THE IMPACT OF MOBILE BUSINESS LITERACY INTERVENTIONS ON LOAN REPAYMENT: AN APPLICATION TO MICROFINANCE

by

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THE IMPACT OF MOBILE BUSINESS LITERACY INTERVENTIONS ON LOAN REPAYMENT: AN APPLICATION TO MICROFINANCE

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ABSTRACT

With 26% of the world living on less than $3.20 per day with little to no access to financial liquidity, Microfinance Institutions (MFI's) have become critical in encouraging entrepreneurship to reduce poverty in the developing world. However, MFI clientele often suffer from financial stress due to poor loan compliance. As such, we examine how loan compliance could be improved through the use of financial/business education interventions (facilitated by mobile apps) undertaken by MFIs. Conceptualizing financial literacy as a form of learning, we estimate the association between financial/business education app adoption and loan repayment behavior using individual-level data from a microfinance non-profit based in the Dominican Republic. We find that the adoption of a simple app has a strong association with positive behavior among borrowers. Specifically, the empirical analysis indicates a strong relationship between mobile app adoption and loan repayment compliance. Clients who downloaded the app are at least 60% less likely to allow a loan to go in arrears when compared to those who did not download. Furthermore, the effect does not vary across gender, business type, and other related variables. We conclude with positive implications for mobile technology adoption in developing economies, especially among the financially vulnerable.

TABLE OF CONTENTS

INTRODUCTION

According to the World Bank, poverty affects 1.9 billion million people worldwide who live on $3.20 or less daily. Muhammad Yunus founded the first microfinance non-profit, the Grameen Bank, as a means to alleviate poverty. He noticed that the traditional banking system excludes the materially poor because they do not have the collateral or credit scores needed to receive loans. Yunus proposed that society can utilize all human capital by giving the impoverished the financial capital that they need to start microbusinesses, using their skills to earn a living for themselves. Traditionally, the impoverished had to turn to loan sharks to obtain this essential funding. However, these loans came with large interest rates that would entirely consume profits, causing the loan recipient to remain in poverty. Seeing this problem, the Grameen Bank began to extend low-interest loans to the poorest of the poor, allowing these individuals to utilize their skills to raise themselves from poverty. Ultimately, Yunus's work earned him the 2006 Nobel Peace Prize.

Researchers have proven that microfinance is an effective form of poverty alleviation when conducted properly (Hamdinio and Wan Sabri 2012). However, in a myriad of countries, systematic issues affect MFI's that the organizations fail to address. Many microfinance users have not received adequate levels of education, resulting in business and financial illiteracy. As a result, many clients fail to repay their loans, placing them in danger of MFI's cutting them off and them remaining in poverty (Sangwan, Nayak, and Samanta 2020). Many MFI's have attempted to tailor their approaches to reduce this risk of default, creating operational changes, like customizing loan products to the needs of individual clients (Dufhues, Geppert, and Buchenrieder 2003). However, these organizational changes do not address the real issue at hand, lack of financial and business education.

Financial education has proven to impart needed knowledge and skills to students to increase loan repayment (Fernandes, Lynch, and Netemeyer 2014). Some MFI's have begun to implement business/financial education mobile applications for their clients. In doing so, the NGO's hope to solve the systematic issue of maleducation in their client populations, increasing their loan repayment and personal success levels. Mobile apps hold great promise in extending financial/business lessons to all MFI clients as they can tailor lessons to learning different learning styles and even teach the illiterate with audio and video lessons (Ozata and Keskin 2014). We assess the association between downloading a business/financial education app and MFI client payment delinquency in hopes that such interventions will increase the success and reach of these NGO's and their customers. Essentially, these mobile apps could help to solve the systematic problem of poor financial education in MFI client populations, increasing client success and loan repayment. This conversion to positive loan payment behavior will allow the MFI's to extend loans to more individuals, helping even higher numbers of people to rise from the cycle of poverty.

RESEARCH QUESTIONS

1. What is the impact of mobile business/financial education applications on loan compliance?
2. Does the effect vary across borrowers, loan products, or business types?

LITERATURE REVIEW

This study is related to three streams of three literature: microfinance, financial literacy, and mobile apps. We proceed with a review of each field of research.

Microfinance

Those who operate MFI's often do so in order to contribute to an important social change, the end of poverty. As a result, these organizations often extend loans out of emotion or altruism, not for financial return (Galak, Small, and Stephen 2011). Hence, they give capital to those that traditional banks write off as too high of risks to help. These individuals often have very limited education and minimal business and financial literacy. Studies have found that, within the context of microfinance, those with low income and little financial literacy often have higher default rates (Sangwan, Nayak, and Samanta 2020). This places MFI's in a difficult position: they want to target and help the poorest of the poor with their services. However, this core customer base has a predisposition to high default rates, resulting in undesirable consequences for both MFI's and their clients.

A pattern of default can cause an MFI to cease its work with that client. As a result, that individual loses his/her ability to take out loans with the organization, stunting the growth of their microbusiness or causing it to fail. Consequently, that person will likely and remain in the cycle of poverty. Also, an MFI having a high volume of clients who default results in lower returns for the MFI. Consequently, the organization may need to reduce the number of loans that it extends, allowing fewer individuals to rise from poverty.

