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DATA-DRIVEN ANALYSIS OF ATTENDANCE PATTERNS IN GROUP-BASED MICROFINANCE PROGRAMS: EVIDENCE FROM INDONESIA

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Abstract

This study examines attendance patterns in Weekly Group Meetings (Pertemuan Kelompok Mingguan/PKM) within a group-based microfinance program. Attendance is not treated merely as a frequency indicator, but as a behavioral pattern influenced by both individual and group dynamics. Using a data-driven approach, this study applies K-Means clustering to identify attendance behavior patterns and Decision Tree classification to analyze socio-economic characteristics associated with these patterns. The results reveal three distinct participation clusters: active, moderate, and passive participation. The findings demonstrate that attendance behavior is heterogeneous and cannot be fully explained by measurable socio-economic variables alone. Instead, participation reflects a complex interaction between individual characteristics and group social dynamics. By integrating social participation theory with machine learning methods, this study provides a more comprehensive understanding of participation behavior in community-based microfinance programs.

Keyword: *attendance patterns, microfinance, machine learning.*

A. INTRODUCTION

Group-based microfinance programs rely heavily on member participation, particularly in structured activities such as Weekly Group Meetings (PKM). Attendance in these meetings functions not only as an administrative indicator but also as a reflection of engagement and commitment within the group.

However, attendance patterns are rarely stable. Empirical observations show fluctuations over time, indicating that participation is shaped by multiple interacting factors. Previous studies have largely treated attendance as a static quantitative measure, overlooking its behavioral and dynamic nature.

Moreover, within the Indonesian microfinance context, research integrating **social participation theory** with **data-driven approaches** remains limited. Existing studies tend to focus on economic outcomes rather than the structural patterns of participation behavior.

This study addresses these gaps by:

1. Conceptualizing attendance as a **behavioral pattern rather than a binary variable**
2. Applying **machine learning techniques to uncover latent participation structures**
3. Integrating **computational analysis with social theory**

By combining clustering and classification techniques, this study provides a deeper understanding of participation dynamics and offers a novel contribution to microfinance research.

2. Literature Review

Participation in collective activities is widely understood as a continuum rather than a binary condition. Arnstein (1969) conceptualizes participation as a ladder, where individuals occupy different levels of engagement.

Bandura (1977) further explains that behavior is shaped through social interaction and observational learning. In group-based microfinance settings, repeated interactions contribute to the formation of participation patterns.

From a microfinance perspective, Armendáriz and Morduch (2010) emphasize the importance of group dynamics and peer monitoring in sustaining participation.

Recent studies highlight the growing relevance of machine learning in analyzing complex socio-economic behaviors. Chen and Liu (2021) demonstrate that data-driven approaches are effective in uncovering non-linear patterns in financial behavior. Similarly, Khandker and Koolwal (2020) show that social interaction significantly influences participation in microfinance programs. In the Indonesian context, Nugroho and Sari (2022) find that participation is shaped by both institutional structures and social dynamics.

Despite these advances, limited research integrates machine learning with social participation theory, particularly in developing countries. This study attempts to bridge that gap.

3. Methodology

This study employs a quantitative data mining approach consisting of two stages:

1. Clustering (K-Means)

Used to identify latent attendance patterns.

2. Classification (Decision Tree)

Used to analyze socio-economic predictors:

- Age
- Duration of membership
- Number of dependents

- Occupation
- Marital status

The machine learning approach is used as an **exploratory analytical tool**, not for deterministic prediction.

B. RESEARCH METHOD

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While Decision Tree offers interpretability, its relatively low accuracy (~39%) indicates limitations in capturing complex relationships. Decision Tree models are prone to:

- Overfitting
- Instability
- Limited non-linear modeling capacity

Future research is recommended to incorporate:

- **Random Forest**
- **Gradient Boosting**

to improve predictive performance and robustness.

