Towards a hybrid risk assessment model for microenterprise finance for the unbanked microenterprises in South Africa

Boitumelo T Nkaelang
Tshwane University of Technology
South Africa

Sunday O Ojo
Tshwane University of Technology
South Africa

Victor W Mbarika
Affiliation
United States

Abstract

Credit scoring is perceived as an important innovation for microfinance institutions in managing the credit risk of their clients. Increase in defaults has necessitated microfinance institutions to improve their credit analysis by incorporating objective procedures. Various studies have confirmed that credit scoring can increase efficiency and reduce costs for microfinance. However, the take up of credit scoring has been slow and is still in early stages. South Africa has about 5 million SMMEs of which 94% are estimated to be microenterprises. These businesses are informal and often doesn't have collateral and credit history. These characteristics makes it difficult for financial institutions to assess their reliability, utility and risk. Financial institutions interactions with clients calls for trust and reputation investigation. A credit risk assessment model can help provide means to implement risk assessment suitable to mobile micro-enterprise loans, for the unbanked to be evaluated effectively and for financial institutions to strategically provide good loans and avoid financial loss due to underperforming loans. A hybrid system is proposed to demonstrate how micro-enterprise lending operations with intelligent decision making can deliver faster speed, improved consistency and reliability throughout the entire lending process with scalability. Design science principles will be followed to investigate and classify an algorithm to be embedded in the decision support system.

Keywords
Risk assessment model, microenterprise, South Africa, microenterprise finance

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Introduction

Traditionally microfinance institutions (MFIs) would not have access to credit bureau and most of their clients are self-employed and living in poverty. Moreover, because of the informality of their businesses they do not keep records and do not have proof of income. As a result of these, MFIs sought multiple mechanisms for screening and for enforcement problems in order to reduce the risk of default. Among other tactics that are used is the incentive mechanism of group lending, collateral substitutes and regular repayment schedule. Kono and Takahashi (2010) argues that group lending alleviates the problem of moral hazard only if the group can coordinate its members decisions and achieves higher repayment rates and the returns are sufficiently higher. Group lending can be an effective and efficient way to reduce the high transaction costs in both searching reliable borrowers and ensuring the repayment of credit. Morduch (1999) argues that dynamic incentives can be enhanced further if borrowers can anticipate a stream of increasingly larger loans. Furthermore, some authors argue that regular repayment schedule can help MFIs maintain high repayment rates (Armendariz and Morduch, 2010; Morduch, 1999). This is due to the reasoning that regular repayments screens out undisciplined borrowers at an early stage and it gives early warning to loan officers and peer group members about potential problems among other things.

Overtime microfinance institutions realised that as much as these methods are able to assist in screening and enforcing repayment discipline they were time consuming, costly and inefficient. Mainly because, subjective judgement assessment requires a fair amount of time per applicant and is expensive for the lender. Evaluating the loan proposal and defining the terms for each particular client is costly to the MFI and reduces their profitability (Babu & Singh, 2007). And these points serves true for the South African context where microenterprises are widely spread and not densely populated. Some authors (Hand, 1998; Lewis, 1992) have stated that judgemental approach lacks quantification of credit. Furthermore, they noted that borrowers' characteristics are analysed in this approach sequentially rather than in combination thereby ignoring their correlation. Another important issue to note is the cognitive bias by loan officers in processing information that affects their beliefs, so that they may be a victim of behavioural bias and appear irrational. Balthazar (2006) has discovered that studies of behavioural finance usually show that credit analysts are good at identifying what the strengths and weaknesses of a borrower are, however integrating all the information into the final rating is not always done consistently.

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As a result there was a need for microfinance to innovate and determine if credit scoring which was used by formal financial institutions can help improve their processes. Vigano (1993) contemplated that a suitable creditworthiness analysis is crucial for MFIs especially in developing economies. Schreiner (2000) declared scoring as the next important technological innovation in microfinance and argues that it will not replace the loan groups or loan officers and that it will never be as effective as it is in rich countries. Mainly because the author thinks that much of the risk of microloans is unrelated to characteristics that can be quantified inexpensively. Bumacov & Ashta (2011) perceive the introduction of credit scoring in microfinance as a new stage in the history of credit scoring. Ibtissem &Bouri (2013) argues that academic researches regarding credit scoring models for MFIs is yet at an embryonic stage and opinions on its applicability are divergent. Bumacov & Ashta (2011) also acknowledges that credit scoring has been struggling to enter the market for the last decade and faces resistance from microfinance consultants who would like to differentiate the market from banking. Moreover, they emphasize that credit scoring does not have to be rediscovered, but adjusted and promoted in order to cut the transaction costs and make credit available to the excluded as long as the credit risk can be measured and controlled.

