A deep learning approach to risk management modeling for Islamic microfinance

Klemens Katterbauer[1], Philippe Moschetta[2]

[1,2] Euclid University, Central Africa Republic

Corresponding Author [1*]: katterbauer@euclidfaculty.net
Contact Author [2]: philippe.1@euclidfaculty.net

Abstract— **Islamic Microfinance rides two recent growing trends: conventional microfinance and Islamic banking. It offers financial flexibility to the poorest strata of the population in different Muslim countries by borrowing and mixing techniques from these two sources. In particular, risk management and loan qualifications tend to be similar to those operating inside conventional and Islamic financial institutions. The loan approval process heavily relies on scoring applicants mostly on their financial criteria. This paper aims to demonstrate that an alternative framework based on artificial intelligence improves traditional financial techniques. This framework also resonates more with the fundamental and specific values of Islamic Microfinance as it captures some non-financial attributes of the applicant that are informationally rich. We first present the critical components of this novel approach. Then, we apply it to a business case (approximately 30,000 applications to a microfinancing institution in the Central African Republic) to demonstrate its usefulness.**

Keywords-component; Islamic microfinancing, artificial intelligence, risk management, Shariah law, data-driven study

I. Introduction

A. *The Islamic Microfinance Context*

Microfinancing has been a growth area of modern finance in developing countries. It provides individuals with modest financing options. It allows them to escape poverty and overcome some of the restrictions encountered in conventional banking based on strict demand for collateral and strong credit history. Deprivation continues to be a significant challenge in many Muslim communities: more than 500 million individuals live on less than 2 US Dollars per day in Indonesia, Pakistan, India, Bangladesh, Egypt, and Nigeria. These individuals struggle given the lack of sufficient liquidity, savings management, and ability to transfer and receive money [1]. Islamic microfinance has been posited as an innovative instrument for poverty alleviation.

In contrast with traditional microloans, Shariah-compliant financing options offer a more suitable answer for Muslim borrowers [2]. We often see a recourse to a blend between conventional high-interest microfinancing and their Islamic version, but both rely on the existence of collateral.

The first advantage of the Islamic option with collateral (e.g., jewelry or gold) is the continual roll-forward of the loan with a flexible repayment schedule that allows the monetization of the collateral by following the cash inflow/outflow borrower's profile. This option is open without the need to re-enter a loan application process every time the borrowing re-starts [3]. The second advantage of the Islamic microfinancing option is the safekeeping of the collateral by the lender at a very low cost [4]. Finally, the overall cost to the lender tends to be more competitive than the conventional option.

The limitation of this Islamic financing option is two folds. First, the lender usually restricts these loans to the acquisition of an asset and prohibits discretionary spending. Second, the absence of financial interest on the microloan prevents the significant growth of the loan book for the lender, particularly when the financial interest is computed to cover the risk of late payment or even of a write-off.

Due to the importance of managing late payment and default risk in the context of riba-free loans (i.e., absence of financial interest), assessing the overall financial risk associated with Islamic microfinance is paramount for the sustainability of this market.

European Journal of Islamic Finance - ISSN: 2421-2172
DOI: 10.13135/2421-2172/6202- Published by the University of Turin
https://www.ojs.unito.it/index.php/EJIF/index

Received: 11/08/2021 - Accepted for publication: 20/07/2022 - Published: 29/07/2022

B. *Financial risk in Islamic Finance*

Risk management for financial institutions includes several broad risk categories: market risk, credit risk, operational risk, and liquidity risk. Market risk arises from changes in market prices (e.g., interest rates, commodity prices). Credit risk derives from the possibility that the debtor does not repay the debt in total, and the recovery on the net value of the pledged asset does not cover the unpaid balance. Operational risk covers negative situations caused by failed internal processes, fraud, collusion with the debtor, mere incompetence of the credit officer, or inadequate collection processes. Another critical risk is the liquidity risk, which implies that there is not sufficient liquidity in the market to buy or sell assets. These risks are present in Islamic finance, so conventional risk techniques used to manage them are also relevant.

A difference with conventional risk analysis arises with the quantum of risk that the institution should allow: "it [*gharar*] is not as well defined as *riba*, and a ruling of permissibility based on *gharar* could take into account a cost-benefit analysis." [5]. It explains why the level of risk acceptable in Islamic finance can differ from one institution to another. On the one hand, one could consider risk as intrinsic to any financial transaction, hence not a reason to exclude from a pure loan a risk element. On the other hand, one could be willing to eliminate any trace of this notion on a loan. The risk is then transferred to an ancillary Islamic transaction that takes place simultaneously as the loan transaction.

We observe an analogous Islamic debate about the degree of risk inclusion with the concept of 'haram' food. For example, the Shafie school seeks to eliminate any *najis*-components in 'halal' food to avoid potential contamination. In contrast, other schools may accept a minute percentage of non-halal ingredients. Similarly, uncertainty related to the price is equally prohibited in Islamic finance [6]. Therefore, risk modeling techniques in Islamic finance institutions should filter only permissible risks. Consequently, risk modeling should specify whether the variation in asset quality or reimbursement price is part of the risk model.

