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Inclusion of peer group and individual low-income earners in M-Shwari micro-credit lending: a hidden Markov model approach

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Abstract: The M-Shwari micro-credit lending system has excluded the low income earners as they lack good financial options due to volatile and fluctuating income. This paper proposes a decision support system for credit scoring and lending of the low income earners who are customers of M-Shwari using the hidden Markov model. The model emits the credit scores of the customers, both for the peer groups and the individual customers. The learning and training of the model utilises the customers’ socio-demographics, telecommunication characteristics and account activities. The peer groups have higher credit scores and are more attractive to offer credit facilities using M-Shwari when compared to the individual borrowers.

Keywords: peer group; low-income earners; electronic finance; M-Shwari; micro-credit lending; hidden Markov model; HMM; individual.


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1 Introduction

In the year 2012, a partnership between Safaricom Kenya (a telecommunication company) and the Commercial Bank of Africa (a registered commercial bank in Kenya) started a mobile-based microcredit facility dubbed M-Shwari (‘Shwari’ means calm in Swahili) based on the M-Pesa platform. The product offers a combination of savings and access to micro-credit loan and the target market was to capture both the banked and unbanked in an effort to increase financial inclusion (Cook and Mckay, 2015). The platform, M-Pesa (‘M’ for mobile and ‘Pesa’ is Swahili for money), was started by Safaricom Kenya in the year 2007 as a mobile phone-based money transfer system. M-Pesa has become one of the most successful mobile phone based financial services in the developing world (Jack and Suri, 2011). Kenya is one country where there are more mobile money accounts than deposit accounts with commercial banks (Deesai, 2012). The use of M-Pesa is mostly limited to transfer of funds between account holders with minimal saving patterns exhibited by the users who have each cut a niche depending on their needs (Mbiti and Weil, 2011).

Some of the features of M-Shwari are: allow customers to save and access credit; the cost of moving money between M-Pesa and M-Shwari is free; account maintenance is free; no transfer of funds between M-Shwari and a bank account, only between M-Shwari and M-Pesa, then M-Pesa to a bank account; and credit scoring algorithm used for accessing a loan from M-Shwari is based on a set of telecommunication variables from Safaricom data related to airtime, M-Pesa transactions, airtime credit and length of time as a customer (Cook and Mckay, 2015). The use of these set of variables is similar to behavioural scoring which is a dynamic process as the frequent changes in the customer activities are observed and updated in the mobile system (Liu and Zhong, 2012). The features highlighted by Cook and Mckay (2015) limit the ability of the low income earners to access M-Shwari due to limited resources, thus the low income market
segment is excluded from financial inclusion as they lack good financial options. Their income is volatile, fluctuating daily and they lack reliable ways to harness the power of their low income (FSD, 2014). Challenges remain on how M-Shwari can capture credit quality of the low earners who are limited to deposit average cash in their accounts, have minimal usage of airtime and other services offered by the telecommunication company, Safaricom Kenya. One advantage of this product is that it enables customers to save as little as one shilling (USD 0.01) and access a micro-credit loan of a minimum of one hundred shillings (USD 1.0). This is an opportunity for the low income earners who are customers of M-Shwari and excluded from the formal banking sector to access credit facilities.

The use of mobile credit has increased the ability of consumers to apply and receive loan over mobile devices, avoiding the expense and paperwork of traditional loan application. The existence of mathematical algorithms that are able to collect, sift through the applications and apply weightings to the data means that the evaluation of the loan applications requires no human intervention (Blechman, 2016). Basically, the loan application decisions are automated with customer relations being handled remotely via customer call centres, repayments and collections managed through short message reminders (Hwang and Tellez, 2016).

