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Islamic Personality Model as Psychometric Tool to Assess Creditworthiness of Micro Financing

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Abstract

This study aims to develop an Islamic personality model as a psychometric tool to assess creditworthiness as an alternative predictive character analysis for micro businesses. The method designed to formulate the proposed model coded in R Studio uses two approaches. First, we modify Moslem Religiosity Personality Inventory and then frame a structural model based on Partial Least Square. Subsequently, we use the random forest technique to see the model's accuracy. The result shows a valid and reliable model and performs with 89.47 % accuracy with an Area Under Curve -Receiver Operating Characteristic of 90.06 %. This model implies a solution to strengthen the assessment of the character of creditworthiness of a potential micro-business and helps Islamic Financial Institutions to assess prospective micro-business to determine credit risk and pricing.

Keywords:
micro financing; credit scoring; Islamic personality; creditworthiness

How to Cite:

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INTRODUCTION

Microbusinesses play a vital role in the economy (Tambunan, 2019) since it dominates 98.67 % of the market. However, it reflects an unhealthy and growing structure in that micro-business is not rising in class. Improving the capability of micro-sector businesses requires solving two main problems. First, trust from financial institutions due to information asymmetry (Agarwal & Hauswald, 2006; Aggarwal & Yousef, 2000; Becchetti & Ponzo, 2011), namely how to effectively select potential partners who have a level of creditworthiness for willingness to repay (creditworthiness) through the process financing analysis (credit scoring analysis). Second, selecting Islamic financing contracts can reduce high transaction costs (Aggarwal & Yousef, 2000; Obaidullah et al., 2008). Consequently, micro-business is required to undertake a creditworthiness analysis process called credit scoring, which predicts financing risk (Abdou et al., 2016; Safitri et al., 2019; Dubina & Kang, 2019; Gool et al., 2010).

In general, credit scoring provided by Islamic financial institutions is also still traditional. It only relies on historical data, thus preventing access to financing for micro-sector partners, many of whom ultimately need a credit score (Vidal & Barbon, 2019; Dubina & Kang, 2019). Dimensions of character and personality, such as social and religious, become rarely assessed in microfinancing, though Islam highlights the critical role of trust and integrity in each transaction (Rabecca et al., 2018).

Even though the previous research confirmed the importance of credit scoring in Islamic finance (Abdou et al., 2016), the use of psychometric data in credit scoring has the advantage of excellent predictive ability in mitigating credit risk (Rabecca et al., 2018). The definition of personality is the organization of a dynamic psychophysical system within a person that will determine the characteristics of the person's behavior. Previous research showed that psychometrics is helpful in improving credit information (Arráiz et al., 2016). Overall conclusions from numerous industrial and organizational psychology studies concurred that personality traits, intelligence, and honesty/integrity were strongly connected with the skills needed to perform the work (Klinger et al., 2013). Additionally, psychological tests that evaluated these three variables had a larger impact on predicting job performance than interviews, peer reviews, reference checks, biographies, and work experience. Microfinance borrowers are also affected by these findings—personality qualities and intelligence help to identify entrepreneurs who can repay a loan.

The obstacle of this research is the need for theories on measuring personality from the Islamic perspective. Islamic personality and religiosity, and the development of religiosity theory by Glock & Stark and Francis Sahin, which adopts a Christian dimension, received attention from Steven Eric Krauss, who compiled The Muslim Religious Personality Inventory (MRPI) to fill the measurement gap. The MRPI instrument (Krauss, 2005) concludes that Islamic personality and religiosity are the levels of one's awareness of God as understood in the monotheistic Islamic view of life. Moreover, several other researchers also created models and instruments based on Islamic personality that helped develop Islamic personality theory (Mujib, 2017; Mohd et al., 2016; Othman et al., 2014; Mahudin et al., 2016; Francis & Sahin, 2008).

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The essential addition of this research to the available literature is in two ways. First, it focuses on formulating the model as a psychometric tool and testing our hypothesis. This study shows that Islamic personality can affect creditworthiness by employing MRPI (Krauss, 2005) and Islamic personality theory (Mujib, 2017) to build an innovative credit scoring inventory based on Islamic Personality. This approach will be fruitful due to market competition within Islamic financial institutions to speed up the administration process. Understanding Islamic characters and religious personalities will take time and resources. Next is to measure the prediction accuracy of the new psychometric tools. According to our findings, Islamic personality has a significant effect on creditworthiness. Furthermore, the variable of aqidah, ibadah, and attitude has significant effects, direct or indirect, through Islamic personality towards the creditworthiness of micro borrowers.