These techniques are particularly relevant for regulators. Their importance has been generally increased with each financial crisis. The Basel Accords, set up in the 1980s, tried to establish for financial institutions an international standard for minimal capital requirements with a particular focus on credit risk. The Basel II agreement (viz. the Revised Capital Framework) broadened these terms in the aftermath of the 2007-08 financial crisis and incorporated, besides minimal capital requirements standards related to supervision and discipline in financial markets [7]. Similar to the Basel Accords, in case an Islamic financial institution faces unexpected losses, partners /shareholders are required to forgo a portion of the profit or, in the worst case, provide additional equity.

For Islamic microfinance institutions, these remedies are more difficult to implement. These institutions are not usually run for profit. They cannot absorb through their gains the credit losses. In addition, the lack of future profitability limits the recourse to fresh funds charitable sources. Hence the heightened need to control for risk to minimize the amount of risk that the institution's management can take [8].

In this paper, we will first review the current practice that conventional financial institutions use to assess the borrower's suitability. Then, we will present a novel framework based on Artificial Intelligence (AI) techniques that will extract from the borrower's profile an informational advantage compared to conventional techniques. We will show that this advantage optimizes the risk/reward equilibrium of the financial institution and also chimes with the Islamic values that are the cornerstones of these institutions. Finally, we will test this possibility through a business case of approximately 30,000 applications to a microfinancing institution in the Central African Republic.

II. Three levels of Financial Risk Models

A. *Conventional Risk Model*

To manage the overall risk of a financial institution, the Basel regulations impose a minimum coverage ratio of 8% defined by:

$$\frac{\text{regulatory capital}}{\text{risk-weighted sum}} \geq 8\ \%$$

The denominator in this model is computed by multiplying a pre-defined risk factor (specific to each class of loans) by the nominal value of the loan. The main advantage of this model is its simplicity. The regulator can easily audit the computation and track the evolution from one reporting period to the other. The main drawback is the absence of the covariance effect between loans. This absence can work in two different directions. For example, the benefit of a diversification strategy with negatively correlated loans is not reflected in this ratio. The potential negative impact of having correlated loans in different classes is not translated either. Furthermore, the effectiveness of this ratio is heavily dependent on the methodology used to determine the risk factor associated with each class of loans.

A different approach is the utilization of a factor sensitivity measure. This measure can be expressed for the value of a portfolio

$$V_n = f(t_n, Z_n)$$

at time n, as

$$f_{z_i}(t_n, Z_n) = \frac{\partial f}{\partial z_i}(t_n, Z_n)$$

The factor sensitivity approach is important to analyze the portfolio's robustness with respect to a change in risk-factor. However, it is difficult to aggregate all sensitivities together to determine the overall riskiness of the loan portfolio [9].

The most conventional approach to risk modeling is utilizing a loss distribution approach. The main objective is to estimate the loss L_{n+1} given a probability distribution F_L that is estimated

European Journal of Islamic Finance - ISSN: 2421-2172
DOI: 10.13135/2421-2172/6202- Published by the University of Turin
https://www.ojs.unito.it/index.php/EJIF/index

Received: 11/08/2021 - Accepted for publication: 20/07/2022 - Published: 29/07/2022

from historical data. The challenge that arises from this is to determine the distribution and its parameters [10].

A widely used parameter used for risk assessment is the standard deviation. However, this depends on the context, and the standard deviation may be inadequate for several applications. Specifically, the standard deviation is only defined for distributions that fulfill $E(L^2) < \infty$. Probability distributions with fat tails (i.e., kurtosis > 3) do not fulfill this criterion. Additionally, the standard deviation does not distinguish between positive and negative events as it sums the absolute deviation from the mean equally.

A critical alternative measurement criterion is the Value-at-Risk (VaR) quantifier. The VaR is defined as

$$VaR_\alpha(L) = \inf\{l \in \mathbb{R}: P(L > l) \leq 1 - \alpha\}$$

which implies that for each confidence level $\alpha \in ([0,1])$ the probability that the loss L exceeds l is less than $1 - \alpha$.

While the VaR is an important measurement criterion and has attracted the attention of regulators, it has considerable limitations [7]. Specifically, it does not provide any information on the magnitude of the expected loss. The shape of the loss curve after the VaR point does not impact the VaR calculation. The computation of the expected loss is necessary. It is defined as

$$ES_\alpha(L) = E(L | L \geq VaR_\alpha(L))$$

These computations present a statistical challenge due both to their limited number of degrees of freedom and to specific probability distribution assumptions on the data that underlie them [9].

