within 30 days in a month	0.217†	0.144†

30 days payment rate in the past 3	average 30 days payment rate of the previous three months	0.125†	0.121†
Number of loans	total number of loans taken in a month	0.002†	0.007†
Number of loans in the past 3	total number of loans taken in the previous three months	0.000†	0.003†
Age of Borrowing	number of days since the first loan was granted	0.000†	0.000†
Age on network	number of days since the phone number was activated on the network	0.000†	0.000
Total recharge	total amount recharged in a month (in USD)	0.016†	0.002**
Is recharge greater than last 3	dummy variable indicating whether the total recharge for this month is greater than the average recharge of the previous three months	0.006***	0.008**
Is recharge greater than market average	dummy variable indicating whether this borrower's total recharge amount is greater than the average subscriber's recharge amount for this month	0.010***	0.003

Total usage	total amount used in a month on all MNO's services (in USD)	0.010 †	0.001 *
Is usage greater than last 3	dummy variable indicating whether the total usage for this month is greater than the average usage of the previous three months	0.004 **	0.005
Is usage greater than market average	dummy variable indicating whether this borrower's total usage amount is greater than the average subscriber's usage amount for this month	0.016 †	0.014 ***
Total loan	total loan amount taken in a month (in USD)	0.003 ***	0.030 †
Service fee rate	average percentage of service fee (or interest) paid per loan	0.270 †	0.326 †
Ratio of loan to recharge	total loan amount divided by total recharge amount	(0.003) **	0.017 ***
Airtime balance	the sum of loans and recharges in the month minus total usage amount (in USD)	0.009 †	0.010 †

Significance codes: 0 '†' 0.001 '***' 0.01 '**' 0.05 '*'

3.4.2.1. Repayment patterns

Unsurprisingly, the variables related to repayment patterns (the computed probability of payment, the average loan duration, and the 30 days repayment rates of the loans taken in the past month and previous three months respectively) are significant predictors of the 30 days repayment rate. These variables are even stronger predictors for consumers with an increased credit limit, suggesting that the repayment behavior of borrowers should be considered before increasing their credit limit, as people with good repayment history are more likely to maintain this payment behavior after a credit limit increase.

3.4.2.2. Rate of credit increase

For participants with increased credit limits, the new credit limits as well as their ratio of increase negatively correlates with repayment rates. The higher the new credit limit and the bigger the increase, the less likely participants are able to fully service their loans within 30 days. This result seems to indicate that higher credit limits negatively affect repayment rates regardless of the participants past repayment behavior and total amounts borrowed. Since the new credit limits were computed based on patterns of previous borrowing and repayment, the participants who received higher credit limits were those with good repayment rates in the past and/or high levels of borrowings.

3.4.2.3. Length of borrowing and phone number ownership

As mentioned by Soman and Cheema (2002), we also find that how long a person has been borrowing (i.e., “age of borrowing”) is also a significant, positive factor in their repayment behavior, regardless of whether their credit limit was increased. The more experienced a borrower is, the more likely they are to pay their loans within 30 days. However, the number of days since a person acquired their phone number (i.e., “age on network”) is a significant predictor of 30 days repayment rate only for people with increased credit limit. This result may also be linked to the fact that people are reluctant to change their phone numbers often, especially for those who have held the same phone number for a longer period of time. Thus, people would rather pay their airtime loan than change phone numbers by defaulting on their loan.

3.4.2.4. Airtime recharge and use

The total amounts of airtime that people recharge and use in a month were also significant predictors of their repayment rates for the following month, particularly for borrowers whose credit limits were increased. It appears that increasing credit limits encourages repayment for those borrowers whose airtime usage and recharge were already higher than the average subscriber of the MNO.

Paradoxically, higher service fees charged on loans seemed to result in better loan repayments across both treatment groups. This can be explained by the fact that smaller loan denominations incur higher service fee rates. Thus, this predictor might indicate that people who borrow in smaller denominations (amounts) tend to be better payers than those who borrow in bigger amounts, notwithstanding the higher fees (in comparison to loan amount) that small loans attract.

In the next section, we discuss what these results reveal about the effects of changing credit limits on borrowers' behavior and present some recommendations for digital lenders in general. We also reflect on the use of randomized experiments as a research method for ICTD studies.

3.5. DISCUSSION

3.5.1. Results Implications

As noted by previous studies, access to credit is crucial in helping people cope with unexpected financial shocks. However, the results of this study show that it is also important to investigate the optimal loan amount that can be extended to people. Past work demonstrated that mobile phone users with limited economic means borrow airtime to smooth out their consumption of communication services (Barriga-Cabanillas & Lybbert, 2020). Our results show that when credit limits are increased, people borrow more airtime as an alternative to purchasing it, leading to higher default rates.

In our study design, people had their credit limit increased based on the total loan amount taken in the previous month, as well as their repayment pattern. Those with the highest increase in credit limits had borrowed bigger amounts as well as made timely repayments. With increased credit limits (i.e., the ability to borrow larger amounts at once), our study participants struggled to repay their loans. Therefore, it appears that the ability of borrowing a large amount at once, instead of multiple smaller amounts, can have a negative effect on repayment. Previous studies had proven inconclusive on the link between loan amount and repayment (Roslan & Karim, 2009; Sharma & Zeller, 1997). Perhaps more pertinent than the total amount borrowed, is the size of single loan installments. Indeed, we observe that people borrowing in smaller denominations were more likely to make timely repayments than those borrowing larger denominations.

In addition, increasing credit limits seems to have the unintended consequence of locking people out of future borrowing. A number of our participants with increased credit limits stopped using their phones altogether and left the mobile network with outstanding loans. Luckily, they still have the opportunity of joining other mobile network operators in the country as the information about their default status is not shared across MNOs. However, millions of defaulters of digital microloans are not so fortunate as lenders report them to credit bureaus (CFI, 2019), barring them from future borrowing and sometimes leaving these borrowers at the mercy of abusive debt collectors.

Finally, this study found that borrowers' response to increases in credit limits is mitigated by factors such as their past repayment patterns and length of time since they started borrowing, akin to credit card users (Soman & Cheema, 2002). These findings have powerful implications for digital microlending. For example, the current high default rates observed among borrowers might be due to a lack of experience in using these products. We may expect that as these services mature and users gain more experience, borrowing might become less influenced by credit limit changes. Meanwhile, people should be given a chance to gain experience in borrowing digital loans with smaller credit limits.

Based on the results of this study, we would recommend that, in general, digital microcredit lenders may wish to limit changing customers' credit limits where possible. Maintaining the same credit limit is beneficial as people seem to be better able to realistically plan their borrowing and keep up with repayments. Changing credit limits, on the other hand, may send a signal to users that makes them change their borrowing and repayment patterns. However, if a customer's credit limit needs to be increased, the lender could consider the following factors that impact future payment:

- Borrowing experience: customers who have been borrowing for a longer period of time seem to be better payers when credit limits are increased. Borrowing experience should not simply be looked at as the number of loans taken, but also the duration since the client started borrowing as this also appears to increase future repayments.

- Product use experience: in addition to borrowing experience, how long a client has been using a particular product may strongly contribute to their repayment rate when their credit limit has been increased. For example, for cash lenders operating through a mobile money service, accounting for the duration since a client started using mobile money, and not just borrowing, might lead to better repayment rates. Some lenders appear to have learned this and are now actively discouraging “spinning”, a practice where people borrow small amounts and repay them quickly in order to have their credit limit increased (Oppong & Mattern, 2020).

- Repayment history: prior to increasing a customer’s credit limit, lenders would benefit from looking at the longest possible repayment history. Although analyzing the payment patterns of the period prior to increasing the credit limit is beneficial, the lender would also benefit by looking at the customer’s repayment history from further in the past.

- Borrowing amounts: in addition to repayment history, people who borrow small amounts tend to remain good payers after the credit increase. This borrowing pattern might indicate that either the client has a high “consumer spending self-control”, preferring to borrow only the amount they need or that the client is not cash strapped and, thus, able to service their loan.

3.6. LIMITATIONS AND CONCLUSION

This study was conducted with a specific lending product: airtime loans for facilitating communication. Therefore, it might be limited by specific aspects present in airtime usage that might differ from the usage of other products. For example, the usage of telecommunication services might be more difficult to change in a short time.

Additionally, our partner lender charges a service fee that does not compound over time. Unlike interest charges from other digital lending products, the airtime loans in this study attract a fixed service fee that is charged regardless of the duration of the loan. Thus, borrowers might not have the same incentive to pay sooner to avoid compounding interest on their loan as they might for other digital loans. Finally, other factors resulting from the implementation of this specific airtime loan might affect the generalization of this study. For example, repayments are deducted automatically from the customer's account when they recharge. The results from this study might have been different if customers had to actively repay their loans, as is the case for a number of digital lending products. All these factors, therefore, call for similar studies to be conducted with other lending products in order to obtain a more complete picture of the effects that increasing credit limits has on borrowers' behavior under other lending conditions.

The results of this quantitative work could be enriched by a qualitative study that would interview participants to better explore their views of credit limit and how its changes impact their mental models. For example, while this study has shown that people change their borrowing and telecommunication usage behavior in response to changes in their credit limit, a qualitative study might be better suited to uncover the reasons, from the borrowers' perspective, behind these changes.

Overall, our results indicate that increasing credit limits negatively affect repayment rates, future borrowing and can lead borrowers to stop using the service. However, the effects of credit limit increases on borrowers are mitigated by factors such as how long they have been using a particular service, and their borrowing experience. Based on these findings, we have proposed a number of recommendations to digital microlenders about increasing their customers' credit limits.

Chapter 4 – Vivid Interventions to Increase Payment of Short-term Loans[20]

4.1. INTRODUCTION

Unsecured digital loans provide an opportunity for people facing liquidity constraints to conveniently borrow money without the need for collateral. The ability to quickly access consumer loans may be particularly important in developing countries where most people are employed in the informal sector with irregular income, and where national safety nets and financial infrastructure may be less established (Bharadwaj et al., 2019). In fact, such loans now dominate the consumer loan landscape in a number of developing countries (CFI, 2019; Kaffenberger, 2018; Mazer et al., 2020).

However, the lack of collateral means that digital lenders have few ex post avenues for enforcing repayment, especially in developing countries where the institutions charged with enforcing contracts may be weak (Menkhoff et al., 2012). This situation, coupled with the lack of data on financial histories of borrowers that could help in credit risk assessment, has resulted in relatively high default rates for digital loans (CFI, 2019; Kaffenberger, 2018). As a consequence, lenders tend to price this increased risk through high interest rates (Francis et al., 2017), hurting mostly poor borrowers (Fafchamps, 2013).

[20] This work benefited from extensive feedback from Hal E. Hershfield, an associate professor of marketing, behavioral decision making, and psychology at the UCLA School of Management. Hal's feedback was especially useful in refining this study's methodology.

As a partial remedy, previous interventions have relied on reminders to borrowers regarding their upcoming loan repayments. These reminders are perhaps the least costly mechanism for lenders to increase repayment rates (Cadena & Schoar, 2011), and helps explain why research has extensively investigated methods for increasing the effectiveness of reminders, particularly text messages, in eliciting loan repayment. Nonetheless, the results from this body of research remain mixed. For example, in traditional microlending, strategies that have improved the effectiveness of text reminders include adding the loan officer's name in the reminder (Karlan et al., 2012), and framing loan repayment as a moral issue (Bursztyn et al., 2019). On the other hand, "honor pledges" (i.e., promises to pay) and reminders of these have been found to have limited effectiveness in increasing repayment rate of digital loans (Bhanot, 2017). In a desperate move, some digital lenders resort to targeting defaulters' social connections in order to shame them into repaying their loans[21,22]. This tactic, in addition to being morally questionable, is also ineffective as borrowers have been shown to retaliate by purposely defaulting (Liao et al., 2020).

The mixed effectiveness of text reminders may be due to one of two reasons: (1) the assumption that untimely repayments solely result from forgetfulness on the part of the borrower; or (2) the borrower is simply unable or unwilling to pay. In the former scenario, recent work suggests that when it comes to intertemporal choices, consumers

[21] Some digital lenders collect phone numbers saved in the borrowers' mobile phones and use these to contact the borrowers' social network (https://www.ft.com/content/16c86479-e88d-4a28-8fa4-cd72bace5104)

[22] There have been reports of some borrowers committing suicide, victim of this practice (https://www.thenewsminute.com/article/harassment-digital-lending-apps-driving-defaulters-suicide-no-action-rbi-139968)

not only need to know about the future consequences of a present-day decision, but also have to *care* about the impact that those decisions will have on their future selves (Bartels & Urminsky, 2015). Theoretically, in the context of digital loans, borrowers not only have to remember due dates, they must also care about the consequences of untimely or missed payments. Indeed, it can be argued that including the loan officer's name in the text reminder may be effective due to a sense of responsibility that the borrower likely feels towards the bank agent (Laudenbach et al., 2018). Similarly, the holders of the credit card issued by Islamic banks in (Bursztyn et al., 2019) in Indonesia cared about repaying their loan since defaulting was framed as a violation of an important Islamic moral norm.