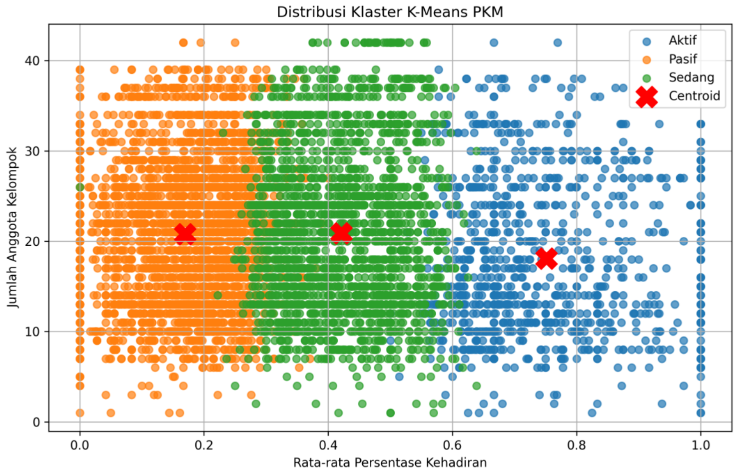
C. RESULT AND DISCUSSION

4.1 Clustering Results

The clustering process reveals three distinct attendance groups:

- Active (~75%)
- Moderate (~42%)
- Passive (~17%)

Figure 1. Distribution of Attendance Clusters

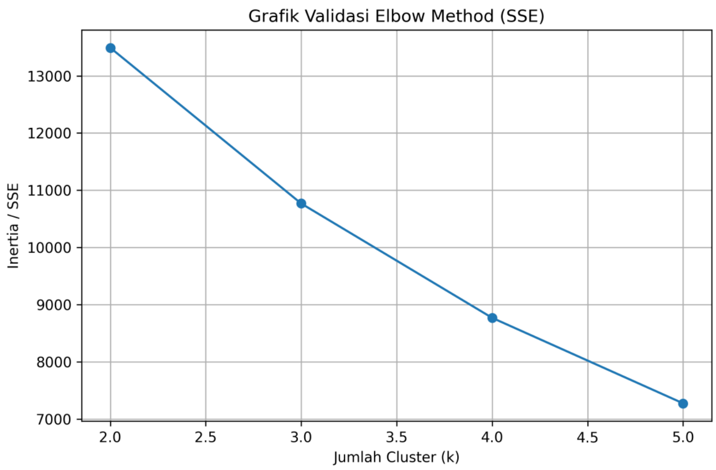


Interpretation: The cluster distribution shows that the majority of members are in the active participation category, but there is a significant proportion in the moderate and passive categories indicating a potential risk of disengagement.

The separation between clusters is relatively clear, although some overlap exists between moderate and passive groups. This suggests that participation is not strictly segmented but rather exists along a continuum.