METHODS

This study used a purposive sample of 115 Muslim respondents who run micro-businesses and have credit histories. Respondents were required to complete questionnaires of 223 initial indicators containing Islamic personality (Krauss et al., 2005; Mujib, 2017). These indicators are subset to three variables: (a) Exogenous variable consists of the Islamic Worldview of 3 variables Aqidah (36 indicators), Worship (27 indicators), and Akhlaq (16 indicators); (b) Intervening Variables consist of Islamic Personalities with three dimensions of Mu'min Personality (16 indicators), Muslim Personality (40 indicators), and Muhsin Personality (79 indicators); (c) Endogenous variables: the creditworthiness of micro-business (9 indicators).

The analysis tools use two main approaches, namely Structural Equation Model – Partial Least Square (SEM-PLS) and Random Forest. Conducting Principal Component Analysis (PCA) as a parameter of validity (Ghazali et al., 2020) carried out the validity test. PCA is used to reduce the number of indicators generated from research instruments. Moreover, the question indicators in the research, which are the adoption of previous research, are quite a lot, 223 questions. PCA can synthesize information by minimizing the loss of information from the original data (Karamizadeh, 2013). This method has been widely used on data with large volumes and dimensions in the scope of machine learning (Barshan et al., 2011; Caggiano et al., 2018; Chahboun & Maaroufi, 2021).

PCA analysis was carried out using the R programming language using the 'psych' package (Revelle. W, 2021). The goal is to produce a principal component with a particular variation that synthesizes variables through the varimax rotation approach. Question items that do not meet the component loading requirements will be excluded. The limit value used is the component loading of 0.60 (Tabachnick & Fidell, 2007). There are two preliminary tests so that PCA can be carried out, namely: (1) Kaiser-Meyer-Oklin of Sampling Adequacy (KMO-MSA) with a minimum score limit of 0.50; and (2) Bartlett's test with a p-value criterion of more than the alpha error degree (Huang et al., 2020). The parameters to test the reliability used Cronbach Alpha for each research variable with a minimum limit of 0.60 (Sekaran, 2003).

This research also proposes supervised machine learning (ML) based classification modeling for predicting the result. This approach can measure how well the level of accuracy of the model in predicting and classifying. The dependent variable or target, creditworthiness, is factored into two classes. Classification of endogenous variables is the sum of respondents' answers to questions on creditworthiness indicators/variables that have been previously reduced using Principal Component Analysis. If the sum of the answer values is greater than or equal to 20 (the sum of five answers with a minimum response of 4) then it is categorized as 'likely to pay' (given code = 1). While the sum of answers that are less than 20 is categorized as 'unlikely to pay (given code = 0).

This study uses several parameters to evaluate the model for testing the accuracy of predictions and classification, namely the level of accuracy (accuracy), precision (precision), sensitivity (sensitivity), specificity (specificity), and Area Under Curve (AUC). First, accuracy measures the model's accuracy in predicting the whole ('1'/'0'). Second, precision measures the model's accuracy in identifying the class '1', which is actually '1'. Third, sensitivity or true positive rate measures all '1' in the sample, what proportion does the model suspect is '1'. Fourth, the specificity or true negative rate measures all '0' in the sample, what proportion does the model suspect is '0'. Fifth, the ROC curve contains the ratio between the false positive rate (1-specificity) and the true positive rate. AUC value below 0.50 indicates the model cannot distinguish between '1' and '0'. The model with 100% (perfect) prediction accuracy has an AUC of 1.00. The level of importance of the independent variable (variable of importance) is also presented to find out which of the many independent variables has the highest importance in the model.

