FireNav Journal
Financial Resilience and National Values Journal
Vol. 1, No. 1, March 2025, pp. 47-59.
https://firenav.upnjatim.ac.id/index.php/firenav/index
E-ISSN 3089-8285

Risk-Based Clustering of Microfinance Institutions in Indonesia: Insights for Strategic Development and Policy Making

Dimas Nugroho Dwi Seputro*, Irma Kurniasari, Refiana Dwi Maghfiroh
Management Department, Faculty of Economics and Business, Universitas Pembangunan Nasional Veteran Jawa Timur, Jl. Rungkut Madya, Gn. Anyar, Kec. Gn. Anyar, Surabaya, Jawa Timur 60294 - Indonesia

Abstract

Purpose: In Indonesia, Microfinance Institutions (MFIs) have gained significant attention as a vital component of economic development. This research is expected to contribute to the strategic development of MFIs as key drivers of economic empowerment and poverty reduction in Indonesia, ensuring their continued relevance and impact in a rapidly changing financial ecosystem through cluster analysis. By clustering provinces according to MFI financial profiles, policy interventions can be more targeted and effective.
Method: This research is quantitative research with secondary data sources from Otoritas Jasa Kuangan (OJK) website. The population in this study are Micro Finance Institutions (MFI) in Indonesia with a total of 23 samples and 9 variables. Data analysis technique using Cluster Analysis.
Findings: Based on the cluster analysis, three clusters of Microfinance Institution (MFI) entities were identified, where: Cluster 1 (High-Risk MFIs): Small-scale MFIs with limited financial activity and higher vulnerability to liquidity issues and defaults. Cluster 2 (Moderate-Risk MFIs): Medium-sized, growing MFIs with balanced financials and potential for further stability through increased customer engagement. Cluster 3 (Low-Risk MFIs): Large, well-established MFIs with strong financials, high deposits, and effective risk management practices
Novelty: This study highlights the integration of fintech solutions by MFIs to improve customer experience, operational efficiency, and financial inclusion. This aspect underscores the transformative impact of technology on traditional financial services. It stands out by combining cluster analysis with a focus on fintech integration and government policy impact, providing a comprehensive and targeted approach to enhancing the strategic development and resilience of MFIs in Indonesia.

Keywords: Microfinance Institution, Cluster Analysis, Risk Analysis, Financial Profiles.

Article history: Received: February 19, 2025; Revised: February 27, 2025; Accepted: March 2, 2025

* Corresponding Author: Dimas Nugroho Dwi Seputro – dimas.seputro.febis@upnjatim.ac.id

INTRODUCTION

In Indonesia, Microfinance Institutions (MFIs) have gained significant attention as a vital component of economic development, particularly in supporting Micro, Small, and Medium Enterprises (MSMEs) over the past four years, from 2020 to 2024. This growing interest is not without reason, as MFIs have played a crucial role in sustaining the economic backbone of Indonesia—MSMEs—during a period marked by unprecedented challenges and rapid changes. One of the most significant catalysts for this development was the COVID-19 pandemic, which struck in early 2020 and left a profound impact on the global economy, including Indonesia. The pandemic severely affected MSMEs, disrupting supply chains, reducing consumer demand, and limiting business operations due to health and safety restrictions. In this context, MFIs, such as Bank Wakaf Mikro (BWM), emerged as essential financial lifelines, offering easier and more flexible access to financing for MSMEs struggling to survive the crisis (Maghfiroh et al., 2021). Unlike traditional financial institutions, MFIs were able to respond quickly to the urgent needs of small business owners by providing microloans with simplified requirements, thus enabling them to maintain their operations and support livelihoods in local communities. Furthermore, MFIs have proven to be more than just providers of capital; they also play a critical role in empowering vulnerable groups, particularly women, who are often disproportionately affected during times of crisis (Marino & Gunawan, 2021; Suaidah & Arjun, 2023). By offering not only financial assistance but also education and capacity-building programs, MFIs contribute to enhancing financial literacy and entrepreneurial skills, enabling women to generate income, support their families, and become more resilient to economic shocks. Consequently, the role of MFIs in Indonesia has evolved beyond traditional microfinancing, positioning them as key agents of social and economic empowerment during a turbulent period.

During this transformative period, another significant shift occurred in the operational landscape of MFIs, driven by the rapid advancement of financial technology (fintech). The pandemic not only accelerated digital transformation across industries but also highlighted the urgent need for innovative financial solutions that could provide safer, faster, and more efficient access to financial services. In response, many MFIs in Indonesia adopted fintech solutions, integrating digital platforms and mobile applications into their services to enhance customer experiences and expand their reach (Artika & Shara, 2021; Winarto, 2020). This strategic shift proved to be a game-changer, as it enabled MFIs to overcome traditional barriers of physical distance and limited infrastructure, allowing them to reach underserved and remote communities that were previously excluded from formal financial systems. By leveraging technology, MFIs could offer digital wallets, online payment systems, and mobile-based loan applications, providing customers with convenient and secure financial transactions without needing to visit physical branches. This digital transformation not only enhanced operational efficiency but also significantly contributed to financial inclusion, which remains a critical challenge in Indonesia, where many people still lack access to formal banking services (Holle & Manilet, 2023). As a result, fintech-enabled MFIs have been able to attract a broader customer base, including younger generations who are more tech-savvy, thereby increasing their market penetration and driving financial inclusion. Moreover, the adoption of fintech has facilitated more effective risk management through data analytics and credit scoring algorithms, enabling MFIs to make more informed lending decisions and minimize default risks. Consequently, the integration of fintech into MFIs' operations has not only revolutionized the way financial services are delivered but also enhanced their sustainability and growth potential in an increasingly digital economy.