Baer, Goland & Schiff (2013) argues that lenders can use big data to create meaningful value for their enterprise, better outcomes for borrowers, and significant social impact. That is, there is an opportunity for lenders to chart another path, using increased computing power and new sources of information and data (including mobile-phone usage patterns, utility-bill payment history, and others) to build better risk models. These disputes a claim made by Schreiner (2000) on the notion that data cannot be collected inexpensively because lenders cooperating with other stakeholders can make responsible lending decisions in low-touch and low-cost ways (Baer, Goland & Schiff; 2013).

In this study a hybrid credit risk model is proposed for microenterprise loans for unbanked micro-entrepreneurs of South Africa. The rest of this paper is organised as follows. The credit scoring models currently being used for micro-entrepreneurs are discussed followed by a brief discussion on methodology on how the model will be developed. Then results are discussed as to provide reasons why a unique approach for micro-entrepreneurs is important. Lastly, the approach used for the study and the classification methods are discussed followed with a conclusion of the research paper.

Credit scoring models in microfinance

Vigano (1993) developed a credit scoring model for microfinance in Burkina Faso that linked defaults to 53 traits at a rural bank. Due to the small sample the 53 traits had to be condensed to 13 factors, obscuring individual effects. Schreiner (1999) developed a model of costly arrears at a lender in Bolivia, the model pinpoints traits that influence risk and more important predicts risk better than naïve models. The model developed was not enough to accept or reject applicants without a standard evaluation. That is, the model was not pre-evaluation but rather post evaluation. Some authors (Schreiner, 1999; Bumacov & ashta, 2011; Van Gool et al., 2011; Baklouti & Bouri, 2013) concluded that credit scoring techniques in microfinance can only be incorporated as a complement rather than as a substitute to the subjective judgement approach. Carmona & Araujo (2011, Brazil) have discovered that the use of credit scoring models supplies subsidies to the institution, aiding it in the prevention and reduction of insolvency and in the decrease of its

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operational costs. Van Gool et al. 2011 reckons that advances in solving the reject inference problem for microfinance credit scoring purposes are definitely needed and the discriminatory power performance of credit scoring systems remains weak. Baklouti (2014) acknowledges the problem of the lack of quantified subjective information and has proposed an approach that measures the soft factor, which uses the entrepreneurs' personality psychological traits of overconfidence and emotional intelligence to determine creditworthiness. Furthermore the author argues that the improvements of the discriminatory power through new nonparametric models and reject inference techniques are important for improving the credit scoring accuracies in the microfinance credit process.

In Ghana a fuzzy logic approach has been necessitated as a result of the inability of many MFIs to recover loans from their clients which was leading to their collapse (Farouk Ibn et al., 2014). Fuzzy logic was used in order to reduce loan default among the MFIs so as to ensure their continuous existence. Support Vector Machine (SVM) has been explored in Bangalore to improve the accuracy rate of classification and it was concluded that it is a better classification technique compared to traditional techniques (Madhavi & Radhamani, 2014). Elias et al. (2012) proposed a hybridized credit scoring that simplifies the complexity exhibited by other models in the interpretation of the credit scoring process. The model has low reliability and leaves a wide scope for improvement and research of alternative credit score in MFIs.

The different studies that have been conducted had varied sample sizes to test the models with 15 being the smallest and 39956 being the largest sample. Various modelling techniques were used which includes, logit regression, discriminant analysis, random utility model and fuzzy logic among others. Various input variables were used which ranged between 5 and 18 and this demonstrate that there is no standard number of input for credit scoring. WWB (2003) argues that in high income countries scorecard with 15-20 variables is enough to construct powerful scoring model. Furthermore, they believe that due to the absence of detailed client information in microfinance, more variables are required to build a strong model.