RESULT AND DISCUSSIONS

Table 1. KMO-MSA, Bartlett, and Reliability Test

Indicator/Variable	No. of Question	KMO MSA	Bartlett Test *pvalue*	*Cronbach Alpha*
Tauhid Rububbiyah (TR)	5	0,81	0,00	0,92
Tauhid Uluhiyah (TU)	5	0,74	0,00	0,87
Tauhid Asma Washifat (TA)	5	0,78	0,00	0,80
Believe to Allah (IA)	3	0,69	0,00	0,79
Believe in Angels (IM)	3	0,48	0,00	0,50
Believe in Holy Scriptures (IQ)	6	0,84	0,00	0,82
Believe in Messenger (IR)	3	0,71	0,00	0,85
Believe in Judgment Day (IH)	3	0,65	0,00	0,69
Beileve in Qodho & Qodar (IO)	3	0,62	0,00	0,72
Ibadah/Worship (IB)	27	0,90	0,00	0,94
Personal Attitude/moral (AP)	6	0,59	0,00	0,49
Social Behaviour (AS)	10	0,76	0,00	0,76
Mu’min Personality (KI)	16	0,88	0,00	0,91
Muslim Personality (KU)	40	0,86	0,00	0,94
Muhsin Personality (KM)	79	0,79	0,00	0,96
Creditworthiness (Dependent)	9	0,73	0,00	0,74

Source: Research finding

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Table 1 shows that almost all indicators/variables have met the criteria for parameters, except for IM and AP indicators/variables. This result is presumably because several questions need to be more significant. This condition can be overcome using the PCA method, which issues questions with a low component loading value. After excluding indicators with low component loading (Appendix 1), the PCA analysis was carried out again, and the results are presented in Table 5. The number of questions was reduced from 223 to 136. These results increased the Cronbach Alpha reliability value, especially for indicators/variables that did not meet the reliability requirements at first. The reliability of the IM indicator/variable increased from 0.50 to 0.60, and the AP increased from 0.49 to 0.71. Thus, all indicators/variables have met the reliability requirements.

Table 2. PCA Analysis Outcome

Indicator/Variabel	*Component Loading Range*	Varians proportion	Sig.
Tauhid Rububbiyah (TR)	0,80-0,91	76%	0,00
Tauhid Uluhiyah (TU)	0,67-0,91	67%	0,00
Tauhid Asma Washifat (TA)	0,77-0,86	65%	0,00
Believe to Allah (IA)	0,80-0,86	70%	0,00
Believe in Angels (IM)	0,84	71%	0,00
Believe in Holy Scriptures (IQ)	0,60-0,81	53%	0,00
Believe in Messenger (IR)	0,85-0,89	76%	0,00
Believe in Judgment Day (IH)	0,70-0,85	62%	0,00
Beileve in Qodho & Qodar (IO)	0,74-0,87	64%	0,00
Ibadah/Worship (IB)	0,61-0,83	50%	0,00
Personal Attitude (AP)	0,88	78%	0,00
Social Behaviour (AS)	0,63-0,82	51%	0,00
Mu'min Personality (KI)	0,60-0,81	54%	0,00
Muslim Personality (KU)	0,63-0,76	50%	0,00
Muhsin Personality (KM)	0,60-0,82	47%	0,00
Creditworthiness (Dependent)	0,66-0,83	58%	0,00

Source: Research finding

From Table 2 can also be seen that all questions have a range of component loading values that meet the requirements (more than 0.60). The variance proportion value explains how much variation the question component has successfully explained to the indicator. The value of the smallest component proportion is the KM indicator/variable at 47%. This condition happens because of the many questions on the indicator/variable, so forming one component produces relatively low variation. However, the formation of one component on all indicators/variables has been deemed sufficient and significant.

Table 3. First Stage Measurement Evaluation Model

Latent Variable	Indicator number	Value Range of *Loadings*	CA	ρ
Aqidah	34	0,19-0,64	0,96	0,89
Worship	18	0,41-0,72	0,94	0,89
Moral	9	0,49-0,66	0,86	0,81
Personality	70	0,43-0,65	0,98	0,97
Creditworthiness	5	0,58-0,69	0,81	0,77

Source: Research finding

There are three main parameters in evaluating the measurement model internal consistency, convergent validity, and discriminant validity. Indicators that have a loadings value of less than 0.50 will exclude from the model. From 223 question indicators after evaluating the measurement model using Principal Component Analysis, 136 indicators were obtained shows in Table 3. From a total of 136 indicators, there are still indicators in the latent variable that do not meet the requirements for a minimum loadings value of 0.50. These indicators are found in all latent variables, except creditworthiness.

