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Development of a Character Evaluation Model in Risk Management for Microfinance in Individuals of Small Medium Enterprise

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ABSTRACT: This study develops a character evaluation model for PT.XYZ's customers in microfinance credit risk management. Integrating psychological and industrial engineering approaches, this research assesses customer personality using the International Personality Item Pool Big-Five Factor Marker-25 (IPIP BFM-25). The five personality dimensions, which are Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, are assessed to classify customers according to their credit risk level. Decision Tree is employed for the classification of customers into risk groups, and the latter are represented graphically with Traffic Light Analysis (TLA) color codes green (low risk), yellow (medium risk), and red (high risk). Research reveals that the predictors of the classification of credit risk are most powerful for conscientiousness and neuroticism, with more conscientiousness equating to less risk and more neuroticism equating to more risk. Most of the customers are medium-risk, and more assessment is necessary prior to granting credit. The study reveals advantages of applying tests of psychology for making financial judgments, giving a better method to financial institutions than traditional financial standards for assessing creditworthiness. The approach enhances risk forecasting quality, assists with the minimization of non-performing.

KEYWORDS: Customer Character, Credit Risk, Decision Tree, IPIP BFM-25, Traffic Light Analysis

INTRODUCTION

Microfinance has emerged as a pivotal tool for economic development, particularly in low-income regions, by providing financial services to underserved populations. However, the sector faces numerous challenges that threaten its sustainability and effectiveness. One of the primary challenges is the management of various risks, including credit risk, operational risk, and default risk. These risks are exacerbated by the unique characteristics of microfinance institutions (MFIs), which often operate without traditional collateral mechanisms, making effective risk management crucial for their survival and growth [1,2].Credit risk is particularly significant in the microfinance sector, as MFIs primarily lend to individuals and small businesses with limited financial histories. The absence of conventional risk mitigation tools such as collateral necessitates robust credit risk management practices. Studies indicate that effective credit risk assessment can lead to improved loan performance and reduced default rates [3,4]. Moreover, the relationship between the size of the loan portfolio and risk management strategies is critical, as larger portfolios may require more sophisticated risk management frameworks to mitigate potential losses [5][6].

Operational risk also poses a significant challenge for MFIs, particularly in regions where financial literacy is low. The lack of understanding among borrowers regarding financial products can lead to mismanagement of loans, increasing the likelihood of defaults [7,8] Furthermore, the operational costs associated with providing microfinance services can be high, particularly when targeting low-income populations, which can strain the financial sustainability of MFIs [9] Effective operational risk management practices are essential to ensure that MFIs can continue to serve their target populations without compromising their financial health [10,11].

Conventional credit evaluation systems, while foundational to the financial industry, exhibit several weaknesses that can hinder their effectiveness in accurately assessing creditworthiness. One major limitation is their reliance on historical data and traditional metrics, which often fail to capture the complexities of modern borrowers' financial behaviors and circumstances. Traditional credit scoring methods struggle to adapt to the rapidly changing financial landscape, where machine learning and predictive analytics could provide more nuanced insights into borrowers' creditworthiness [12]. The inability to incorporate real-time data and behavioral indicators limits the predictive power of these systems, making them less reliable in assessing risk. Another significant weakness is the lack of transparency and interpretability in conventional credit scoring systems. Many traditional models operate as "black boxes," where the decision-making process is not easily understood by either borrowers or lenders. This lack of transparency can lead to mistrust among consumers, particularly when they are denied credit without a clear explanation of the reasons behind the decision [13].

Additionally, conventional credit evaluation systems often fail to consider non-financial factors that can impact a borrower's ability to repay loans. For instance, social and environmental factors, which are increasingly recognized as important indicators of creditworthiness, are typically overlooked in traditional assessments [14]. This oversight can lead to a narrow understanding of risk and may result in missed opportunities for lending to borrowers who, despite lacking traditional credit metrics, may demonstrate strong repayment potential based on other criteria. the reliance on demographic factors and historical transaction data can introduce biases into the credit evaluation process. Studies have shown that traditional credit scoring can disproportionately affect certain demographic groups, leading to systemic inequities in access to credit [15,16] As a result, there is a growing call for more inclusive and holistic approaches to credit evaluation that consider a wider array of data sources, including behavioral data and social capital, to create a more equitable lending environment [17][18].