Past studies have found a myriad of ways to increase loan repayment for MFI's. For example, customizing microcredit products' repayment schedules, interest rates, and more to clients' needs has proven to increase success and repayment (Meyer 2002); (Dufhues, Geppert, and Buchenrieder 2003). This means that microbusiness owners respond better to flexibility from MFI's, rather than rigid schedules that may not line up with their own personal or business needs. Additionally, MFI's often distribute loans to groups rather than individuals. This allows for successful group members to help those who have experienced trouble due to a crisis or a bad month of business and cannot make their payment. Cassar, Crowley, and Wydick (2007) found that the ability to choose the individuals that clients have in their loan groups increases loan repayment. By giving MFI clients the ability to select with whom they would like to work with, they prefer individuals with whom they have preexisting relationships and trusted (Cassar, Crowley, and Wydick 2007). As such, clients have a higher likelihood of wanting to help group members with whom they have close ties and believe that they can rely on, increasing loan repayment.

Studies have also found that offering clients bonuses rather than sanctions decreased their likelihood of strategic default (Brihaye, Pril, Labie, and Périlleux 2019). Essentially, MFI clients do not always have the foresight needed to see past whatever current struggle they face. When times get hard and making a payment becomes too difficult, microbusiness owners may strategically default on their loans in order to reduce their financial burden, even if they will lose the ability to take out loans with the organization. However, when MFI's motivate timely payment with incentives, like bonuses, a client's likelihood of strategic default diminishes. The prospect of receiving a reward motivates more strongly than the potential to lose their ability to work with the MFI.

While these studies show that there are a variety of ways to prevent loan default, none address this underlying cause, systematic financial and business illiteracy. Many MFI clients receive insufficient and/or ineffective education, resulting in this phenomenon. Consequently, these approaches may never completely eradicate non-strategic default.

Financial and Business Literacy

As discussed, the lack of financial and business knowledge in MFI clients has a significant effect on their likelihood of loan default (Sangwan, Nayak, and Samanta 2020). Individuals who have not received needed financial lessons simply are not as well equipped to repay loans with success. This point proves crucial to MFI's because women, the illiterate, and those with only primary-level education have proven to have lower financial literacy (Karakurum-Ozdemir, Kokkizil, and Uysal 2019). Microfinance organizations tend to target these exact groups with their services. For example, Grameen Bank, the renowned, first microfinance non-profit, focuses on extending loans to impoverished women who often have not received much education. The organization's founder, Muhammad Yunus (1999), found that women tend to use microloans to start businesses and support their families, while men tend to squander the funds. These findings show the need for MFI's to extend financial education to their clients. However, a debate has arisen as to the effectiveness of financial and business education.

Kaiser and Menkhoff (2017) conducted a study to test if financial education truly could boost financial literacy. The researchers found that financial education resulted in the same learning outcomes as other topics. However, the study also found that specific functions, like the handling of debt, and certain populations, such as those living in low and lower-middle income economies, require more intense learning at a teachable moment (Kaiser and Menkhoff 2017). Essentially, when individuals partake in long-term financial learning, they receive as good of results as those studying other fields, proving that the topic is not too difficult or unintelligible when compared to other academic fields. Individuals can increase their financial literacy. However, the impoverished need more help to achieve these high learning outcomes.

Furthermore, studies have proven that long-term financial learning leads not just to learning outcomes but to substantially improved default rates as well (Fernandes, Lynch, and Netemeyer 2014); (Argawal, Amromin, Ben-David, Chromsisengphet, and Evanoff 2010). These studies assessed the results that financial education has on actual financial outcomes in fields, like real estate. They found that individuals who took financial courses over a long-term period did not just learn concepts but actually improved their loan repayment behavior. Properly executed financial education has improved loan default in a variety of fields. As such, these lessons have the potential to improve repayment amongst MFI client populations as well.

Furthermore, the mobile app studied focuses not just on financial literacy but on business literacy in general, including topics like image, quality control, and more. While these lessons have not proved to increase loan repayment, studies have found them to help individuals launch their businesses more quickly (McKenzie and Woodruff 2014). As a result, clients who utilize these lessons could have the opportunity to expand their operations and open more microbusinesses with increased ease.

Mobile Applications

By the year 2013, 91% of adults in the US owned smartphones (Urban and Sultan 2015). Though this amount decreases in developing nations, a significant portion, 45%, of adults in emerging economies own smartphones as well (Silver and Taylor 2019). This high level of computing power available in a compact size to 3.5 billion people worldwide has ushered in the era of mobile applications (apps) (O'Dea 2020). Apple's iPhone allowed application developers for the first time to sell their coded creations through the iTunes AppStore, supplying entertainment, assisting in learning languages, checking bank balances, and more. Consequently, Apple users downloaded 180 billion apps by June 2017. Taking 87% of all mobile phone use, consisting of an average of 2.5 hours per day, apps have become an essential means of communication and engagement between organizations and their clients (Narang and Shankar 2019).

Mobile apps have also increased in popularity as a means of educating individuals. Popular education apps, like Duolingo and Udemy, can teach their users almost anything: languages, coding, advanced mathematics, and more. These software options prove particularly beneficial because of their monetary efficiency, portability, accessibility, and their ability to cater to a variety of learning styles. Education mobile apps can offer lessons in many different formats. A video will effectively teach audial/visual learners, while a text transcription will work better for those who learn best with just visual stimuli. An MP4 file will effectively teach audial learners, while activities will work better for experiential learners. Mobile applications can offer whole or aspects of lessons to cater to each of these learning preferences (Ozata and Keskin 2014). Another study found that, due to these features, mobile learning results in strong satisfaction and learning outcomes (Yu, Zhu, Yang, and Chen 2019). Essentially, no matter how an individual prefers to learn, apps can easily format lessons to suit those needs. Furthermore, studies have shown mobile apps as a promising means of educating the illiterate and underserved (Kim, Miranda, and Olaciregui 2008). As apps can format lessons in audio files and videos, those who cannot read can still obtain important knowledge, skills, and news through pre-recorded, verbal lectures. As such, mobile apps have become strong platforms to facilitate education in a variety of subjects to a variety of individuals.