The second and third criteria in evaluating the measurement model are testing convergent validity and discriminant validity. Average variance extracted (AVE) threshold of 0.50 can be used to evaluate convergent validity. Contrary to this, discriminant validity can be assessed by evaluating the cross-loading parameter. Indicators with discriminant validity are those with a high correlation between indicators of the same latent and indicators with low or no correlation between indicators of different latent (Henseler et al., 2015). In this process, 58 indicators were excluded because they did not meet the requirements, especially discriminant validity so the remaining 78 indicators formed the SEM-PLS model.

Table 4 Evaluation of Convergent Validity

Latent Variable	AVE
Aqidah	0,41
Worship	0,51
Moral	0,53
Personality	0,49
Creditworthiness	0,47

Source: Research finding

Based on Table 4 and the remaining 78 indicators, the AVE value for each latent variable is obtained. Several variables have an AVE value of less than 0.5, namely Aqidah, Personality, and Collectability variables. However, it is still acceptable when the composite reliability (ρ) value is more than 0.60 (Fornell & Larcker, 1981; Lam & Maguaire, 2012).

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Based on Table 5, the value for all variables is more than 0.60 so it is still acceptable. After being tested again, the results of the discriminant validity matrix (attachment) gave good results, namely, all correlations in one variable were given the highest value when compared to correlations to other variables. All evaluation indicators of the measurement model, namely internal consistency, convergent validity, and discriminant validity, have given good results and meet the requirements. The structural model was evaluated with a confidence interval as the hypothesis was developed, as shown in Figure 1.

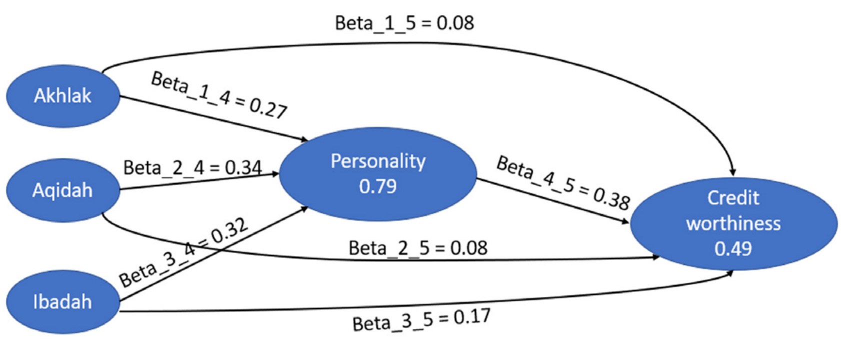
Table 5. Final Stage Measurement Evaluation Model

Latent Variable	Number of Indicators	Interval Loadings Value	CA	ρ
Aqidah	10	0,57-0,65	0,91	0,87
Worship	11	0,53-0,71	0,92	0,87
Moral	8	0,53-0,66	0,84	0,80
Personality	44	0,51-0,64	0,97	0,95
Creditworthiness	5	0,59-0,69	0,81	0,77

Source: Data, 2021

Quite interesting results were obtained from the overall hypothesis testing based on the existing samples. Figure 1 is the inner model of structural SEM-PLS. Between each of the pillars, Aqidah and Akhlak/morals do not directly influence creditworthiness as a variable. At the same time, ibadah has a direct influence on creditworthiness. However, when measured through the personality variable, the three pillars provide a significant and one-way relationship to creditworthiness. Thus, the measurement of collectability through Islamic personality influenced by the three pillars of Aqidah, ibadah, and Akhlak/morals gives the results of a significant relationship to collectability.

Figure 1. SEM Structural Model



Source: Research finding

A structural relationship is significant if there is no 0 value between the lower and upper percentiles (Gudergan et.al, 2008). As shown in Table 6, the structural model in figure 1 was tested directly (directly), indirectly (indirectly), and overall (total). After knowing the significance of the relationship between latent variables, the next step is to evaluate the structural model with parameter R^2. There are several references in determining how good this R^2 value is. Based on the processing results, the R2 value for the Personality variable was 0.79 or 79%. Meanwhile, the value of R^2 for the collectability variable was 0.49 or 49%. 'Strong' and 'medium' are the two categories of values (Chin, 2010). The research model also shows that 79% of the factors influencing Islamic Personality are related to Aqidah, Worship, and Attitude. Aqidah, Worship, Attitude, and Personality explain 49% of creditworthiness factors.