Drawing on theoretical and empirical work on the ways that consumers relate to their future selves, we investigate the effectiveness of vivid reminders that emphasize the benefits of timely payment to borrowers. Working with a mobile phone airtime lender in Rwanda, we find that reminders, whether vivid or simple, have minimal impact on repayment rates and loan duration. We argue that these findings may be due to the product design and the study implementation, and discuss avenues for future work.

This study makes three novel contributions to the body of literature. First, this work extends prior research on vividness and future selves (e.g., Hershfield et al., 2018) by exploring the effectiveness of a vivid intervention on payment of short-term loans, particularly in the context of digital loans in developing countries. Second, this work tests the effectiveness of a novel intervention. Whereas prior work has tried to encourage consumers by having them project present-day interests onto their future selves, here, we bring the future to the present by asking people to imagine future consequences as if they were happening to their present self. Finally, from a practical and methodological perspective, this work tests the effectiveness of vivid messages that are delivered through short text messages (SMS) in order to promptly and more easily reach the millions of people who own mobile phones.

The rest of this chapter is organized as follows: in the next section, we draw on the literature on reminders for loan repayment, and on the concept of present and future selves to introduce the study hypotheses. Section 3 presents the study background, while section 4 expands on the methodology, including the experiment design and the data collected. We present the results of the study in section 5, while we discuss their implications before concluding in section 6.

4.2. RELATED WORK AND HYPOTHESES

4.2.1. Text Reminders for Loan Repayment

Prior work has investigated the effectiveness of text messages in increasing on-time payment for various types of loans, such as microfinance loans and credit card debts. However, the results of these studies remain mixed.

On the positive side, a number of studies have highlighted the idea that sending reminders via text messages may increase timely repayments. For example, working with a microfinance institution in Uganda, Cadena and Schoar (2011) demonstrated that simple reminders through text messages (SMS) can be effective at reducing default rates. The authors used a field experiment approach that comprised a control group, a group that received 25% cash equivalent of the current loan if they paid on-time, a group that received a 25% reduction of the interest rate for the next loan, and a group that received SMS reminders every month, three days before the payment was due. Though all treatments had similar effectiveness, borrowers with smaller loans than the median of $450 responded strongly to the cash and SMS treatments, while those with larger loans responded to the interest reduction treatment and not the messaging. SMS reminders may thus be as effective as giving cash incentives when it comes to increasing repayment of small loans. Regarding the content of the messages, Bursztyn et al. (2019) demonstrated that messages related to morality, such as messages that state that "non-repayment of debts by someone who is able to repay is an injustice" can be more effective at increasing repayment rates than various forms of money incentives (e.g., cashback on timely repayments). Similarly, Karlan et al. (2012) found that including the name of the loan officer who dealt with the borrower increased loan repayment for non first-time borrowers, suggesting that borrowers feel a sense of personal responsibility towards the loan officer, particularly when they had dealt with them before. This sense of personal responsibility vis-à-vis a bank agent or loan officer has also been shown to be relevant when loan repayment communications are conducted through a phone call (Laudenbach et al., 2018). Customers of a large German bank that issues consumer loans were significantly less likely to default when they received a phone call reminding them to pay their outstanding loan from a random bank employee than when the call was automatically generated.

However, certain types of text reminders have proven less effective at increasing loan repayment. For example, Bhanot (2017) found that “honor pledges” and reminders of these pledges had an insignificant impact on repayment behavior of the customers of LendUp, a US-based online lender. Based on previous studies in lab settings that demonstrated that people have a preference for keeping their promises (Vanberg, 2007), Bhanot instead argued that these types of interventions may not be effective for borrowers, and particularly those facing financial hardships. The study by Karlan et al. (2012), referenced earlier, found that neither the positive framing of messages (“to have a good standing, please pay on time”) nor the negative framing of messages (“to avoid a penalty, please pay on time”) impacted the repayment behavior. Similarly, the timing of the messages did not seem to influence loan repayment rates.

Based on these studies, it would seem that simple or generic reminders that are not personalized to the recipients may have less effect on repayment behavior. This leads to our first set of hypotheses:

- $\mathbf{H_{1a}}$: simple reminders will not increase repayment rates compared to no reminders.
- $\mathbf{H_{1b}}$: simple reminders will not decrease the number of days before a loan is fully settled compared to no reminders.

Indeed, Bartels and Urminsky (2015) argue that “informational interventions” (for example reminders) are sometimes ineffective in promoting far-sighted behavior (such as saving and loan repayment) due to the fact that these interventions assume that people fail to act simply because they forget to do so. Instead, the authors, through a series of experiments, identified that the effectiveness of reminders likely depends on whether people care about the consequences that defaulting might have on their future selves. In the following section, we review some of the work on people’s relationships with their future selves and the ways this bond can be strengthened.

4.2.2. Relationships with Future Selves

A growing body of literature has explored how an emotional connection to one's future self impacts intertemporal decision making (Hershfield, 2011). Intertemporal decisions are those taken in the present but whose consequences play out over time (Berns et al., 2007), such as quitting smoking or joining a gym to enjoy better health in the future, investing in further study to increase future income, and saving in the present in order to have more disposable income at retirement. Philosophers, psychologists, and economists alike have contended that these intertemporal decisions are affected by how similar people feel they currently are to their future selves (Frederick, 2003; Hershfield, 2019; Parfit, 1971; Schelling, 1984).

Early empirical work demonstrated that the amount of perceived similarity between current and future selves was an important predictor of asset accrual (Ersner-Hershfield et al., 2009) as well as patient decision-making in laboratory contexts (Bartels & Rips, 2010; Bartels & Urminsky, 2011). Furthermore, Bartels and Urminsky (2015) showed that intertemporal decisions are affected by two distinct factors: (1) a person's awareness of the impact of current decisions to their future self, and (2) how much they value those future outcomes. For example, for a person to save for the future, they have to be both aware that saving now will result in extra available money to spend in the future, *and* have to care about having that extra money. Therefore, to increase the effectiveness of text reminders for loan repayment, an intervention should aim to increase the bond that borrowers have with their future selves such that they can be made to be more aware of, and care about, the consequences that defaulting on the present loans will have on their future selves.

How can such connections be enhanced? We contend that there are three overall approaches that may be effective in the microloan setting: (1) through vivid depiction of the consequence to the future self; (2) by bringing the consequence from the future to the present; and (3) by explicitly mentioning the cause of the expected consequence of untimely payment.

4.2.2.1 Enhancing Vividness

In much the same way that charities employ emotional pictures of charity recipients as a way of provoking empathy (and thus donations), so too it may be the case that vivid portrayals of the future self can bolster emotional identification with those selves. Though there has not been any formal definition of what constitutes a vivid intervention, per se, Nisbett and Ross (1980) ascribed three characteristics to vivid information, namely that it is “(a) emotionally interesting, (b) concrete and imagery-provoking, and (c) proximate in a sensory, temporal, or spatial way.” Vividness, Loewenstein (1996) argued, works in part by “intensifying immediate emotions associated with thinking about the outcome.”

Prior studies have used two methods to implement a vividness intervention: (1) through the use of virtual reality or age-progressions to let participants interact with a vivid, visual depiction of their future self; or (2) by asking participants to vividly imagine their future selves (for example, through a letter-writing task) (Hershfield et al., 2018). Both of these methods appear to affect people’s intertemporal decisions on various aspects of their lives, including finance (Hershfield, 2011; Sims et al., 2015), health (Kuo et al., 2016), ethical decision-making and delinquency (Van Gelder et al., 2015), academic planning (Chishima & Wilson, 2020), and anxiety, especially during the COVID-19 pandemic (Chishima et al., 2021).

However, interventions that rely on age-progression and/or virtual reality are more readily conducted in lab settings where study participants can be connected to virtual reality hardware or contexts in which age-progression algorithms can be easily introduced. More low-touch interventions, such as ones that rely on letter-writing exercises, as used by Chishima and Wilson (2020), may still require an engaging context in which consumers can fully immerse themselves in the exercise. In digital microlending, where small loans are disbursed to borrowers through feature phones, both types of interventions are likely to be more difficult to implement.

Based on this prior work, we posit that making vivid the consequences of default on the future ability to borrow might increase on-time repayment rates, resulting in our second set of hypotheses:

- **H_{2a}**: vivid reminders that emphasize the consequences of untimely repayment to the future self will increase repayment rates compared to simple reminders.
- **H_{2b}**: vivid reminders that emphasize the consequences of untimely repayment to the future self will decrease the number of days before a loan is fully settled compared to simple reminders.

4.2.2.2. Bringing the Future Self to the Present

Theoretical work has suggested that people tend to view their future selves as different from their present selves (Parfit, 1971), even equating their future selves with other people (Ersner-Hershfield et al., 2009; Pronin & Ross, 2006). Whether a future self is truly considered a different person, however, may matter less than what *sort* of different person that future self is. That is, is the future self considered to be more like a stranger? Or someone like a best friend who shares interests with the current self (Whiting, 1991). In a field study with university employees, Bryan and Hershfield (2012), for instance, showed that when the future self was framed as another person, but one who engendered a sense of responsibility, employees were more likely to increase their retirement contributions, compared to a status quo message. Such framing, however, had less of an impact on employees who a priori reported lower levels of emotional connection with their future selves. Thus, another way to incentivize loan repayment behavior may be to not only frame the future self as another person, but also one that shares interests with the current self.

Here, we suggest that one way of doing so could be through asking consumers to imagine that the consequences of defaulting on their loans were experienced by their present-day selves. Such a framing, we contend, forces consumers to implicitly identify with the feelings of their future selves. More formally:

- **H_{3a}**: vivid reminders that emphasize consequences to the "present self", as if the consequences were taking place today, will increase repayment rates compared to vivid reminders that show consequences to the "future self."
- **H_{3b}**: vivid reminders that emphasize consequences to the "present self", as if the consequences were taking place today, will decrease the number of days before a loan is fully settled compared to vivid reminders that show consequences to the "future self."

4.2.2.3. Making the Cause Explicit

Finally, we hypothesize that reminders that mention the consequences of untimely repayments or default to the "present self" could be made more vivid (and thus increase their effectiveness) when the causes of these consequences are explicitly mentioned:

- **H_{4a}**: vivid reminders that explicitly mention the causes of consequences to the "present self" will increase repayment rates compared to "present self" vivid reminders that do not explicitly mention the causes.
- **H_{4b}**: vivid reminders that explicitly mention the causes of consequences to the "present self" will decrease the number of days before a loan is fully settled

compared to “present self” vivid reminders that do not explicitly mention the causes.

4.2.3. Study Pre-registration

Prior to the start of the experiment, we pre-registered this study at https://aspredicted.org/6es4j.pdf. We pre-registered the text messages that each treatment group would receive, the two outcome variables of interest, namely the seven-day repayment rate as well as the loan duration of fully repaid loans, and the type of analysis we planned to conduct. However, we did not include the participants of the second mobile service provider (referred in this manuscript as $\text{Provider}_{\text{single-loan}}$), since our partnership started after the pre-registration. In addition, though we specified that our main question was whether “telling borrowers to imagine not being able to borrow in the present due to late past payments make them more likely to pay their current loan in time”, we did not explicitly mention all the four hypotheses above. Nevertheless, the central question of this study remained the same.

4.3. STUDY CONTEXT

This study was conducted in collaboration with an airtime lender with markets spanning multiple countries across Africa, the Middle East and Southeast Asia. This study, however, focused on Rwanda, an East African country, where the lender works with the second and third largest mobile network operators (MNOs). These two MNOs had merged approximately two years prior to the start of this study. However, their telecommunication systems were still separate by the end of the study period.

Most mobile phone subscribers in Africa use a prepaid system, in that they have to load money on their account before using their phones for calls, texts, and Internet surfing. When their account runs out of money, they have to recharge, usually with top-up cards, to continue using their phones. This system is different from a postpaid one, where subscribers receive their bills at the end of a usage period (usually a month). As of September 2019, nearly every mobile phone subscriber in Rwanda was a prepaid customer (RURA, 2019).

The airtime lender provides qualifying subscribers of the two MNOs the option to borrow airtime using their mobile phones in cases where they are unable to purchase airtime. The lender uses the same credit risk assessment method across both MNOs to decide who can borrow, as well as the highest amount subscribers can borrow at once. These amounts, stated in the local currency, range from as little as $0.02 to $0.32, divided in seven discrete amounts, referred to as “denominations.” For this service, the lender charges a fixed service fee (or commission) based on the denomination. Table 7 shows the list of denominations as well as the service fee that they attract. The amounts are converted in US Dollars.

