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DIGITAL CREDIT TERMS AND LOAN DEFAULT AMONG UNIVERSITY STUDENTS IN UGANDA

(A case study of COBAMS, Makerere University)

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ABSTRACT

The study's purpose was to establish the relationship between digital credit terms and loan default/payment. The study execution was based on quantitative approach with primary data being collected from 254 sample of students of both graduate and undergraduate programs of the College of Business and Management Sciences of Makerere University. Correlation and regression was conducted and a dprobit model was used for estimation purposes. the results indicate that 79.5% of the respondents were undergraduate students. The results further indicate a significant relationship between education level and loan default/payment with a p value of 0.023 at 95% level of confidence. We recommend that since the current credit terms do not consider education level, digital credit providers must take it up and incorporate it in the credit appraisal framework

KEYWORDS: Digital credit terms, loan default/payment and Education level

1. INTRODUCTION

Uganda's economy has been stable despite the COVID 19 pandemic shock. The economic growth improved to an estimated 6.3% (African Development Bank Group, 2019). This is reflected in the stability of inflation at around 3.7% and the shilling appreciation against the United States dollar of 1.2%. The Ministry of Finance, Planning and Economic Development's economic performance report (2020) indicates that Uganda's financial sector did well in the year 2020 with growth in private sector credit of about 0.8%. Whereas the private sector credit indicates an improvement, Uganda's interest rates on credit are still high, ranging between 18% to 24%. This is expensive for any borrower.

The economy's under development and poverty levels at hand, influence households' inadequate income to support their families. This is translated to the education sector where youths pursuing university or tertiary education may fail to get means of acquiring essential services. One of the sources of financing university students' requirements is debt. The study by Oosterbeek and Van den Broek (2009) indicate the factors influencing borrowing behavior for university students in Netherlands to include; debt aversion, failure to find employment and funding education.

It is noted that, Uganda's youth employment statistics indicate that 67.9 percent of youths are underutilized while 14.7% are not employed at all (International Labour Organization report, 2015).

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Vol. 3, No. 02 Mar-Apr; 2021

The youths who are in the age ranges of 19-29 are prone to financial constraints because they have neither jobs for incomes nor access to cheap and easy financial services. In any case, financial institutions require collateral which they do not possess in addition to high interest rates.

Youths at Uganda's institutions of higher learning require facilitation, this is in form of tuition fees, daily maintenance and data for internet access. This kind of service is not afforded by parents or guardians. Therefore, it is expected that if the youths have no source of income, yet they have to spend, they are left with an option of borrowing. It is against this backdrop that the study investigated the lending and borrowing environment for University students.

The university students are early adopters of new technologies. They invent and always try out many technologies available on the market. Since Uganda's credit market has a lot of impediments to credit access, many innovations have been introduced as interventions to let people gain access to credit facilities. For instance, digital credit providers involve partnering with banks or third party such as Financial Technologies (FINTECH) and telecommunication companies such as; Mobile Telecommunication Network (MTN) and Airtel to champion loans on the mobile telephone to provide digital credit. Since university students are youthful and would risk for opportunities, the probability for taking up credit facilities amidst financial challenges may be high.

Lenders provide credit on specific terms to hedge against default risks. The traditional loans through financial institution counters are provided on well documented credit terms. However, digital loans especially through mobile phones are provided without clear terms of credit. Understanding the credit terms for the digital credit facilities is important to the current consumers and the potential consumers.

According to Mazer & McKee (2017) digital credit refers to credit products—including digital payments products such as mobile money—that are delivered fully via digital channels, such as mobile phones and the internet. Groupe Spéciale Mobile Association (2016) defines digital credit as "a credit service which is available on basic mobile devices, and allows customers to borrow an unsecured loan and repay within a specific timeframe via mobile money". This is in agreement with Carlson (2017) who defines Digital credit as unsecured loans where credit decisions are made instantaneously based on mobile data and loans are requested, delivered, and repaid electronically.

According to Consultative Group to Assist the Poor (2016), digital credit differs from traditional credit in three key ways: digital credit is instant: the time taken from loan application to approval to disbursement is minimal, often less than 24 hours; it is automated: creditworthiness and loan decisions are determined by automated processes rather than by people; and it is remote: interactions between lenders and borrowers take place over digital channels, rather than in person (Chen & Mazer 2016).