Table 6. Path Coefficient of Variable D*irect*, *Indirect*, and *Total Effect*

Variable Relations	*Direct Effect*	*Indirect Effect*	*Total Effect*
Personality → Creditworthiness	0,38	-	0,38
Aqidah → Creditworthiness	0,08	0,13	0,21
Worship → Creditworthiness	0,17	0,13	0,30
Akhlak → Creditworthiness	0,08	0,10	0,18

Source: Research finding

There are several other criteria to consider besides the path coefficient and R^2 value, especially when assessing the suitability of the resulting model. The parameters used in this study are the standardized root mean square residual (SRMR) and Stone-Geisser (Q2) (Garson, 2016). From table 7, in general, all model fit criteria give good results. The SRMR value of 0.064 is still below the 0.080 thresholds. Consequently, the value model fits the data since there is not much difference between the actual value and the value in the model. For Variable Personality and Creditworthiness variables, Q2 is 0.44 and 0.39, which are close to the R2 value for Collectability and greater than 0. This value also indicates the model is relevant and fits the data. Using the SEM-PLS approach above, we conclude that Aqidah, Worship, and Attitude have a significant impact on creditworthiness through the Personality variable. Subsequently, predicting creditworthiness requires this information.

Table 7. The Evaluation Result of Model SEM PLS

Variable	R^2	SRMR	Q^2
Aqidah	-		-
Worshio	-		-
Attitude	-	0,064	-
Personality	0,79		0,44
Creditworthiness	0,49		0,39

Source: Research finding

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One of the most important things in building a predictive model using ML such as RF is the need for a class balance. The class imbalance will greatly affect the value and accuracy of the model (Luque et.al, 2019). From 115 samples, the dependent variable creditworthiness as a proportion of likely to pay ('1') of 61.7%, while unlikely to pay ('0') is 38.3%. Although it does not have a perfect class balance, it is still acceptable because it is still classified as a slight imbalance or a ratio higher than 1:4 (Krawczyk, 2016).

Figure 2. Number of Tree and Out of Bag

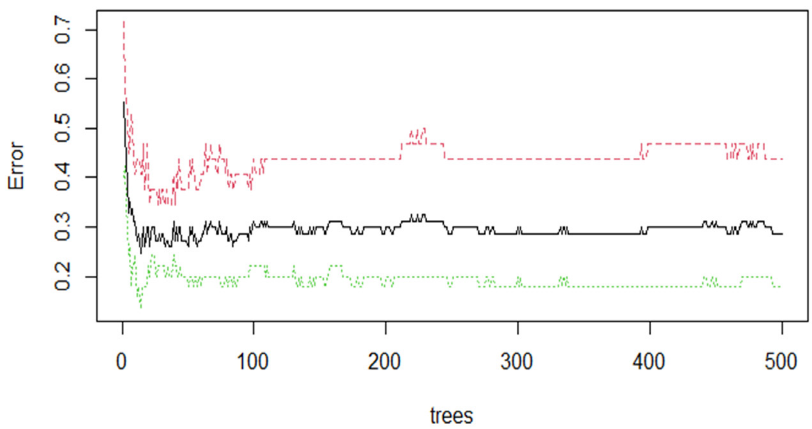

Figure 2 shows that by default the RF model provide OOB, which tends to be stable. The RF model is built on a training dataset of 77 samples with the default setting, which is 500 classification trees with the number of randomized indicators in each split of 11 indicators (which is rounded off from the square root of the number of samples). This modeling results in a stable out-of-bag (OOB) error of 31.17%. The RF model is then tuned to find the optimal split value so that it can reduce the OOB value. The split value (mtry) is obtained by 10 after the tuning process. Then, the RF model was rebuilt with 500 classification trees and produced a new model with the OOB value down to 28.57%. Although not very good, this value is still acceptable considering a large number of independent variables and the sample size is not too large.