HYPOTHESIS

Based on the established knowledge of past studies and conceptualizing financial literacy as a form of learning, we developed the following theory. MFI clients who download and use business/financial education mobile applications will gain important financial knowledge because these interventions can be tailored lessons to a variety of learning styles (Yu, Zhu, Yang, and Chen 2019). Even the illiterate can obtain needed knowledge through pre-recorded audio or video lectures. The knowledge that they obtain will allow users to gain financial expertise over the long term, increasing their financial literacy (Kaiser and Menkhoff 2017). This boost in financial literacy will cause positive microloan repayment behavior (Fernandes, Lynch, and Netemeyer 2014). *Figure 1* displays this phenomenon in a graphical display.

METHODOLOGY

Data Collection

By partnering with Esperanza International, an acclaimed MFI that operates in the Dominican Republic, we analyzed data from the NGO's actual operations. First, the MFI shared its data on its 10,995 clients from September of 2018 to November of 2019. These customers had created a total of 14,757 loan accounts. This difference between clients and loan accounts means that the same client could have multiple loans in their name simultaneously. This data gave extensive information on each client and each of their loan accounts, like gender, income, loan amount, loan activation date, the type of business that they run, etc. Most importantly, this dataset tracks payment behavior, whether or not the client has paid off their loan, is paying it on time, is in arrears, or has defaulted.

Next, Esperanza International worked with Move Up, an education-focused NGO, to implement a business education mobile app. This app offers needed lessons in finance and business skills, ranging from bookkeeping to quality control, to MFI clients. Offering the lessons in the form of an application allows users to access these lectures whenever they have a spare moment and to do so within the comfort of their homes. Screenshots of the app, *images 1, 2, and 3,* can be found in Appendix II.

We utilized the company's data from its first draft of the app, which used a provider named Instancy. Instancy's reporting gave the name of the individual who downloaded the application, their email, the percentage of each course that they completed, the date that they downloaded the app, the date that they began using the app, and the last day that they accessed the service. A total of 184 unique users downloaded the app. These 184 users were associated with 315 loans because of Esperanza clients' ability to take out multiple loans simultaneously. During the analysis stage of this project, Esperanza abandoned its work with Instancy and began to utilize the services of another provider, called Ed App. This change will allow for more robust reporting as the organization continues to study the effects of such mobile apps on loan repayment.

Before we discuss descriptives and modeling, we must explain some caveats within the data. First, the mobile app and client data lacked temporal ordering. The datasets did not track the clients' payment behaviors before and after their date of download. It merely, showed a snapshot of their financial standing with Esperanza on the day that the company extracted the data. Without this time-sensitive information, one cannot assume causation in the effects studied. Additionally, we assessed the actual population of Esperanza clients who downloaded the app, not a random sample. As such, those who downloaded the app may have already had a predisposition to pay loans on time. Due to the lack of randomization of downloaders, we can only infer association, not causation.

Data Descriptives

First, we combined Esperanza's client dataset with those of the education app. By matching user and client information according to the names associated with the files, we consolidated the data into one table. This consolidation would later give us the ability to conduct regressions and descriptive statistics.

Next, this combined table required extensive data cleaning. Dataset errors tended to fall into two categories: name misspellings and outliers. Many Dominicans have extravagant names spelled in a variety of fashions. This factor combined with lower literacy levels and user error led to many individuals misspelling their names either in the Esperanza dataset, in that of Instancy, or in both. Consequently, the combined dataset would track one client's information in multiple, separate rows. We searched for app users missing columns of client information and matched them to the corresponding client rows.

Next, outliers persisted throughout the data set. For example, some clients had claimed that they supported several hundred dependents. Others stated that they had incomes of several million pesos. In order to rectify these claims and others, we calculated the outlier bounds for all quantitative, continuous variables and removed any data points that laid outside of those boundaries. This changed the datasets from unruly distributions to skewed, but reasonable, ones.

We then created categorical variables within the dataset in order to run regressions and descriptive statistics. This involved assigning numbers to represent certain qualitative variables. The two most important categorical variables were the "Download" and "In Arrears" variables. "Download" displayed a 0 if the client had not downloaded the app and a 1 if they had. "In

Arrears" produced a 0 if the user had paid their loan on time or had paid off the loan, showing a 1 only if Esperanza considered the client in arrears. This means that the loan recipient was late on their payment, the first step towards default. We also created a time-sensitive download variable which displayed a 1 if the client downloaded the app before taking out their loan. However, this variable failed to aid us because only about 15 clients had downloaded the app before taking out their most recent loan. This small sample size proved insignificant in statistical tests and models.

In an attempt to hold all else equal, we used a variety of categorical and continuous control variables, removing other effects that could inhibit the phenomenon occurring between x and y. These variables consisted of demographic variables: gender, dependents, and household income. Furthermore, we included information on client businesses and MFI activity: business type, loan product type, loan amount, total loans, principal paid, and the branch office of the MFI with which that they work.