The remarkable growth and transformation of MFIs in Indonesia would not have been possible without the strategic support of government policies aimed at creating a conducive environment for microfinance development. Recognizing the critical role of MFIs in promoting financial inclusion and supporting MSMEs, the Indonesian government has implemented a series of regulatory frameworks to encourage the sustainable growth of the sector. One of the most influential policies was the enactment of Law No. 1 of 2013 on Microfinance Institutions, which provided a legal foundation for MFI operations and ensured better governance and consumer protection (Yaqin, 2021). By establishing clear guidelines on licensing, supervision, and reporting requirements, this regulation has helped formalize the microfinance sector, increasing public trust and attracting more investors. Research has shown that MFIs operating under this regulatory framework have significantly contributed to local economic growth and poverty alleviation, as they can offer tailored financial products that address the specific needs of underserved communities (Riski & Shauqi, 2023; Romadoni & Herianingrum, 2020). Furthermore, the government has actively fostered collaboration between MFIs and public agencies through various economic empowerment programs, including interest rate subsidies and capacity-building initiatives for micro-entrepreneurs. This partnership approach has proven effective in enhancing community welfare by providing MSMEs with not only financial capital but also the knowledge and skills needed to grow their businesses sustainably (Wahab & Mahdiya, 2023). As a result, government policies have played an instrumental role in shaping the development of MFIs in Indonesia, ensuring that they remain resilient and relevant in an evolving financial landscape.

Despite the remarkable achievements and significant impact of MFIs on financial inclusion and poverty alleviation, there are still critical research gaps that need to be addressed to deepen our understanding of the challenges and opportunities faced by MFIs in Indonesia. One of the most pressing gaps lies in the limited exploration of the mechanisms through which MFI services lead to poverty reduction and improved community welfare. Although many studies have demonstrated the positive impact of MFIs on poverty alleviation, there is still a lack of detailed analysis on how financial products and services specifically contribute to enhancing the livelihoods of vulnerable groups. For instance, research by Gunawan and Muzayanah (2023) highlighted the role of MFIs in reducing poverty, but it did not provide a comprehensive explanation of the pathways through which financial inclusion translates into sustainable economic empowerment. Additionally, while the adoption of fintech has been widely recognized as a catalyst for expanding financial access, there is still a need for in-depth research on how technology integration influences MFI operational efficiency and customer outcomes. Moreover, the dynamic regulatory landscape poses another area for further investigation, as existing studies have not fully examined how government policies impact the sustainability and scalability of MFIs in different regional contexts. Addressing these research gaps would provide valuable insights for policymakers, practitioners, and academics, enabling them to develop more targeted and effective strategies for maximizing the social and economic impact of MFIs in Indonesia.

To contribute to filling these research gaps, this study focuses on analyzing the relationship between the structure of assets, liabilities, and equity in Indonesian MFIs and their impact on loan disbursement and financial risk management. By examining the financial dynamics of MFIs at the provincial level, this research aims to provide a comprehensive understanding of how financial structures influence lending capacity and performance across diverse regional markets. Specifically, this study seeks to answer two critical research questions: First, how do regional MFI clusters influence loan performance and financial risks? Second, what are the implications for financial sustainability? By addressing these questions, the study aims to offer practical recommendations for policymakers to design supportive regulations and targeted interventions that promote the growth of MFIs, enhance financial inclusion, and minimize financial risks. Ultimately, this research is expected to contribute to the strategic development of MFIs as key drivers of economic empowerment and poverty reduction in Indonesia, ensuring their continued relevance and impact in a rapidly changing financial ecosystem.

Cluster Analysis is a statistical method used to group objects based on their similarity, ensuring that objects with similar characteristics belong to the same cluster (Haumahu & Yonlib, 2020). Generally, cluster analysis is divided into two methods: Non-Hierarchical and Hierarchical. In the Non-Hierarchical method, the number of clusters is predetermined, while the Hierarchical method determines the number of clusters through further analysis. The Hierarchical method is subdivided into two approaches: agglomerative (merging) and divisive (splitting). In this research, the hierarchical cluster analysis method is employed, which includes

Single Linkage Method, Complete Linkage Method, Average Linkage Method, Ward's Method, and Centroid Method. One of the main challenges in cluster analysis is determining the optimal number of clusters. To address this, a validity test using the Silhouette Index based on Euclidean distance is applied. The results of this cluster analysis can assist governments and regulators in formulating tailored economic policies for each province in Indonesia, particularly based on the financial data of Microfinance Institutions (MFIs). By clustering provinces according to MFI financial profiles, policy interventions can be more targeted and effective.

LITERATURE REVIEW

Concept and Workflow Cluster Analysis

Cluster Analysis is one of the multivariate techniques used to classify objects into distinct groups, where each group has different characteristics from one another. Objects within the same group have relatively close distances to other objects in that group. The characteristics of objects within a single group tend to have high similarity, while the characteristics of objects between different groups have low similarity. The steps in cluster analysis are as follows Data Standardization, Determining Similarity Measures, Choosing Clustering Procedures, Determining the Number of Clusters, and Interpreting Cluster Results (Hamelia & Sumargo, 2019).

The fundamental concept of cluster analysis revolves around two main measurements: distance and similarity. Distance quantifies the dissimilarity between objects, while similarity measures their closeness. These concepts are critical in cluster analysis, as the grouping process relies heavily on the principle of proximity. Distance measures are typically applied to quantitative data, whereas matching-type measures (e.g., similarity indices) are suitable for qualitative data. In practice, distance calculations often use the Euclidean distance, originally designed for two-dimensional observations.

Several studies highlight the superiority of Euclidean distance. Mohibullah, et. al (2015) argue that the Euclidean method is more effective than other distance metrics, particularly for small-scale datasets. Nishom (2019) further explains that Euclidean distance outperforms Manhattan and Minkowski distances in accuracy. Additionally, Sinwar & Kaushik (2014) compared Euclidean and Manhattan distances using real and synthetic datasets, concluding that Euclidean distance demonstrates better performance in terms of iteration efficiency.