Credit terms in this context refer to standards or negotiated terms offered by the lender to the borrower that control the monthly and total credit amount, maximum time allowed for repayment, and the amount or rate of late payment penalty (Kakuru, 2008). In this study, digital credit terms are meant to be the terms issued to all potential borrowers on digital platforms.

Loan default is about the inability of the borrower to fulfill the terms in a credit agreement, especially settling the principal and instalment amounts (Balogun & Alimi, 1990). This position was re-emphasized by Ameyaw-Amankwah (2011), loan default occurs when an individual fail to make the required contracted amounts on borrowing.

On a global scale, digital credit terms appear to be the common cause of loan defaults for digital borrowers (Consultative Group to Assist the Poor, 2018). However, in Uganda, studies have not yet provided evidence of the contribution of credit terms to digital loan defaults. Uganda's research on digital credit lending and borrowing is limited. The closest study by Ebong and Babu (2020) concentrated on the factors that drive demand for credit in highly-density Kampala markets. This study, however, concentrated on digital credit terms and loan default among University students in Uganda. The study, therefore, intended to interrogate the credit terms provided by the digital lenders commonly through telecommunication companies to borrowers.

The study was conducted at Makerere University Kampala. Being an academic institution with majority of its students ranging between 19 – 30 years of age, Makerere University has many youths who can be potential digital borrowers. The borrowers of digital credit in the university often get money to solve short term challenges, such as medical, food, transport and clothes. The students in Makerere University were estimated at 33,288 according to the Makerere University Revenue Service Unit (2017). Most of these students don't have jobs yet they get financial challenges. Therefore, they need emergency loans to survive during the semester. Digital credit has now seemed to be the only way for them to meet their short-term needs. However, many cannot pay back the loans, citing high interest rates and short grace period. If analytics and big data accurately predicts repayment in our context, digital credit providers may not need to bother about credit terms. This research, therefore, seeks to investigate the relationship between credit terms and loan default among digital borrowers in Makerere University Kampala.

The study is organized in the following way: section one is about background of the study, section two is the literature review of the study, section three presents the study methods, section four presents the study findings, section five is about the discussion of findings and section six is about the study conclusions and recommendations.

1.1. Theoretical framework

Information asymmetry theory

Auronen, (2003) states that the theory of information asymmetry makes it difficult to distinguish between good or bad borrowers and it arises when gaining information on the characteristics or on the behavior of the borrower is costly for the financial institution. The theory explains that in the market, the party that possesses more information on specific item to be transacted (in digital credit case the lender) is in a position to negotiate optimal terms for the transaction than the other party (in this case, the borrower). Asymmetric information makes it difficult for a would-be creditor or insurer to be sure whether the expected probability distribution over state-contingent payoffs associated with a contract promise is the one being represented by the seller or not. Information asymmetry cause adverse selection (Wilson, 2008). For this study, the borrowers cannot easily access information about credit terms, so sometimes they borrow with ignorance of the terms thus adverse selection of the digital credit facility.

2. LITERATURE

2.1. credit terms and loan default

Siaw, Ntiamoah, Oteng, and Opoku (2009) indicated that, high interest charged by the microfinance banks has been discovered to be the reason behind the alarming loan default. The lending rates to borrowers in Uganda are high, often up to 21% per year (Mugume & Rubatsimbira, 2019). This is partly because these lenders face a higher risk of loan defaults than mainstream banks due to lack of borrower data to support lending decisions. Commercial banks in Uganda charge interest rates of around 24% per annum while digital credit lenders charge the highest interest rate (108%) per annum. An explanation for digital credit may be that low-income people have a complex understanding of the costs of borrowing and may factor in transaction costs, a major feature of the cost of borrowing for the poor. If the interest rate for a loan is high, then the risk of default also gets high. Kimuyu and Omiti (2000) point out that high interest rates not only transfer incomes from borrowers to lenders but also occasion a debt burden on borrowers reducing borrowers' stakes in solvency and increasing the risk for default.