Table 7: List of denominations and their corresponding service fee

Denomination (in USD)	**Service Fee (as % of denomination)**
0.02	75.00%

0.09	16.67%
0.11	30.00%
0.14	17.04%
0.16	23.33%
0.21	20.00%
0.32	15.00%

The lender uses the same denominations and service fees in both MNOs, with borrowers who qualify for high denominations also allowed to borrow any smaller denominations. For example, users who qualify to borrow $0.11 can also borrow $0.09 and $0.02. However, the subscribers of the first provider are allowed to borrow multiple times until they reach their highest assigned denomination before any payment is required to borrow furthermore. By contrast, the subscribers of the second provider can only borrow once and have to repay that loan before they are allowed to borrow again. For example, a subscriber of the first provider (MNO) that qualifies to borrow $0.14 and only borrows $0.09, is allowed to further borrow $0.02 without having to repay the first loan. A subscriber of the second provider (MNO) that qualifies to borrow $0.14 and only borrows $0.09, will have to repay in full that loan before being allowed to borrow again. Therefore, we shall refer to the two MNOs as $\text{Provider}_{\text{multiple-loans}}$ and $\text{Provider}_{\text{single-loan}}$, respectively, to show the differences in the lending system.

The most popular loan amounts in the three months prior to our study were $0.09 (29.24% in $\text{Provider}_{\text{multiple-loans}}$ and 28.21% in $\text{Provider}_{\text{single-loan}}$), $0.14 (21.20% in $\text{Provider}_{\text{multiple-loans}}$ and 22.71% in $\text{Provider}_{\text{single-loan}}$) and $0.21 (19.42% in $\text{Provider}_{\text{multiple-loans}}$ and 29.60% in $\text{Provider}_{\text{single-loan}}$). The median loan amount was $0.11 in

$\text{Provider}_{\text{multiple-loans}}$ and \$0.14 in $\text{Provider}_{\text{single-loan}}$. The popularity of these denominations can be explained by the fact that both MNOs offer voice and text “bundles” priced at these amounts. For example, a bundle priced at \$0.11 gives a customer 40 minutes of calling other subscribers of the same MNO (in-network calls) and 40 text messages that can be sent to subscribers on any MNO in Rwanda (in-network and out-of-network SMS).

Payments with a fixed service fee are automatically deducted from the borrowers’ account when they recharge. Thus, to repay their loans, borrowers simply have to recharge their mobile phone account. The loan duration is expected to be seven days. However, prior to our study, borrowers were never informed of this fact. In reality, people are declared to be in default if they have not recharged their account within 90 days, as this is also the churn period used by the two MNOs; i.e., subscribers are considered to have left the network after 90 consecutive days of inactivity.

In the next section, we describe the study methodology.

4.4. METHODOLOGY

4.4.1. Study Design

4.4.1.1. Treatments

In this study, we explored whether vivid reminders for borrowers of short-term, digital microloans (airtime loans, in this case) would increase repayment rates and shorten loan duration. To make the consequences of non-payment vivid, our reminders called on borrowers to imagine these consequences as if they were happening to their "present self". In addition, another group of reminders provided the reason for this potential consequence. Finally, we compared these reminders to those that sought to make vivid the consequence of untimely repayment to the borrower's "future self". Therefore, this experiment had five groups, including three treatment groups and two control groups, viz:

1. **No reminder**: this group did not receive any reminder at all.
2. **Simple reminder**: "Your loan is due today."
3. **Future self**: "How would you feel next week if you couldn't borrow to make an urgent call? Pay now to continue enjoying the service."
4. **Present self**: "How would you feel right now if you couldn't borrow to make an urgent call? Pay now to continue enjoying the service."
5. **Present self + reason**: "How would you feel right now if you couldn't borrow because of untimely payments last month? Pay now to continue enjoying the service."

The "future self" reminder asked the borrower to imagine the consequence of an untimely payment, namely the inability to borrow again, as if happening to their future self; whereas the "present" reminders (i.e., the "present self" and "present self + reason") brought the consequence to their present self. These last two treatment groups were different in that the "present self + reason" reminder highlighted the fact that the consequence would derive from the lack of timely repayment, whereas the simpler "present self" only stated the consequence.

In addition to these three treatment groups, we had two control groups. The first control group did not receive any reminders about their loans, whereas the second control group received the "simple reminder". This simple reminder text controls for the effect of simply knowing about due payment; i.e., that our messages simply made borrowers aware of their due loans (see Bartels & Urminsky (2015)).

At the beginning of the study, prior to sending out reminders, we first modified the message that people saw after successfully borrowing to notify them that they were expected to fully repay the loan within seven days. Previously, consumers were simply told,

> "Dear customer, you have borrowed <*borrowed amount*>. The service fee is <*fee amount*>, you will pay <*borrowed amount* + *fee amount*> when you recharge your account."

To avoid any confusion when our participants received a reminder, we changed this message to,

> "You have borrowed <*borrowed amount*> payable within 7 days. The service fee is <*fee amount*>. You will pay <*borrowed amount* + *fee amount*> when you recharge your account."

For example, if a person borrowed the $0.02 denomination, they would receive this message at the time of borrowing,

> "You have borrowed $0.02 payable within 7 days. The service fee is $0.015. You will pay $0.035 when you recharge your account."

The amounts were stated in the local currency. The lender implemented this change for *all* their customers in both markets two weeks prior to the start dates of sending out the reminders.

All our messages were translated in Kinyarwanda, the native language of virtually all Rwandans (see appendix A). These reminders were sent on the seventh day from the time the loan was granted, in case the loan had not been fully repaid. Since previous research has shown that the timing of reminders does not have any effect on repayment rates (Karlan et al., 2012), we opted to send out all our reminders at 9:00 AM to give people ample time to recharge their accounts. The reminders were sent as pop-up short message service (SMS). These are different from the traditional SMS in that pop-up SMS do not go straight to the phone's message inbox. Instead, they appear (i.e., pop-up) and stay on the screen until the user decides to either save it in their inbox, or simply delete the message. We adopted this approach to maximize the likelihood that phone users would see our reminders. In addition, SMS is a popular communication channel in Rwanda, with subscribers of both networks exchanging more than 13.5 million SMSs each month on average.

We started to send out the reminders to Provider$_{\text{multiple-loans}}$'s subscribers on September 26, 2019 and to Provider$_{\text{single-loan}}$'s subscribers on October 1, 2019. These reminders were sent until June 30, 2020 to the subscribers of both MNOs. Thus, the experiment lasted approximately nine months.

4.4.1.2. Study Participants

This study used a randomized controlled trial approach to measure the effectiveness of vivid reminders. The experiment involved approximately a third of active borrowers in each of the two MNOs. We define an "active borrower" as a person who borrowed at least once in the three months prior to the start of the experiment. Thus, we randomly sampled 500,000 active borrowers out of a total of 1,538,324 in $\text{Provider}_{\text{multiple-loans}}$; while in $\text{Provider}_{\text{single-loan}}$, our sample size was 125,000 out of a total of 370,864 active borrowers. These participants were randomly assigned to either one of the three treatment and two control groups, such that each group had the same number of participants (i.e., 100,000 each in $\text{Provider}_{\text{multiple-loans}}$ and 25,000 each in $\text{Provider}_{\text{single-loan}}$).

The study participants were not actively recruited. In addition, no reward for participating in the study was offered, and the participants were not aware of the ongoing experiment. Like all the lender's clients, they would have simply noticed a change in the message they received upon successful borrowing that the loan was due in seven days. We did not make any changes to the borrowing process and credit risk assessment for any of the five groups, and kept them similar to what borrowers were already used to. Moreover, our participants would not have been aware that others were not receiving reminders.

4.4.2. Data

The dataset for this study consists of details about loans issued to our participants during the experiment period. For every loan taken by our randomly selected participants, the lender shared with us these details: (1) an anonymized identifier of the borrower; (2) the date and time of when the loan was issued; (3) the loan amount; (4) the associated service fee; (5) the date and time of the latest payment; and (6) the total amount paid thus far. This dataset covered the experiment period as well as the month prior to the start of the experiment (i.e., August for $\text{Provider}_{\text{multiple-loans}}$ and September for $\text{Provider}_{\text{single-loan}}$).

Table 8: Descriptive stats for $\text{Provider}_{\text{multiple-loans}}$

	Number of unique borrowers	**Number of loans**	**Median loan amount**
No reminder	77,184	1,736,999	$0.11
Simple reminder	77,169	1,763,134	$0.11
Future self	77,028	1,768,463	$0.11
Present self	76,812	1,732,760	$0.11
Present self + reason	77,111	1,756,949	$0.11

Table 9: Descriptive stats for $\text{Provider}_{\text{single-loan}}$

	Number of unique borrowers	**Number of loans**	**Median loan amount**
No reminder	18,044	266,863	$0.14
Simple reminder	17,869	264,670	$0.14
Future self	17,879	260,843	$0.14
Present self	17,961	265,264	$0.14

Present self + reason	17,867	260,112	$0.14

Tables 8 and 9 show some descriptive statistics of the study datasets. Approximately 77% of participants in $\text{Provider}_{\text{multiple-loans}}$ and 72% of participants in $\text{Provider}_{\text{single-loan}}$ took at least one loan during the experiment period. The average number of loans per participant was ≈ 22.73 in $\text{Provider}_{\text{multiple-loans}}$ and ≈ 17.70 in $\text{Provider}_{\text{single-loan}}$, while the median loan amount was $0.11 in $\text{Provider}_{\text{multiple-loans}}$ and $0.14 in $\text{Provider}_{\text{single-loan}}$. The differing average number of loans and median loan amounts between the two MNOs could be due to the fact that people in $\text{Provider}_{\text{multiple-loans}}$ are allowed to borrow multiple times till they reach an assigned credit limit, while those in $\text{Provider}_{\text{single-loan}}$ can only have one outstanding loan regardless of their assigned credit limit. To borrow further, $\text{Provider}_{\text{single-loan}}$'s subscribers have to fully pay the outstanding loan. Therefore, these subscribers have an incentive to borrow the highest amount they can at once, while the subscribers of $\text{Provider}_{\text{multiple-loans}}$ can borrow smaller amounts multiple times. Finally, it appears that our treatment (the various reminders) did not change the median loan amount as this stayed the same across the various experiment groups in the same MNO.

4.5. RESULTS

In this section, we report the results of this study on the effect of the reminders on two aspects of loan repayment:

- **seven-day repayment rate**: the percentage of the total loan amount that was fully repaid within seven days.
- **loan duration**: for fully repaid loans, the number of days it took borrowers to complete repayment.

We start by presenting the overall effectiveness of the treatment in both MNOs, before delving into the differences between the treatment groups. Finally, we show the effect of the reminders on these two variables over time (mostly by month) during the experiment.

4.5.1. Overall Effectiveness of Reminders

Table 10: Average repayment rates and loan duration

	Provider$_{\text{multiple-loans}}$		**Provider$_{\text{single-loan}}$**	
	Repayment Rate	**Loan Duration**	**Repayment Rate**	**Loan Duration**
No reminder	70.85%	10.20	77.50%	6.49
Simple reminder	71.51%	9.92	77.97%	6.37
Future self	71.56%	9.77	77.62%	6.45
Present self	70.85%	10.11	77.79%	6.42
Present self + reason	71.02%	10.02	77.47%	6.53

Table 10 shows the percentage of loan amount fully repaid within seven days as well as the average number of days that fully repaid loans lasted, across all the experiment and control groups in both $\text{Provider}_{\text{multiple-loans}}$ (where people are allowed to borrow multiple times till they reach a set credit limit before payment becomes mandatory to borrow further) and $\text{Provider}_{\text{single-loan}}$ (where people are only allowed to have an outstanding loan, regardless of the loan amount vs their credit limit).

These results indicate that participants in our various treatment groups had a relatively larger improvement of their repayment rates in $\text{Provider}_{\text{multiple-loans}}$ than in $\text{Provider}_{\text{single-loan}}$, though the changes remained small (the largest increase was less than a percentage point). Indeed, an ANOVA analysis revealed that there was a statistically significant improvement ($F(4, 385291) = 22.87$, $p < 0.001$) on the seven-day repayment rate for the borrowers in $\text{Provider}_{\text{multiple-loans}}$ who received reminders compared to the control group that did not receive any reminder. Whereas the effect of reminders on the seven-day repayment rate for borrowers in $\text{Provider}_{\text{single-loan}}$ remained insignificant ($F(4, 89611) = 0.95$, $p > 0.1$). These analyses were conducted while controlling for factors that might influence the repayment rate, such as the average loan amount and service fee, the number of years since a borrower took their first loan (an indication of borrowing experience), and the number of years the borrower had been active on the network. These control variables were all significant in both MNOs, except the number of years a borrower had been active on the network, which did not seem to have a significant impact on the repayment rate for $\text{Provider}_{\text{multiple-loans}}$'s borrowers.