Therefore, the researcher wants to examine the character of customers with the Development of a Character Evaluation Model in Risk Management for Microfinance in Individuals of small medium enterprises. The method used is to combine the science of psychology with the science of industrial engineering. The International Personality Item Pool Big-Five Factor Marker-25 (IPIP BFM-25) is a concise instrument designed to assess the Big Five personality traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Its application in various fields, including customer personality assessment, has garnered attention due to its potential to enhance understanding of consumer behavior and preferences [19].

One concern is the potential for oversimplification of complex human behaviors into broad personality categories. While the Big Five model provides a useful framework, individual behaviors can be influenced by situational factors that are not captured by personality assessments alone (Xue, 2023). Businesses should consider integrating personality assessments with other data sources, such as behavioral analytics and customer feedback, to gain a more comprehensive understanding of their customers. The use of decision trees as a classification method for grouping customers based on risk levels has gained traction in various sectors, particularly in finance and customer relationship management. Decision trees offer a transparent and interpretable approach to classification, making them particularly suitable for applications where understanding the rationale behind decisions is crucial. One of the primary advantages of decision trees is their ability to handle both categorical and continuous data effectively. This flexibility allows businesses to incorporate a wide range of customer attributes when assessing risk levels. The effectiveness of decision trees in risk classification can be influenced by the quality of the input data. Inaccurate or incomplete data can lead to misleading classifications, underscoring the importance of data quality in the decision-making process. Organizations must ensure that their data collection and preprocessing methods are rigorous to maximize the effectiveness of decision tree models [21].

Traffic Light Analysis (TLA) as a visualization system can significantly enhance credit decision-making processes by providing a structured and intuitive way to assess customer risk levels. By employing a traffic light metaphor—where green indicates low risk, yellow indicates moderate risk, and red indicates high risk—financial institutions can quickly interpret complex data regarding customer profiles and behaviors. This approach simplifies the decision-making process and allows for immediate visual feedback, which is crucial in high-stakes environments such as credit assessment. One of the key advantages of TLA is its ability to integrate various data sources into a cohesive visualization.

METHOD

The IPIP BFM-25, a concise measure of five core personality traits, has been used effectively in various studies to assess customer character and trust in banks. In a study, Azzahra et al. showed that personality traits significantly influence consumer trust and loyalty, using the IPIP-BFM-25 [22]. Similarly, Akhtar and Sumintono's study validated the psychometric properties of the IPIP-BFM-25, confirming its reliability and dimensionality through Rasch analysis on a large sample [23]. These findings underscore the relevance of character traits in predicting customer behavior, which can be crucial for tailoring financial products to meet customer needs.

In the context of credit risk assessment, decision trees serve as a powerful tool to categorize customers based on their creditworthiness. The decision tree methodology allows for a systematic classification of borrowers into risk categories, which facilitates informed lending decisions. In a study, Mustofa et al. highlighted that perceived risk significantly influences credit decisions among micro, small, and medium enterprises (MSMEs), suggesting that understanding customer profiles through personality traits

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can improve risk assessment [24]. Furthermore, integrating personality insights with traditional credit scoring models can result in more nuanced credit risk evaluations, as noted by Khashei and Mirahmadi, who emphasize the importance of a data-driven approach to credit scoring [25].

Traffic light analysis provides a visual framework for interpreting credit decisions, allowing stakeholders to quickly assess risk levels associated with different borrowers. This method enhances transparency and aids in decision-making processes by categorizing borrowers into 'red', 'yellow', and 'green' zones based on their risk profiles. The use of visual aids in financial decision-making has been supported by research that emphasizes the cognitive benefits of visual information processing(Puspasari & Herwiyanti, 2021). By employing traffic light analysis, financial institutions can streamline their credit evaluation processes, making them more accessible and understandable for both analysts and clients.