Testing the level of prediction accuracy of the RF model is carried out based on testing data containing 38 samples. Using these data, the model is tested and the performance results are presented in Table 8. It shows that: First, the level of accuracy of the model in predicting creditworthiness is 89.47%. This accuracy is obtained from (True Positive + True Negative) / (number of positive samples + number of negative samples). (11 + 23) / 38 x 100 % = 89.47 %. Second, this model has a precision level of 78.57% (Precision = True Positive / (True Positive + False Positive) or 11 / (11+3) = 78.57 %. Third, sensitivity of 91.67% means that this model is 91.67% and often succeeds in predicting a sample with a value of 1, so in its original condition it is indeed 1. TPR is calculated by TP/(TP+FN) or 11 / (11+1) = 91, 67 %. Fourth, a specificity of 88.46% indicates that this model often predicts that 88.46% of a sample has a value of 0, so in its original condition it is indeed 0. This TNR is measured by TN/TN + FP, or 23 / (23+3) = 88.46 %.

Table 8. RF Accuracy in Predicting Creditworthiness

Prediction Model	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	AUC-ROC (%)
Random Forest	89,47	78,57	91,67	88,46	90,06

Source: Research finding

The RF Model can make predictions quite well based on the testing dataset. Based on the Confusion Matrix in Figure 3 above, the model's accuracy in predicting collectability/creditworthiness is 89.47%. In quadrants 1 and 11, unlikely-to-pay borrowers are correctly classified as unlikely-to-pay borrowers. While in quadrant 2, there is one likely-to-pay borrower incorrectly classified as unlikely to pay borrowers. In quadrant 3, three unlikely-to-pay borrowers are incorrectly classified as likely-to-pay borrowers. Similarly, in quadrant 4, 23 likely-to-pay borrowers are correctly classified as likely-to-pay borrowers.

Figure 3. Confusion Matrix Model RF

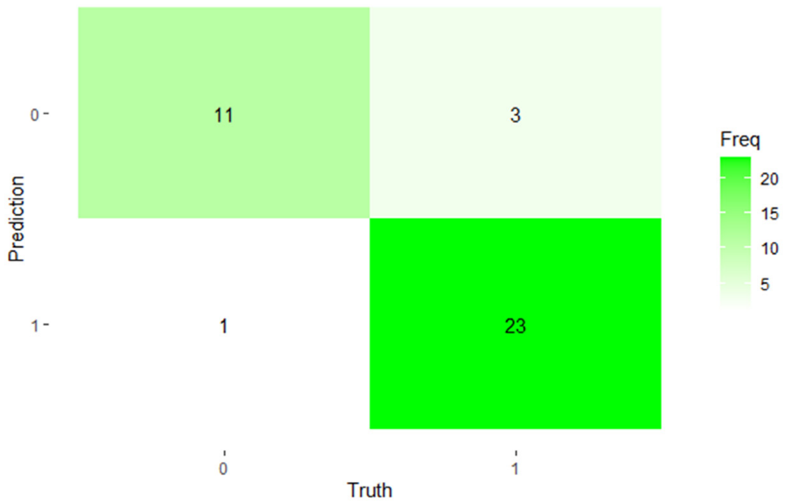

Figure 4 show ROC (Receiver Operating Characteristic) curve, contains a comparison between the false positive rate (1-specificity) and the true positive rate, which can be calculate as follows:

False Positive Rate (FPR) = False Positive / (False Positive + True Negative) = 11.53%

True Positive Rate (TPR) = True Positive / (True Positive + False Negative) = 91.67 %

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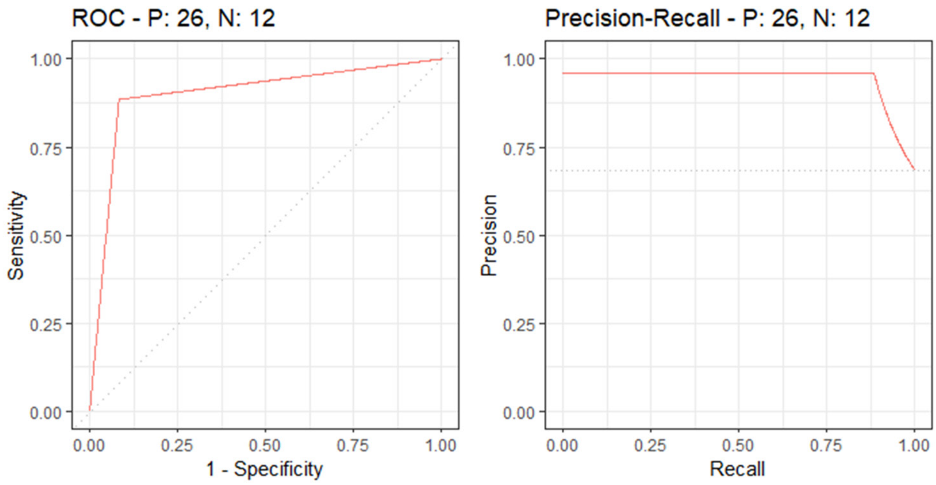
Figure 4. ROC Curve for RF Model