First, the categorical, control variables included gender, business type, loan product type, and branch. Gender assigned a 0 for males and a 1 for females. The business type variable gave a 0 to clients who offered services and a 1 to those who sold products. The loan product type variable assigned a 0 to individuals who received group loans and a 1 for those who obtained individual loans. Lastly, branch gave a number to signify each of Esperanza internationals branch offices: 1for Santo Domingo, 2 for El Seibo, 3 for Hato Mayor, 4 for La Romana, 5 for Puerto Plata, 6 for Samaná, 7 for San Pedro de Macorí, 8 for Santo Domingo East, 9 for Santo Domingo North, and 10 for Santo Domingo West.

Next, the continuous variables consisted of dependents, household income, loan amount, total loans, and principal paid. Dependents tracks the number of non-working persons who live in a client's home. This could consist of children, grandchildren, elderly family members, etc. Household income tells the sum of Dominican pesos that client families (only if they live under the same roof) earn monthly. Loan amount states the number of pesos that a client received from their most recent loan. The total loans variable indicates the total number of loans, both completed and current, that the client has taken out with Esperanza. Lastly, principal paid teaches how much of their most recent loan a client has paid back. With the variables created, the analysis could begin.

First, descriptive statistics aided in gaining an understanding of needed information about the sample, such as the number of clients, how many clients downloaded the application, how many clients paid their loans on time, and more. The tables in Appendix II show the average characteristics of the Esperanza client population studied.

Table 1 shows that we analyzed MFI clients who, on average, have about 2 dependents, bring in a household income equivalent to about $350 USD in monthly income, and take out loans of about $300 USD. *Table 2* indicates that Esperanza predominantly caters to females and those who offer products rather than services in their businesses. *Table 2* also shows that about 20% of Esperanza clients are considered "In arrears," meaning that they paid their loan late or have failed to pay thus far. This peaked our interests and we utilized model-free evidence to further investigate this phenomenon.

The results of *Table 3* showed that a significantly higher percentage of MFI clients who had not downloaded the education app were considered in arrears. Esperanza considered 20.52% of non-downloaders and only 4% of downloaders in arrears. In order to determine if these results proved statistically significant, we conducted a T-test. The p-value output of 0.079 showed that this phenomenon had significance only at a 90% confidence interval. Nonetheless, we decided to further investigate this phenomenon by running regressions.

Statistical Model

We selected regressions as the main test due to their ability to determine if an association exists between one or more *x's*, independent variables, and a *y*, the dependent variable, and give insight as to why the phenomenon occurs. In order to begin creating regression models, we used the following dependent and independent variables.

- Dependent variable (in arrears or not)

$$y_{ij} = \begin{cases} 1 \; if \; loan \; j \; was \; not \; repaid \; (Arrears) \\ 0 \; otherwise \end{cases}$$

- Independent variable (downloaded app or not)

$$D_i = \begin{cases} 1 \; if \; customer \; i \; downloaded \; app \\ 0 \; otherwise \end{cases}$$

These two variables of primary interest would teach whether an association exists between downloading business/financial education apps and certain payment behaviors with MFI clientele. Furthermore, we decided to run both linear and logistic regressions as a robustness check, only assuming a result to be true if it proved significant in both models.

Linear Regression

Linear regressions allow us to quantify the linear relationship that lies between an *x* and a *y* (Kleiser 2020). As such, the results of linear regressions are graphically depicted as a straight line passing through a scatterplot. This model has two main purposes: to predict an outcome, within reason, and see how the independent variable(s) influences the dependent variable. Though we do not attempt to predict an outcome due to data limitations, linear regressions can be a powerful tool in finding an association between a *y* and one or more *x's* (Kleiser 2020). As such, it will help to see whether a relationship exists between downloading the app and timely loan repayment. The regression uses the following equation.

Equation 1. Linear Regression

$$y_{ij} = \beta D_i + \boldsymbol{\gamma Controls} + e_{ij}$$

This type of model assumes that data is continuous in nature, going from negative to positive infinity, and has a normal distribution. Additionally, this model requires homoscedasticity, meaning that the error term is the same across all independent variables. The model also assumes that *x's* do not have multicollinearity. This means that the *x's* must be fixed and independent of each other (Kleiser 2020).

Logistic Regression

In order to ensure that the results are not an artifact of functional/model choice, we also estimated a logistic regression (given that the dependent variable is binary and categorical in nature). Logistic Regression serves as a special form of regression built to work with a binary *y*. At its core, this model estimates the odds of *y* occurring given various values of *x* (Kleiser 2020). As such, it makes sense that its equation, listed below, is a modified version of the linear regression that sets itself equal to the odds equation.

Equation 2. Logistic Regression

$$\frac{p}{1-p} = \beta D_i + \boldsymbol{\gamma Controls} + e_{ij}$$

This model serves a dual purpose, to determine the probability that something occurred based on an observed discrete variable and observed independent variables and to predict, within range, whether or not the event will occur (Kleiser 2020). Logistic regressions exist because utilizing a binary *y* violates one of the main assumptions of linear regressions, that the model uses a continuous *y* (Kleiser 2020). For this reason, we relied most heavily on logistic regression.