In summary, most regulators prefer the ethical transparency and auditability of such established statistical models primarily based on a limited number of frequently used statistical assumptions. Therefore, understanding the model becomes more important than understanding the data. Financial institutions are then tempted to make the data fit the statistical model they use, or that has been prescribed by the regulator rather than developing a fit-for-purpose alternative [11]. The great financial crisis of 2008-2009 has amply demonstrated that most risk models did not sufficiently capture capital risks. They were not comprehensive enough to include extreme events and underestimated their true frequency, particularly the sharp increase of covariance between loans at times of general financial stress.

Nevertheless, we posit it is possible to reconcile regulators' needs and improved outcomes in risk management. We hypothesize that techniques derived from AI offer an efficacious alternative in building an adequate risk model. These models will support better decision-making for financial institutions while allowing regulators to monitor risk policies.

B. Artificial Intelligence Risk Model

AI has gained considerable traction in a variety of different industrial and business applications. It allows novel insights from semi-structured data. It facilitates automatized decisions at a lower cost compared to a human-only process.

In the Islamic microfinance context, it considers a variety of different quantitative and qualitative factors germane to the specificity and originality of that industry. We can identify at least four areas of relevance: 1) the loan decisions in microfinance are numerous and repetitive, 2) the Islamic finance construct of these pure loans put pressure on the cost structure of the financial institutions and requires a high level of automation, 3) Shariah law promotes the avoidance of specific types of uncertainties 4) the tracking of the coverage ratio collateral/loan must be done frequently to minimize the default risk. [12]. At the same time, AI can draw inferences from a large and evolving database of user data. It can be optimized continuously. Therefore, it can train itself in adequate conditions. Nevertheless, as it is frequent with AI-driven decision processes, machine learning models provide little explainability. It may cause uncertainty in the final go/no go result [13]. So, financial institutions may be at a loss to explain to loan applicants why they have rejected the loan request. It may also require constant monitoring to avoid embedded biases that could run contrary to the notion of fair and equal treatment, a value highly promoted by Islamic Finance for the Umma at large.

If we examine now the steps followed by conventional machine learning models, they start out with a pre-processing step to analyze and filter the data.

The first step comprises data filtering and data imputation, as well as the management of data outliers. This phase is critical for ensuring that the machine learning model is robust and extracts the core features in the data [14].

The second step is the choice between regression and classification, representing a significant differentiation between AI models. Whether to utilize a classifier or regression model depends on whether one wants to estimate the potential loss or value depreciation or aims at classifying the risk incurred. Concerning classifiers, one can distinguish either 1) heterogeneous, 2) individual or 3) homogeneous classifiers.

Heterogeneous classifiers combine the predictions from various types of models and involve stacking, averaging, and hill-climbing algorithms. Individual classifiers conventionally incorporate logistic regression, support vector machines, neural networks and decision trees. Finally, homogeneous classifiers combine the predictions from multiple similar models and achieve diversity through sampling. Such models are called bagging, random forest and boosting. Researchers can also use these algorithms similarly for regression purposes. They also exploit hyperparameter optimization to optimize model performance [15].

In the third step, data scientists, when faced with a large number of parameters, follow a nonlinear optimization approach to achieve adequate optimization results. They determine a globally optimal set of hyperparameters via genetic optimization. The optimization relies on the principles of natural selection to find a globally optimal solution. A critical aspect of

European Journal of Islamic Finance - ISSN: 2421-2172
DOI: 10.13135/2421-2172/6202- Published by the University of Turin
https://www.ojs.unito.it/index.php/EJIF/index

Received: 11/08/2021 - Accepted for publication: 20/07/2022 - Published: 29/07/2022

genetic programming is the importance of the initial solution and the evolution of the population to find the most optimal solution. While the framework's performance depends on the measurement criterion used, a considerable improvement may be achieved from intelligent optimization [15].

After that step, they face the challenge of explainability. Transparency about the factors influencing decision-making is crucial in Islamic finance, given that risk sharing is a crucial feature of Islamic finance instruments. Most machine learning models have an inherent but rudimentary form of explainability. While this may not be in the form of a single equation with a few parameters, the impact of the various input data on the model may be conventionally determined by a feature analysis. Tree-based models enable with relative ease to measure the impact of each model feature and how these features interact with each other. Quantified as feature importance, the impact on the model evaluation metric is determined via changing a single variable in the tree. This subsequently allows the determination of the model quality. To test the importance of a variable, data scientists perform a sensitivity analysis on the quality of the model. The most relevant variables generate the most important changes in quality. Therefore, they can address from these most influential variables the explainability challenge [9] and provide in layman's terms a simplified causal explanation to loan applicants.

A final consideration generally absent from the classic risk management model for financial institutions flows from a compulsory Environmental, Social and Governance (ESG) assessment. Certain elements of the ESG schema have been included *ab initio* in the Islamic finance conceptual framework. For example, environmental sustainability is a crucial component of Islamic finance as Shariah law stipulates that financing projects detrimental to the environment are forbidden [7]. Islamic finance forbids other sectors detrimental to a safe environment for humankind like pornography, gambling, or the military industry. In terms of governance, equality between the financial partners is another component of Islamic finance. Given these ESG concerns, AI is particularly well-suited to comprehensive risk modeling that promotes an inclusive approach by combining numerical with non-numerical data. While the conventional models focus on the financial profitability of the loan, Islamic microfinance must incorporate other ethical considerations that are often more difficult to measure in a purely numerical way.