In this paper, we propose a decision support system based on hidden Markov model (HMM) to estimate the credit scores and credit quality levels as low, medium and high (LMH) of the M-Shwari low income customers. The parameters for the HMM are derived from the dynamics of the customers’ deposits, withdrawals, usage of M-Pesa services, airtime, length of time the customer has been with Safaricom Kenya, and the socio-demographic factors of age, gender and marital status. A need exists to leverage customer access to a mobile phone with data of customer subscriptions to and use of voice, short message services and digital payments for credit lending process (Hwang and Tellez, 2016). We note that HMM can be utilised to build a classification model to classify the customers into different risk groups (Benyacoub et al., 2014). The study then compares the peer group borrowers and individual borrowers to analyse which of the two outperforms the other in terms of credit scores. The purpose is to introduce peer group lending to the already existing individual lending with M-Shwari micro-credit mobile facility. Group lending is a joint liability that allows individuals to replace physical collateral by social collateral. The data for credit scoring is easily accessible to Safaricom Kenya as long as a customer uses the telecommunication services. This is to offer low income earners a peer group micro credit facility that is mobile-based with an aim of increasing financial inclusion in Kenya from the current rate of 82.5% adults (FSD, 2016).

We develop a decision support system that can enable M-Shwari to incorporate peer group lending through credit scoring using the HMM. No known research work that has developed such a decision system to support mobile-based peer groups lending. Section 2 considers the literature review on HMM, socio-demographic characteristics, peer group lending and role of micro credit in an economy. Section 3 present the HMM, its mathematical components and the singular value decomposition (SVD). Section 4 has the credit scoring using HMM, how to estimate the HMM data with simulation and the selection of the peer groups. The results are presented in Section 5 and conclusions in Section 6.
2 Related work

The users of M-Shwari are able to save with a possibility of accessing a micro-credit loan and this promotes individual outcomes (FSD, 2010). As lending is at the heart of an economy financial architecture, M-Shwari could offer a life line for the micro-credit challenges due to lack of information of the low income customers (Deesai, 2012). The perceptions about mobile banking and technology determine the rate of adoption as income alone is not a sufficient indicator (Ivatury and Pickens, 2006). A study by FSD (2016) notes that 17.5% of the adult population in Kenya does not have access to any form of financial services. An individual is more likely to use a mobile phone followed by an informal group (known as chamas in Swahili), a bank, savings and credit organisations and then a micro-finance institution for financial services. The MobiScore system is a consumer credit default model based on mobile phone calling details recorded by telecommunication companies. This type of data is easily accessible, can leverage the lack of financial histories in developing countries and increase access to credit (Pedro et al., 2015).

A need exists on how the low income segment of the market can access financial services as this enhances financial inclusion. M-Shwari can cover this gap. Studies on micro-credit facilities observe that a positive change in income is observable when the poor use these facilities (Ahlin and Jiang, 2008; Chavan and Ramakumar, 2002). A key pointer is the poor to save and access credit as this brings an economy from stagnation to full development. The ability to accumulate savings and use of other variables for credit scoring is critical to assist the low income earners benefit from micro-credit program (Ahlin and Jiang, 2008).

The financially responsible customers are often excluded from credit due to lack of historical financial data (Pedro et al., 2015). The use of alternative big data, machine learning and artificial intelligence models could reduce the cost of credit, lending operational costs and risks and the monitoring processes of the credit. The role of big data and alternative information for credit scoring and lending is expected to increase exponentially in the future (Jagtiani and Lemieux, 2017). The mobile phone usage data to infer personality traits or the socioeconomic status is known to have a positive relationship with financial behaviour (Pedro et al., 2015).

The applications of HMM for solving different problems are available. Netzer and Srinivasan (2008) developed a customer relationship dynamics model to estimate the effects of encounters between the customer and the firm, customer firm relationship. A model for the default rates in a bond portfolio using HMM is undertaken (Crowder et al., 2005). A model for credit card transaction processing sequence as a stochastic process using HMM shows a drastic reduction in the number of false positive transactions (Srivastava et al., 2008). The HMM is dynamic in observing a sudden downgrading of a customer credit worthiness. Quirini and Vannucci (2014) note that HMM and related tools are essential to assess the credit risk in order to gain profitability in the complex and fluctuating credit market.

A model based on HMM (Hassan and Nath, 2005) for the stock market forecasting showed a 100% accuracy rate in the prediction. Ntwiga (2016) study used social network (media) data to credit score obligors and estimate default rates in a loan portfolio using HMM. The model has an accuracy rate of between 53% and 73% and offers promising prospects of using social data to improve on credit risk modelling. The work of Daniel and Grissen (2015) did not use HMM but the mobile phone usage data to predict loan
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In a developing country, the behavioral signatures in mobile phone data are able to predict default with accuracy than the approach of credit scoring using financial histories. If the data is used, the bank can reduce defaults by 41% while still accepting 75% of the borrowers.