Both the dependent and independent variables of main interest are binary. As such, using this model allows us to assess whether or not downloading the mobile app is a predictor of timely loan repayment. Furthermore, this phenomenon causes the relationship between x and y to be bounded by 0 and 1. This formatting removes the effect's linear nature, fitting on a scatterplot not as a straight line, but an s-curve (Kleiser 2020). As such, logistic regression more aptly fits this type of data.

We must reassess other assumptions used in linear regressions as well. This model cannot assess linearity or homoscedasticity. Furthermore, errors cannot be normal as logistic regressions use the assumption that the data follows a logistic distribution. The data still cannot have multicollinearity; however, one cannot conduct a test to see if this condition exists. As such, one must assess whether or not this state exists by looking at correlations within the dataset (Kleiser 2020).

Interaction Variables Used in Both Models

Lastly, we created a variety of interactions, which would test if the effects seen between downloading the app and loan repayment compounded or diminished when including other variables. This would allow us to examine whether downloading the mobile app had a blanket effect on payment behavior across all MFI clients or if it varied based on certain characteristics. These interactions would assess the loan, business, and demographic characteristics of the MFI clients studied. As such, the interactions would show whether the mobile app should be targeted at certain groups who see better payment outcomes than others, increasing the NGO's profits. These variables could also teach if certain populations do not receive an effect from downloading the app. Reducing its focus on these individuals would allow the MFI to save funds it would have used to advertise its services to them. These interaction variables included download and total loans, download and business type, and download and gender. Download and total loans shows the total amount of loans taken out by those who downloaded the app. Download and business type tells whether a client offers a product or a service if they have downloaded the application. Lastly, download and gender displays the gender of those who have downloaded the app.

RESULTS

Model Accuracy

The model has contributed a variety of outputs which leads to our conclusions; however, before drawing inferences from the information, one must assess the accuracy of the data. After running confusion matrices of the logistic regression, the main tool used to assess the effects studied, the researchers found that the model had a 79.45% accuracy rate, also known as a hit rate. This promising output shows that the model does hold credibility. Nonetheless, it does have one caveat. Most people in the dataset do not go in arrears. Therefore, the models predict those who do not go in arrears with higher accuracy than those who do.

Regression Outputs

Table 4 shows that our variable of main interest, download, proved to have a negative and significant relationship to the in arrears or not variable in both models. As such, we found an association between MFI clients downloading financial and business education apps and having timely payment behavior.

Table 4 also showed that other control variables have significant relationships with the in arrears or not variable. First, business type's negative and significant relationship to the *y* proved that offering a product rather than a service in a microbusiness increased the likelihood of timely loan repayment. Furthermore, having taken out more total loans with the MFI caused this same effect. This phenomenon makes sense as, in order to receive a new loan, MFI clients must pay off their previous loan. Thus, these individuals already have a history of positive repayment.

One other variable of interest had an intriguing result as well. Typically, MFI's offer their loans to women, as Muhammad Yunus (1999) wrote about their increased propensity to repay their loans and use them properly when compared to men. As such, one would expect to see an association between males and negative payment behavior. However, this does not exist. *Table 4* indicates that the gender variable is insignificant, meaning that no relationship lies between a particular gender and going in arrears. This is likely due to the fact that Esperanza has already selected credit-worthy males.

Interaction Effects

Additionally, *Table 4* shows all three interactions proved insignificant. The first of these data points indicates that no association exists between people of a certain gender who downloaded the app and poor repayment behavior. This aligns with the fact that gender proved insignificant in both regressions as well. As such, having a particular gender does not cause any additional association with timely loan repayment after downloading the app. Next, the interaction between app downloaders and business type had an insignificant result. As such, the relationship between product providers and timely loan repayment remains; however, downloading the app does not cause any further effect on this phenomenon. Lastly, the download and total loans interaction proved insignificant as well. Though the linear regression output shows significance, the logistic regression output states the opposite. This inconsistency caused us to qualify this interaction as insignificant. Essentially, the relationship between having taken out a higher number of loans and positive payment behavior remains; yet, no further effect ensues by downloading the app. These interactions' insignificant outputs teach us that downloading the app has a blanket effect on all MFI clients, not causing stronger or weaker payment behavior based on the variables investigated.

Odds Ratio

The logistic model utilizes the odds ratio concept:

$$Odds\ ratio = \frac{p(event)}{p(no\ event)}$$

This equation gives the odds ratio output, helping to interpret the magnitude of the effect studied. To interpret the results given in *Table 5*, subtract 1 from the odds ratio output. This will show the odds of an outcome occurring expressed as a decimal. As such, results below 1 are negative odds, results greater than 1 are positive odds, and results equal to 1 indicate a 0% likelihood.

Table 5 shows that a 91.15% effect exists between the *x* and *y*, meaning that a downloader in this study was 91.15% less likely to go in arrears. This effect seems far too high and likely comes from the limitations previously stated: lack of temporal ordering and lack of a random sample of downloaders. As such, we decided to use the lower bound of the confidence interval instead, stating that at least a 60.47% effect exists between the *x* and *y*. However, even that seems like far too large of a magnitude. Consequently, we do not place much weight upon this output but do state that it displays that a relationship truly exists between the two variables.