Regarding loan duration, sending borrowers reminders (treatment) seemed to have a statistically significant effect in both MNOs, even in $\text{Provider}_{\text{single-loan}}$ where the impact of reminders had been non-significant on the repayment rates. The results were $F(4, 8696608) = 130.6$, $p < 0.001$ for $\text{Provider}_{\text{multiple-loans}}$ and $F(4, 1251186) = 4.88$, $p < 0.001$ for $\text{Provider}_{\text{single-loan}}$. These ANOVA analyses were conducted while controlling for the total loan amount, inclusive of the service fee. The reduction in loan duration was relatively small, but remained larger in $\text{Provider}_{\text{multiple-loans}}$ than in $\text{Provider}_{\text{single-loan}}$ (see table 10).

In the next section, we analyze the results through our stated hypotheses, especially looking at the difference between the reminders that emphasize the consequence of default to the borrower' future self and the reminders that bring the self to the present. These later reminders emphasize the consequence of untimely repayment to the borrower's present self. For clarity, we separate the analysis by providers and outcome variables, i.e., loan repayment rate and the duration of fully repaid loans.

4.5.2. Statistical Differences Between Groups

4.5.2.1. Seven-Day Loan Repayment Rate

Table 11: ANOVA with planned contrasts results for $\text{Provider}_{\text{multiple-loans}}$ on repayment rate

Coefficients	**Estimate**	**Std. Error**	**t-value**	**Cohen's d**
Intercept	0.5528768	0.0032765	168.740^{***}	

Simple Reminder vs No Reminder	0.0053325	0.0009925	5.373***	0.037766
Future Self vs Simple Reminder	-0.0011697	0.0012159	-0.962	0.005681
Present Self vs Future Self	-0.0058168	0.0012165	-4.782***	0.027469
Present Self + Reason vs Present Self	-0.0017795	0.0009928	-1.792$^{.}$	0.009674
Average loan amount (in USD)	0.8454504	0.0101168	83.569***	
Average service fee (in USD)	-0.6041723	0.0088415	-68.334***	
Average number of years since first loan	-0.0392588	0.0015420	-25.460***	
Average number of years since line activation	-0.0002395	0.0002074	-1.155	

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Since reminders had a significant effect on the repayment rates for Provider$_{multiple\text{-}loans}$'s borrowers, we further investigated this effect by using planned contrasts and computed the effect sizes between the various groups. Table 11 presents the results and shows although some groups were more likely to pay their loans by the seventh day, none of these effects were statistically significant. For example, the two comparisons with the largest differences (simple reminder vs no reminder, and present self vs future self) had Cohen's d of 0.038 and 0.027, respectively. Therefore, we cannot reject the null hypotheses that any of the various reminders practically increased repayment rates compared to the others. These results are similar in Provider$_{single\text{-}loan}$, where reminders did not have any statistically significant effect on the repayment rates.

In the next section, we look at the impact of reminders on loan duration, i.e., how effective reminders are at reducing the number of days participants took to fully repay their loans.

4.5.2.2. Loan Duration

Table 12: ANOVA with planned contrasts results for Provider$_{\text{multiple-loans}}$ on loan duration

Coefficients	**Estimate**	**Std. Error**	**t-value**	**Cohen's d**
Intercept	1.255e+01	1.303e-02	963.152***	
Simple Reminder vs No Reminder	-1.878e-01	1.301e-02	-14.430***	0.014742
Future Self vs Simple Reminder	-9.812e-02	1.589e-02	-6.175***	0.007429
Present Self vs Future Self	1.263e-01	1.590e-02	7.944***	0.017421
Present Self + Reason vs Present Self	2.288e-02	1.296e-02	1.766.	0.004633
Total Loan	-1.753e-02	7.768e-05	-225.667***	

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 13: ANOVA with planned contrasts results for Provider$_{\text{single-loan}}$ on loan duration

Coefficients	**Estimate**	**Std. Error**	**t-value**	**Cohen's d**
Intercept	6.0989219	0.0309274	197.202***	
Simple Reminder vs No Reminder	-0.0442084	0.0258647	-1.709	0.00874
Future Self vs Simple Reminder	0.0389311	0.0317789	1.225	0.005565
Present Self vs Future Self	0.0440883	0.0318438	1.385	0.002131

Present Self + Reason vs Present Self	0.0791767	0.0261205	3.031**	0.007875
Total Loan	0.0019590	0.0001557	12.579***	

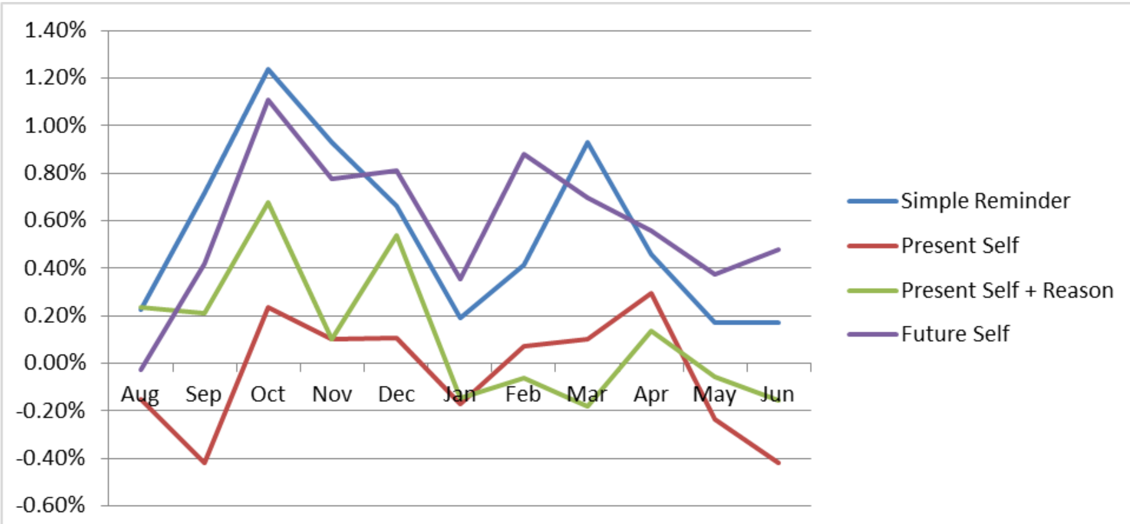
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Using planned contrasts to further explore the effect of the different types of reminders on the loan duration for fully paid loans in both Provider$_{multiple\text{-}loans}$ (table 12) and Provider$_{single\text{-}loan}$ (table 13), we found that reminders had a generally larger effect in the former than in the latter. However, these effects remained practically insignificant in both providers. These results were obtained while controlling for the total loan amount variable (the sum of the loan amount and the corresponding service fee). Thus, there is little evidence to suggest that any of the reminders significantly reduced the loan duration compared to the other groups. This result is similar to the effectiveness of the reminders in increasing repayment rates.

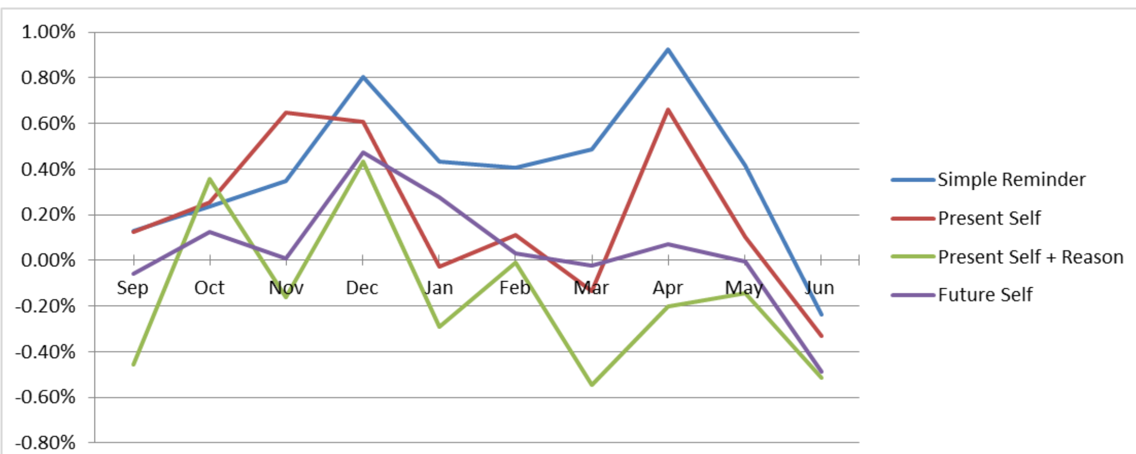
The results in tables 10, 11, 12 and 13 seem to provide evidence for our hypotheses. None of the various groups significantly increased repayment rates and / or reduced the number of days it took our participants to fully settle their loans. However, since this experiment was conducted over a nine-months period, it is possible that the aggregated results described above concealed differences over time. For example, it might be that the effect of the different reminders declined during the experiment period. Therefore, we next examined the effect of reminders on repayment rate and loan duration over the experiment period. In particular, we wanted to explore whether the effectiveness of reminders waned over time as borrowers became used to receiving them.

4.5.4. Long-term Effect of Reminders

4.5.4.1. Monthly Repayment Rate



(a) Provider$_{\text{multiple-loans}}$



(b) Provider$_{\text{single-loan}}$

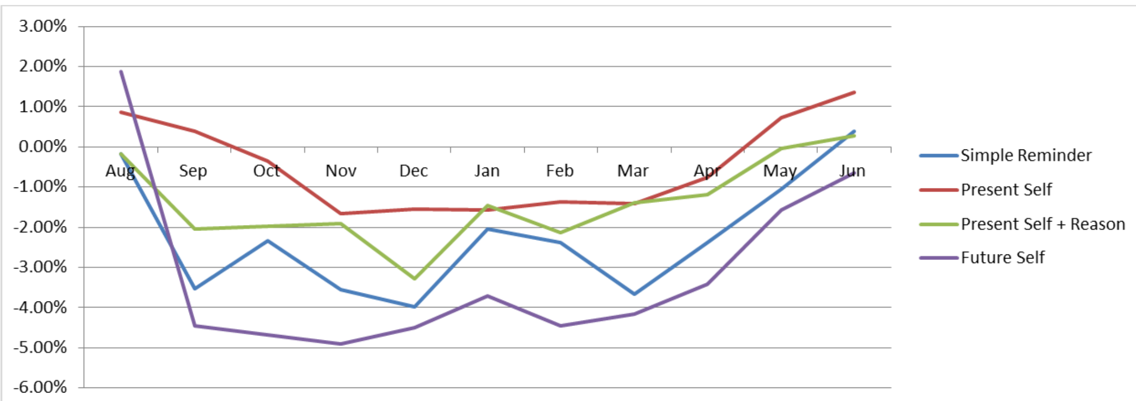
Figure 10: Average repayment rates by month

Figures 10 show the difference in the percentage of loan amount fully repaid within seven days between the treatment groups and the control group. An increase means that more loans were fully settled within seven days in that month compared to the repayment rate of the control group. In the figure, we include the month before we started sending out the reminders (August for $\text{Provider}_{\text{multiple-loans}}$ and September for $\text{Provider}_{\text{single-loan}}$) as an additional baseline.

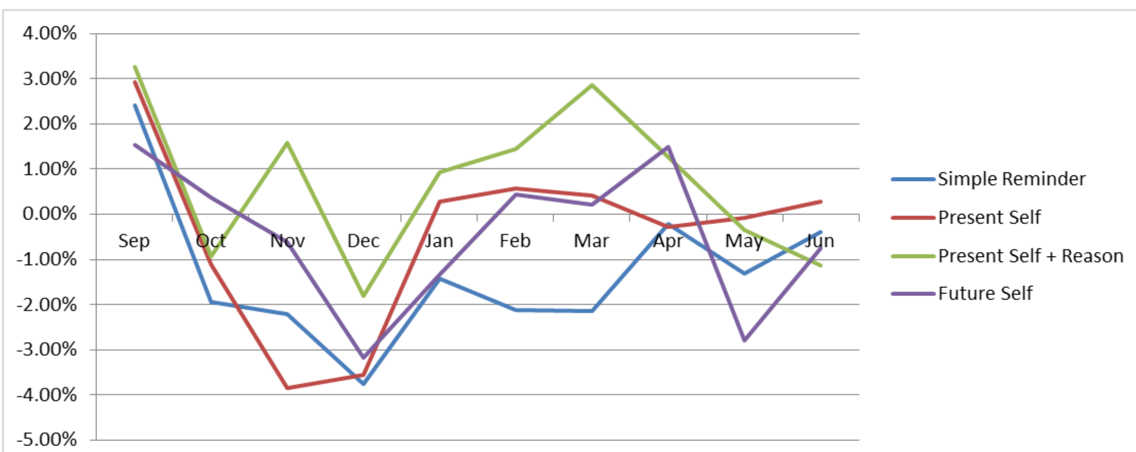
In $\text{Provider}_{\text{multiple-loans}}$, figure 10a shows that people who received the “future self” or simple reminders had the biggest increase in repayment rates and maintained this status throughout the experiment period. Additionally, these two groups’ seven-day repayment rates exhibit some seasonality, rapidly increasing in the first two months of the experiment before a gradual decrease in the following four months. Afterward, the cycle seems to repeat again, though the second peak in March is slightly lower than the first witnessed in October. The marginal gain in repayment rate for the “present self + reason” group, on the other hand, almost completely disappears after four months from the start of the study. Interestingly, the experiment group receiving the “present self” reminders slightly lowered their repayment rate in the first month of the experiment. However, their repayment rate remained similar to the control group throughout the study period, indicating that these types of reminders have virtually no effect on the repayment rate of the borrowers of $\text{Provider}_{\text{multiple-loans}}$.