This method begins the clustering process by identifying two or more objects with the highest proximity. The process continues by merging the next closest objects iteratively until a hierarchical tree structure is formed, illustrating the similarity levels from the most similar to the most distinct. This tree structure is called a dendrogram, which plays a key role in clarifying the clustering process. According to Johnson (1967), the steps of the hierarchical clustering method are as follows Cluster Initialization, Cluster Merging, and Recalculating Distances.

Hierarchical Cluster Analysis

Hierarchical clustering is a grouping technique where the number of clusters is not predetermined. This process is executed through two primary approaches: agglomerative (bottom-up) or divisive (top-down) (Nafisah & Chandra, 2017).

a. Agglomerative Method

The agglomerative method begins by treating each object as a separate cluster. Initially, the number of clusters equals the number of objects. The most similar objects are merged first, and this merging process continues based on the similarity between clusters. As similarity decreases, all subgroups eventually coalesce into a single large cluster. This method is further categorized into Single Linkage, Complete Linkage, Average Linkage, Ward's Method, and Centroid Method.

b. Divisive Method

The divisive method operates inversely. It starts with one large cluster containing all objects, which is then split into two subgroups where objects in one subgroup are distant from those in the other. This splitting process continues iteratively until each object forms its own individual cluster.

To assess the validity of each method used in this study, the cophenetic correlation coefficient is employed. The cophenetic correlation coefficient measures the correlation between the elements of the original dissimilarity distance matrix and the elements produced by the dendrogram (cophenetic matrix). The value of the cophenetic correlation coefficient ranges between -1 and 1. If the value of r-coph is close to 1, it indicates that the resulting clustering process can be considered sufficiently good (Saracli, Dogan, & Dogan, 2013).

A dendrogram is a graphical and mathematical representation of the clustering process generated through hierarchical cluster analysis. Its structure resembles a tree diagram, where branching points represent clusters, and the length of the branches indicates the distance at which objects are merged into a cluster. The dendrogram's structure varies depending on the distance metric and linkage method used. To determine the optimal number of clusters, the dendrogram is cut at the largest merging distance. According to Dillon & Goldstein (1984), the cut is made at the largest merging distance or at a point where the resulting clusters have a more meaningful interpretation. In essence, the cutting point is selected based on the most significant merging distance.

Microfinance Institution Risk Performance

When thinking about future research directions for Microfinance Institutions (MFIs) in Indonesia, there are a few key areas worth exploring further. One of them is examining how well MFIs are performing across different provinces, including how many MFIs exist and what their financial health looks like. We can use clustering analysis to group provinces based on financial indicators like fund placements, total financing, and savings. This way, we can identify regions with similar financial risk profiles and performance levels. Financial risk grouping for Microfinance Institutions (MFIs) in Indonesia can be analyzed using several key variables, including deposits held by MFIs, customer savings, fund placements, loans disbursed to customers, and loans received from external sources. Deposits held by MFIs reflect liquidity and financial stability. Higher deposit levels indicate lower financial risk, as they show a stable source of funds to meet obligations. Customer savings indicate community trust and engagement. A strong savings base enhances financial resilience, reducing liquidity risk. On the other hand, fund placements represent the investment strategies adopted by MFIs. Riskier placements may offer higher returns but also increase exposure to financial risks if investments underperform.

Meanwhile, loans disbursed to customers reflect credit risk exposure (Kadima, 2023). A higher volume of loans can increase credit risk, especially if repayment rates are low, affecting asset quality and profitability. Additionally, loans received from external sources indicate dependence on external funding, which can pose liquidity and interest rate risks, particularly if borrowing costs are high or economic conditions change. By analyzing these five variables, MFIs can better understand and categorize their financial risks. This helps them develop effective risk management strategies to maintain financial stability and ensure long-term sustainability (Gupta et al., 2023).

Cluster analysis can help group Microfinance Institutions (MFIs) in Indonesia based on similarities in key financial variables, revealing different financial risk profiles. For example, Low-Risk MFIs typically have high deposits, strong customer savings, conservative investment strategies, and minimal reliance on external loans. These institutions are generally more stable and show effective risk management, leading to better loan recovery rates and lower chances of default. Moderate-Risk MFIs have balanced financials, with moderate deposits, customer savings, and a mix of internal and external funding. They are usually in a growth phase and could benefit from strategies to increase customer engagement and strengthen their financial base. On the other hand, High-Risk MFIs face more challenges, such as low deposits, high dependence on external funding, and aggressive lending practices, which increase their risk of loan defaults and liquidity issues. These institutions may need to reevaluate their lending strategies and funding sources to minimize risks and improve financial stability. By understanding these clusters, MFIs can better assess their financial health and develop targeted risk management strategies, ensuring sustainable growth and long-term stability (Memon et al., 2021).

METHODS

This research utilizes secondary data obtained from the Otoritas Jasa Keuangan (OJK) in Indonesia regarding the financial summaries of Microfinance Institutions (MFIs) by province (in billion rupiah) for the August 2024 period. The data was published by the OJK on 11 November 2024 through the website www.ojk.go.id under the Data and Statistics menu. Table 1 shows the financial data summary of Microfinance Institutions (MFIs) by province consists of 9 variables, including the following:

Table 1. The financial summaries variables of Microfinance Institutions (MFIs)

Variable	Variable Code	Unit
Number of Microfinance Institutions (MFIs) Entities	X_1	Entities
Assets	X_2	Billion Rupiah
Liabilities	X_3	Billion Rupiah
Equity	X_4	Billion Rupiah
Temporary Musharakah Funds	X_5	Billion Rupiah
Fund Placements	X_6	Billion Rupiah
Loans Disbursed	X_7	Billion Rupiah
Loans Received	X_8	Billion Rupiah
Savings/Deposits	X_9	Billion Rupiah

Source: The processed secondary data (2025)

The financial data of Microfinance Institutions (MFIs) in Table 1 was collected across 23 provinces in Indonesia, including Aceh (1), Bali (2), Banten (3), Bengkulu (4), Special Region of Yogyakarta/D.I. Yogyakarta (5), Special Capital Region of Jakarta/DKI Jakarta (6), Jambi (7), West Java/Jawa Barat (8), Central Java/Jawa Tengah (9), East Java/Jawa Timur (10), South Kalimantan/Kalimantan Selatan (11), Central Kalimantan/Kalimantan Tengah (12), East Kalimantan/Kalimantan Timur (13), Lampung (14), Maluku (15), West Nusa Tenggara/NTB (16), Papua (17), Riau (18), West Sulawesi/Sulawesi Barat (19), South Sulawesi/Sulawesi Selatan (20), West Sumatra/Sumatera Barat (21), South Sumatra/Sumatera Selatan (22), and North Sumatra/Sumatera Utara (23).