Bumacov & Ashta (2011) argues that the new challenge of credit scoring is incorporating and adapting to the issue of information which is often qualitative and informal. Consequently, they say neither Durand nor other scholars treated the topic of using informal data for credit scoring purposes.

It is important to measure impacts on a broad set of behaviours, opportunity sets, and outcomes as the household financial arrangements are complicated in developing countries (Karlan & Zinman, 2010). Mainly, because business outcomes are not a sufficient statistic for household welfare, nor even necessarily the locus of impact of changing access to financial services. In addition, random assignment via credit scoring is a viable tool for an effective way of measuring impacts of expanding access to microcredit. The MECZOP's credit scoring model allows for a greater understanding of all the variables that influence significantly late reimbursement however the model still lacks other determinants of risk that can better address credit risk (Kinda & Achonu, 2012). That is, it

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lacks predictive power and has still to define scoring thresholds that correspond to acceptance, rejection or re-evaluation of an applicant based on credit score.

Klinger, Khwaja & Carpio (2013) explored the use of psychometric assessments by using a multivariate model to assess risk of micro-entrepreneurs. The study examined which psychometric characteristics are associated with higher profitability entrepreneurs and higher frequency of default. Moreover, they suggest that psychometric tools could potentially help, if they have sufficient overall predictive power, to enable increased lending and entrepreneurial growth in emerging markets. As a results, there exist gaps in credit scoring for microenterprise which is caused by issues around predictive power and the variables used.

Methodology

The research leverages on the design science research approach and follows the general design cycle as advocated by Vaishnavi and Kuechler (2004). The important principle of design science research is that knowledge and understanding of a design problem and its solution is required. This study is aimed at developing a hybrid risk assessment model for improved accuracy of credit risk prediction of microenterprises which are normally informal and unbanked. Purposive sampling was used to select participants in this study, mainly because microenterprise lending in South Africa has not matured and the participants with the required knowledge are limited. Microenterprise lending still remains underdeveloped in South Africa with about 10 institutions, with most institutions operating in Limpopo, then Gauteng and North West.

In designing the hybrid risk assessment model the research required knowledge and opinion of loan officers and to understand the reasons why microenterprises defaults. It is important in building a model that can have high accuracy in predicting the risk of a microenterprise. The reason loan officers were selected is because of the subjective knowledge they have in assessing the microenterprises and to understand the risks they face. On the other hand, microenterprises were selected as to provide an understanding on what leads them to default. This information can be incorporated in the risk assessment model so as to take precautions against high defaults rates.

One could argue that getting information from loan officers alone is not adequate for developing a hybrid risk assessment model for microenterprises in South Africa. However, microenterprises are the users of microloans, it was better to understand their needs and also get to understand the challenges they face in their business which at times can be overlooked by loan officers.

Firstly, a survey was conducted with micro-entrepreneurs so as to understand their reasons for defaulting and to further understand how risk assessment is currently being carried out. 20 clients were interviewed from a financial institution microfinance unit in South Africa out of a sample of 30 at their business or home. Over a week 20 small enterprises who defaulted over 3 months were interviewed to understand the reasons behind their lack of repayments and also to understand how the loan process has been carried out and how processes can be improved.

In order to understand how loan officers evaluates microloans in South Africa a survey was conducted with 5 MFIs in South Africa where loan officers were interviewed. These MFIs were located in three provinces in South Africa, 2 MFIs were in Limpopo, 2 in Gauteng and 1 in Northwest province. The field survey was intended to understand the current loan assessment process carried out by these institutions in order to understand how a risk prediction model can be developed for improved accuracy prediction for microenterprises.

Semi-structured interviews were adopted in this study as they provide the researcher with opportunities to introduce new material into the discussion that was not thought of beforehand, but developed during the course of the interview. Semi-structured interviews were performed with 20 loans officers and credit managers across the selected microfinance institutions based in Limpopo, North West and Gauteng provinces in South Africa. Once data from field was analyzed the researcher organized the data into themes and that became input to the variables for credit scoring model for microenterprises. The results of the surveys are presented as to inform the conceptualization the hybrid risk assessment model for the microenterprises.

Results discussion

Understanding the reasons for defaults, a survey of small enterprises in South Africa

The unbanked business types that formed part of this study ranged from Spaza, tavern, saloon, craftsmen, restaurant/ fast-food and crèche as depicted in Figure1 below. These businesses reflects the typical clients of microfinance institutions.