In $\text{Provider}_{\text{single-loan}}$, figure 10b indicates that the simple reminders were most effective and consistent at keeping the seven-day repayment rates above the rate achieved by the control group throughout the experiment period, except in June. Interestingly, a dramatic rise between March and April (with the peak in repayment rate happening in April) is followed by an equally dramatic decrease till the end of the experiment where simple reminders, like all the other reminders, seem to be worse than not sending any reminders at all when it comes to the percentage of loans fully paid within seven days. The “present self + reason” had a repayment rate lower than that of the control group throughout the study period, except in October and December. In contrast, the “present self” and “future self” groups display more mixed results; though their payment rates are mostly above that of the control group, they seem more volatile between months.

4.5.4.2. Monthly Loan Duration



(a) Provider$_{\text{multiple-loans}}$



(b) Provider$_{\text{single-loan}}$

Figure 11: Average duration for fully paid loans by month

Figures 11 show the difference in the average duration for fully paid loans between each type of reminder and the control group that did not receive any reminders for both MNOs. Hence, in the graphs, negative numbers represent a reduction in the duration of fully settled loans compared to the same duration for the control group.

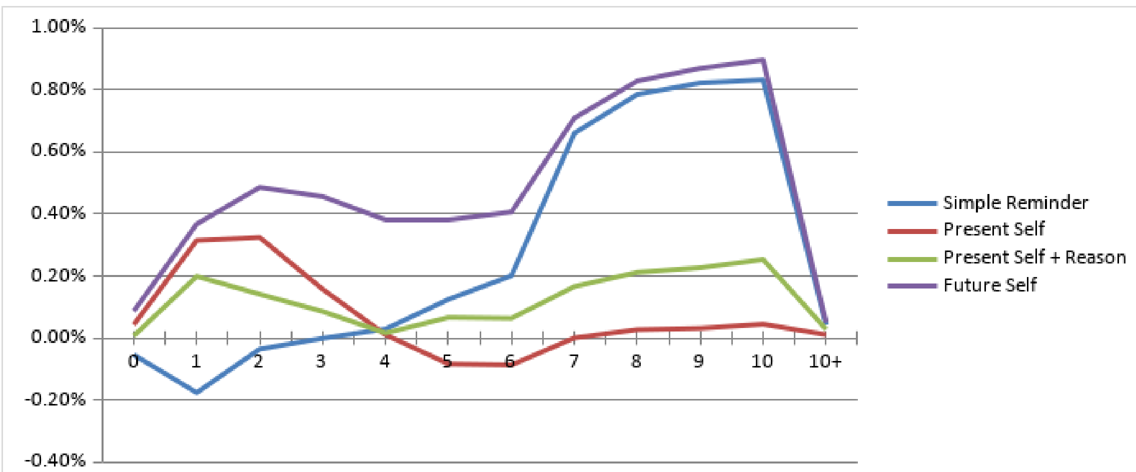
Figure 11a shows that, in $\text{Provider}_{\text{multiple-loans}}$, all reminders, except the “present self”, were associated with an immediate reduction of the average duration of fully paid loans; whereas the “present self” reminders took a few more weeks to become effective, with its performance peeking in November. Figure 11b shows that in $\text{Provider}_{\text{single-loan}}$, on the other hand, only the simple reminders consistently reduced the average duration for fully paid loans throughout the study period, while the participants who received the “present self + reason” reminders took longer to fully pay their loans compared to the study participants who did not receive any reminder at all. The other types of reminders had more mixed results in $\text{Provider}_{\text{single-loan}}$.

From January, the effectiveness of reminders in reducing the duration of fully paid loans in $\text{Provider}_{\text{multiple-loans}}$ begins to attenuate. By the end of the experiment period in June, all participants, except those receiving the “future self” reminders, were taking longer to fully settle their loans compared to the participants who were not receiving any reminder. This trend suggests that the effectiveness of reminders reduces over time, even becoming counterproductive in reducing the duration of fully paid loans. The trend of the effectiveness of reminders seems to be less clear in $\text{Provider}_{\text{single-loan}}$. Here, the performance of reminders does not considerably change over time in either direction;

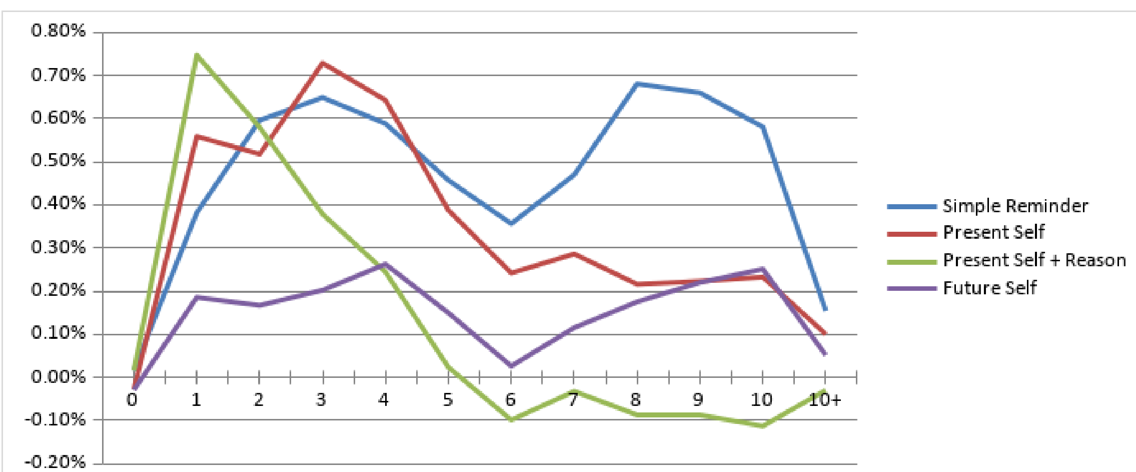
neither improving nor worsening when compared to not sending reminders. However, there seems to be a seasonality in the effectiveness of reminders, where the loan duration contracted from the start of the experiment to December, widening between December and March before falling again.

4.5.3. Effect of Reminders on Daily Repayment Rate

To better understand how borrowers in both MNOs reacted upon receiving the different reminders, we compared the daily repayment rates of the experiment groups.



(a) Provider$_{\text{multiple-loans}}$



(b) Provider$_{\text{single-loan}}$

Figure 12: Daily repayment rates

Figures 12 show the cumulative difference in full loan repayment by day, between the treatment groups and the “no reminder” control group. An increase means that more loans were fully settled on that day compared to those in the control group and a decrease, the opposite.

Looking at the figures, the repayment rates seem to have two peaks in $\text{Provider}_{\text{single-loan}}$ (around the second and third day, and the eighth and tenth day) and only one in $\text{Provider}_{\text{multiple-loans}}$. On the one hand, though receiving the “simple” or the “future self” reminders seem to encourage the $\text{Provider}_{\text{single-loan}}$’s borrowers to repay their loans, these two groups appear to have already experienced a first peak in repayment on the third day after borrowing. On the other hand, the two “present” reminders appear to have only a negligible effect on repayment rates. These two groups have high repayment rates in the first three days after borrowing, before these are drastically reduced. The repayment rates barely increase on the seventh day, when reminders are sent. Thus, figure 12b confirms the results in table 8, showing that reminders have minimal impact on the repayment rates of borrowers in $\text{Provider}_{\text{single-loan}}$.

In $\text{Provider}_{\text{multiple-loans}}$, the “future self” group had the highest repayment rate throughout the loan duration. Additionally, this group drastically increased its repayment rate compared to that of the control group on the seventh day, when the reminders were sent. The participants in the “simple reminder” group had the sharpest increase of their repayment rate in response to receiving the reminders. This increase was such that their repayment rate became almost the same as that of the “future self” group on the days when reminders were sent. Both the “future self” and “simple reminder” groups kept increasing their repayment rates in the subsequent days. This suggests that the influence of these two types of reminders may remain for a few days after the reminders have been sent. Finally, the study participants in the two “present” groups seem to respond the least to reminders. In fact, their repayment rates were higher in the first two days after taking the loan than on the seventh day when they were reminded of their due loans. Moreover, the “present self” reminders barely improved the repayment rate compared to not receiving any reminder at all.

4.6. DISCUSSION AND CONCLUSION

In this study, we wanted to explore whether text reminders for loan repayment could be made more effective with vividness. Based on the literature, we hypothesized that borrowers could be made aware of their due loans and made to care about the consequences of untimely payment via text reminders that, (1) made vivid these consequences to their future self; (2) brought these consequences to the borrower’s present self; and / or (3) made it explicit that the consequences would be due to untimely repayment. We posited that these types of reminders would increase the repayment rates and reduce the loan duration. However, the results from this randomized control trial suggest no meaningful improvement for either metric (repayment rate and loan duration). This outcome may be due to two factors.

First, the lack of significant effect of reminders may be due to the automatic repayment of these loans. As mentioned in section 3, the total amount due (borrowed amount and service fee) is automatically deducted from the user's account when they purchase airtime. Therefore, it may be that people who are in need of communicating and able to recharge their account for communication do so without waiting for the reminders. This point may be supported by our results which show a relatively bigger improvement in $\text{Provider}_{\text{multiple-loans}}$ than in $\text{Provider}_{\text{single-loan}}$. In $\text{Provider}_{\text{single-loan}}$, where people can only have one outstanding loan at a time, the repayment rate for the control group was much higher (≈ 77% vs ≈ 71%) and the loan duration much lower (≈10 days vs ≈6 days) than in $\text{Provider}_{\text{multiple-loans}}$. Figure 12b shows two peaks of loan repayment: the first around days 2 and 3 after borrowing, and the second around days 7 and 8, which corresponds to when people received reminders. This contrasts to figure 12a where we see only one peak of payment around days 7 and 8, when reminders are sent. This indicates that perhaps reminders are more effective when people do not have other imperatives for repayment, such as the need for communication through their mobile phones. In a future study, we want to explore the effectiveness of these reminders with cash loans, where repayments are not automatically deducted from borrowers' accounts.

Second, it may be that our text reminders failed to make vivid the consequences of untimely payment. A number of prior studies on vivid interventions were conducted in lab settings where participants could interact with virtual portrayals of their future self or were asked to vividly imagine their future self (Hershfield et al., 2018), and where outcomes were based on hypothetical scenarios. In contrast, our experiment delivered text reminders to participants in the real world with their reactions measured in actual loan repayment. This raises two possibilities: either our text messages were not vivid enough, or perhaps loan repayment may be difficult to influence in the real-world, where people may be facing financial hardships, as noted by Bhanot (2017). A lab experiment with text-based vivid reminders could explore the first possibility, while a follow-up survey and interviews to our experiment may investigate the observed outcome.

Chapter 5 – Conclusion

5.1. SUMMARY

The studies in this dissertation aimed to examine a range of approaches that may be used to reduce consumer default rates of digital microloans. Default rates, along with inflation, are the main drivers of interest rates charged on loans. By leveraging the ubiquity of mobile phones, digital lenders have greatly reduced the cost of lending. However, default rates still remain relatively high, especially when compared with traditional lenders. Therefore, by reducing default rates, it is hoped that borrowers could benefit from lower interest rates, and consumers from a greater range and better suited products, such as longer term loans.

In the first study, I showed how lenders can more effectively screen customers prior to extending loans by using limited mobile phone data, such as data on airtime recharge. During this experimental study, I found that recharge datasets, which have limited privacy-sensitive information, complemented by datasets of past loans, contain enough signal to effectively screen borrowers. In addition, models trained on these datasets generalize well to new borrowers with limited credit history. I also observed that loan default seemed to be greatly influenced by the amount lent to the consumer. Therefore, I investigated further the influence of credit limit increases on loan default in the second study. I found that, similar to credit cardholders, increasing credit limits generally increased the likelihood of default. However, this link is moderated by certain factors such as the borrower's experience, their payment history and the loan amount. Both of these studies are ex ante, presenting lenders with a number of usable tools to reduce default rates prior to extending loans. However, the lack of collateral and limited venues for enforcing loan repayment means that digital lenders are constrained in their ability to recover issued loans. Thus, the final study in this dissertation explored whether reminders for loan repayment could be made more effective using vividness. The study found that reminders, whether vivid or not, had limited impact on repayment and loan duration.

5.2. CONTRIBUTION

This dissertation makes contributions in three major areas of the field of information communication technology for development (ICTD): 1) product design, 2) method design, and 3) theory.