This research employs Hierarchical Cluster Analysis using R software. The data analysis begins with processing the dataset to examine descriptive statistics for the nine variables, followed by data standardization, selection of similarity measures (e.g., Euclidean distance), clustering procedures (e.g., Ward's linkage method), determination of the optimal number of clusters (e.g., using the dendrogram or silhouette index), and interpretation of the clustering results.

RESULTS AND DISCUSSION

Descriptive statistics in this study are used to provide an overview and summarize the financial report data of Microfinance Institutions (MFIs). The analyzed variables include Number of Microfinance Institutions (MFIs) Entities (X1), Assets (X2), Liabilities (X3), Equity (X4), Temporary Musharakah Funds (X5), Fund Placements (X6), Loans Disbursed (X7), Loans Received (X8), dan Savings/Deposits (X9). These descriptive statistics include measures such as mean, median, standard deviation, minimum, and maximum values for each variable, providing an initial understanding of the data distribution and characteristics.

Table 2 was derived from the financial statements of Microfinance Institutions (MFIs) across 23 provinces in Indonesia, as of August 2024, reveal significant diversity in their financial performance and structure. The number of MFI entities varies widely, with most provinces having only a few, while some have as many as 111. This uneven distribution suggests differing levels of financial inclusion and economic activity across regions. Similarly, assets and equity are substantial but vary greatly among provinces, indicating that wealth and resources are not evenly distributed. Meanwhile, liabilities also show significant disparities, reflecting different financial strategies and risk profiles among the MFIs.

Table 2. Descriptive Statistics

Variable	Mean	Median	Std. Deviation	Minimum	Maximum
X_1	10.913	2	24.9361	1	111
X_2	4,476,733,334.47	4,224,763,653	2,458,629,673.34	17,711,667	8,418,666,865
X_3	1,709,892,895.82	1,089,791,674	2,108,636,428.58	3	6,431,007,391
X_4	3,192,211,982.86	3,684,674,843	2,132,555,816.55	14,196,267	8,138,938,608
X_5	622,257,524.08	0	1,876,919,391.16	0	8,188,155,442
X_6	3,385,398,289.52	3,701,848,962	2,725,266,544.61	2,991,947	9,959,147,257
X_7	1,675,646,329.86	21,374,169	2,225,263,572.63	192	6,285,328,933
X_8	691,729,980.82	0	1,792,621,609.41	0	6,768,509,565
X_9	1,089,293,368.65	276,745,645	1,612,003,380.57	0	5,676,671,391

Source: The processed secondary data (2025)

Temporary Musharakah Funds, loans disbursed, and loans received demonstrate a high concentration in certain provinces, as many MFIs report zero or minimal amounts. This indicates that only a few regions actively engage in these financial activities, potentially due to local economic conditions or regulatory environments. Savings and deposits also show considerable variation, with some provinces accumulating large amounts while others have very little. These findings highlight a striking disparity in financial resources and activities among MFIs in Indonesia, suggesting opportunities for more balanced financial development and targeted policy interventions to enhance financial inclusion across all regions.

The first step before clustering is data standardization. If all data have the same units, standardization is not necessary. However, if these variables have different units, standardization must be carried out to equalize the scale and reduce the gap between variables. In this case, because variables have different units, data standardization is an important step. After obtaining standardized data, a correlation test between the independent variables is then carried out. The following is a summary of the correlation of financial report data for Microfinance Institutions (LKM) as of August 2024 which has been standardized.

Table 3. Coefficient Correlation Test

Method	Cophenetic Correlation
Single Linkage	0.991857
Average Linkage	0.9934442
Complete Linkage	0.9925414
Centroid	0.9884159
Ward	0.8565345

Source: The processed secondary data (2025)

To determine the best method to use in cluster analysis, one can compare the cophenetic correlation values of each method. The method with the highest cophenetic correlation value is chosen, as it significantly influences the results of the cluster analysis. From Table 3, it is known that the Average method has the highest cophenetic correlation value, which is 0.9934442. Therefore, the cluster analysis process applies the hierarchical clustering method, using Euclidean distance and the Average method. To determine the optimal number of clusters from the standardized data, the hierarchical clustering method uses the Silhouette method for validation. Based on Figure 1, the Silhouette method suggests that the optimal number of clusters for this case is 2 clusters. However, considering that the clustering will be based on risk levels, this study will form 3 clusters: a low-risk group, a moderate-risk group, and a high-risk group. This approach ensures that the clustering aligns with the objective of categorizing entities based on their risk profiles, even though the Silhouette method indicates 2 clusters as optimal. The decision to use 3 clusters is driven by the practical need to differentiate entities into distinct risk categories for better analysis and decision-making.