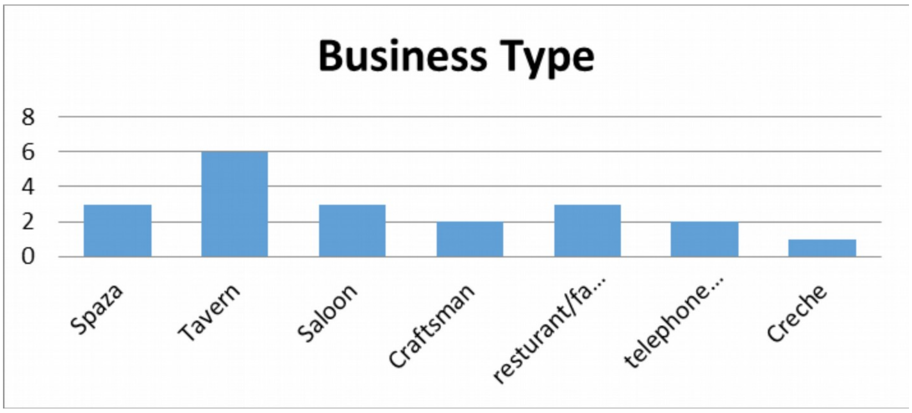

Figure 1: Business type

The loan amounts ranged from as low as R1000 to R50 000 maximum, the loans terms ranged from 6 months to 12 months being the maximum loan repayment terms. The majority of businesses were taverns and second popular were tuckshops/ spaza, saloon

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and fast-food restaurants. The education background of the clients varied, having few with only primary education and majority having matric or some form of high school education while few had certificates and diploma.

Different business types indicate different risk profiles in terms of arrears. Clients operating taverns had the most representation of arrears. This factor was attributed to taverns making up a larger portion of the portfolio, and as a result they have a large influence on the overall portfolio risk default. The arrears for the taverns were attributed to the seasonality of the businesses which was not properly taken into account when the assessment was made. Moreover, the craftsmen (plumber and a carpenter) were affected by seasonality and erratic demand of their services. From this it can be concluded that it is important to understand seasonality of the business for the unbanked as they affect the demand of their services and the ability of these institutions to make repayments. Failure of taking this factor into account can lead these institutions to default even if it is not intentional.

It was discovered that crime is also an area of concern for these businesses mainly because some reported theft of stock as a hindrance to making repayments. As a result it is important to determine the security threats to the business and ensure the business have the necessary security for their businesses. Secure businesses premises are of importance as there is no insurance for their stock and this sets them back when a burglary takes place. Understanding the environment and circumstances for the unbanked is very important as can be seen and as a result financial institutions are required to learn so that they can make good judgment.

The spaza shop owners complained about tough price competition from other foreign owned shops as a hindrance to their business as they could not sell their stock fast enough. The researcher discovered that the competition was not correctly assessed on the loan application forms. The Spaza owners complained about the low prices charged by their competitors and how that made things difficult for them. Spaza owners requires education about cooperative buying (where spaza shops group themselves and buy in bulk) as a way to enjoy big discounts so that they can easily compete with their competitors.

Key findings can be summarized as follows:

- Seasonality

From the clients studied with the exception of 3, incorrect assessment of repayment capacity is the reason for non-repayment. Clients were granted loans or amounts significantly higher than they have the capacity to repay. Some of the business have shown there are dependent on specific cycles and such information needs to be taken into account when making a decision.

- Business understanding and evaluation

There is limited experience or understanding of these businesses to make informed credit decisions. For example, taverns and shebeens who require loans to increase their stock which they could easily get from SAB on credit. In all cases where this reason was used the loan was used for another purpose.

- Credit history

The absence of credit records by the majority of the businesses renders this method not suitable for the unbanked and requires an appropriate method of assessing credibility of the unbanked. The absence of the required information used by this method renders it a useless measure for assessing the unbanked.

- Loan usage

In most cases it was evident that the loan was not used for the intended purpose and only in limited cases the loan usage was verifiable. Majority of clients indicated that used portion of the money for personal use and not for the business while several clients used the loan for venturing into a different business than the one the application was made for.