5.2.1. Product Design

Each study in this dissertation presents practical recommendations for product design that can help foster digital microlending for the benefit of all participants including borrowers, lenders and policy makers.

The first study showed that the frequency of airtime recharging and borrowing, as well as the maintenance of a minimum balance are key factors when identifying borrowers with a high likelihood of loan repayment, supporting the belief that stability is strongly linked to loan repayment (Björkegren & Grissen, 2018). This finding has powerful implications for both lenders and borrowers. For lenders, it indicates that the frequency of credit transactions (e.g., bank deposits) rather than the amounts, as well the maintenance of a minimum balance are predictive of creditworthy borrowers. For borrowers, it shows that they may be able to improve their credit profile by making regular deposits, however small. If lenders incorporate these features in their models, people with low but regular income, as well as those who maintain a small, but consistent balance on their account may become eligible borrowers. They could further improve their credit profiles by making regular payments towards their loans.

The second study found that borrowers of digital microloans behaved similarly to credit cardholders in that when their credit limits were increased, borrowing levels, as well as default rates, increased. By linking the behavior of digital borrowers to credit cardholders, digital lenders and policy makers are able to leverage the expansive work conducted in the credit card industry. For example, the literature on credit card use has found multiple causes for the increases in borrowing after a credit limit increase, such as low “consumer spending self-control” (Bearden & Haws, 2012) and the illusion of an increased income (Lin et al., 2019). By understanding the borrowers’ characteristics using these frameworks, lenders may anticipate the effect of increasing credit limits. In addition, I also found that the length of time an airtime user had been borrowing and the length of time they had been using their mobile phone impacted their response to increases in credit limit, similar to the findings by Soman and Cheema (2002) on the effect of borrowing experience on credibility. This is potentially significant, and may allow lenders to better identify borrowers more likely to respond favorably to a credit increase, thus helping mitigate the potential default rate increases identified above. This likewise supports my policy proposal from the first study, in that lenders could benefit from increasing their extension of credit to low-income but experienced borrowers in developing contexts.

The third study identified that, contrary to my hypothesis, neither vivid reminders nor simple text reminders seemed to increase timely repayment rates and reduce default rates. Although further work should be taken in this area, I tentatively suggest that there may be a range of psychological and contextual factors, yet to be fully explored, which may limit borrowers' abilities to repay on time. Lenders may therefore benefit from attempting to explore some of these factors, particularly within the specific country and regional contexts in which they are operating. Individual client meetings or, where appropriate, focus group discussions with borrowers might help lenders explore these factors and may reduce the potentially catastrophic effects of high borrower default rates. One area of particular interest may be the psychological effect of debt burden. In the second study, I capped the increase of credit limit to the total amount taken by the borrower in the previous month. However, people who were able to pay smaller loan amounts suddenly defaulted when their debt became larger, but still smaller than the total they had paid back in the previous month. This seems to indicate that there may be a threshold when a debt becomes difficult to pay by people who seemingly have the means to do so. This again suggests that lenders may benefit from some degree of caution when raising the amount that a customer can borrow.

5.2.2. Methodological Contribution

The three studies in this dissertation make methodological contributions by using the randomized control trial (RCT) method at large scale. Randomized experiments, which are increasingly used in development economics (Banerjee & Duflo, 2009), have to date found limited adoption in ICTD studies which mostly employ observational research methods such as case studies (Walsham & Sahay, 2006). However, randomized experiments can be particularly well-suited for exploring causal relationships between treatments and outcomes (Babbie, 2020). Such knowledge can lead to robust results (Nan et al., 2021) able to facilitate effective policy-making (Ilavarasan, 2017) and provide relevant avenues for further research. By working with a large digital microloan lender, I was able to leverage their infrastructure which expands across multiple countries and serves millions of customers, potentially identifying a number of novel correlations that can be explored in further research.

In addition, the third study in this dissertation experimented with a novel approach to implementing vivid interventions via simple text messages. Prior work had implemented vivid interventions using high-touch processes such as letter-writing (Chishima & Wilson, 2020) and virtual reality animations (Hershfield, 2011; Sims et al., 2015). Both methods are difficult to scale, especially in the context of resource constraints in which ICTD researchers operate. Developing alternative approaches using vivid intervention methods may help increase its applicability across different domains and research contexts.

5.2.3. Theoretical Contribution

Through the third study, this document extends current theoretical work around vividness and future self. Prior studies in this field sought to encourage consumers to make decisions that benefited their future selves by asking them to project their present-day interests into their future selves (Hershfield & Bartels, 2018). In contrast, this study aimed to make the future vivid in the present by asking participants to imagine future consequences as if they were happening to their present self. Such framing, I had hypothesized, would increase the vividness of future consequences by making borrowers identify with the feelings of their future selves.

5.3. LIMITATIONS AND FUTURE WORK

The work presented in this document reveals a number of research opportunities that I hope to pursue in the future. For example, all three studies used anonymized data of mobile phone users and analyzed the results at an aggregate level. However, prior research found differences in usage of mobile phones based on factors such as gender, wealth, education and other socioeconomic indicators (Blumenstock & Eagle, 2012). Therefore, it remains crucial to explore the effects of the interventions in this document on different groups to minimize any possible unintended consequences, such as algorithmic bias.

This dissertation was conducted on a specific product: airtime loan. As mentioned throughout the document, this product had two unique features that set it apart from other types of digital loans: (1) payments were automatically made when a borrower recharged their account; and (2) defaulting on a loan meant that the borrower could not use their mobile phone for communication and would have had to change phone numbers. Essentially, the borrower’s phone number acted as a collateral, though a minor one. This is different from other digital lending products, such as cash loans, where borrowers have to actively make payments and where defaulting may only impact future borrowing. Although I expect the interventions described here (e.g., increasing credit limits) to have similar effects on other types of digital lending, I hope to extend the external validity of these studies by conducting similar experiments with other lenders. One such project involved working with a home solar equipment provider; though the current pandemic forced this to be postponed.

Additionally, this research raises questions of consent when it comes to conducting research with mobile phone service providers. In many developing countries, people connect to mobile networks by purchasing subscriber identification module (SIM) cards and by providing their identification details, such as names and date of birth. People are rarely given information about how their data is used and shared, and whether they may be part of experimental studies. However, a number of countries have started to enact laws and regulations similar to the European Union’s General Data Protection Regulation (GDPR), placing user’s privacy and consent at the heart of data collection, transfer, processing and storing. As these laws become more widespread, there will likely be a need for effective methods for informing mobile phone users and for obtaining their consent for data collection and analysis.

Finally, there is a need to give borrowers greater insight into the methods and data used to assess their creditworthiness. As the use of alternative data sources, such as mobile phones, becomes more widespread in the financial industry, this transparency of processes will become increasingly important and will potentially allow customers to better meet the requirements of lenders. For example, borrowers who are given a clear explanation of the reasons for their loan application denial may be better able to take appropriate steps to improve their credit profile. In addition, borrowers who opt out of having some of their data used in credit scoring should not face hurdles in borrowing. This may be particularly important in contexts with lower levels of client data security and weak data protection laws.

Appendix A: Original Vivid Text Reminders

Type of reminder	**Message in Kinyarwanda**	**Translation to English**
Simple reminder	Uyu niwo munsi wa nyuma wo kwishyura ideni rya <*loan amount*>.	Your loan is due today.
Future self	Mu minsi iri imbere, nucyenera guhamagara bikanga; uzabigenza ute? Ishyura ideni ryawe maze ushobore gutira no guhamagara igihe cyose ubikeneye.	How would you feel next week if you couldn't borrow to make an urgent call? Pay now to continue enjoying the service.
Present Self	Uramutse ucyeneye guhamagara byihuse ugasanga ntibishoboka wabigenza ute? Ishyura ideni ryawe maze ushobore gutira no guhamagara igihe cyose ubikeneye.	How would you feel right now if you couldn't borrow to make an urgent call? Pay now to continue enjoying the service.
Present self + reason	Uramutse ukeneye guhamagara byihutirwa bikanga kubera ideni ufite wabigenza ute? Ishyura ideni ryawe maze ushobore gutira no guhamagara igihe cyose ubikeneye.	How would you feel right now if you couldn't borrow because of untimely payments last month? Pay now to continue enjoying the service.

Bibliography

Abdullah, S., & Quayes, S. (2016). Do women borrowers augment financial performance of MFIs? *Applied Economics*, *48*(57), 5593–5604.

Abdul-Muhmin, A. G., & Umar, Y. A. (2007). Credit card ownership and usage behaviour in Saudi Arabia: The impact of demographics and attitudes toward debt. *Journal of Financial Services Marketing*, *12*(3), 219–234.

Ahmed, H., & Cowan, B. W. (2019). *Mobile Money and Healthcare Use: Evidence from East Africa* (No. w25669). National Bureau of Economic Research. https://doi.org/10.3386/w25669

Ampah, S. N., Ambrose, J. O., Omagwa, J. O., & Frimpong, S. (2017). Effect of Access to Credit and Financial Services on Poverty Reduction in Central Region of Ghana. *International Journal of Business and Social Science*, *8*(8).

Babbie, E. R. (2020). *The Practice of Social Research*. Cengage Learning.

Baek, E., & Hong, G.-S. (2004). Effects of family life-cycle stages on consumer debts. *Journal of Family and Economic Issues*, *25*(3), 359–385.

Balyuk, T. (2019). *Financial Innovation and Borrowers: Evidence from Peer-to-Peer*

Lending. https://doi.org/10.2139/ssrn.2802220

Banerjee, A. V., & Duflo, E. (2009). The experimental approach to development economics. *Annual Review of Economics*, *1*(1), 151–178.

Banerjee, A. V., & Newman, A. F. (1993). Occupational Choice and the Process of Development. *The Journal of Political Economy*, *101*(2), 274–298.

Barriga-Cabanillas, O., & Lybbert, T. J. (2020). *Liquidity or Convenience? Heterogeneous Impacts of Mobile Airtime Loans on Communication Expenditure*.

Bartels, D. M., & Rips, L. J. (2010). Psychological connectedness and intertemporal choice. *Journal of Experimental Psychology. General*, *139*(1), 49–69.

Bartels, D. M., & Urminsky, O. (2011). On Intertemporal Selfishness: How the Perceived Instability of Identity Underlies Impatient Consumption. *The Journal of Consumer Research*, *38*(1), 182–198.

Bartels, D. M., & Urminsky, O. (2015). To know and to care: How awareness and valuation of the future jointly shape consumer spending. *The Journal of Consumer Research*, *41*(6), 1469–1485.

Bearden, W. O., & Haws, K. L. (2012). How low spending control harms consumers. *Journal of the Academy of Marketing Science*, *40*(1), 181–193.

Berns, G. S., Laibson, D., & Loewenstein, G. (2007). Intertemporal choice--toward an integrative framework. *Trends in Cognitive Sciences*, *11*(11), 482–488.

Bertaut, C. C., & Haliassos, M. (2006). Credit cards: facts and theories. *The Economics of Consumer Credit*. https://books.google.com/books?hl=en&lr=&id=X8ZaBJpRiTsC&oi=fnd&pg=PA181&dq=Credit+cards+facts+theories+Bertaut+Haliassos&ots=MfJL-N1s0d&sig=_-tsmFx-K7Vmtjw0dXLzq5nSQPk

Bhanot, S. P. (2017). Cheap promises: Evidence from loan repayment pledges in an online experiment. *Journal of Economic Behavior & Organization*, *140*, 246–266.

Bharadwaj, P., Jack, W., & Suri, T. (2019). *Fintech and Household Resilience to Shocks: Evidence from Digital Loans in Kenya* (No. w25604). National Bureau of Economic Research. https://doi.org/10.3386/w25604

Björkegren, D., & Grissen, D. (2018). *Behavior Revealed in Mobile Phone Usage Predicts Loan Repayment*. https://doi.org/10.2139/ssrn.2611775

Blumenstock, J. E., & Eagle, N. (2012). Divided we call: disparities in access and use of mobile phones in Rwanda. *International Journal of Intelligent Information Technologies*. https://itidjournal.org/index.php/itid/article/download/894/894-2560-1-PB.pdf

Blumenstock, J. E., Eagle, N., & Fafchamps, M. (2016). Airtime transfers and mobile communications: Evidence in the aftermath of natural disasters. *Journal of Development Economics*, *120*, 157–181.

Brehanu, A., & Fufa, B. (2008). Repayment rate of loans from semi-formal financial institutions among small-scale farmers in Ethiopia: Two-limit Tobit analysis. *The Journal of Socio-Economics*, *37*(6), 2221–2230.

Brown, I., & Mues, C. (2012). An experimental comparison of classification algorithms for imbalanced credit scoring data sets. *Expert Systems with Applications*, *39*(3), 3446–3453.

Bryan, C. J., & Hershfield, H. E. (2012). You owe it to yourself: boosting retirement saving with a responsibility-based appeal. *Journal of Experimental Psychology. General*, *141*(3), 429–432.