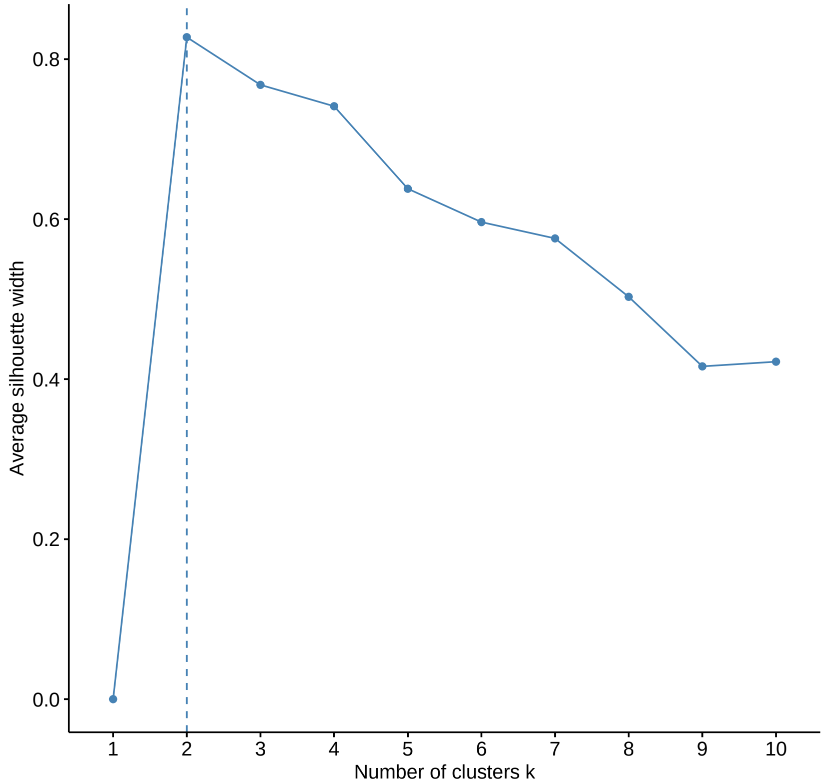

Figure 1. Optimal numbers of clusters
Source: The processed secondary data (2025)

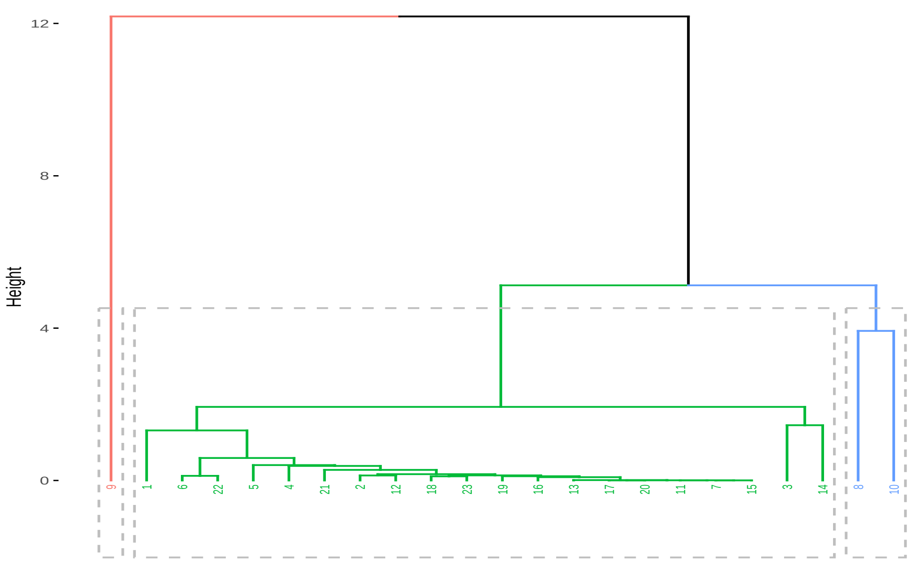

Figure 2. Cluster dendrogram
Source: The processed secondary data (2025)

By observing the longest gap in Figure 2, it can be seen that an appropriate cut will result in 3 clusters of Microfinance Institution (MFI) entities, where Cluster 1 (green line) consists of 20 MFI entities, Cluster 2 (blue line) consists of 2 MFI entities, and Cluster 3 (red line) consists of 1

MFI entity. Based on the clustering results using R software, Table 3 shows the members of each cluster are as follows:

Table 3. Coefisien Correlation Test

Cluster	Entity
1	Aceh (1), Bali (2), Banten (3), Bengkulu (4), D.I. Yogyakarta (5), DKI Jakarta (6), Jambi (7), Kalimantan Selatan (11), Kalimantan Tengah (12), Kalimantan Timur (13), Lampung (14), Maluku (15), NTB (16), Papua (17), Riau (18), Sulawesi Barat (19), Sulawesi Selatan (20), Sumatera Barat (21), Sumatera Selatan (22), Sumatera Utara (23)
2	Jawa Barat (8), Jawa Timur (10)
3	Jawa Tengah (9)

Source: Processed secondary data (2025)

Characteristics of Each Entity Cluster

To obtain the characteristics of each cluster, an analysis of the average values of the cluster members was conducted to understand the profile of each cluster for each variable, as presented in Table 4.

Table 4. Characteristics of each entity cluster

Variable	Cluster 1	Cluster 2	Cluster 3
Number of Microfinance Institutions (MFIs) (Entities)	3	41	111
Assets (Billion Rupiah)	15,60	296,45	736,04
Liabilities (Billion Rupiah)	4,58	138,47	362,35
Equity (Billion Rupiah)	8,57	151,80	211,67
Temporary Musharakah Funds (Billion Rupiah)	2,44	6,19	162,02
Fund Placements (Billion Rupiah)	6,35	81,54	220,27
Loans Disbursed (Billion Rupiah)	8,11	198,94	469,86
Loans Received (Billion Rupiah)	1,24	4,58	22,36
Savings/Deposits (Billion Rupiah)	2,91	123,00	276,75

Source: The processed secondary data (2025)

Based on Table 4, cluster 1 consists of 3 microfinance institutions (MFIs) with relatively low levels of assets (15.60 billion Rupiah), liabilities (4.58 billion Rupiah), and equity (8.57 billion Rupiah). They have minimal temporary Mushtarakah funds (2.44 billion Rupiah) and fund placements (6.35 billion Rupiah). The loans disbursed (8.11 billion Rupiah) and received (1.24 billion Rupiah) are also low, indicating limited financial activity. Savings and deposits are modest at 2.91 billion Rupiah. Cluster 1 can be categorized as High-Risk MFIs. These institutions have low deposits, limited customer savings, and minimal reliance on external loans, but their small scale and low financial activity suggest potential liquidity issues and higher vulnerability to defaults. Their conservative approach might not be sufficient to mitigate risks associated with their limited financial base.