Compared to actual data, the model can predict with precision the 'likely to pay' class of 78.57% and the 'unlikely to pay' class of 91.6%. The AUC (Area Under Curve) value as shown in Figure 4 (Receiver Operating Characteristic model) of 90.06% indicates that the RF model has a good ability to predict creditworthiness, which is shown by the ROC curve approaching the point (0.1) An AUC value below 0.50 indicates the model cannot distinguish between '1' and '0'. The model with 100% (perfect) prediction accuracy has an AUC of 1.00. From the ROC curve and AUC values above, it can be concluded that the performance of the Random forest algorithm for the Islamic personality-based credit scoring model can predict all test data perfectly.

CONCLUSION

Based on testing with the SEM-PLS approach, it can be concluded that all religiosity factors, such as aqidah, ibadah/Worship, and akhlak/morals, significantly affect the level of creditworthiness through the mediating variable Islamic Personality. Partially, the aqidah variable has no significant direct effect on creditworthiness because it only gets a direct effect coefficient value of 0.08 with a percentile range of -0.04-0.21. However, the Aqidah variable indirectly affects creditworthiness through personality aspects with an indirect coefficient value of 0.13 and a percentile range of 0.08-0.16. The direct relationship between Aqidah and creditworthiness in the previous hypothesis is not significant. Thus, the Personality variable is a fully mediating variable in the relationship between Aqidah and creditworthiness (personality variable as full mediation).

The worship variable has a positive effect both directly and indirectly on the creditworthiness of micro business partners, worship directly obtains a direct coefficient value of 0.17 with a percentile of 0.06-0.31, while an indirect coefficient value of 0.13 and a percentile range of 0.08 - 0.16. This result explains that the more disciplined and orderly a person's Worship in terms of time, procedures that meet legal and harmonious requirements, and specialty, the better the level of creditworthiness, where the variable Islamic personality is Part Mediation. Meanwhile, the morality variable has no significant direct effect on creditworthiness, because it only gets a direct effect coefficient value of 0.08 with a percentile range of -0.04-0.20. However, the Aqidah variable has an indirect effect on creditworthiness through personality aspects. The indirect effect coefficient value is 0.10 with a percentile range of 0.06-0.12. The direct relationship between morals and creditworthiness in the previous hypothesis is insignificant. Thus, the personality variable acts as a total mediating variable in the relationship between morals and creditworthiness, whereas the personality variable acts as full Mediation.

Meanwhile, the Islamic Personality factor significantly affects the creditworthiness level of potential partners with a direct effect coefficient of 0.38 and a percentile value range of 0.25-0.48. The most dominant dimension in this personality model is the Conscientiousness (C) dimension, which means that potential partners tend to be individual characters who tend to be more careful and orderly in acting or considerate in making a decision. Positive characteristics on the dimension are reliable, perfectionist, wise, diligent, responsible, and achievement-oriented. Have high self-discipline and can be trusted.

In terms of predictability, based on dataset testing, Islamic personality-based credit scoring capital processed with Random Forest Machine Learning can be used to make predictions quite well, with a model accuracy rate in predicting collectability of 89.47%. The credit scoring model can predict the 'likely to pay' class of 78.57% and the 'unlikely to pay' class of 91.6%. The AUC value, as in the ROC model, is 90.06% indicating that the Random Forest model performs well in predicting creditworthiness. Consequently, this Islamic personality-based credit scoring model holistically shows a strong foundation in developing the quality of the Know Your Customer (KYC) process in Islamic Financial Institutions (IFI), through their involvement in this process and focus on meeting the needs and desires of their customers, especially micro sector financing. In essence, IFI must have a deep understanding of potential financing partners one by one and should not be generalized. IFI must be able to provide financing "to the right person with the right risk and price" so that the pricing of micro business can be distinguished according to the risk of his personality.

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