According to Makorere (2014), grace period is the period given by the financial institution to the borrower before the first installment is due. In other words, it is considered to be the time between when the loan was disbursed to the loan applicant and when the first installment is paid. While conducting a study in Tanzania, Makorere (2014) found out that most of the financial institutions tend to provide a grace period of one month only, which was seen not to be sufficient for the small business enterprise owners to start realizing enough revenue for them to start paying their loans. In digital credit, however, loan terms are typically no longer than a month (e.g., M-Shwari) but may be as short as a week (e.g., Airtel Malawi). SACCOs have grace period of three months on principal repayments, though interest payments are due during the grace period. If the loan term is too short, the borrower fails to generate revenue to enable him/her make repayments while a longer loan term may make the client extravagant and the client may in the end fail to pay back. The short grace period of digital credit is most likely to cause high default rates.

Furthermore, Microfinance Institutions can evaluate their needs, assess their character and capacity for repayment and determine the appropriate loan amount using financial expertise. The size of the loan, which in most cases is directly related to the size of the borrower, the age of the company, or the length of the bank-borrower relationship, can also be an indicator of credit risk (Jiménez & Saurina, 2003). Smaller loans like those of digital credit tend to involve small or newly created companies, whose risk is greater and, therefore, whose loans will be subject to higher rates of default. Digital loan amounts are not very large - the average M-Shwari loan is about USD 12 (Cook & McKay, 2015). By contrast, loans to large companies tend to be lower risk due to their generally greater financial solidity. Additionally, large scale loans tend to undergo much more rigorous screening, thus resulting in a lower level of credit risk. Since digital credit is small, instantaneous and accessed mostly during shocks, the likelihood of default is high after the borrower has fulfilled his/her need.

According to Zeller (1994) collateral value requirements deter SME borrowers from seeking credit. However, collateral requirement does not apply in digital credit. Digital credit providers use non-traditional data (in particular, mobile money, airtime usage, mobile call data records, bill payments to Internet browsing patterns and social media behavior) to create a new way to assess consumer risk, determine the creditworthiness of previously “invisible” consumers, and consequently offer convenient, quicker, and often cheaper loans to the previously underserved large groups of individuals without collateral or traditional scores. Safavian, Fleisig, and Steinbuks (2006) observed that commercial banks usually provide larger loans, longer repayment periods, and lower interest rates when borrowers offer collateral. This means that a borrower who cannot provide the type of assets lenders require as collateral often gets worse loan terms (a case of digital credit) than otherwise because they are more likely to default. Indeed, Lehmann and Neuberger (2001) note that borrowers who provide more collateral receive a better rating.

Empirical findings by Yeboah and Oduro (2021) indicate that, education is a significant factor influencing loan default. This is to say that education influences a person to pay or not to pay the loans. Jote (2018) established that manager’s education level affects business’ ability to re-pay the borrowed credit. Mustafe, Willy and Muhammed (2019) avow a significant positive relationship between education level and loan repayment. Implying that the more the person attains advanced education qualification, the more likelihood he will pay the loan facilities extended to him.

In addition to the above conditions, age of the borrower is identified as another influencer of loan repayment (Absanto & Aikaruwa, 2013). It was established in Nigeria that farmers at a relatively young age have better credit repayment culture compared to older farmers (Ojiako, Idowu & Ogbukwa, 2014). May be, at an advanced age, about 40 years, farmers get more social challenges but with less energy to work in gardens. In contrast, Pasha and Negese (2014) argue that in Ethiopia, the older the microfinance borrowers, the better the credit repayment history. Less default is expected from older persons as opposed to the young borrowers. The above discussion therefore leads to the following hypothesis: HI: Digital credit terms have a significant and positive effect on loan default/payment among university students at Makerere (COBAMs).

3. METHODOLOGY AND DATA

3.1. Methodology

To establish the relationship between digital credit terms and Loan default among university students in Uganda. A quantitative cross-sectional approach was employed. The cross-sectional approach was used because data was collected at a particular point in time (Creswell, 2009).

The study population consisted of 750 students from the College of Business and Management sciences at Makerere University (Admission list, Registrar's office 2018). The College of Business and Management Sciences has the highest number of students at Makerere University, this justifies the ease of obtaining an adequate sample size. The target population comprised the third year undergraduates doing Bachelor of Commerce (250), Bachelor of Business Administration (150), Bachelor of Arts in Economics (150) and Masters students (200) because these have been in possession of mobile telephones for at least two years using either airtel or MTN and are eligible to borrow than those in first and second year.