C. Islamic Microfinance AI Risk Model

We have developed a novel AI Islamic risk management framework for assessing credit risk for Islamic microfinancing institutions. The framework determines both individual and overall credit risk for the Islamic microfinancing market. Furthermore, the framework incorporates a recommendation engine that enables individuals without formal financial qualifications to review Islamic microloans. It also contains the value risk of the underlying asset [7].

To develop the framework, we have utilized a random forest approach. Random forest methods belong to the class of ensemble learning techniques [16]. In these techniques, the random forest consists of multiple decision trees where the trees are trained by either bagging or bootstrapping. Bagging is an advantageous ensemble technique for enhancing accuracy. Individual decision trees are combined into different bags. From these bags, we select the bag with the highest accuracy to be further branched out. Then, increasing the number of trees that are incorporated leads to an increase in the precision of the estimates or classification. A critical benefit of random forest trees is the reduction of the limitations of the decision trees, specifically when it comes to overfitting [17].

Our framework benefits from the effective way that random forest algorithms handle missing data. In addition, they do not need excessive hyperparameter tuning to achieve reasonable predictions. We illustrate in Figure 1 the various types of nodes are encountered in a random forest algorithm [17]. We start with the root node, followed by the decision nodes and then the leaf nodes. Each decision node may have multiple leaves or decision nodes. A decision node with multiple leaves represents a subtree.

Information theory provides insights into the way decision trees and random forests operate. Specifically, the critical objective for a decision tree is to maximize its entropy or information gain, which is a measure of uncertainty [18]. Given a set of independent variables, entropy increases when the uncertainty is reduced. Higher entropy means that a higher degree of uncertainty has been removed during the training of the decision trees. The main advantage of the random forest method is that the segregation of the nodes is performed randomly through bagging. This process allows the use of different samplings for the training phase.

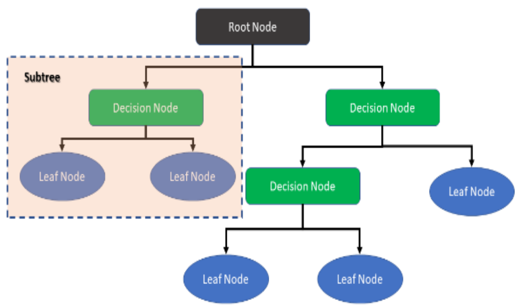


Figure 1:Graphical illustration of random forest algorithm.

Our framework separates the risk management model into three sub-models: 1) the estimation of the individual credit risk, 2) the classification of risk and, 3) the maximum acceptable loan amount. Furthermore, the sub-models also estimate the expected value at risk for the entire Islamic microfinance institution. It also offers alternative recommendations for loan applicants in case they do not qualify for a conventional microloan.

European Journal of Islamic Finance - ISSN: 2421-2172
DOI: 10.13135/2421-2172/6202- Published by the University of Turin
https://www.ojs.unito.it/index.php/EJIF/index

Received: 11/08/2021 - Accepted for publication: 20/07/2022 - Published: 29/07/2022

III. CASE STUDY

A. Data sources and structure

To evaluate the AI-driven Islamic Risk Model for microfinancing, we collected from an Islamic microfinancing institution a dataset of approximately 30,000 loan takers and applicants in the Central African Republic. The dataset was augmented with data based on general demographic, income, and societal norms when the data was not complete. The reference data were taken from a variety of sources, such as the European Country of Origin Information Network, the World Bank, the International Monetary Fund, and the United Nations statistics [19, 20].

Table 1: Dataset parameters categorized according to personal data, Islamic values, and financial data.

Data Columns	Type
Gender	Personal Data
Age	
Job	
Marital Status	
Number Children	
Wife is working	
Number of mobile phones	
Number of children studying	
Zakat Amount Paid per Year	Islamic values
Participates in Islamic volunteering	
Committed crimes	
Number of crimes committed	
Went to an Islamic school	
Monthly Salary	Financial Data
Monthly Overall Income	
Monthly Loan repayment	
Monthly expenditure	
Number successfully repaid loans	
Number defaulted loans	
Value of collateral	

For the risk modeling framework, we analyzed initially the dataset to discern potential correlations and relationships within the data. The structure of the collected data for each individual loan applicant is outlined in Table 1. The collected data were categorized into three different types: personal data, data related to Islamic values, and financial data.

B. Data visualisation

In this section, we describe the data distributions and composition of the initial dataset. In Figure 2, we outline the dataset's age distribution and marital status. The histogram values are all indicated in per cent. The distribution shows that most of the applicants were married, with a few being single (less than 5 % for each age group) and a lesser number (less than 2 %) being divorced or widowed.