Researchers have considered the influence of socio-demographic characteristics on credit risk of consumers. The male customers have a higher probability of default compared to the female clients, but the recovery rates were found to be similar between the male and female customers (Marrez and Schmit, 2009). For the age factor, the age group of 20–25 years old are more likely to default compared to the group of 61–70 years old. The work of Marrez and Schmit (2009) further considers the age, gender and marital status among other variables. The young cardholders have a higher chance of default compared to the older cardholders. The married defaults in 24% of the cases while the single customers tend to default in 36% of the cases when marital status was considered. Gender and marital status are statistically significant in affecting default rates for credit card holders.

The socio-demographics are key in this study but we also wish to compare the credit scores of the peer group borrowers and individual borrowers for optimality. Group lending yields a higher safeguard to the financial institution compared to individual lending (Bhole and Ogden, 2010) as group lending outperforms individual lending (Gomez and Santor, 2003). For a peer group lending to be effective, the size of the loan, level of trust and enforcement of social norms with the group or surrounding neighbourhood are important (Gomez and Santor, 2003). In peer groupings, as the group size increases, efficiency reaches a moderate threshold and recommends a group of four to ten members in group borrowing (Ahlin and Jiang, 2008).

3 Hidden Markov model

An HMM is a double embedded stochastic process with two hierarchy levels in which the system being modelled is assumed to be a Markov process with an unobserved state. This field of HMM became more acceptable after a seminal paper was published by Rabiner (1989). In a Markov model, the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. In HMM, the state is not directly visible (hidden) but output, dependent on the state, is visible. Each state has a probability distribution over the possible emissions. This sequence of emissions gives some information about the hidden states (Ntwiga, 2016).

HMMs are capable statistically to characterise and estimate the signal in a precise and well defined manner (Rabiner, 1989). These models are inexpensive, intuitive and versatile for modelling stochastic processes, to estimate and track activities based on noisy information. States involved are finite and state space is known but the current state of the process is not known with certainty and has to be estimated from whatever evidence is available (Bilmes, 2006).

HMMs are increasingly becoming popular due to its strong statistical and theoretical structure which forms a basis for its wide applications. Hassan and Nath (2005) outlines some advantages of HMM from its strong statistical foundation, ability to handle new data robustly, predict similar patterns efficiently, computationally efficient to develop and
evaluate due to availability of training algorithms. Bilmes (2006) observes that HMM are ideal given enough hidden and observation distributions and sufficient training data.

However, every model has its limitations: HMMs are based on Markov property that the probability of being in a given state at time \( t \) depends only on its state at time \( t - 1 \); the amount of data for training HMM is large and sometimes hard to obtain; the observations in the model are assumed to be independent and this is normally violated in most cases; the distribution of individual observation parameters are best represented as a mixture of Gaussian densities (Ntwiga, 2016). Despite these limitations, HMM is an ideal model for credit scoring purposes.

We classify M-Shwari customers based on their credit scores and credit quality levels as captured by use of their socio-demographic factors, age, gender and marital status; the customer characteristics with the telecommunication company, length of being a user of the mobile services, usage of airtime and M-Pesa services; and M-Shwari account activities, account balance, saving ratio, duration the money is saved and the general account rating of each member. The general account rating is estimated using SVD. We refer to these ten factors as the credit scoring factors (CSF). Due to the low amount and frequency of deposits and withdrawals, the customers have to run the accounts for a period of between three to six months to offer enough data to capture their credit worthiness. In general, the CSFs are basically derived from the deposits and withdrawals of the customer from the M-Shwari account. We have assumed that they deposit amounts of less than one dollar at any given time as these customers are assumed to be poor and living below the poverty line. The M-Shwari system can detect these poor customers by coding the system to detect amounts below one dollar and mark them as transactions for the poor and unbanked.

The CSFs are estimated through simulation and form the entries of a real-valued matrix for HMM learning and training. A transition matrix \( A_{2 \times 2} \) has good and poor scores for the customers and the observation matrix \( B_{2 \times 3} \) has the three credit quality levels of LMH. The two matrices are derived from the historical data of the customers using the CSFs.