It was discovered that lack of understanding into the business operations of the unbanked is a hindrance in decision making and as a result wrong decisions were made in accepting large loan amounts for these businesses which lead them to default. The unbanked provided ambitious and over-estimated incomes and it was not verified whether such businesses have that potential. Majority of these business owners does not have any credit record while some had. And as a result credit record use does not serve any purpose for this market and another measure is required. It was confirmed that these businesses does not have any records of their income and as a result financial institutions needs a method of verifying that the data is correct so to avoid over-capitalizing these businesses and burdening them with debt. The researcher identified some inconsistencies into how the loan officers carried out the loan application assessment, that is they did not understand or have the required knowledge in performing due diligence of the businesses.

From the findings it is clear that the evaluation process needs to be improved, new methods are required. Credit managers and loan officers do not always have the necessary knowledge and require tools that can assist make this process more efficient and effective.

Interview results with loan officers

In literature the variables to the target market are important in developing a credit scoring model and have an impact on the reliability of the model and the accuracy to predict risk. As a result of trying to understand variables important for MFIs in evaluating risk, loan officers were asked the following questions:

- What are the characteristics of a successful loan re-payer for the unbanked?
- Which people related variables distinguish a micro-entrepreneur that is performing well from those not performing well? Defaulters vs non defaulters
- Which micro-entrepreneur variables make the most significant contribution to business performance objectives?
- How would you tell that the applicant have current and potential abilities, attitudes and aspirations to meet future needs of their business?

The results from the interviews with loan officers corroborated with the survey when it

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comes to the importance of taking notice of seasonality of the business and lack of credit history of micro-entrepreneurs. Furthermore, loan officers emphasized the importance of understanding the business environment of informal microenterprises as it plays an important role in their evaluation. Business context takes into account issues around the type of business, seasonality, location and security. There was consensus among loan officers that a successful loan re-payer is someone very hardworking with passion and knows the in and out of their business. It was discovered that a knowledgeable micro-entrepreneur will be familiar with every important aspect of the business and lack of knowledge in these critical areas will be seen as a red flag when making credit risk assessment. Knowledge in business regard the client's knowledge on the cycle of business, profit, cycle of stock and quantity as important factors. Furthermore, culture and norms plays an important role in how the micro-entrepreneur behaves which will determine whether they intend to make their loan repayments and this can be measured by honesty and entitlement.

Loan officers argued that understanding the business context can provide guidance to an MFI regarding the environment and the amount it can advance to the micro-entrepreneur based on its current context and the affordable repayment amount. Demonstrating commitment in business was seen as another important measure which can provide guidance on whether the business can succeed based on how committed a micro-entrepreneur is to the business. Therefore, it can be concluded that credit risk for a microenterprise is dependent in the knowledge of business, commitment in business, culture and norms, and understanding the business context.

Credit scoring for unbanked microenterprises in South Africa

Developing a loan scoring for the unbanked poses interesting problems mainly because the kind of information used and the environment they operate in. As a result the selection of prediction algorithm needs to take into account all the factors of the unbanked to be able to add value to financial institutions and the unbanked. A solution with high prediction reliability is needed and credit risk model with the variables as depicted in Figure 2 is proposed for South Africa. Credit risk prediction model for microenterprises in South Africa is dependent on knowledge in biz, commitment in biz, biz context, and culture and norms.

Figure 2: Credit risk

The variables for credit risk prediction for unbanked microenterprises in South Africa can be defined as follows:

Knowledge in biz is defined as the extensive pool of knowledge which can be the understanding of customers' needs, business environment and skills of entrepreneur or staff. These knowledge is central to the ability of the entrepreneur developing the business to be successful. Having the right knowledge of the business enables the entrepreneur to run the business more efficiently, decrease business risks and exploit opportunities to the full. Knowledge in biz can be found in the experience in business, design and processes, and documents and planning of the entrepreneur.

The following key factors are seen as important sources of knowledge in business:

- Cycle of biz: this refers to the knowledge of the up's and down's of operating the business; fluctuations in economic activity. That is being aware of the changes your business grows through and be able to plan for the period.
- Profit: is the understanding of the difference between the price of stock and taking the products to market. The entrepreneur needs to have a clear understanding of their income from the business.
- Stock cycle: understanding the movement of the inventory of the business, that is how frequent the business replenishes stock and the quantities.
- Stock quantity: understanding the amount of stock required and being able to track it.