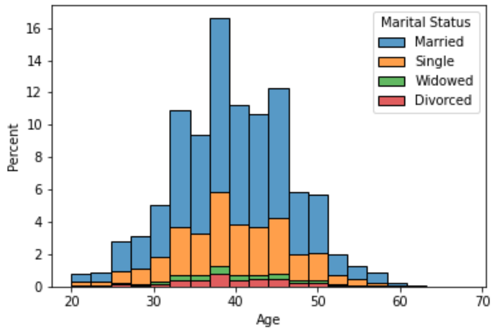


Figure 2: Histogram of the age distribution and marital status.

The data outline that almost 38 per cent of the women are married, while around 17 per cent are single. The overall statistics outline that the dataset contains more women as compared to men in the dataset. Given that the average income of men is typically higher than women's, with many Islamic microfinance businesses primarily being run by women, this is mirrored in the dataset. This situation is outlined in Figure 3 that clearly outlines that men have a shifted and flatter salary distribution as, which clearly outlines than men have a gone and flatter salary distribution compared to women. Another interesting statistic is the comparison between overall monthly income and the attendance of an Islamic school. Figure 4 outlines the statistics, which do not seem to significantly impact. To understand gender-induced effects on marital status, we visualise the distribution of the data in Figure 5 their distribution and colour each by their marital status. 60 per cent of the dataset is made up of women. In comparison, the remaining 40 per cent constitute men. Most of the individuals are married, with a further 33 per cent being single.

European Journal of Islamic Finance - ISSN: 2421-2172
DOI: 10.13135/2421-2172/6202- Published by the University of Turin
https://www.ojs.unito.it/index.php/EJIF/index

Received: 11/08/2021 - Accepted for publication: 20/07/2022 - Published: 29/07/2022

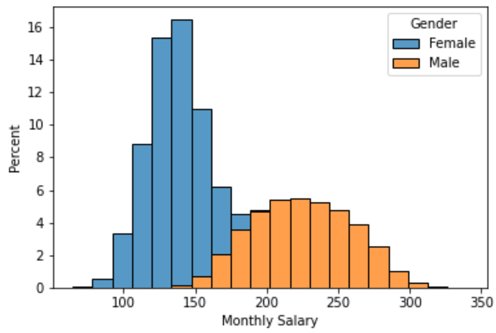


Figure 3: Histogram of the salary distribution for different genders.

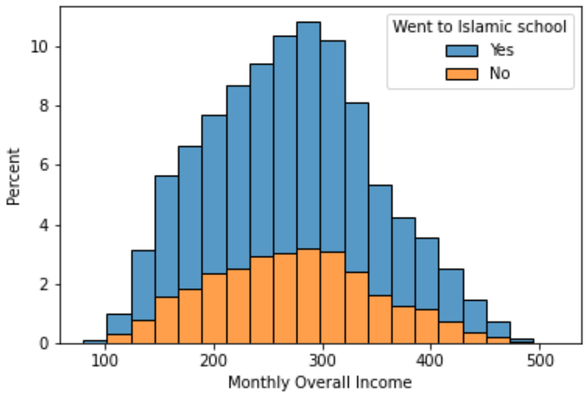


Figure 4: Histogram comparison of overall monthly income versus attendance of Islamic school.

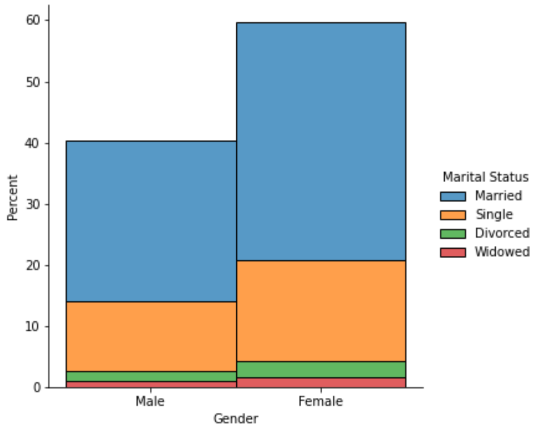


Figure 5: Comparison of the distribution of males and females according to their marital status.

C. *Data interpretation*

To analyze the data in greater detail, we performed hypothesis testing to ascertain visually observed trends. The first visual observation is that the salary levels of the male is considerably higher than those of women. To analyze this, we performed a statistical 2-sampled Z-test. The T-test is an inferential statistical test to assess whether two groups exhibit a significant difference in their respective means. Given that we know from the dataset the two groups' population variances and a large sample size, the Z-test is more adequate to determine the difference. To statistically prove that the distributions for men and women are not equal, we utilise the null hypothesis that the means of the two groups are identical and aim to reject the null hypothesis. Performing the analysis and calculating the p-value, we could easily reject the null hypothesis that the two means are identical. Analysing the histograms in Figure 3, we can observe that the earnings for males are considerably higher as compared to women. Furthermore, we perform statistical analysis with the null hypothesis that the income shall be independent for women whether they operate a business or not. This hypothesis could be rejected, indicating our previous results.