An HMM can be characterised by the following: number of states in the model, state transition probabilities, observation probability distribution that characterises each state, initial state distribution, and the observation symbols (Rabiner, 1989).

- The number of states \( (M = 2) \) in the model with the set of states denoted as:
  \[ S = \{ S_1, S_2 \} = \text{\{Poor, Good\}} \]

- The state transition probability distribution
  \[ A = \{ a_{ij} \} \text{ where } a_{ij} = P[q_{t+1} = S_j | q_t = S_i], t = 1, 2, ..., T \]

- The number of distinct observation symbols \( (K = 3) \) per state. We denote the set of observation symbols corresponding to the physical output of the system being modelled as:
  \[ V = \{ v_1, v_2, v_3 \} = \text{\{Low, Medium, High\}} = \{ L, M, H \} \]

- The observation symbol probability matrix
  \[ B = \{ b_j(k) \}, \text{ where } b_j(k) = P[v_k | S_j], 1 \leq j \leq M \]
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- The initial state probability vector
  \[ \pi = \{\pi_i\} \text{ where } \pi = P[q_i = S_i], 1 \leq i \leq M \]

  We use the notation \( \lambda = (A, B, \pi) \) as the set of parameters of the model

Figure 1 An HMM with two ergodic state transitions and three observation symbols for the M-Shwari peer groups and individual customers (see online version for colours)

3.1 Singular value decomposition

The SVD is a matrix factorisation method that has been used widely in different applications ever since an efficient algorithm for its computation was developed. SVD is a powerful and important technique in matrix computations and analysis as it reduces high dimensional and highly variable set of data to a lower dimensional space that exposes the substructure of the original data more clearly (Carla and Mason, 2012; Ntwiga, 2016). The low rank matrix factorisation method is widely employed in various applications using the best rank one approximation (Tang et al., 2014; Ntwiga et al., 2016). The data extracted with SVD is then scaled in the interval \((0, 1]\) to estimate the individual customer parameters for the HMM training and learning.

4 Credit scoring

Credit scoring improves the forecast accuracy and decreases the default rates by 50% or more and this has seen a significant increase in the number of credit scoring analysis being undertaken (Liu and Zhong, 2012). The probabilistic relationship between M-Shwari customer account activities, the credit scores and the credit quality level are estimated by the HMM. The classifications offer insights on who among the low earners,
that is, the peer borrowers and individual borrowers have strong credit scores and those with weak credit to qualify for a micro-credit loan. The groups are selected randomly based on the computer ordering. The customers are allowed to operate the M-Shwari accounts for a minimum of three months, called the initial period, \( \tau \). We can allow the initial period to vary between three and six months, \( \tau \in [3, 6] \). During this period, the customer account activities and the other CSF are accumulated to have enough data for initial HMM training and learning. The first credit scoring and credit classification is done either at \( \tau = 3, 4, 5, \) or \( 6 \) months and on a monthly basis thereafter.

Let \( Y_i \) be the credit score of customer \( i \) at time period \( t \) with \( i = 1, 2, \ldots, N \). We express \( Y_i = P(\text{O}_1, \text{O}_2, \ldots, \text{O}_t | \lambda) \) as the credit score from the observations during the initial period \( \tau \). This is the initial score that is expected to change at each time period \( t \).

The time \( \tau \) forms the time period \( t = 1 \) and time increment is observed from the fourth month (\( t = 2 \)), fifth month (\( t = 3 \)) and so on with \( t \in [\tau, T] \), where \( T \) is the duration of estimating the M-Shwari customers credit scores and credit quality levels. Let \( \alpha_i, i = 1, 2, \ldots, N \) be the number of customers in a given credit quality score at a time period \( t \), where \( \alpha = \{L, M, H\} \). The estimation of the credit quality level is based on the credit score which is emitted directly by the HMM. The model emits the credit score and credit quality level at the same time. The credit quality levels are dynamic as they are based on credit scores which changes according to the prevailing conditions of the deposits and withdrawals from the M-Shwari customer account.