A sample design refers to the technique or the procedure the researcher would adopt in selecting items for the sample (Kothari, 2004). In this case, simple random sampling was adopted to select the students who would participate in the study based on the clusters of Bachelor of Commerce, Bachelor of Business Administration, Bachelor of Arts in Economics and Masters. A sample of 254 respondents was used for the study basing on the Krejcie & Morgan (1970) sample size calculator. The sample was drawn from students that have mobile phones and have ever obtained a loan facility with any digital credit provider (i.e. MTN & Airtel) in Uganda. The students colist for sampling purposes were obtained from the office of the College president.

In this study, data collection was conducted by administering a questionnaire. This was designed on a 5 point Likert scale ranging from strongly disagree (1) to strongly agree (5) were used to collect primary data directly from the field. The adapted survey questionnaire was divided into three sections; biographic information, digital credit terms and nature of default. A 5-point Likert scale was used showing (1)" strongly disagree", (2) "disagree", (3) "slightly agree", (4) "agree", (5) "strongly agree".

The questionnaire was administered by well-trained research assistants. The questionnaire administration took a maximum period of 15 minutes.

To ensure reliability, the questionnaire was pre-tested on 40 respondents before the actual surveys. The constructs were reliable where credit terms scored 0.877, nature of default scored 0.765, and relationship between credit terms and loan default scored 0.915. This indicates that the data collected was reliable. Javali (2011) confirms that the preferred statistical index that is used to measure reliability of the measuring instrument for collecting primary data is Cronbach's alpha. Where Cronbach's alpha was greater than 0.7 ($\alpha > 7$), the researcher concluded that the data collected using survey was reliable.

3.2. Data analysis

Data were analyzed first by way of descriptive, exploratory factor analysis was conducted to reduce on the factors which are not fit for the constructs, thereafter, pairwise correlation matrix was used to determine the suitability of variables to conduct regression analysis. The exclusion criteria are, for any correlation whose coefficient is 0.8 or above, the variables may need transformation, otherwise, they may not be fit for regression. After the correlation process, the regression was conducted using the probit model and marginal effects (dprobit) to establish the extent of the relationship between credit terms and loan default. To generate the probit model, the scale factors were transferred to binary at both dependent and independent variable. The marginal effects were used because constants and coefficients in modelling do not provide adequate economic meaning. The analysis software employed was (Stata version 15). The regression model employed was expressed as below;

$$Y=\alpha + \beta_1 X_I + \beta_2 X_2 + \beta_3 X_3 + +e$$

Where,
Y= loan default – as measured by complete non repayment & payment after intervention
α = constant term
X_1 – independent variable: interest rate on digital credit
X_2 – independent variable: grace period of digital credit
X_3 - independent variable: loan size
e- Error term

3.3. ETHICS CONSIDERATION

Ethics is an important aspect of business research. Participants needed confidence that their involvement in research would neither lead to violation of their rights nor harm them. Permission to conduct research with participants was sought and the researcher ensured that he obtained participants' consent freely before the survey were conducted. Confidentiality as far as respondents' views is

ISSN 2582-2292

Vol. 3, No. 02 Mar-Apr; 2021

concerned was maintained throughout the study as respondents were not required to disclose their identity and no names were identified for those participating in the study. Finally, I obtained permission from the graduate administration office to conduct this research.

4. FINDINGS AND RESULTS

This section presents the findings of the study. The section covers the characteristics of the respondents, the descriptive, the factor analysis, the correlation and regression analysis.