Finally, we evaluated whether the attendance of an Islamic school affects the income level. The null hypothesis is that there is a difference in income level between those who attended and those who did not participate in. The idea was rejected, implying that there is no difference.

D. *AI-driven loan application model*

Having analysed the data and its validity, we then aimed to develop an Islamic AI-driven risk model to determine whether an individual qualifies for an Islamic microfinancing loan. In addition, the model utilises a risk rating approach driven by deep learning to indicate a maximum loan amount. That maximum corresponds to a high probability of repayment.

To evaluate the performance of the framework for the loan qualification of individuals, we performed a confusion matrix comparison. The framework performs on the training and testing dataset well, achieving perfect accuracy scores (Figure 6). This strong estimation performance is due to a variety of reasons. First, there is a strong correlation between the monthly income and collateral value in determining an individual's qualification for a loan. Higher-income individuals with sufficient collateral easily qualify for an Islamic microfinance loan due to the increased probability of repayment. Furthermore, the criminality score of the individual may also impact the estimates significantly. Figure 6: Confusion Matrix plot for the qualification of individuals for an Islamic microfinance loan.

To evaluate which features have the most substantial impact on the estimation, we determined the feature importance based on: 1) the mean decrease in impurity and 2) feature permutation. The former calculates the mean and standard deviation of the accumulation of the impurity decrease within each tree. Then, the mean and the standard deviation are used to measure the impact. For the latter, the features are computed based on a left-out test set. Their advantage is that they are less susceptible to a bias towards high cardinality features.

To ensure robust calculation of the feature importance, we compared the results for both versions and displayed the results in Figure 7. The results indicate that the number of crimes and

European Journal of Islamic Finance - ISSN: 2421-2172
DOI: 10.13135/2421-2172/6202- Published by the University of Turin
https://www.ojs.unito.it/index.php/EJIF/index

Received: 11/08/2021 - Accepted for publication: 20/07/2022 - Published: 29/07/2022

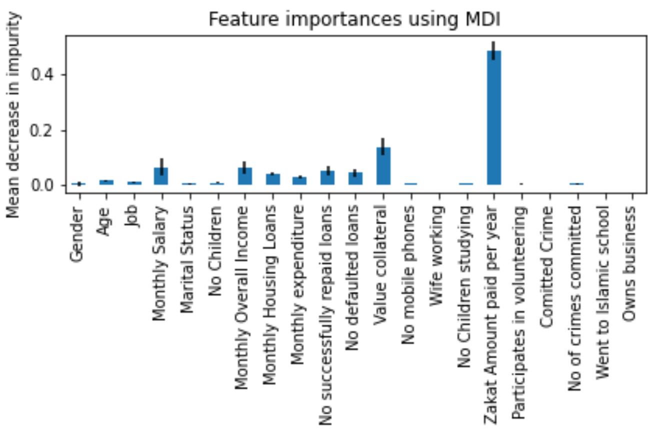
whether a crime was committed are the essential features determining whether someone qualifies for a loan in addition to their Islamic credentials, such as the amount of Zakat they pay per year. The amount of Zakat plays a critical role as it is an implicit factor correlated to honesty and commitment to the well-being of others. Following religious prescriptions and being a law-abiding citizen fits well with the objectives of Islamic finance. This would contrast with conventional risk management models that primarily focus on income levels to assess the qualification for a loan. The amount Zakat paid is a handy parameter as more significant amounts of Zakat paid also implies that the individual aims to benefit society to support those less well-off.

Figure 7: Feature importance for both mean decrease in impurity and feature permutation for the qualification of individuals for an Islamic microfinance loan.

Once completing the loan qualification step, we turned to the evaluation of the credit default risk of the applicant. We created five risk categories, from shallow risk (A) to severe (E). Figure 8 the confusion matrix for both the training and testing dataset. The credit default risks are consistent with a high classification score for both the training and testing dataset. Figure 8: Confusion Matrix plot for the credit default risk of individuals for an Islamic microfinance loan.

To evaluate the feature importance impact on the various risk categories (Figure 9), we can observe that the value of Zakat is the most important before the value of the collateral. These Islamic results are aligned with conventional microfinance data that utilise Islamic values and contribution to society as a critical parameter for evaluating creditworthiness and risk.