4.1 Group borrowers

The customers are classified into \( k \) groups with the selection being random with \( k \geq 2 \). Let \( n_k \) be the group size of group \( k \), then, \( N = \sum_{j=1}^{k} n_j \), where \( N \) is the number of customers. The number of the randomly selected groups is estimated with \( k(k+1)/2 \geq N \), which is expressed as \( k^2 + k - 2N \geq 0 \). The Newton Raphson method is used to estimate the size of each group.

Let \( Y_k = P(\text{O}_1^k, \text{O}_2^k, \ldots, \text{O}_t^k | \lambda_k) \), where \( \lambda_k = (A_k, B_k, \pi_k) \), estimated from the members forming group \( k \). The observations are the emissions from the HMM during and after the initial period. Let \( w_n \) be the number of peer group members in a given credit quality level at time \( t \), where \( w = \{L, M, H\} \). The estimated credit quality level is based on the credit score, the HMM emissions.

We do not have benchmark data set available for this study. Simulation, from the uniform distribution, using MATLAB version 7.0.1 is implemented to test the system, assuming that each low income customer has an equal chance of emitting any of the three credit quality levels (low, medium or good).

5 Results

A comparison between the peer group borrowers and the individual borrowers aids in understanding the variations and similarities between the two groups.
Table 1 highlights the mean number of customers in the individual borrowers category versus the peer group borrowers. The peer group members have a superior mean score as the groups in the medium and high credit levels combined ranges between 85% and 91% compared to the individuals whose medium and high credit levels mean score ranges between 74% and 77%. The peer group borrowers have higher credit scores when compared against the individual borrowers.

Table 2 shows that the peer groups are more stable in terms of retaining the groups in their respective credit quality levels based on the credit scores as compared to the individual members. We observe that the group dynamics are more stable compared to the individual members dynamics. An indication that groups offer a more stable credit scores and retain their credit quality levels over long duration of time.

Table 1  Mean values for the credit quality levels of the group and individuals at different time periods

<table>
<thead>
<tr>
<th>Time (years)</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>τ = 6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>0.228</td>
<td>0.586</td>
<td>0.186</td>
<td>0.088</td>
<td>0.882</td>
<td>0.030</td>
</tr>
<tr>
<td>1.0</td>
<td>0.258</td>
<td>0.526</td>
<td>0.216</td>
<td>0.132</td>
<td>0.828</td>
<td>0.040</td>
</tr>
<tr>
<td>1.5</td>
<td>0.258</td>
<td>0.507</td>
<td>0.235</td>
<td>0.150</td>
<td>0.748</td>
<td>0.102</td>
</tr>
<tr>
<td>2.0</td>
<td>0.247</td>
<td>0.496</td>
<td>0.257</td>
<td>0.132</td>
<td>0.740</td>
<td>0.128</td>
</tr>
</tbody>
</table>

Table 2  95% confidence intervals for the peer groups and individuals

<table>
<thead>
<tr>
<th>Time (years)</th>
<th>Customers</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>k = 10</td>
<td>(−0.080, 0.594)</td>
<td>(0.287, 1.085)</td>
<td>(−0.097, 0.211)</td>
</tr>
<tr>
<td>N = 85</td>
<td>(0.186, 0.477)</td>
<td>(0.336, 0.635)</td>
<td>(0.111, 0.255)</td>
<td></td>
</tr>
<tr>
<td>1.5</td>
<td>k = 6</td>
<td>(−0.145, 0.478)</td>
<td>(0.494, 1.145)</td>
<td>(−0.080, 0.108)</td>
</tr>
<tr>
<td>N = 45</td>
<td>(0.112, 0.518)</td>
<td>(0.354, 0.824)</td>
<td>(−0.004, 0.197)</td>
<td></td>
</tr>
</tbody>
</table>

Table 3 highlights the observations made on the individual borrowers and the peer group borrowers when the initial period is varied from three months to six months. This is the time when the initial data for learning and training the HMMs is accumulated. The peer group borrowers need only three months as the initial period to observe their account activities with M-Shwari. The individual borrowers need a minimum of four months as the initial period to track their account activities to achieve the required results. This indicates that the groups are more attractive to lend to as compared to the individuals.