Cluster 2 includes 41 MFIs with significantly higher assets (296.45 billion Rupiah), liabilities (183.47 billion Rupiah), and equity (151.80 billion Rupiah). They have more substantial temporary Mushtarakah funds (6.19 billion Rupiah) and fund placements (81.54 billion Rupiah). The loans disbursed (198.94 billion Rupiah) and savings/deposits (123.00 billion Rupiah) are much higher, indicating a more active and established financial presence. Cluster 2 can be categorized as Moderate-Risk MFIs. These MFIs have balanced financials, with moderate deposits and customer savings. They are likely in a growth phase, with a mix of internal and external funding. While they show stability, they could benefit from strategies to increase customer engagement and further strengthen their financial base to reduce risks.

Cluster 3 represents the largest group of 111 MFIs with the highest levels of assets (736.04 billion Rupiah), liabilities (362.35 billion Rupiah), and equity (211.67 billion Rupiah). They have the most significant temporary Mushtarakah funds (162.02 billion Rupiah) and fund placements (220.27 billion Rupiah). The loans disbursed (469.86 billion Rupiah) and savings/deposits (276.75 billion Rupiah) are the highest among all clusters, indicating a very active and large-scale financial operation. Cluster 3 can be categorized as Low-Risk MFIs. These institutions have high deposits, strong customer savings, and a robust financial base. Their conservative investment strategies and minimal reliance on external loans contribute to their stability. They demonstrate effective risk management, leading to better loan recovery rates and lower chances of default.

MFI clusters influence loan performance and financial risks

Understanding how regional Microfinance Institutions (MFIs) perform and manage risks starts by looking at their unique characteristics. By grouping MFIs into high-risk, moderate-risk, and low-risk categories, we can better grasp their challenges and successes. High-risk MFIs, for instance, often struggle with cash flow and defaults, while low-risk ones thrive due to strong management. This classification helps stakeholders tailor strategies to support each group effectively.

Smaller MFIs, labeled as high-risk, face tough hurdles. Their limited scale and narrow range of services make them prone to cash shortages and late repayments. A study by Mwakujonga & Komba (2024) found that many of these institutions lack proper tools to assess borrowers, leading to higher default rates. Governance issues, like inefficiencies in decision-making (Purwanto, 2020), and outdated risk practices further strain their stability. Without better systems to track loans or diversify offerings, these MFIs remain stuck in a cycle of financial stress.

Mid-sized MFIs in the moderate-risk category show promise. They strike a balance between growth and caution, often using technology to streamline operations and engage clients. For example, some have introduced mobile banking, making it easier for borrowers to repay loans on time (Lwesya & Mwakalobo, 2023). By educating clients on financial management (Annannab et al., 2022), they've reduced defaults and expanded their customer base. While they're not immune to risks, their adaptability positions them to grow stronger with targeted support.

Large, established MFIs stand out as low-risk players. Their size allows them to diversify services—like offering savings accounts alongside loans—which buffers them during economic downturns (Duho et al., 2021). Rigorous checks on borrowers and advanced risk strategies (Illangakoon et al., 2021) keep defaults low. Strong governance, as noted by Barguellil and Bettayeb (2020), ensures these institutions operate efficiently, even in tough times. Their success highlights how experience and smart management create resilience, setting a benchmark for smaller MFIs to aspire to.

The implications for financial sustainability

Financial sustainability is crucial for Microfinance Institutions (MFIs) as it ensures they can continue providing financial services to underserved communities while remaining operationally viable. Achieving this sustainability, however, is complex and influenced by various operational, economic, and social factors. MFIs must navigate these challenges carefully to maintain their mission of supporting low-income populations while also staying financially healthy.

One key challenge is balancing the social mission of poverty alleviation with the need for profitability. Research suggests that MFIs can achieve financial success while fulfilling their social goals through effective outreach strategies that enhance performance (Fadikpe et al., 2022). This balance allows MFIs to expand their services without losing sight of their core mission. However, focusing too much on profitability can lead to mission drift, where financial goals overshadow social impact, potentially alienating the communities they aim to serve (Bharti & Malik, 2021). To sustain their long-term impact, MFIs must carefully manage this balance.

Operational efficiency and strong governance are also essential for financial sustainability in MFIs. Effective leadership and sound management practices help MFIs manage risks and adapt to changing market conditions, which is vital for maintaining financial health (Detthamrong et al., 2023). Additionally, MFIs that effectively manage their funding sources and maintain a balanced capital structure are better positioned to ensure financial stability and expand their service offerings (Adusei & Sarpong-Danquah, 2021). This operational strength allows MFIs to navigate economic uncertainties more effectively.

Economic factors, such as inflation rates and economic growth, significantly impact the financial sustainability of MFIs. While GDP growth can positively influence their financial health, adverse economic conditions like high inflation and fluctuating interest rates can pose challenges (Memon et al., 2021). To counter these risks, MFIs need strategies that help them remain resilient in changing economic landscapes. By integrating social performance metrics with financial performance indicators, MFIs can maintain their commitment to social impact while ensuring financial sustainability (Ghising, 2022). This dual approach not only supports the long-term success of MFIs but also contributes to broader economic development goals by promoting financial inclusion and empowering marginalized communities (Uddin, 2020).