Bursztyn, L., Fiorin, S., Gottlieb, D., & Kanz, M. (2019). Moral incentives in credit card debt repayment: evidence from a field experiment. *The Journal of Political Economy*, *127*(4), 1641–1683.

Cadena, X., & Schoar, A. (2011). *Remembering to pay? Reminders vs. financial incentives for loan payments*. National Bureau of Economic Research.

Central Bank of Kenya, Kenya National Bureau of Statistics and FSD Kenya. (2016). *The 2016 FinAccess household survey* (F. S. D. Kenya (ed.)).

CFI. (2019). Making Digital Credit Truly Responsible. In *Center for Financial Inclusion (CFI)*. Center for Financial Inclusion (CFI). https://content.centerforfinancialinclusion.org/wp-content/uploads/sites/2/2019/09/Digital-Credit-Kenya-Final-report.pdf

Chen, G., & Mazer, R. (2016). Instant, Automated, Remote: The Key Attributes of Digital Credit. In *Consultative Group to Assist the Poor (CGAP)*. Consultative Group to Assist the Poor (CGAP). https://www.cgap.org/blog/instant-automated-remote-key-attributes-digital-credit

Chien, Y.-W., & Devaney, S. A. (2001). The effects of credit attitude and socioeconomic factors on credit card and installment debt. *The Journal of Consumer Affairs*, *35*(1), 162–179.

Chishima, Y., Huai-Ching Liu, I.-T., & E Wilson, A. (2021). Temporal distancing during the COVID-19 pandemic: Letter writing with future self can mitigate negative affect. *Applied Psychology. Health and Well-Being*. https://doi.org/10.1111/aphw.12256

Chishima, Y., & Wilson, A. E. (2020). Conversation with a future self: A letter-exchange exercise enhances student self-continuity, career planning, and academic thinking. *Self and Identity: The Journal of the International Society for Self and Identity*, 1–26.

Christin, D., Reinhardt, A., Kanhere, S. S., & Hollick, M. (2011). A survey on privacy in mobile participatory sensing applications. *The Journal of Systems and Software*, *84*(11), 1928–1946.

Citizens Advice. (2017). *Uninvited credit limit increases push people further into debt*. https://www.citizensadvice.org.uk/about-us/policy/policy-research-topics/debt-and-money-policy-research/credit-limit-increases-briefing/

Comninos, A. C., Esselaar, S., Ndiwalana, A., & Stork, C. S. (2009). Airtime to Cash: Unlocking the Potential of Africa's Mobile Phones for Banking the Unbanked. *IST-Africa 2009*. https://www.diva-portal.org/smash/record.jsf?pid=diva2:358905

Cook, T., & McKay, C. (2015). How M-Shwari works: The story so far. *Consultative Group to Assist the Poor (CGAP) and Financial Sector Deepening (FSD)*.

Demirgüç-Kunt, A., Honohan, P., & Beck, T. (2008). *Finance for all?: Policies and Pitfalls in Expanding Access*. World Bank.

D'Espallier, B., Guérin, I., & Mersland, R. (2011). Women and repayment in microfinance: A global analysis. *World Development*, *39*(5), 758–772.

Diagne, A. (2002). 12 Impact of Access to Credit on Maize and Tobacco Productivity in Malawi. *: Financial Sustainability, Outreach, and Impact*. https://books.google.com/books?hl=en&lr=&id=hMU4AwAAQBAJ&oi=fnd&pg=PA241&dq=Impact+Access+Credit+Maize+Tobacco+Productivity+Malawi+Diagne&ots=7_Axr_Ojwg&sig=PMsNaUlr-7fL4l7dxZVpqwdzeD8

Diagne, A., Zeller, M., & Sharma, M. (1998). Determinants of household access to and participation in formal and informal credit markets in Malawi and Bangladesh. *Annual Meeting of the American Economics Association, Chicago, Illinois*.

Diagne, A., Zeller, M., & Sharma, M. P. (2000). *EMPIRICAL MEASUREMENTS OF HOUSEHOLDS'ACCESS TO CREDIT AND CREDIT CONSTRAINTS IN DEVELOPING COUNTRIES: METHODOLOGICAL ISSUES AND EVIDENCE*. Food Consumption and Nutrition Division, International Food Policy Research Institute (IFPRI).

Eagle, N., Pentland, A. S., & Lazer, D. (2009). Inferring friendship network structure by using mobile phone data. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(36), 15274–15278.

Ersner-Hershfield, H., Wimmer, G. E., & Knutson, B. (2009). Saving for the future self: neural measures of future self-continuity predict temporal discounting. *Social Cognitive and Affective Neuroscience*, *4*(1), 85–92.

Fafchamps, M. (2013). Credit constraints, collateral, and lending to the poor. *Revue D'économie Du Développement*, *21*(2), 79–100.

Francis, E., Blumenstock, J., & Robinson, J. (2017). *Digital Credit: A Snapshot of the Current Landscape and Open Research Questions*. BREAD Working Paper.

Frederick, S. (2003). Time preference and personal identity. *Time and Decision*, 89–113.

Galor, O., & Zeira, J. (1993). Income Distribution and Macroeconomics. *The Review of Economic Studies*, *60*(1), 35–52.

Gan, C. E. C., Cohen, D. A., Hu, B., Tran, M. C., Dong, W., & Wang, A. (2016). The relationship between credit card attributes and the demographic characteristics of card users in China. *International Journal of Bank Marketing*, *34*(7), 966–984.

Gebre, S. (2018). Blockchain Opens Up Kenya's $20 Billion Informal Economy. In *Bloomberg. com*. Bloomberg. https://www.bloomberg.com/news/articles/2018-06-14/blockchain-is-opening-up-kenya-s-20-billion-informal-economy

Goslar, B. M. (2016). When Customers Count: Blasting New Doorways to Financial Inclusion. In *LinkedIn*. JUMO.WORLD. https://www.linkedin.com/pulse/when-customers-count-blasting-new-doorways-financial-inclusion/

Gross, D. B., Souleles, N., & Others. (2000). Consumer response to changes in credit supply: Evidence from credit card data. *Manuscrit, Université de Chicago et Université de Pennsylvanie, Souleles@ Wharton. Upenn. Edu*.

Gross, D. B., & Souleles, N. S. (2002). Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data. *The Quarterly Journal of Economics*. https://academic.oup.com/qje/article-abstract/117/1/149/1851757

GSMA. (2019). *Digital credit for mobile money providers: A guide to addressing the risks associated with digital credit services*. GSM Association. https://www.gsma.com/mobilefordevelopment/wp-content/uploads/2019/09/GSMA_Digital-credit-for-mobile-money-providers.pdf

GSMA. (2020). *The Mobile Economy - Sub-Saharan Africa 2020*. GSM Association. https://www.gsma.com/mobileeconomy/wp-content/uploads/2020/09/GSMA_MobileEconomy2020_SSA_Eng.pdf

Haile, F. (2015). Determinants of loan repayment performance: Case study of Harari microfinance institutions. *Journal of Agricultural Extension and Rural Development*, *7*(2), 56–64.

Hardeman, B. (2012). Lenddo's Social Credit Score: How Who You Know Might Affect Your Next Loan. In *The Huffington Post*. TheHuffingtonPost.com. https://www.huffingtonpost.com/bethy-hardeman/lenddos-social-creditsco_b_1598026.html?guccounter=1

Hastie, T., Tibshirani, R., & Friedman, J. (2001). *The Elements of Statistical Learning*. Springer New York Inc.

Hazarika, G., & Alwang, J. (2003). Access to credit, plot size and cost inefficiency among smallholder tobacco cultivators in Malawi. *Agricultural Economics* , *29*(1), 99–109.

Hershfield, H. E. (2011). Future self-continuity: how conceptions of the future self transform intertemporal choice. *Annals of the New York Academy of Sciences*, *1235*, 30–43.

Hershfield, H. E. (2019). The self over time. *Current Opinion in Psychology*, *26*, 72–75.

Hershfield, H. E., & Bartels, D. M. (2018). The future self. *Of Thinking about the Future*. https://books.google.com/books?hl=en&lr=&id=srk8DwAAQBAJ&oi=fnd&pg=PA89&dq=future+self+Hershfield+Bartels&ots=w0hc6gWrJ7&sig=-bNWwISLMBXSyEwuSBlBW05Xjzo

Hershfield, H. E., John, E. M., & Reiff, J. S. (2018). Using Vividness Interventions to Improve Financial Decision Making. *Policy Insights from the Behavioral and Brain Sciences*, *5*(2), 209–215.

Hinson, R. E. (2011). Banking the poor: The role of mobiles. *Journal of Financial Services Marketing*, *15*(4), 320–333.

Ilavarasan, P. V. (2017). Bridging ICTD research and policy-making: notes from a systematic review on MSMEs in the low- and middle-income countries. *Information Technology for Development*, *23*(4), 723–733.

Izaguirre, J. C., Mazer, R., & Graham, L. (2018). *It’s Time to Slow Digital Credit's Growth in East Africa*. Consultative Group to Assist the Poor (CGAP). https://www.cgap.org/blog/its-time-slow-digital-credits-growth-east-africa

Johnen, C., Parlasca, M., & Mußhoff, O. (2021). Promises and pitfalls of digital credit: Empirical evidence from Kenya. *PloS One*, *16*(7), e0255215.

Kaffenberger, M. (2018). *Digital Credit in Tanzania: Customer Experiences and Emerging Risks*. Consultative Group to Assist the Poor (CGAP).

Karlan, D., Mann, R., Kendall, J., Pande, R., Suri, T., & Zinman, J. (2016). Making microfinance more effective. *Harvard Business Review*, 2–6.

Karlan, D., Morten, M., & Zinman, J. (2012). *A personal touch: Text messaging for loan repayment*. National Bureau of Economic Research.

Kedir, A. (2003). Determinants of Access to Credit and Loan Amount: Household-level Evidence from Urban Ethiopia. *International Conference on African Development Archives*, 64.

Khandker, S. R., & Others. (1998). *Fighting poverty with microcredit: experience in Bangladesh*. Oxford University Press.

Kinsey, J. (1981). Determinants of Credit Card Accounts: An Application of Tobit Analysis. *The Journal of Consumer Research*, *8*(2), 172–182.

Kuo, H.-C., Lee, C.-C., & Chiou, W.-B. (2016). The Power of the Virtual Ideal Self in Weight Control: Weight-Reduced Avatars Can Enhance the Tendency to Delay Gratification and Regulate Dietary Practices. *Cyberpsychology, Behavior and Social Networking*, *19*(2), 80–85.

Laudenbach, C., Pirschel, J., & Siegel, S. (2018). Personal communication in a fintech world: Evidence from loan payments. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3153192

Liao, L., Wang, Z., Yan, H., & Zhou, C. (2020). When FinTech Meets Privacy: The Consequence of Personal Information Misuse in Debt Collection. *Available at SSRN 3415808*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3415808

Lin, L., Revindo, M. D., Gan, C., & Cohen, D. A. (2019). Determinants of credit card spending and debt of Chinese consumers. *International Journal of Bank Marketing*, *37*(2), 545–564.

Loewenstein, G. (1996). Out of Control: Visceral Influences on Behavior. In *Organizational Behavior and Human Decision Processes* (Vol. 65, Issue 3, pp. 272–292). https://doi.org/10.1006/obhd.1996.0028

Madise, S. (2015). Mobile money and airtime: emerging forms of money. *Available at SSRN 2589058*.

Mandell, A. F., Strawther, M., & Zhu, J. (2015). InVenture: Building Credit Scoring Tools For The Base Of The Pyramid. In *Havard Business Review*. Harvard Business Review. https://hbr.org/product/inventure-building-credit-scoring-tools-for-the-base-of-the-pyramid/SCG513-PDF-ENG

Mazer, R., Giné, X., & Putman, D. (2020). Understanding the Effects of Digital Credit Information Sharing in Kenya. In *Innovations for Poverty Action (IPA)*. Innovations for Poverty Action (IPA). https://www.poverty-action.org/study/understanding-effects-digital-credit-information-sharing-kenya

Menkhoff, L., Neuberger, D., & Rungruxsirivorn, O. (2012). Collateral and its substitutes in emerging markets' lending. *Journal of Banking & Finance*, *36*(3), 817–834.

Mokhtar, S. H. (2011). *Microfinance performance in Malaysia*. Lincoln University.

Mottaleb, K. A., & Kalirajan, K. (2010). Determinants of Foreign Direct Investment in Developing Countries: A Comparative Analysis. *Margin: The Journal of Applied Economic Research*, *4*(4), 369–404.

Nan, W., Zhu, X., & Lynne Markus, M. (2021). What we know and don't know about the socioeconomic impacts of mobile money in Sub-Saharan Africa: A systematic literature review. *The Electronic Journal of Information Systems in Developing Countries*, *87*(2), e12155.

Nisbett, R. E., & Ross, L. (1980). *Human inference: strategies and shortcomings of social judgment*. Prentice-Hall.