RESULT AND DISCUSSION

International Personality Item Pool Big-Five Factor Marker- 25 (IPIP BFM-25)

The description of the research data aims to determine the highest and lowest scores of the big five personality variables (openness to experience, conscientiousness, extraversion, agreeableness, neuroticism) on customers at PT. XYZ. The following is a table of descriptions of the research data which includes the minimum score, maximum score, average score (mean), and standard deviation score on the variables:

Table 1 Descriptions of The Research

Variable	N	Min	Max	Mean	Standard Deviation
Openness to Experience	111	9	23	16.48	2.79
Conscientiousness	111	14	25	19.67	2.64
Extraversion	111	10	22	16.72	2.58
Agreeableness	111	15	25	20.03	2.35
Neuroticism	111	6	25	16.39	4.28

After describing the results of the research data description, the next step is to conduct data analysis to determine the category criteria for each variable in the subject. To obtain the description results of the existing categories, researchers group them into three categories as follows:

1. Categorization of Openness to Experience Dimension Variables

Table 2 Dimension Openness to Experience

Dimension Openness to Experience			
Category	Range Value	Frequency	Percentage
Low	$X < 13{,}69$	13	11,2%
Medium	$13{,}69 \leq X < 19{,}27$	79	72,3%
High	$X > 19{,}27$	19	16,5%
Total		111	100%

Based on the categorization table above, it is known that subjects with an openness to experience personality showed a low category of 13 subjects (11,2%), a medium category of 79 subjects (72,3%), and a high category of 19 subjects (16,5%).

2. Categorization of Conscientiousness Dimension Variables

Table 3 Dimension Conscientiousness

Dimension Conscientiousness			
Category	Range Value	Frequency	Percentage
Low	$X < 17{,}06$	26	23,1%
Medium	$17{,}06 \leq X < 22{,}29$	68	62,6%
High	$X > 22{,}29$	17	14,3%
Total		111	100%

Based on the categorization table above, it is known that subjects with conscientiousness personality showed a low category of 26 subjects (23,1%), a medium category of 68 subjects (62,6%), and a high category of 17 subjects (14,3%).

3. Categorization of Extraversion Variables

Table 4 Dimension Extraversion

Dimension Extraversion			
Category	Range Value	Frequency	Percentage
Low	X < 14,17	21	19,2%
Medium	14,17 ≤ X < 19,7	73	65,3%
High	X > 19,7	17	15,5%
Total		111	100%

Based on the categorization table above, it is known that subjects with extraversion personality showed a low category of 21 subjects (19,2%), a medium category of 73 subjects (65,3%), and a high category of 17 subjects (15,5%).

4. Categorization of Agreeableness Variables

Table 5 Dimension Agreeableness

Dimension Agreeableness			
Category	Range Value	Frequency	Percentage
Low	X < 17,9	16	13,7%
Medium	17,9 ≤ X < 22,33	77	69,7%
High	X > 23,33	18	16,6%
Total		111	100%

Based on the categorization table above, it is known that subjects with agreeableness personality showed a low category of 16 subjects (13,7%), a medium category of 77 subjects (69,7%), and a high category of 18 subjects (16,6%).

5. Categorization of Neuroticsm Variables

Table 6 Dimension Neuroticsm

Dimension Neuroticsm			
Category	Range Value	Frequency	Percentage
Low	X < 12,3	19	17,6%
Medium	12,3 ≤ X < 20,66	73	66,1%
High	X > 20,66	19	16,3%
Total		111	100%

Based on the categorization table above, it is known that subjects with neuroticism personality showed a low category of 19 subjects (17,6%), a medium category of 73 subjects (66,1%), and a high category of 19 subjects (16,3%).

Many customers have personality scores that tend to be moderate in all dimensions. However, the diversity of scores in conscientiousness and neuroticism can affect their decision-making patterns, especially in terms of financial risk management.

Decision Tree

Decision trees facilitate customer segmentation by creating clear rules based on customer attributes. Qian et al. utilized decision trees to segment electronic toll collection customers, transforming the classification results into actionable segmentation rules that improved precision marketing efforts [27]. This ability to derive straightforward rules from complex datasets enables organizations to tailor their marketing strategies and risk management practices to specific customer segments, thereby enhancing overall business performance. The interpretability of decision trees also plays a significant role in their application for risk assessment.

Unlike more complex models, decision trees provide a visual representation of the decision-making process, allowing stakeholders to understand how specific customer characteristics influence risk classifications [28].