In Table 4, the peer group borrowers have high positive linear relationship that range between 0.566 and 0.913. This shows high levels of consistency in the HMM emissions. Consecutive time periods have high correlation values. For the individual borrowers, the linear relationship ranges between 0.357 and 0.515 during these four time periods while for peer groups it ranges between 0.566 and 0.913. Thus, peer groups have consistent strong credit scores from one time period to another; making them good candidates for lending in the M-Shwari platform.
Table 3  Credit quality levels for the group and individuals at the initial time period

<table>
<thead>
<tr>
<th>Initial period, $\tau$ (months)</th>
<th>Individuals (40)</th>
<th>Peer groups (8)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td>3.0</td>
<td>0.325</td>
<td>0.375</td>
</tr>
<tr>
<td>4.0</td>
<td>0.225</td>
<td>0.675</td>
</tr>
<tr>
<td>5.0</td>
<td>0.200</td>
<td>0.750</td>
</tr>
<tr>
<td>6.0</td>
<td>0.225</td>
<td>0.750</td>
</tr>
</tbody>
</table>

Table 4  Correlation coefficients for the peer groups and the individuals based on the HMM observations

<table>
<thead>
<tr>
<th>Time (Months)</th>
<th>Peer (k = 14) groups</th>
<th>Individuals (N = 130)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>1.0</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>2.0</td>
<td>0.707</td>
<td>1.0</td>
</tr>
<tr>
<td>3.0</td>
<td>0.730</td>
<td>0.913</td>
</tr>
<tr>
<td>4.0</td>
<td>0.566</td>
<td>0.681</td>
</tr>
</tbody>
</table>

Table 5  Descriptive statistics for the peer groups and the individual borrowers

<table>
<thead>
<tr>
<th>Statistic</th>
<th>(k = 13)</th>
<th>(N = 110)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L</td>
<td>M</td>
</tr>
<tr>
<td>Mean</td>
<td>0.143</td>
<td>0.813</td>
</tr>
<tr>
<td>Std dev.</td>
<td>0.143</td>
<td>0.116</td>
</tr>
<tr>
<td>CV (%)</td>
<td>100.4</td>
<td>14.3</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.554</td>
<td>–0.459</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2.025</td>
<td>2.104</td>
</tr>
</tbody>
</table>

The highlights in Table 5 shows that the peer group borrowers mean score is higher for the medium and high credit quality levels compared to the individual borrowers. The variability of the peer groups in the three credit scores of LMH are higher compared to the same scores in the individual borrowers. Group dynamics could be a possible cause of these variations. Kurtosis for the peer group lies in the range of 2, which is lighter tails; and that of the individual borrowers between 1.5 and 3.1 showing that the individuals had both heavier and lighter tails. The extreme outcomes have occurred more in the individual borrower’s category than the peer group borrower’s category.

Figure 2 shows the dynamics of the credit quality levels based on the credit scores of the peer groups and individual borrowers. The peer group category had a superior performance in terms of the credit quality based on credit scores as opposed to the individual customers. This emphasises the importance of using the peer groups as a means of lending due to the strong credit scores they possess.

The bar graph of the percentages of individuals and peer groups credit quality levels based on the credit scores for a period of four months.
Inclusion of peer group and individual low-income earners

6 Conclusions

The deposits and withdrawals of the low income earners can be harnessed to estimate the credit scores and credit quality levels of the agents when an appropriate classification technique like HMM is used. The analysis for the peer groups when compared to the individual borrowers showed sharp contrasts. The peer groups have high levels of consistency, higher credit scores and credit quality levels. The linear relationship between the credit scores at consecutive time periods are high and positive for the peer groups when compared to those of the individual members. Therefore, the peer group outperforms the individual borrowers in terms of the credit scores and credit quality levels.

Safaricom Kenya could enhance financial inclusion through its micro credit facility by incorporating peer group lending in the M-Shwari mobile facility decision system. This decision support system can enhance the financial inclusion in Kenya by increasing the users of M-Shwari, a microcredit facility to gain access to credit. This can encourage and increase the rate of savings among the low income customers through peer groups with a view to access a credit facility. The data for the analysis is easily accessible from the customer usage of the telecommunication services and the groups acts as a social collateral to replace physical collateral.

An extension of this work is to consider how M-Shwari can introduce savings groups (called chamas or saccos in Kenya) to encourage group savings and borrowing amongst themselves using their own funds. The M-Shwari will act as an agent to keep the funds and assist in disbursing them to the members.
References