Simulation

The odds ratio output shows us that app downloaders were at least 60.47% more likely to pay their loans on time. Assuming this to be true, at least 60.47% of new downloaders should not go in arrears. This simulation applies this effect to new app downloaders as the application's penetration in Esperanza's client population increases. This allows us to estimate a minimum of how many clients will be considered in arrears after the effect of downloading the app activates. With fewer clients in arrears, MFI's earn higher revenues. Going in arrears is the first stage to loan default, causing these NGO's to lose money. With lower funds, MFI's cannot extend their services to as many impoverished individuals, decreasing the reach of their missions. Furthermore, a history of going in arrears and defaulting on loans can cause MFI's to cease working with a client, inhibiting their rise from poverty.

With regressions displaying at least a 60.47% effect between app adoption and positive payment behavior, *Table 6* shows the potential benefit of increasing app penetration within the Esperanza client population from the status quo of 1.67% to 2.67%, 5% and 10% of all customers. In order to do so, we multiplied 60.47% times the total number of downloaders who would be considered in arrears. This gave an approximation of the number of downloaders who would now be associated with positive repayment behavior. Next, they subtracted this result from the total number of clients considered in arrears to display the potential reduction of poorly repaying MFI customers. The results showed that a linear relationship exists between the number of individuals who use the app and the number of clients who have an association with timely loan repayment. Essentially, as more people download mobile learning interventions, MFI's could see a direct relationship with this growth and the number of their clients who repay their loans on time.

Table 6 shows the strong, potential benefit of utilizing resources to increase app penetration. Growing the number of adopters to just 10% of the client population caused a minimum of a 4.5% (134 person) reduction in the total number of clients in arrears.

CONCLUSION

We conclude that an association exists between microloan repayment and the downloading of business/financial education mobile apps. Those who downloaded the application had significantly better loan compliance than those who did not. However, we cannot prove causation between the downloading of the app and the positive payment behaviors exhibited due to a lack of temporal ordering in the data and the use of an unrandomized sample. Few clients downloaded the app before they had taken out their most recent loan. As such, this small population size proved too insignificant to study. Additionally, those who downloaded the app after taking out their loan could already have begun the habit of paying their loans on time before installing.

Moreover, we used the population of Esperanza International's clients who actually downloaded the application. Consequently, we did not have the opportunity to select a random sample of clients to study. This could mean that the studied population already had a propensity to pay off their loans on time. Due to these data limitations, we cannot say that downloading mobile business interventions causes an improvement in financial literacy and, as a result, payment behavior among MFI clients. However, we do conclude that MFI clients who downloaded the business/financial application have a higher likelihood of timely loan repayment.

Furthermore, even though MFI's typically lend to women as a means to decrease the probability of default, males who downloaded the app did not display any different loan repayment behavior. Additionally, Esperanza clients who provide product offerings in their microbusinesses usually have a lower likelihood of going in arrears. However, this effect did not compound when clients downloaded the app. Higher amounts of total loans, both past and present, that a client had taken out had a positive effect on the client's likelihood of repayment as well. Yet, downloading the application, once again, did not cause any further outcome on this effect. As such, it seems that downloading the business/financial education mobile app has a blanket effect across all MFI client populations, not causing females, product providers, or more experience loan recipients to increase their likelihood of repayment more than males, service providers, or clients who have had fewer loans.

Furthermore, using this study as a model to predict the future growth of successful, paying clients shows promising results for MFI's. The 60.47% association between app adopters and timely payment shows that increasing app penetration from 1.67% to 10% of the total client population could a minimum of a 4.5% decrease in the number of clients who would fall in arrears. As such, business/financial education mobile apps hold promise as a means to solve the systematic issue of undereducation and poor financial literacy amongst MFI clients. This aid will cause an increase in loan repayment amongst MFI clients, increasing these organizations' revenues and allowing them to extend loans to more individuals attempting to rise from poverty.

CONTINUED RESEARCH

This research shows promise lies in the use of business/financial education mobile applications in the field of microfinance. However, due to data restrictions, it could not show causality. Future research should consider collecting data with temporal ordering to explore causation. Furthermore, the ability to create a randomized sample of app users among an MFI's client base will help to reveal whether this education initiative can solve the problem of poor loan repayment in microfinance. Utilizing a random sample will take away the possibility that the downloaders studied already had a propensity to pay on time.

A variety of future projects could stem from this research as well. One could investigate whether general business or financial lessons contribute to stronger repayment among MFI clients. This study would help these organizations to make even more effective education interventions by offering more lessons that return better results.

Another study of vital importance could repeat the steps conducted here and include whether or not the clients actually used the app or just downloaded it. This research would allow us to assess the benefit of MFI clients utilizing a business/financial education mobile app over a long-term period, not just downloading it. Furthermore, it would show whether the actual learning outcomes of the courses cause a further, positive effect on payment behavior.

Lastly, a study could test the long-term effects of mobile learning on microbusiness success, examining not just if MFI clients gain better repayment habits but higher profits to bring home to their families.

APPENDIX I: WORKS CITED

Agarwal, Sumit, et al. "Financial Literacy and Financial Planning: Evidence from India." SSRN Electronic Journal.

Brihaye, Thomas, et al. "Positive Versus Negative Incentives for Loan Repayment in Microfinance: A Game Theory Approach." Review of Development Economics, vol. 23, no. 2, 2019, pp. 577-597.

Cassar, Alessandra, Luke Crowley, and Bruce Wydick. "The Effect of Social Capital on Group Loan Repayment: Evidence from Field Experiments." The Economic Journal, vol. 117, no. 517, 2007, pp. F85-F106.

Dufhues T, Geppert M, Buchenrieder G. Combining quantitative and participatory methods in conjoint analysis. *Savings and development*. 2003;27(3):281-294. http://www.econis.eu/PPNSET?PPN=378234838.