4.1. Demographic findings of the study

Figure 1: Sex of the respondent

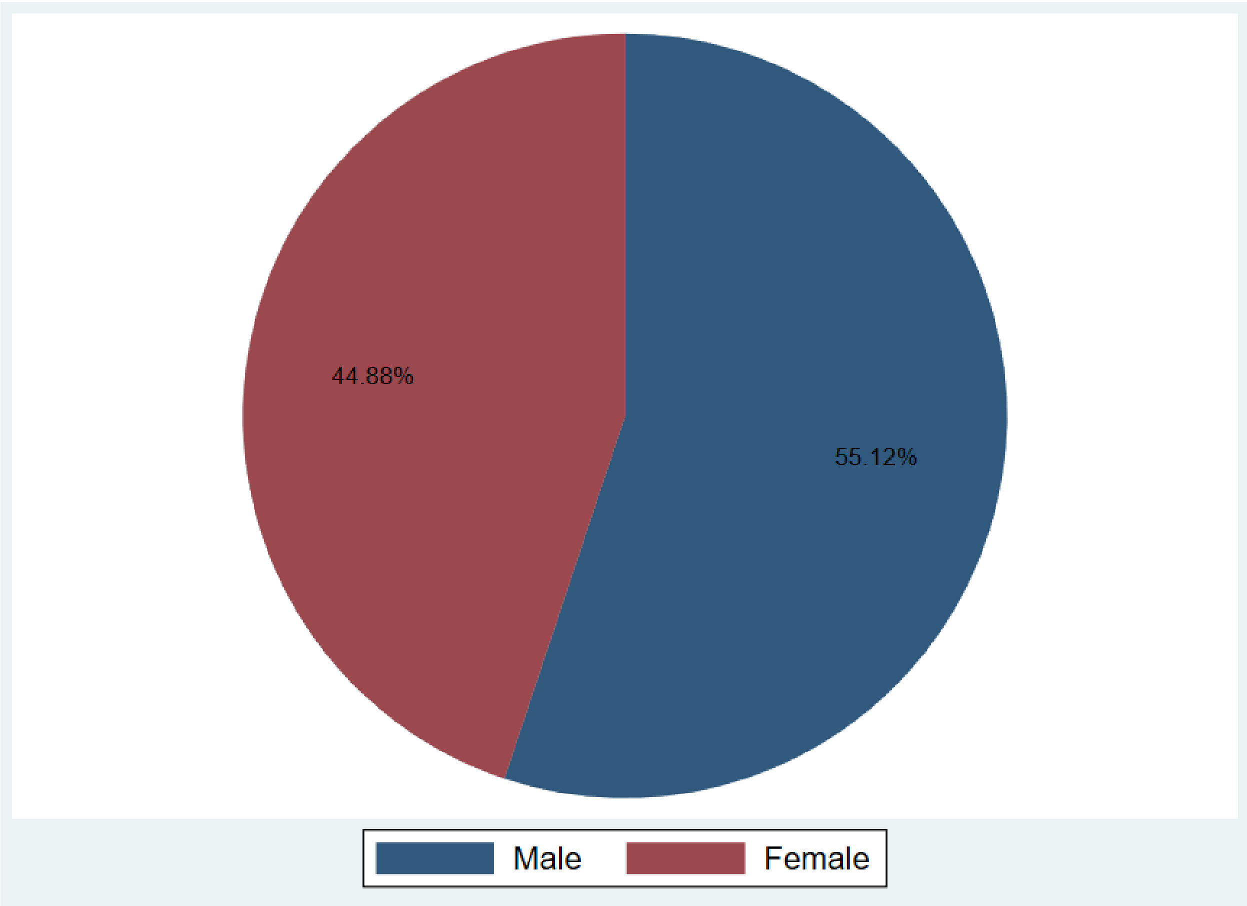

Figure 1 above shows that the study registered more male respondents at 55.12% compared to female respondents at 44.88%. This implies that male students are more active whenever an activity is introduced at the College of Business and Management Sciences.

ISSN 2582-2292

Vol. 3, No. 02 Mar-Apr; 2021

Table 1: Age of respondent

age of the respondent	Freq.	Percent	Cum.
18-27	198	77.950	77.950
28-37	39	15.350	93.310
38-47	17	6.690	100.000
Total	**254**	**100.000**	

Source: Primary data

Table 1 above indicates that the college of Business and Management Sciences has more students in the age range of 18-27 years. These are 198 out of 254 who responded to this study. This is 77.97%. The next age range was represented by 15.35%. This implies that more students at College of Business and Management Sciences are youths.

Table 2: Education level

Education	**Frequency**	**Percent**	**Valid percent**	**Cumulative percent**
Undergraduate students	202	79.5	79.5	79.5
Masters students	52	20.5	20.5	100
Total	**254**	**100**	**100**	

Source: Primary data

Table 2 indicates that the most respondents to this study were students pursuing undergraduate programs. This implies that, undergraduate students are readily available for initiatives introduced at the College than the postgraduate. This is perhaps because they are unemployed and have no extra commitments outside the University.