Commitment in biz is dedicating oneself to making the business succeed. That is, binding ones time, energy, values and emotions to the business. It's important that the entrepreneur commit to their goals and vision of the company and believe in its potential. The following key factors are important demonstrating an entrepreneur's commitment:

- Hardworking: is taking the business seriously and doing it well and rapidly.
- Bookkeeping: is regularly keeping track of the accounts of the business. This enables the entrepreneur know their income and movement of their stock.

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- Passion: is having compelling enthusiasm towards the business.
- Product monitoring and diversity: refers to the know-how of the needs of your market and be able to change as the target market needs evolves and be able to respond to their needs.

Biz context is having a good understanding of the current environment and the context the business is operating in. These are important in assisting the funder to help strategize around key issues important to the success of the business. That is being aware of the risk/ challenges the business is prone to and understanding the potential and realistic income thereof. The following factors are important to understanding the biz context:

- Type of business: refers to the business entity and its activities.
- Seasonality: refers to understanding the different economic cycles goes through, that is when is the peak season and low season of the business as they have a great impact on the ability of the business to make income.
- Location: The area the business is located in. whether the business in based in a township, rural area or town, as these issues have an impact on the success of the business and assist in knowing where the operations are taking place. The location of the business serves as a reference point.
- Security: understanding the security threats the business is prone to and what measures has the business put in place to deal with the issues if they are to arise. Furthermore, based on the area understand the crime rate and its impact on the business concerned.

Culture & Norms is the patterns of behaviour and attitudes in a given entrepreneur which they consider to be normal. There are certain behaviours and values which some entrepreneur tend to conform to and are seen as important in determining their attitude in making loan repayments. The following factors are important:

- Honesty: is the quality of upright and fair, being able to openly provide the right information about the business and not withhold it.
- Entitlement: this refers to the mentality of having a right to have or get something and doesn't see the need to act responsibly.

The proposed credit risk variables will be explored with neural networks, genetic algorithm and fuzzy logic as the artificial intelligent techniques for credit scoring. It is envisaged they can enable high prediction reliability for microloans. Neural Networks (NNs) are mathematical representations inspired by the functioning and reasoning of the human brain. Fuzzy logic will be used to improve the interpretability of NNs. Genetic algorithm can assist with searching for the optimal solution by a number of modifications of strings of bits called chromosomes. The chromosomes are the encoded form of parameters of the given problem.

The unbanked does not have a large enough database with homogenous variables. This characteristic rules out the use of the statistical techniques such as logistic regression (Wiginton, 1980) or cluster analysis (Edelman, 1992). Dealing with the unbanked requires a multi criteria decision for loan provision because several factors must be taken into consideration. Artificial intelligence like neural networks and genetic algorithms provide a new alternative to statistical methods in building non-linear, complex real world systems. It is reported that techniques that uses neural networks and genetic algorithms have reported to have achieved higher prediction accuracy than those using LDA and logistic regression and other methods (West, 2000; Desai, Crook & Overstreet, 1996; Jensen, 1992; Piramuthu, 1999; Desai et.al 1997). However, the artificial intelligence techniques have its drawback in credit evaluation that is their inability to explain the reasoning for the decisions made. Hence, the use of the fuzzy system for the advantage of transparency it provides.

Conclusions and recommendations

From the arguments made by the different authors, credit scoring cannot replace the judgement of a loan officer which means there is a need for developing a credit scoring model that incorporates the personal judgement of loan officers. It is envisaged that if credit scoring can mimic the judgement of loan officers it can be able to lead to improved processes for microfinance as loan officers can concentrate more of their time on growing the loan books as opposed to spending more time on assessing microenterprises . The researcher believes that understanding the process of judgement by loan officers and the criteria they use can be able to contribute to developing credit scoring models with strong prediction of risk. Neural networks and genetic algorithms have reported to have achieved higher prediction accuracy than those using LDA and logistic regression and other methods, hence are proposed for the hybrid risk assessment model for microenterprises in South Africa.

References

Arturo Elias, Alejandro Padilla and Felipe Padila. 2012. Credit scoring for microfinance institutions in Mexico an ensemble and hybridized approach. 2012 international conference on Technology and Management. Lecture notes in Information Technology, Vol. 21.