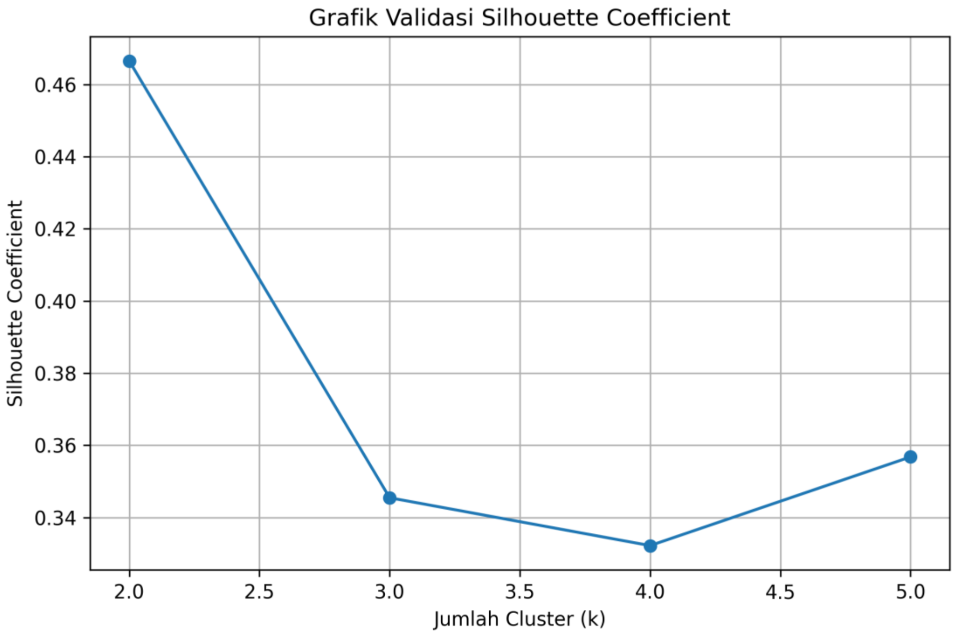
4.2 Cluster Evaluation

Figure 2. Elbow Method



Interpretation: The elbow point at k=3 indicates that the data structure naturally forms three main groups, making it valid for use in the analysis. The elbow point indicates that three clusters provide the optimal structure.

Figure 3. Silhouette Score



Interpretation: A moderate silhouette value indicates that the clusters are fairly well separated, although there is overlap that reflects the dynamic nature of participation.

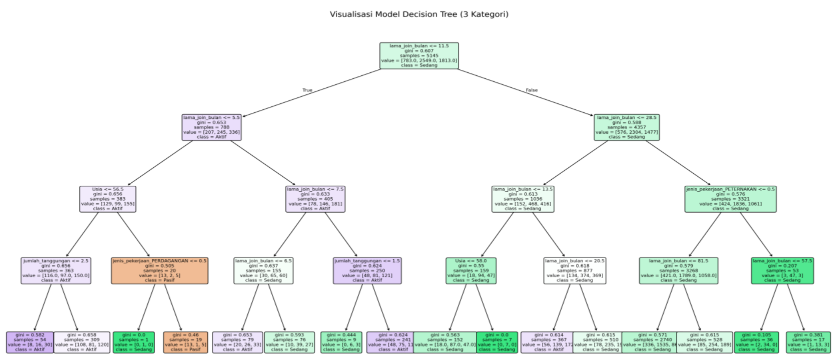
The moderate silhouette value suggests acceptable cluster separation with some overlap.

4.3 Decision Tree Results

The Decision Tree model identifies key predictors:

- Age
- Duration of membership
- Number of dependents

Figure 4. Decision Tree Model



However, the model achieves relatively low accuracy (~39%), indicating that attendance behavior cannot be fully captured by observable variables.

Table 1. Model Evaluation

Metric	Value

Metric	Value
Accuracy	39.16%
Precision	0.33
Recall	0.33
F1-score	0.33

Interpretation: The relatively low accuracy value indicates that socio-economic variables are not sufficient to comprehensively explain attendance behavior.

4.4 Discussion

The existence of participation clusters supports Arnstein's (1969) concept of participation as a continuum. Members do not simply participate or not; they occupy varying levels of engagement.

The fluid boundaries between clusters align with Bandura's (1977) theory, where behavior evolves through interaction and observation.

These findings are consistent with Khandker and Koolwal (2020), who highlight the role of social interaction in shaping participation.

Compared to previous studies in Indonesia, which primarily rely on descriptive approaches, this study provides a more nuanced, data-driven understanding of participation behavior.

Importantly, the low predictive power of the Decision Tree suggests that **latent social variables**—such as leadership, trust, and group cohesion—play a critical role.

D. CONCLUSION

This study demonstrates that attendance in PKM should not be viewed as a simple frequency measure but as a behavioral pattern shaped by complex interactions.

The integration of clustering and classification provides a more comprehensive understanding of participation dynamics. While measurable variables offer partial explanations, social interaction remains a critical underlying factor.

From a practical perspective, interventions should not be uniform. Instead, strategies should be tailored based on participation clusters, with particular attention to groups in transitional states.

Ultimately, the success of group-based microfinance programs does not depend solely on member recruitment, but on the ability to sustain meaningful participation dynamics over time. This study demonstrates that data-driven approaches can uncover hidden behavioral structures, enabling more adaptive, evidence-based interventions in community empowerment programs.

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