ISSN 2582-2292

Vol. 3, No. 02 Mar-Apr; 2021

Table 3: The Mean, standard deviation, minimum, maximum and range of the data

Variable	N	mean	Sd	min	max	cv	range
Age	254	1.287	0.583	1	3	0.453	2
Gender	254	1.449	0.498	1	2	0.344	1
Occupation	254	1.083	0.276	1	2	0.255	1
Educ level	254	1.205	0.404	1	2	0.336	1
varying grace period & loan size	254	3.098	1.352	1	5	0.436	4
varying grace period & rate	254	3.024	1.433	1	5	0.474	4
rate encourages willing to pay	254	3.543	1.332	1	5	0.376	4
rate encourages repayment	254	3.567	1.177	1	5	0.330	4
no interference from loan officers	254	3.524	1.306	1	5	0.371	4
no legal framework	254	3.571	1.245	1	5	0.349	4
Loan size & customer default	254	2.717	1.388	1	5	0.511	4
Information provided	254	3.051	1.361	1	5	0.446	4

Table 3, indicates the average age ranges of the respondents were 1.287. this is not to say that respondents were under age, but the age ranges were clustered in four groups of 18-27, 28-37, 38-47 and 48-57. The average education qualification was 1.205, this is also because the education level was categorical.

The data needed not to be transformed into logs because the min and max values were not wide. In this case, they were single digits.

ISSN 2582-2292

Vol. 3, No. 02 Mar-Apr; 2021

4.2. Reliability Test

The reliability test indicates Cronbach's alpha of 0.8303. This is to confirm that the questionnaire measured the constructs for digital credit and loan default/payment consistently.

4.3. Factor analysis

The factor analysis was conducted to determine the items with the highest factor loadings. These items were used in further data analysis. We used component factor loadings and Varimax rotation method.

Table 4: Factor analysis for credit terms

Rotated Component Matrix[a]			
	Component		
	Grace period	Interest rate	Loan size
Grace period varies with loan size	.833		
Grace period varies with interest rate	.747		
Grace period varies with savings	.664		
Interest rate enhances willingness to pay		.793	
Interest rate encourages first time borrowers		.717	
Interest rate remains fixed throughout the repayment period		.525	
Loan size depends on credit history			.688
Loan size varies with the level of saving			.687
Loan is not enough for the intended purpose			.582
Eigen values	**2.812**	**1.413**	**1.19**
% of Variance	**25.562**	**12.844**	**10.175**

Table 4 indicates that all components of the credit terms (grace period, interest rate and loan size) have Eigen values greater than 1. This shows that the components can be used for further analysis. The table 4 also indicates that all factors with factor loadings above 0.6 can be used for further analysis.

ISSN 2582-2292

Vol. 3, No. 02 Mar-Apr; 2021

Table 5: Factor analysis for loan default

Rotated Component Matrix[a]		
	Component	
	Payment after intervention	Complete non-repayment
Lack of interface with loan officers when processing the loan	.798	
Absence of strict legal regulation on digital credit	.735	
Grace period provided by digital credit providers	.559	
Loan size leads to complete non-repayment		.775
Inability to understand all the T&C leads to complete non-repayment		.711
Lack of collateral on digital credit leads to complete non-repayment		.645
Eigen values%	**2.532**	**1.262**
% Variance	**28.132**	**14.017**

Table 5 indicates that both components of loan default/payment have an Eigen value exceeding 1. This implies that both components can be confidently used for further analysis. The factors which are above 0.6 can be taken further for analysis. They have the highest factor loadings.

4.4. Correlation between credit terms and loan default

Table 6: Pairwise correlations matrix

Variables	(varying_graceperiod & Laonsize)	(varying_graceperiod & rate)	(rate_encouragewillingness)	(rate_encouragerepayment)	(no_interface_loan officer)	(no_legal_framerk)	(loansize_customer)	(information_provided)
(1) varying_graceperiod &loansize	1.000							
(2) varying_graceperiod &rate	0.452* (0.000)	1.000						
(3) rate_encourage willingness	0.130 (0.038)	0.258* (0.000)	1.000					
(4) rate_encourage repayment	0.005 (0.943)	0.105 (0.097)	0.320* (0.000)	1.000				
(5) no_interface_loan officers	0.029 (0.647)	0.122 (0.052)	0.220* (0.000)	0.025 (0.695)	1.000			
(6) no_legal_framework	0.074 (0.237)	0.121 (0.054)	0.167* (0.008)	0.045 (0.472)	0.406* (0.000)	1.000		
(7) loansize_customer	0.002 (0.971)	-0.042 (0.502)	-0.256* (0.000)	-0.046 (0.462)	-0.134 (0.033)	-0.055 (0.386)	1.000	
(8) information_provided	-0.033 (0.603)	-0.114 (0.069)	-0.050 (0.425)	0.031 (0.621)	-0.057 (0.362)	0.083 (0.187)	0.091 (0.146)	1.000

**** p<0.01, ** p<0.05, * p<0.1*

The correlation matrix in table 6 above, indicates no variable with a correlation coefficient of 0.8 and above. Therefore, there is no need for data transformation. The variables can be used to run the regression analysis.