Fernandes, Daniel, John G. Lynch, and Richard G. Netemeyer. "Financial Literacy, Financial Education, and Downstream Financial Behaviors." Management Science, vol. 60, no. 8, 2014, pp. 1861-1883.

GALAK, JEFF, DEBORAH SMALL, and ANDREW T. STEPHEN. "Microfinance Decision Making: A Field Study of Prosocial Lending." Journal of Marketing Research, vol. 48, no. SPL, 2011, pp. S130-S137.

Garg, Rajiv, and Rahul Telang. "Inferring App Demand from Publicly Available Data." MIS Quarterly, vol. 37, no. 4, 2013, pp. 1253.

Gomila, Robin. "Logistic or linear? Estimating causal effects of treatments on binary outcomes using regression analysis." (2019).

Hamdinio, Hamdan, and Wan Hussin Wan Sabri. "Is microfinance program in Malaysia really effective in helping the poor?." World Review of Buisiness Research 2.1 (2012): 79-97.

Kaiser, Tim, and Lukas Menkhoff. "Does Financial Education Impact Financial Literacy and Financial Behavior, and if so, when?" World Bank Economic Review, vol. 31, no. 3, 2017, pp. 611-630.

Kim, Paul, Talia Miranda, and Claudia Olaciregui. "Pocket school: Exploring mobile technology as a sustainable literacy education option for underserved indigenous children in Latin America." International Journal of Educational Development 28.4 (2008): 435-445.

Kleiser, Susan. “Regression Analysis.” Marketing Analytics. 27 Apr. 2020, Fort Worth, TX. Texas Christian University.

Kleiser, Susan. “Logistic Regression Analysis aka ‘Logit’.” Marketing Analytics. 27 Apr. 2020, Fort Worth, TX. Texas Christian University

Karakurum-Ozdemir, K., M. Kokkizil, and G. Uysal. "Financial Literacy in Developing Countries." Social Indicators Research, vol. 143, no. 1, 2019, pp. 325-353.

Meyer RL. The demand for flexible microfinance products: Lessons from bangladesh. *Journal of International Development*. 2002;14(3):351-368. https://onlinelibrary.wiley.com/doi/abs/10.1002/jid.884. doi: 10.1002/jid.884.

McKenzie, David J., and Christopher Woodruff. "What are we Learning from Business Training and Entrepreneurship Evaluations Around the Developing World?" World Bank Research Observer, vol. 29, no. 1, 2014, pp. 48-82.

Narang, U., and V. Shankar. "Mobile App Introduction and Online and Offline Purchases and Product Returns." Marketing Science, vol. 38, no. 5, 2019, pp. 756-772.

O'Dea, S. “Smartphone Users Worldwide 2020.” Statista, 28 Feb. 2020, www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/.

OZATA, F. Z., and Nilgun O. KESKIN. "Students’ Preferences and Opinions on Design of A Mobile Marketing Education Application." Turkish Online Journal of Distance Education, vol. 15, no. 1, 2014, pp. 189-205.

Sangwan, Sunil, Narayan C. Nayak, and Debabrata Samanta. "Loan Repayment Behavior among the Clients of Indian Microfinance Institutions: A Household-Level Investigation." Journal of Human Behavior in the Social Environment, 2020, pp. 1-24.

Taylor, Kyle, and Laura Silver. Smartphone Ownership is Growing Rapidly Around the World, but Not always Equally. Pew Research Center, 2019.

Urban, Glen L., and Fareena Sultan. "The Case for "Benevolent" Mobile Apps." MIT Sloan Management Review, vol. 56, no. 2, 2015, pp. 31-37.

Yu, ZG, et al. "Student Satisfaction, Learning Outcomes, and Cognitive Loads with a Mobile Learning Platform." Computer Assisted Language Learning, vol. 32, no. 4, 2019, pp. 323-341.

Yunus, Muhammed. Banker to the Poor. Public Affairs, 1999.

APPENDIX II: FIGURES, TABLES, AND ANALYSIS OUTPUTS

Figure 1. Conceptual Map of Mobile App Adoption's Relationship to Financial Outcomes

Table 1. Descriptive Statistics Using Continuous Variables

Continuous Variables		
	Mean	SD
Dependents	2.225	1.495
Income	17644.15	5585.682
Loan Amount	15148.71	5698.451
Principal Paid	10030.68	6230.676
Average Number of Loans	4.525	5.468

Table 2. Descriptive Statistics Using Categorical Variables

Categorical Variables	
	Percentage
Download	1.67% downloaded
Gender	22.31% male
Business Type	76.86% product offering
Loan Product Type	10.22% individual loans
In Arrears	20.17% in arrears

Table 3. Model Free Evidence: Account State by Download or Non-Download

Account State by Download or Non-Download			
	Closed	Default	In Arrears
Non-download	43.88%	1.11%	20.52%
Download	51.11%	0.00%	4.13%