MDI



Feature Permutation

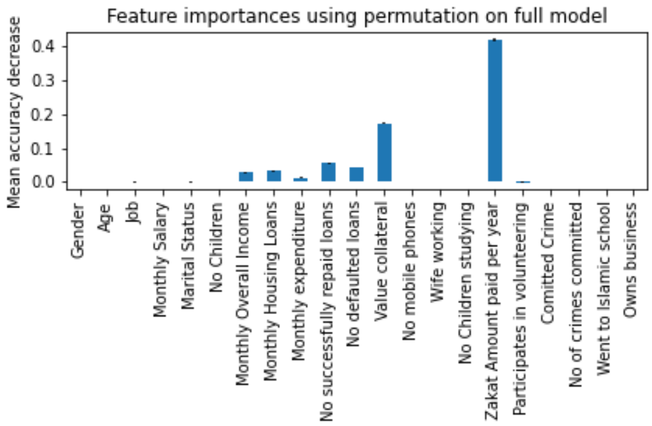


Figure 9: Feature importance for both mean decrease in impurity and feature permutation for the credit default risk for an Islamic microfinance loan.

As a final step, we estimate the maximum loan an individual can support for a low level of risk. We developed a random forest framework to estimate the maximum loan amount. The estimation results for the training and testing dataset are presented in Figure 10. For the maximum loan amount, it outlines the target vs predicted result. Both summarise strong estimation results with a coefficient of determination of 0.9 and 0.85, respectively. The main objective of the model is to take into account Islamic factors such as Zakat payments and the number of committed crimes. While the number of committed crimes and the attendance of an Islamic school only marginally affects the maximum overall amount, the amount of Zakat paid represents a key parameter in determining the ability to pay back the funds.

Figure 10: Regression plot for the maximum number of individuals for an Islamic microfinance loan.

In summary, the most important parameters to the model are the amount of Zakat paid, number of committed crimes and the value of collateral.

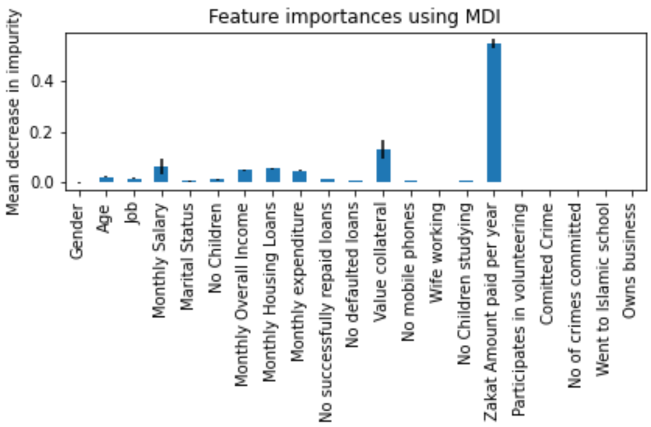
Interestingly, by using the difference between the MDI and feature importance based on permutation, the amount of Zakat paid as well as value of collateral, in addition to the number of crimes committed are the most critical parameters.

Comparing this to conventional risk management, the model outlines the stronger focus on Islamic values and behavioral parameters as compared to solely numerical and income derived parameters. While these parameters are taken into account, contributions to the society in the form of Zakat are utilized as benchmarks in order to assess the qualification. Thereby, the financial institution aims to correlate factors such as honesty and high charity contributions with a better credit rating and likelihood of repayment. This has been observed in multiple

Received: 11/08/2021 - Accepted for publication: 20/07/2022 - Published: 29/07/2022

instances where individuals tried to take advantage of situations and lacked honesty, and in the end aimed to severe and take advantage of the business environment [21]. While treachery may pay off for the loan taker that may gain an unfair advantage from dishonesty, the microfinance institution may experience considerable losses. Hence, a stronger focus on social parameters, such as charity contributions and faith may be key parameters to enhance microfinance efficiency and overcome the challenges of conventional risk management models.

MDI



Feature Permutation

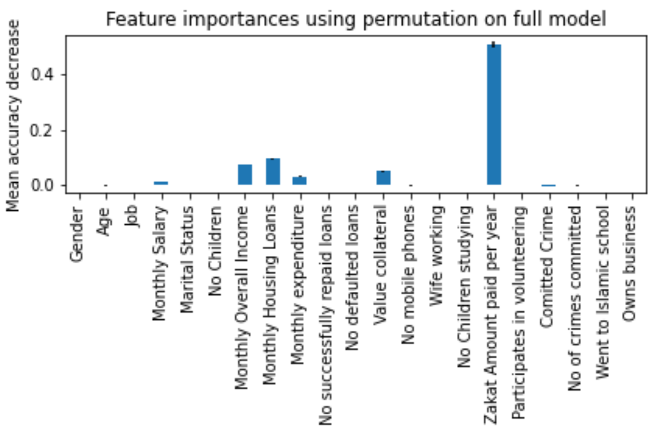


Figure 11: Feature importance for both mean decrease in impurity, and feature permutation for the maximum loan value for an Islamic microfinance loan.