Asuri Venkata Madhavi and Radhamani G. 2014. Improving the credit scoring model of microfinance institutions by support vector machine. International Journal of Research in Engineering and Technology.

Beatriz Armendáriz & Jonathan Morduch, 2010. "The Economics of Microfinance, Second Edition," MIT Press Books, The MIT Press, edition 2, volume 1, number 0262014106, June.

Balthazar, L., (2006). From Basel 1 to Basel 3. New York, Palgrave McMillan.

Bumacov, V. & Ashta, A. 2011. The conceptual framework of credit scoring from its origins to microfinance. Second European Research Conference on Microfinance, Groningen, the Netherlands.

Beatriz Armendáriz & Jonathan Morduch .2010. The Economics of Microfinance. The MIT Press.

Baklouti Ibtissem and Abdelfettah Bouri. 2013. Credit Risk Management in Microfinance: The conceptual Framework. ACRN Journal of Finance and Risk Perspectives. Vol 2 Issue 1 Nov. 2013, p.9.

Baklouti Ibtissem. 2014. A psychological approach to microfinance credit scoring via a classification and regression tree. Intelligent Systems in Accounting, Finance and Management Volume 21, Issue 4.

Steyn, J., Van Belle, J.P. (Eds.). 2015. Beyond development. Time for a new ICT4D paradigm?
Proceedings of the 9th IDIA conference, IDIA2015, Nungwi, Zanzibar: 314-326
ISBN: 978-0-620-68395-1

Bailey Klinger, Asim Ijaz Khwaja & Carlos del Carpio. 2013. Enterprising Psychometrics and Poverty Reduction.

Dean Karlan and Jonathan Zinman. 2010. Expanding microenterprise credit access: Using randomized supply decisions to estimate the impacts in Manila.

Edelman, D. B. 1992. An application of cluster analysis in credit control, IMA Journal of Management Mathematics, 4 (1), pp 81-87.

Hand, D., J. 1997. Construction and assessment of classification rules. Chichester: John Wiley.

Ibtissem, B. and Bouri, A. 2013. Credit Risk Management in Microfinance: The Conceptual Framework.

John C. Wiginton (1980). A Note on the Comparison of Logit and Discriminant Models of Consumer Credit Behavior. Journal of Financial and Quantitative Analysis, 15, pp 757-770. doi:10.2307/2330408.

Kono, Hisaki and Kazushi Takahashi. 2010. "Microfinance Revolution: Its Effects, Innovations, and Challenges." Developing Economies, 48(1): pp.15-73.

Lewis, E, .M. 1992. An introduction to credit scoring, Anthena press, San Rafael, CA.

Morduch, J. 1999. The promise of microfinance. Journal of economic literature, 37, 1569-1614.

Ousseni Kinda and Audrey Achonu. 2012. Building credit scoring model for the savings and credit mutual of the Potou Zone (MECZOP)/Senegal. The Journal of Sustainable Development.

Soumitro Chakravarty, Amar Nath Jha. 2013. Viability of "Credit Scoring in Microfinance" for Developing Countries.

Tobias Baer, Tony Goland, and Robert Schiff. 2013. New credit-risk models for the unbanked. McKinsey & Company.

Schreiner, M. 2002. Scoring: The Next Breakthrough in Microfinance? Occasional Paper 7. Consultative Group to Assist the Poorest (CGAP). Washington DC.

Schreiner, M. 2004. Benefits and Pitfalls of Statistical Credit Scoring for Microfinance. Savings and Development 8(1):63-86.

Vaishnavi, V. and Kuechler, W. 2004. "Design Science Research in Information Systems" January 20, 2004.

Viganò, L .1993. A Credit Scoring Model for Development Banks: An African Case Study. Savings and Development 17(4):441–482.

West, D. 2000. Neural network credit scoring models, Computers & Operations Research, 27 (11-12) pp 1131-1152.

Wiginton, J.C. 1980. "A note on the comparison of logit and discriminant models of consumer credit behavior", Journal of Financial Quantitative Analysis 15, pp 757-770.I2.

WWB (Woman World Banking). 2003. Credit scoring in microfinance: Guidelines based on experience with WWB affiliates in Colombia and the Dominican Republic.