Oppong, K., & Mattern, M. (2020). African Digital Credit Goes West. In *Consultative Group to Assist the Poor (CGAP)*. Consultative Group to Assist the Poor (CGAP). https://www.cgap.org/blog/african-digital-credit-goes-west

Parfit, D. (1971). Personal Identity. *The Philosophical Review*, *80*(1), 3–27.

Pronin, E., & Ross, L. (2006). Temporal differences in trait self-ascription: when the self is seen as an other. *Journal of Personality and Social Psychology*, *90*(2), 197–209.

Quach, M., Mullineux, A., & Murinde, V. (2005). Access to credit and household poverty reduction in rural Vietnam: A cross-sectional study. *The Birmingham Business*. https://www.researchgate.net/profile/Victor_Murinde/publication/266043032_ACCESS_TO_CREDIT_AND_HOUSEHOLD_POVERTY_REDUCTION_IN_RURAL_VIETNAM_A_CROSS-SECTIONAL_STUDY/links/54d342a80cf250179181cd01/ACCESS-TO-CREDIT-AND-HOUSEHOLD-POVERTY-REDUCTION-IN-RURAL-VIETNAM-A-CROSS-SECTIONAL-STUDY.pdf

Reagan. (2020). Twiga leverages on fintech innovation to provide credit facility to Twiga vendors. In *Twiga Foods*. Twiga. https://twiga.com/2020/06/10/twiga-leverages-on-fintech-innovation-to-provide-credit-facility-to-twiga-vendors/

Roslan, A. H., & Karim, M. Z. A. (2009). Determinants of microcredit repayment in Malaysia: The case of Agrobank. *Humanity & Social Sciences Journal*, *4*(1), 45–52.

Ruiz, S., Gomes, P., Rodrigues, L., & Gama, J. (2017). Credit Scoring in Microfinance Using Non-traditional Data. *Portuguese Conference on Artificial Intelligence*, 447–458.

RURA. (2019). *ACTIVE MOBILE-CELLULAR TELEPHONE SUBSCRIPTIONS AS OF SEPTEMBER 2019*. Rwanda Utilities Regulatory Authority. https://rura.rw/fileadmin/Documents/ICT/statistics/Mobile_telephone_Statistics_report_as_of_September_2019.pdf

San Pedro, J., Proserpio, D., & Oliver, N. (2015). MobiScore: towards universal credit scoring from mobile phone data. *International Conference on User Modeling, Adaptation, and Personalization*, 195–207.

Schelling, T. C. (1984). Self-Command in Practice, in Policy, and in a Theory of Rational Choice. *The American Economic Review*, *74*(2), 1–11.

Schicks, J. (2010). Microfinance Over-Indebtedness: Understanding its drivers and challenging the common myths. *Centre Emile Bernheim (CEB) Working Paper*, *10*, 047.

Sharma, M., & Zeller, M. (1997). Repayment performance in group-based credit programs in Bangladesh: An empirical analysis. *World Development*, *25*(10), 1731–1742.

Shema, A. (2019). Effective credit scoring using limited mobile phone data. *Proceedings of the Tenth International Conference on Information and Communication Technologies and Development - ICTDX '19*. the Tenth International Conference, Ahmedabad, India. https://doi.org/10.1145/3287098.3287116

Shema, A., & Acuna, D. E. (2017). Show Me Your App Usage and I Will Tell Who Your Close Friends Are: Predicting User's Context from Simple Cellphone Activity.

Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems, 2929–2935.

Shilton, K. (2009). Four billion little brothers?: Privacy, mobile phones, and ubiquitous data collection. *Communications of the ACM*, *52*(11), 48–53.

Sikder, R., Uddin, M. J., & Halder, S. (2016). An efficient approach of identifying tourist by call detail record analysis. *Computational Intelligence (IWCI), International Workshop on*, 136–141.

Sims, T., Bailenson, J., & Carstensen, L. L. (2015). Connecting to your future self: Enhancing financial planning among diverse communities using virtual technology. *GERONTOLOGIST*, *55*, 311–311.

Soman, D., & Cheema, A. (2002). The Effect of Credit on Spending Decisions: The Role of the Credit Limit and Credibility. *Marketing Science*, *21*(1), 32–53.

Speakman, S., Mibuari, E., Markus, I., & Kwizera, F. (2017). Mobile phone-based Credit Scoring. *NetMob Book of Abstracts*, 8–10.

Steidle, R. P. (1994). Determinants of bank and retail credit card revolvers: An application using the life-cycle income hypothesis. *Consumer Interests Annual*, *40*(1), 170–177.

Stewart, J. (2014). *Systems and methods for using online social footprint for affecting lending performance and credit scoring*. Google Patents.

Suri, T., & Gubbins, P. (2018). How is digital credit changing the lives of Kenyans? Evidence from an Evaluation of the impact of M-Shwari. In *FSD Kenya*. FSD Kenya. https://s3-eu-central-1.amazonaws.com/fsd-circle/wp-content/uploads/2018/10/23160405/Mshwari-Briefs-10-23-18-1.pdf

Vanberg, C. (2007). *Why Do People Keep Their Promises?-[Dataset]: An Experimental Test of Two Explanations*. Universität.

Van Gelder, J.-L., Luciano, E. C., Weulen Kranenbarg, M., & Hershfield, H. E. (2015). Friends with my future self: Longitudinal vividness intervention reduces delinquency: Vividness of the future self reduces delinquency. *Criminology; an Interdisciplinary Journal*, *53*(2), 158–179.

Vashistha, A., Anderson, R., & Mare, S. (2018). Examining Security and Privacy Research in Developing Regions. *Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies*, 25.

Walsham, G., & Sahay, S. (2006). Research on information systems in developing countries: Current landscape and future prospects. *Information Technology for Development*, *12*(1), 7–24.

Wang, G., Hao, J., Ma, J., & Jiang, H. (2011). A comparative assessment of ensemble learning for credit scoring. *Expert Systems with Applications*, *38*(1), 223–230.

Wang, H., Calabrese, F., Di Lorenzo, G., & Ratti, C. (2010). Transportation mode inference from anonymized and aggregated mobile phone call detail records. *13th International IEEE Conference on Intelligent Transportation Systems*, 318–323.

Wang, L., Malhotra, N. K., & Lu, W. (2014). Determinants of credit card debt: Differentiating between revolving credit debt and petty installment loan in China. *Journal of Consumer Behaviour*. https://onlinelibrary.wiley.com/doi/abs/10.1002/cb.1474

Wathome, F. N. (2020). *Effects of Digital Credit on Financial Inclusion of the Youth in Kenya: A Survey of Kangemi, Nairobi County*. United States International University-Africa.

Whiting, J. E. (1991). Impersonal Friends. *The Monist*, *74*(1), 3–29.

World Bank. (2016). World Development Report 2016: Digital Dividends. *World Bank Group: Washington, DC*.

Yang, P., Zhu, T., Wan, X., & Wang, X. (2014). Identifying significant places using multi-day call detail records. *Tools with Artificial Intelligence (ICTAI), 2014 IEEE 26th International Conference on*, 360–366.

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    - Teaching Assistant for Information Policy

- **Carnegie Mellon University in Rwanda** August 2013 to May 2015
    - Teaching Assistant for Wireless Communications
    - Teaching Assistant for Computer Science Principles for Practicing Engineers
    - Teaching Assistant for Fundamentals of Telecommunications and Computer Networks

PROFESSIONAL EXPERIENCE

Pave Financial, Inc. (Los Altos – United States) January 2020 to Present

Founding Data Scientist

- Creating analytics pipelines to inform product offerings.
- Improving product features with machine learning techniques.

ComzAfrica Rwanda Limited (Kigali – Rwanda) Janvier 2018 to February 2022

Data Science Consultant

- Creating credit scoring systems based on machine learning techniques to improve credit risk assessment of borrowers of microloans through mobile phones.

Tega Holdings Limited (Kigali – Rwanda) August 2014 to June 2015

Co-founder and Lead USSD Application Developer

- Co-founded this company with two other people. The company won a grant of $20,000 from the Institute for War & Peace Reporting (IWPR) Rwanda, to develop a USSD application that sells bus tickets through the mobile money platform.
- Led the efforts to develop the USSD app.

Village Mobile Movie (Kigali – Rwanda) September 2014 to July 2015

Co-founder and Lead Application Developer

- Co-founded this company to provide movie projections in remote parts of Rwanda.
- Led the development of a USSD app to gather feedback from viewers.
- Led the development of an Android app that let franchisees manage their businesses.
- This company was later acquired by Waka-Waka.

Edulink Holdings Limited (Kampala – Uganda) August 2010 to February 2012

Information Technology Officer

- Led the implementation of the IT infrastructure and policies to support more than 150 users
- Maintained the integrity of the company business and financial data.

- Conducted daily maintenance of the IT infrastructure (troubleshooting, backups, monitoring and performance)
- Training of users on the usage of new technologies.

Better Data Limited (Kampala – Uganda) May 2008 to August 2010

Intern, then hired as a Junior Programmer

- Part of a team that developed a web application that allowed operators in a call center to quickly retrieve information stored in a database and communicate back to clients. The database was stored in MySQL and the business logic implemented using HeiTML (HTML extended and interactive, http://radpage.com/).
- Maintained and monitored clients' IT infrastructure for optimal performance.

PUBLICATIONS

- Refereed Journal Papers
  - **Shema, A.** (2021). Effects of increasing credit limit in digital microlending: A study of airtime lending in East Africa. *The Electronic Journal of Information Systems in Developing Countries*, e12199.
  - **Shema, A.**, & Garcia-Murillo, M. (2020). Do mobile phones help expand social capital? An empirical case study. *Social Inclusion, 8*(2), 168-179.
  - Huang, Y., **Shema, A.**, & Xia, H. (2016). A Proposed Genome of Situated and Mobile Crowdsourcing and Its Design Implications for Encouraging Contributions. *International Journal of Human-Computer Studies*.

- Schmidtke, H. R., Yu, H., Masomo, P., Kinai, A., & **Shema, A.** (2014). Contextual Reasoning in an Intelligent Electronic Patient Leaflet System. In *Context in Computing*, (pp. 557-573). Springer New York.

- Refereed Conference Papers
  - Zeng, T., **Shema, A.**, & Acuna, D. E. (2019, March). Dead science: Most resources linked in biomedical articles disappear in eight years. In *International Conference on Information* (pp. 170-176). Springer, Cham.
  - **Shema, A.** (2019, January). Effective Credit Scoring Using Limited Mobile Phone Data. In *Proceedings of the Tenth International Conference on Information and Communication Technologies and Development*. ACM.
  - **Shema, A.**, & Bézy, M. (2018, March). Bringing Life Where There Is No Light: A Low-Cost Movie Projection and Data Collection Solution for Underserved Areas. In *International Conference on Innovations and Interdisciplinary Solutions for Underserved Areas* (pp. 90- 99). Springer, Cham.
  - **Shema, A.**, & Garcia-Murillo, M. (2016). The Impact of Mobile Phones on Social Capital in Developing Countries. *44th Research Conference on Communication, Information and Internet Policy* (TPRC 2016).

- Refereed Workshop Papers
  - **Shema, A.**, & Acuna, D. E. (2017, May). Show Me Your App Usage and I Will Tell Who Your Close Friends Are: Predicting User's Context from

Simple Cellphone Activity. In Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems (pp. 2929-2935). ACM.

- **Shema, A.**, & Huang, Y. (2016). Indoor collocation. Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct - MobileHCI '16.

- Posters
    - Huang, Y., Xia, H., & **Shema, A.** (2016). The Mobile Crowdsourcing Genome. Collective Intelligence Conference.

GRANTS

- Academic grants and fellowships
    - Fellowship worth $5,000 from the Digital Credit Observatory (DCO), a program of the Center for Effective Global Action (CEGA), in support of my work on credit limit in digital microlending
    - TPRC Junior Fellow from May 2019 to September 2021

- Non-academic grants
    - Part of 2 different teams that won 2 grants from the Institute for War & Peace Reporting (IWPR) Rwanda, for a total of $40,000.

PROFESSIONAL ASSOCIATIONS

- Student member of ACM (Association of Computing Machinery)
- Student member of IEEE Computer Society

ACADEMIC INVOLVEMENT / CAMPUS SERVICE

- Academic Involvement
    - Reviewer for the CHI Conference (2017)
    - Reviewer for the iConference (2016 and 2017)
    - Student volunteer for the Tenth ICTD Conference (2019)

- Campus Service
    - Doctoral Student Representative in the Faculty Committee (2016 – 2017)
    - Doctoral Student Representative in the Personnel Committee (2015 – 2016)

SKILLS

- Research Methods: Qualitative techniques (interviews, focus group), quantitative techniques (experimental design, survey design)
- Programming Languages: Python, Java, HeiTML (HTML extended and interactive), SQL, and C.
- Mobile Platforms: Android-based application development
- Big Data Tools: Hadoop and MapReduce, Apache Spark, and R.
- Spoken Languages: Fluent in English, French, Swahili, Kinyarwanda and Lingala