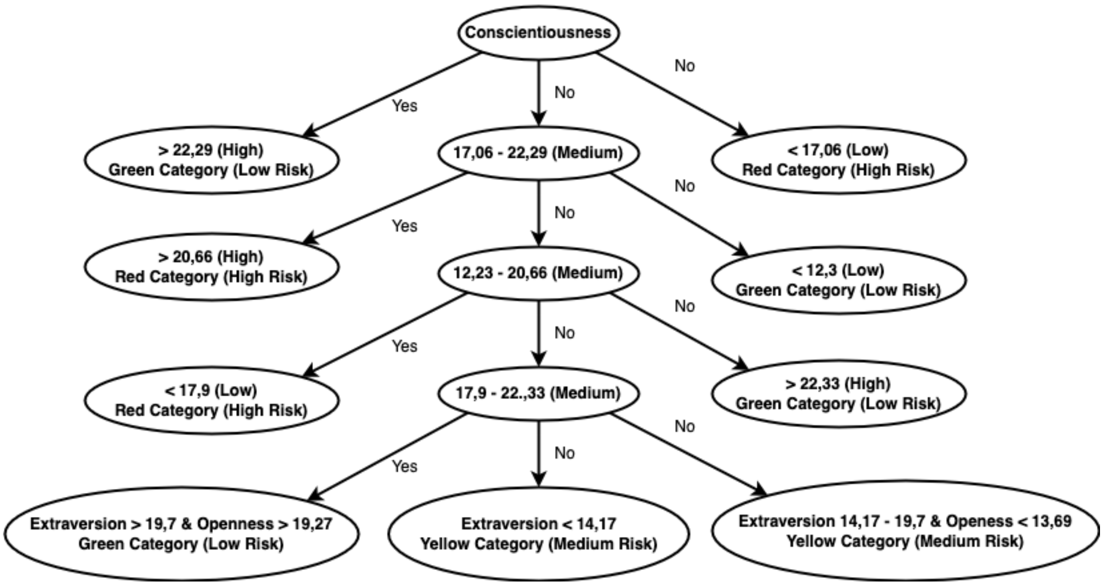

Figure 1. Decision Tree

Traffic Light Analysis (TLA)

Traffic Light Analysis is intelligent traffic light systems have demonstrated that real-time data collection and analysis can optimize traffic flow and improve decision-making [29] [30]. TLA can similarly leverage real-time customer data, such as credit scores, income levels, and spending patterns, to dynamically adjust risk assessments. This adaptability is essential in the financial sector, where customer circumstances can change rapidly, and timely decisions are critical [31]. Moreover, the traffic light system's simplicity enhances communication among stakeholders. Just as traffic light systems provide clear signals to drivers, TLA can convey risk levels to credit analysts and decision-makers in an easily understandable format. This clarity can reduce the likelihood of misinterpretation and facilitate more informed discussions regarding credit approvals or denials [32].

Table 7 Traffic Light Analysis

Category	Criteria	Interpretation
Green (low risk)	High Conscientiousness (≥ 22,26) Low Neuroticism (< 12,1) High Agreeableness (> 22,32) High Extraversion & Openness	The customer is trustworthy, has a good level of discipline and emotional stability, and is easy to work with. Low credit or investment risk.
Yellow (medium risk)	Medium Conscientiousness (17,04 - 22,26) Medium Neuroticism (12,1 - 20,64) Medium Agreeableness (17,7 - 22,32) Medium or Low Extraversion and Openness	Customers tend to be conservative or cautious. Additional analysis is needed before making financial decisions.
Red (high risk)	Low Conscientiousness (< 17,04) High Neuroticism (> 20,64) Low Agreeableness (< 17,7)	Customers are less responsible, have poor emotional stability, and are difficult to work with. High risk in financial decision making

CONCLUSION

In this research, customer character as measured by IPIP BFM-25 was seen to be significant in determining credit risk. The most prominent factors contributing to risk classification are Conscientiousness and Neuroticism, whereby customers who score high on conscientiousness tend to be better behaved and financially stable, whereas those who score high on neuroticism are more prone to risk due to impulsive decision making. The Decision Tree methodology allows for systematic risk classification of customers, with Traffic Light Analysis allowing simple interpretation of findings through a visualization system of Green (Low Risk), Yellow (Medium Risk), and Red (High Risk). The majority of the customers are in the medium risk group, indicating that additional analysis is needed before a credit decision can be made. The implication of this study is that financial institutions can enhance the validity of credit evaluation by incorporating a personality-based approach in risk evaluation. Use of this data-driven methodology can help make more transparent and valid credit decisions, as well as reduce the risk of non-performing loans.

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