Table 4: Linear and Logistic Regression Outputs

Dependent Variable = In Arrears or On Time	Linear Regression			Logistic Regression			
	Estimate	Std. Error		Estimate	Std. Error		
(Intercept)	0.183	0.019	***	-1.359	0.130	***	
Download	-0.241	0.065	***	-2.413	0.824	**	Main Interest
Gender	-0.001	0.009		-0.028	0.057		Control
Dependents	0.002	0.002		0.014	0.016		Control
Business Type	-0.032	0.009	***	-0.201	0.056	***	Control
Household Income	-1.000	0.000	.	-1.000	0.000		Control
Loan Amount	0.000	0.000	***	0.000	0.000	***	Control
Loan Product Type	-0.026	0.015	.	-0.136	0.103		Control
Total Loans	-0.007	0.001	***	-0.069	0.007	***	Control
Principal Paid	-1.000	0.000	***	0.000	0.000	***	Control
Branch	0.016	0.002	***	0.092	0.010	***	Control
Download X Total Loans	0.010	0.004	*	-0.225	0.734		Interaction
Download X Business Type	0.015	0.059		0.092	0.059		Interaction
Download X Gender	0.013	0.064		0.599	0.760		Interaction
N	14757.000						
R Squared	0.089						
Adjusted R Squared	0.088						
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1							

Table 5. Linear Regression Odds Ratio Output

Odds ratio and 95% Confidence interval			
	OR	2.50%	97.50%
(Intercept)	0.257	0.1991	0.3315
Download	0.0895	0.0147	0.3953

Table 6. Effect of App Penetration Growth on the Number of Clients In Arrears

% Growth in App Penetration of Total Population				
	Status Quo (1.67%)	2.67%	5%	10%
Number of Downloaders	184	294	550	1100
Number of Clients In Arrears	2976	2940	2909	2842
% Change in Number of Clients In Arrears		1.20%	2.25%	4.51%

Image 1. Ed App Homepage

Image 2: Lesson Overview

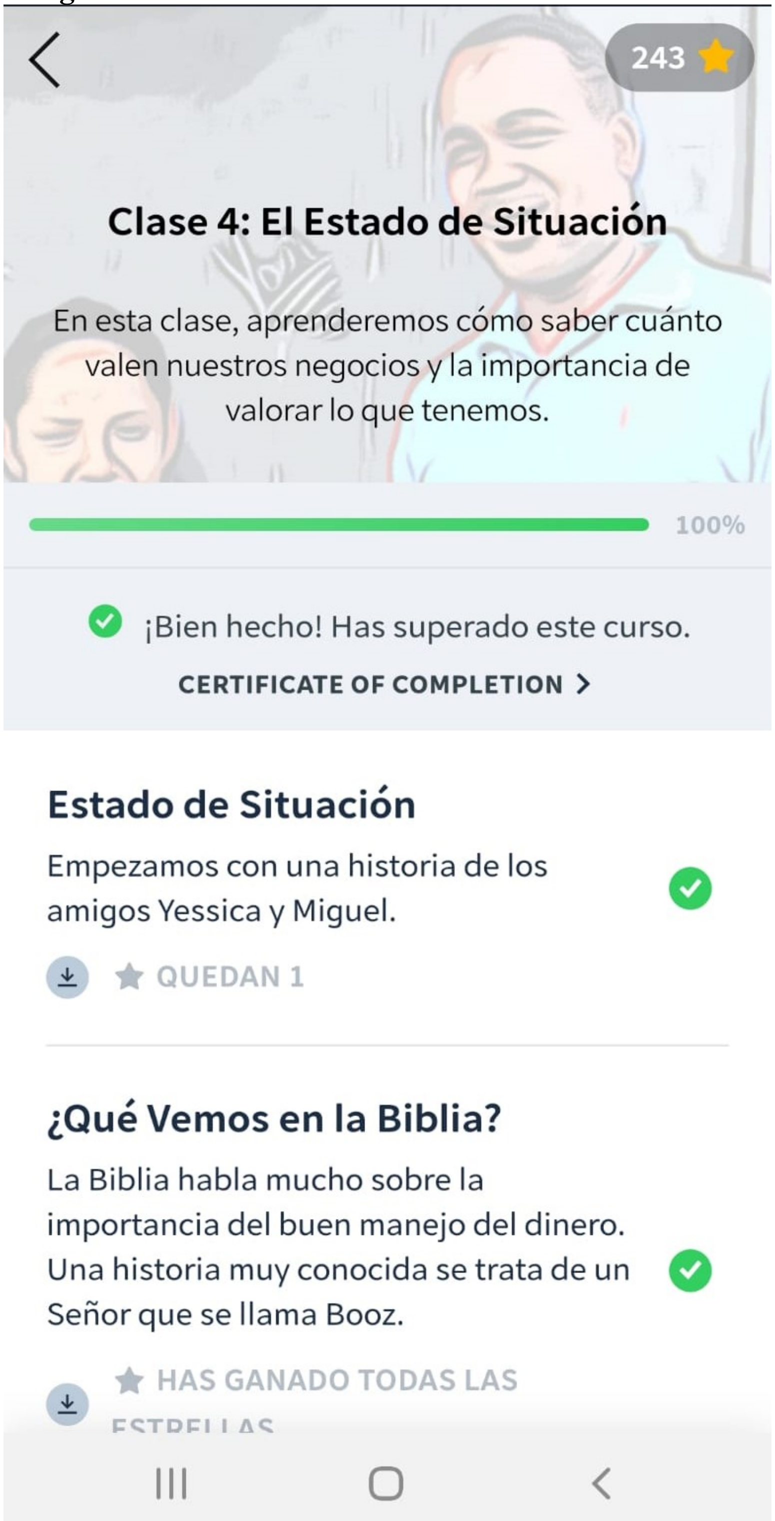

Image 3. Financial Lesson