CONCLUSION

The cluster analysis of Microfinance Institutions (MFIs) revealed three distinct groups, each with unique financial characteristics and risk profiles. Cluster 1 consists of high-risk MFIs, which are generally smaller institutions with limited financial activities. These MFIs are more vulnerable to liquidity issues and loan defaults, making them riskier compared to others. Cluster 2 includes moderate-risk MFIs that are typically medium-sized and experiencing growth. They maintain balanced financials and have the potential to become more stable by increasing customer engagement. Lastly, Cluster 3 represents low-risk MFIs that are well-established, financially strong, and effectively manage their risks with high deposit levels and robust financial practices.

Based on their risk profiles—high-risk, moderate-risk, and low-risk—Microfinance Institutions (MFIs) reveals distinct operational dynamics that significantly influence loan performance and financial stability. High-risk MFIs, typically smaller entities with limited services, face major challenges like cash flow shortages and high default rates due to weak borrower assessment and governance inefficiencies. In contrast, moderate-risk MFIs show growth potential by balancing expansion with sound risk practices, leveraging technology, and improving client financial literacy. Low-risk MFIs, being larger and more established, benefit from diversified financial products, rigorous credit checks, and strong governance, ensuring stability and resilience even in economic downturns. This classification not only provides a clearer understanding of MFI performance but also helps stakeholders tailor strategies to enhance financial sustainability and growth across different risk categories.

Financial sustainability for Microfinance Institutions (MFIs) hinges on effectively balancing social impact with profitability, maintaining operational efficiency, and navigating economic challenges. By achieving this balance, MFIs can expand their outreach without compromising their mission of poverty alleviation. Strong governance and effective risk management are crucial for stability, while strategic financial planning helps them withstand economic fluctuations. Additionally, integrating social and financial performance metrics ensures MFIs remain committed to empowering marginalized communities while achieving long-term sustainability and contributing to broader economic development goals.

REFERENCES

Adusei, M. & Sarpong-Danquah, B. (2021). Institutional quality and the capital structure of microfinance institutions: the moderating role of board gender diversity. *Journal of Institutional Economics, 17*(4), 641-661. https://doi.org/10.1017/s1744137421000023

Annannab, H., Bakar, A., & Khan, S. (2022). Operational risk management and performance of cooperative microfinance in Thailand. *International Journal of Social Sciences and Economic Review*, 17-24. https://doi.org/10.36923/ijsser.v4i1.148

Artika, D. & Shara, Y. (2021). Analisis peran financial technology dalam meningkatkan keuangan inklusif pada umkm kota medan. *Indonesian Journal of Business Analytics, 1*(2), 237-248. https://doi.org/10.54259/ijba.v1i2.78

Barguellil, A. & Bettayeb, L. (2020). The impact of microfinance on economic development: the case of Tunisia. *International Journal of Economics and Finance, 12*(4), 43. https://doi.org/10.5539/ijef.v12n4p43

Bharti, N. & Malik, S. (2021). Financial inclusion and the performance of microfinance institutions: does social performance affect the efficiency of microfinance institutions? *Social Responsibility Journal, 18*(4), 858-874. https://doi.org/10.1108/srj-03-2020-0100

Detthamrong, U., Nguyen, L., & Chansanam, W. (2023). Leadership and group management: key success factors for microfinance institutions in Chaiyaphum province, Thailand. *Sustainability, 15(*14), 11192. https://doi.org/10.3390/su151411192

Dillon, W.R. & Goldstein, M. (1987). Goldstein: Multivariat Analysis: Methods and Applications. *Biom. J. 1987. 29*(6):755-756. http://dx.doi.org/10.1002/bimj.4710290617

Duho, K., Duho, D., & Forson, J. (2021). Impact of income diversification strategy on credit risk and market risk among microfinance institutions. *Journal of Economic and Administrative Sciences, 39*(2), 523-546. https://doi.org/10.1108/jeas-09-2020-0166

Fadikpe, A., Danquah, R., Aidoo, M., Chomen, D., Yankey, R., & Dong-mei, X. (2022). Linkages between social and financial performance: evidence from Sub-Saharan Africa microfinance institutions. *Plos One, 17*(3), e0261326. https://doi.org/10.1371/journal.pone.0261326

Ghising, T. (2022). Social performance management and sustainability of microfinance institutions. *International Research Journal of MMC, 3*(4), 17-20. https://doi.org/10.3126/irjmmc.v3i4.48858

Gunawan, M. & Muzayanah, I. (2023). The role of access to agribusiness microfinance institutions (lkm-a) on poverty reduction: case study in Kuningan district. *Jurnal Bina Praja, 15*(2), 357-372. https://doi.org/10.21787/jbp.15.2023.357-372

Gupta, A., Gupta, S., & Sapra, R. (2023). Dampak risiko keuangan terhadap kinerja keuangan lembaga keuangan mikro: tinjauan pustaka. *Sacheta, 2*(2), 67-72. https://doi.org/10.55955/220007

Hemelia & Sumargo, B. (2019). Pengklasifikasian Pengguna Internet Lingkungan Pedesaan Menurut Jenjang Pendidikan di Indonesia Menggunakan Metode Cluster Average Linkage. *Jurnal Statistika dan Aplikasinya. 3*. 1.

Holle, M. & Manilet, A. (2023). Indeks inklusi keuangan indonesia (analisis kontribusi sektor usaha lembaga keuangan mikro). *Investi Jurnal Investasi Islam, 4*(2), 550-569. https://doi.org/10.32806/ivi.v4i2.139

Haumahu, G., & Yonlib W. A. N. (2020). Penerapan Analisis Klaster Hierarki untuk Pengelompokkan Kabupaten/kota di Provinsi Maluku Berdasarkan Konsumsi Kalori Penduduk. *Variance, vol. 2, no. 2*, 2020, pp. 75-79, https://doi:10.30598/variancevol2iss2page75-79.