4.5 Regression analysis

The study's major objective was to investigate the relationship between credit terms and loan default/payment among digital borrowers of Makerere University students in Kampala. The initial equation was $Y=\alpha + \beta_1X_I + \beta_2X_2 + \beta_3X_3 + e$ (as explained in methods section). However, after factor analysis and correlation, the equation was transformed to be; Loan payment after intervention=i.age +grace period + i. Occupation +interest rates + i. Education level+ i. Gender. This form of equation was employed because age, gender, occupation and education level were categorical variables. The actual equation was expressed as shown in the brackets (xi, noomit: asdoc dprobit loancat i.age gracpp i. Occupation intrate i. Educ_level I. Gender).

We adopted a dprobit model because, the data was transformed to binary for both dependent and independent variables. In addition, the marginal effects were taken care of because of the constant which had no economic meaning.

Table 7: Regression model

loancat	dF/dx	Std.Err.	z	P>z	x-bar	[95%	C.I.]
_Iage_2*	-0.158	0.130	-1.270	0.205	0.165	-0.413	0.097
gracpp*	-0.067	0.065	-1.010	0.311	0.688	-0.195	0.060
_IOccu~2*	0.059	0.125	0.450	0.655	0.059	-0.186	0.303
intrate*	0.008	0.063	0.130	0.900	0.515	-0.116	0.132
_IEduc~1*	-0.231	0.078	-2.280	0.023	0.844	-0.383	-0.079
_IGend~1*	0.113	0.062	1.830	0.067	0.540	-0.008	0.234
obs. P		0.696					
pred. P		0.704	(at		x-bar)		

Where; Gracpp = grace period, Occu= occupation, intrate = interest rate, Educ= education level and Gend=gender of the respondent.

The model in table 7 above indicates that only education level is Significant and positively related with loan default. Loan default as explained in methods is represented by, ability to pay or not to pay after intervention has been administered.

In this study, we realize that most respondents were undergraduate students. The regression results indicate that its only Educ_level which is significant. However, the negative marginal effect of -0.231 implies that, after undergraduate level, the chances of a student paying back/defaulting the digital credit after application of intervention is 23.1%. After undergraduate, it is expected that any borrower will have the capacity and moral authority to pay back the digital loan before any intervention is applied. In this case, we confirm the hypothesis that, digital credit terms have a significant and positive effect on loan default/payment among university students at Makerere (COBAMs). The digital credit providers in the current arrangement do not consider education level as an important credit term. So the lending mechanism is currently missing this.

5. DISCUSSION OF FINDINGS

The study findings revealed only education level as the significant factor in estimating the relationship between digital credit terms and loan default/payment. In this study, the estimated p value was 0.023, implying a significant relationship. The reported marginal effect of -0.231, implies that, after undergraduate, the chances of a student defaulting of digital credit is 23.1%. The results are in agreement with Jote (2018) who established that manager's education level affects the credit repayment. The results are also consistent with, Mustafe et, al (2019) who established a significant positive relationship between education level and loan repayment in Somalia. At the same time, the study results concur with Yeboah and Oduro (2021) who established that education is a significant factor influencing loan default.

6. CONCLUSIONS AND RECOMMENDATIONS

It can be concluded that, whereas there are other credit terms for digital credit lending for instance grace period, interest rates and occupation, in Makerere University, education level of the borrower is the only significant factor influencing loan default/payment of digital credit. Currently, education level is not being considered by providers of digital credit to be a viable credit term.

Since the study has established education level as a significant credit term, we advise the digital credit providers to consider incorporating education level as criteria for evaluating digital credit borrowers before extending digital credit. This may provide better safe guard to credit borrowing in Uganda as it has been proved to work elsewhere for instance in Nigeria, Ghana and Somalia.

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