IV. Conclusion

We have presented in this paper a novel AI-driven approach to financial risk management for Islamic microfinancing. The data-driven framework overcomes a key challenge in incorporating Islamic values in the provisioning of Islamic microfinancing for determining eligibility for loans, credit risk, and the maximum overall amount. The results from the framework represent a critical step towards strengthening loan governance and evaluating loan applicants fairly. A distinctive feature is to capture the loan applicant's attitude vis-à-vis Islamic values. This value element is generally absent from conventional microfinance that primarily focuses on income levels and collateral. An additional benefit of this model is the absence of a loan officer's personal views on the individual who applies for a loan, reducing biases against the most disadvantaged and processing costs. This approach represents a positive step toward enhancing access to Islamic microfinancing.

V. References

[1] B. Kustin, "Islamic (Micro)finance - culture, context, promise and challenges," Bill & Melinda Gates Foundation, 2015.

[2] M. Uddin, "Determinants of Loan Default of Low-Income Borrowers in Urban Informal Credit Markets: Evidence from Dhaka City.," *European Journal of Business and Management,* vol. 11, no. 26, pp. 105-114, 2019.

[3] M. El-Komi and R. Croson, "Experiments in Islamic microfinance," *Journal of Economic Behavior & Organization,* vol. 95, pp. 252-269, 2013.

[4] H. Begum, M. R. Alam, A. S. A. Alam and A. H. Awang, "Islamic microfinance as an instrument for poverty alleviation.," *Advanced Science Letters,* vol. 21, no. 6, pp. 1708-1711, 2015.

[5] B. Shanmugam and Z. R. Zahari, A primer on Islamic Finance, New York: Research Foundation of CFA Institute, 2009.

[6] C. Paldi, "Understanding riba and gharar in Islamic finance.," *Journal of Islamic Banking and Finance,* vol. 2, no. 1, pp. 249-259, 2014.

[7] N. Al Rahahleh, M. I. Bhatti and F. N. Misman, "Developments in risk management in Islamic finance: A review.," *Journal of Risk and Financial Management,* vol. 12, no. 1, p. 37, 2019.

[8] M. K. Hassan and R. N. Kayed, "The global financial crisis, risk management and social justice in Islamic finance.," *Risk Management and Social Justice in Islamic Finance,* 2009.

[9] P. Christoffersen, Elements of financial risk management., Academic Press, 2011.

[10] S. Byoun, J. Kim and S. S. Yoo, "Risk management with leverage: Evidence from project finance.," *Journal of Financial and quantitative analysis,* vol. 48, no. 2, pp. 549-577, 2013.

[11] H. Gazali, J. Jumadi, N. Ramlan, N. Rahmat, S. Uzair and A. Mohid, "Application of Artificial Intelligence

Received: 11/08/2021 - Accepted for publication: 20/07/2022 - Published: 29/07/2022

(AI) in Islamic Investments," *Journal of Islamic Finance,* pp. 70-78, 2020.

[12] T. Lin, "Artificial intelligence, finance, and the law," *Fordham Law Review,* p. 531, 2019.

[13] M. Nasri, "Application of artificial neural networks (ANNs) in prediction models in risk management.," *World Applied Sciences Journal,* vol. 10, no. 12, pp. 1493-1500, 2010.

[14] P. Giudici, "Fintech risk management: A research challenge for artificial intelligence in finance.," *Frontiers in Artificial Intelligence,* vol. 1, p. 1, 2018.

[15] N. Bussmann, P. Giudici, D. Marinelli and J. Papenbrock, "Explainable AI in fintech risk management.," *Frontiers in Artificial Intelligence ,* vol. 3, p. 26, 2020.

[16] L. Tang, F. Cai and Y. Ouyang, "Applying a nonparametric random forest algorithm to assess the credit risk of the energy industry in China.," *Technological Forecasting and Social Change ,* vol. 144, pp. 563-572, 2019.

[17] M. Schonlau and R. Y. Zou, "The random forest algorithm for statistical learning.," *The Stata Journal ,* vol. 20, no. 1, pp. 3-29, 2020.

[18] N. Ghatasheh, "Business analytics using random forest trees for credit risk prediction: a comparison study.," *International Journal of Advanced Science and Technology,* vol. 72, pp. 19-30, 2014.

[19] Austrian Red Cross, "Central African Republic - SSPTW 2019," European Country of Origin Information Network, Vienna, 2019.

[20] W. A. K. Kouame, H. T. Edjigu, N. Ouattara and S. Tomi, "Central African Republic Economic Update : The Central African Republic in Times of COVID-19 - Diversifying the Economy to Build Resilience and Foster Growth," World Bank Group, Washington, 2020.

[21] A. Bhide and H. Stevenson, "Why Be Honest If Honesty Doesn't Pay," Harvard Business Review, 1 October 1990. [Online]. Available: https://hbr.org/1990/09/why-be-honest-if-honesty-doesnt-pay. [Accessed 11 December 2021].

European Journal of Islamic Finance - ISSN: 2421-2172
DOI: 10.13135/2421-2172/6202- Published by the University of Turin
https://www.ojs.unito.it/index.php/EJIF/index

Received: 11/08/2021 - Accepted for publication: 20/07/2022 - Published: 29/07/2022