Illangakoon, A., Azam, S., & Jaharadak, A. (2021). Impact of risk management towards sustainability of microfinance industry in Sri Lanka: a case study. *International Journal of Social Sciences and Economic Review*, 01-07. https://doi.org/10.36923/ijsser.v3i4.117

Johnson, S.C. (1967) Hierarchical Clustering Schemes. *Psychometrika, 32*, 241-254. http://dx.doi.org/10.1007/BF02289588

Kadima, A. (2023). Manajemen risiko kredit terhadap kinerja keuangan Lembaga keuangan mikro terpilih. *Jurnal Penelitian Empiris Afrika, 4*(2), 778-784. https://doi.org/10.51867/ajernet.4.2.79

Lwesya, F. & Mwakalobo, A. (2023). Frontiers in microfinance research for small and medium enterprises (SMEs) and microfinance institutions (mfis): a bibliometric analysis. *Future Business Journal, 9*(1). https://doi.org/10.1186/s43093-023-00195-3

Maghfiroh, A., Muna, N., Arifin, M., & Farida, N. (2021). Peran bwm al-fithrah wava mandiri surabaya terhadap umkm (nasabah BWM) yang usahanya terdampak pandemi covid 19: fenomenologi study. *JPSDA Jurnal Perbankan Syariah Darussalam, 1*(2), 122-137. https://doi.org/10.30739/jpsda.v1i2.994

Marino, W. & Gunawan, G. (2021). Upaya pengentasan kemiskinan melalui layanan lembaga keuangan mikro dan program pemberdayaan perempuan di kecamatan rajapolah Kabupaten Tasikmalaya. *Jurnal Inspirasi Bisnis dan Manajemen, 4*(2), 121. https://doi.org/10.33603/jibm.v4i2.4222

Memon, A., Akram, W., Abbas, G., Chandio, A., Adeel, S., & Yasmin, I. (2021). Keberlanjutan keuangan lembaga keuangan mikro dan faktor makroekonomi: kasus asia selatan. *Jurnal Ekonomi Makro dan Keuangan Publik Asia Selatan, 11*(1), 116-142. https://doi.org/10.1177/22779787211007970

Mohibullah, M. Hossain, Z.M. & Hasan, M. (2015). Comparison of Euclidean distance function and Manhattan distance function using k-mediods. *International Journal of Computer Science and Information Security. 13*. 10.

Mwakujonga, J. and Komba, C. (2024). Influence of credit risk management practices on loan performance: a case of selected microfinance institutions in Tanzania. *JPDS, 15*(2), 26-35. https://doi.org/10.4314/jpds.v15i2.3

Nafisah, Q., & Chandra, N. (2017). Analisis Cluster Average Linkage Berdasarkan Faktor-Faktor Kemiskinan di Provinsi Jawa Timur. *Zeta - Math Journal, 3*(2), 31-36. https://doi.org/10.31102/zeta.2017.3.2.31-36

Nishom, M. (2019). Perbandingan Akurasi Euclidean Distance, Minkowski Distance, dan Manhattan Distance pada Algoritma K-Means Clustering Berbasis Chi-Square. *Jurnal Informatika Politeknik Harapan Bersama, vol. 4*, no. 1, 30 Jan. 2019, pp. 20-24, https://doi:10.30591/jpit.v4i1.1253.

Purwanto, P. (2020). Agency cost of credit on microfinance institutions of cooperative and rural bank type. *International Journal of Economics Business and Accounting Research (Ijebar), 4*(03). https://doi.org/10.29040/ijebar.v4i03.1252

Riski, M. & Shauqi, S. (2023). Analisis pengaruh lembaga keuangan mikro syariah dan lembaga pembiayaan syariah terhadap pertumbuhan ekonomi indonesia tahun 2015-2021. *Ihtiyath Jurnal Manajemen Keuangan Syariah, 7*(1), 51-65. https://doi.org/10.32505/ihtiyath.v7i1.5424

Romadoni, A. & Herianingrum, S. (2020). Fungsi lembaga keuangan mikro syariah dalam mendorong keuangan inklusif dan sektor riil (BMT NU Jawa Timur di Sumenep). *Jurnal Ekonomi Syariah Teori dan Terapan, 7*(5), 814. https://doi.org/10.20473/vol7iss20205pp814-825

Saraçli, S., Doğan, N. & Doğan, İ. (2013). Comparison of hierarchical cluster analysis methods by cophenetic correlation. *J Inequal Appl 2013*, 203 (2013). https://doi.org/10.1186/1029-242X-2013-203

Sinwar, Deepak & Kaushik, Rahul. (2014). *Study of Euclidean and Manhattan Distance Metrics using Simple K-Means Clustering*. 2.

Suaidah, S. & Arjun, D. (2023). Urgensi dan peran lembaga keuangan mikro dalam pengentasan kemiskinan dan pengembangan ekonomi umat. *Reinforce Journal of Sharia Management, 2*(1), 75-83. https://doi.org/10.21274/reinforce.v2i1.7416

Uddin, M. (2020). Role of islamic microfinance institutions for sustainable development goals in bangladesh. *Journal of International Business and Management*, 1-12. https://doi.org/10.37227/jibm-2020-64

Wahab, A. & Mahdiya, I. (2023). Peran lembaga keuangan syariah terhadap pertumbuhan UMKM dalam revitalisasi ekonomi pembangunan di indonesia. *Islamadina Jurnal Pemikiran Islam, 24*(1), 109. https://doi.org/10.30595/islamadina.v24i1.11713

Winarto, W. (2020). Peran fintech dalam usaha mikro kecil dan menengah (umkm*). Jesya (Jurnal Ekonomi & Ekonomi Syariah), 3*(1), 61-73. https://doi.org/10.36778/jesya.v3i1.132

Yaqin, A. (2021). Fungsi sosial baitul maal wa tamwil (bmt) pasca uu no 1 tahun 2013 tentang lembaga keuangan mikro. *Mabsya Jurnal Manajemen Bisnis Syariah, 3*(2), 146-163. https://doi.org/10.24090/mabsya.v3i2.5597