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Segmentation of Teachers Using Gower-Based Hierarchical Clustering

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ABSTRACT

The core issue addressed in this study is the reliance of teacher development and welfare policies on aggregated indicators that obscure variations in teachers' demographic, professional, and economic conditions. This research aims to identify teacher profiles across multiple educational levels. The method used in this research is hierarchical clustering utilizing Gower distance applied to mixed-type survey data collected from 376 teachers across all educational levels. The analysis incorporates demographic, professional, and socioeconomic variables, including age, education, years of service, income, economic class, number of dependents, income satisfaction, and interest in technology. The analysis identifies two distinct teacher clusters. The first cluster is characterized by more experienced teachers with longer service periods, relatively stable financial conditions, and higher income satisfaction, while the second cluster comprises younger teachers with shorter teaching experience, lower income levels, and lower financial satisfaction. These findings highlight substantial heterogeneity among teachers and suggest that teacher development and welfare policies should be formulated in a differentiated manner, taking into account career stages and economic conditions, thereby enabling more targeted and data-driven policy interventions.

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A. INTRODUCTION

citizens and the government regarding education. Furthermore, under Law Number 20 of 2003, at least 20% of the National Budget (APBN) and the Regional Budget (APBD) must be allocated to education by the Central Government and the Regional Governments. Education is so essential that it has been regulated by a variety of government regulations and programs. Several aspects are consistently discussed across all policies, from Law 20 of 2003 to Government Regulation No. 57 of 2021 to Government Regulation No. 4 of 2022: National Education Objectives, Forms, Pathways, and the Degree of Education, National Education Standards, Curriculum, Teachers' Responsibilities, and Performance Measurement. Teachers are a significant concern to consider among many others.

A closer examination of government policies indicates that teachers play a significant role in the Indonesian education system (Sari et al., 2020). Teachers are professionals who teach, share, guide, influence, train, evaluate, and appraise their students. Starting in early infancy, primary schools, and secondary education (UU No. 14 Tahun 2006). Given their numerous responsibilities, teachers have been recognized as the most qualified to enhance the performance of other stakeholders in achieving the objective of quality education (Glassow et al., 2023). Teachers' roles may shape students' personalities, influencing their conduct and character development (Gede, 2020). As a result, the distinctive profile of a teacher is critical to producing a better generation (Cattaneo et al., 2025;

Mpiti et al., 2025).

Policies created by the national government applied to every region of Indonesia. Balangan Regency, a regency in South Kalimantan with a total population of 137,603 in 2024, should also follow this national strategy. This aligns with the Balangan Regency's vision to develop villages and organize cities to foster a more advanced and prosperous Balangan. One of the goals is to raise educational attainment. To achieve this objective, a deeper understanding of the region's teacher labor market conditions is needed to develop more effective educational initiatives. Lutfiu and Hoxha (2024) said that the socioeconomic status of educators does not merely affect their personal well-being and financial stability. It also maintains a strong correlation with the quality of classroom instruction, whereby financial satisfaction often translates into greater professional dedication and overall instructional effectiveness.

Balangan Regency had 1,419 primary school teachers, 300 junior secondary school teachers, and 314 upper secondary school teachers over the 2nd semester of 2024/2025. Moreover, the Directorate General of Early Childhood Education, Elementary Education, and Secondary Education's Basic Education Data (DAPODIK) proved that there were 11,159 primary school students, 2,463 junior secondary school students, and 3,507 upper secondary school students. According to these data points, one teacher educates about nine students, showing that the teacher-student ratio is fairly close to the required standards. However, the ratio is insufficient to determine the quality of education. A deeper analysis of teacher characteristics, such as background knowledge, teaching experience, and economic circumstances, is needed to ensure that policies intended to improve the quality of education genuinely meet the field's real requirements. As a result, a teacher's segmentation or profiles approach needs to be used to identify groups of teachers who share similar characteristics (Gil-Flores et al., 2017; Ping et al., 2018). This segmentation leads to more specific and productive educational initiatives, the development of competencies, and reward systems according to the needs of every category (König et al., 2020; Noben et al., 2022).

The problem formulated in this study is that education policies and teacher development programs in Balangan Regency are often designed using aggregate indicators, such as teacher–student ratios and overall qualification levels, which implicitly assume that teachers constitute a homogeneous group. In reality, teachers differ substantially in terms of age, career stage, teaching experience, and economic conditions, including income satisfaction. This lack of differentiated understanding limits the effectiveness of education policies and professional development initiatives, as they may not adequately address the distinct needs and challenges faced by different groups of teachers. Consequently, a data-driven approach is required to identify meaningful teacher groupings that can support more targeted and effective policy formulation.

In the broader context of the issues discussed, segmentation is defined as the process of profiling teachers. It aims to group teachers by similar characteristics. Through this segmentation, competency development strategies, training, and programs for individual teachers can be more precisely matched to the needs of each group. The approach of clustering is one method for data-based segmentation (Dinh et al., 2025; Sun & Yang, 2025). Clustering enables objective categorization of teachers based on specific criteria, without making assumptions about how groups are organized, thereby improving understanding of the variety of teacher profiles in Balangan Regency.

Clustering is an exploratory analysis of data technique used to group objects into identical categories based on similar characteristics (Kaur et al., 2024; Miraftabzadeh et al., 2023). In education, this approach has been used to analyze teacher competencies, training needs, and the adoption of technology trends (Jin & Schmidt-Crawford, 2022; Li et al., 2022). Clustering enables teacher categorization based on multiple variables, including age, highest education, experience in teaching, certification, and financial level (Ridhoni et al., 2023). Hierarchical clustering is an advantageous clustering method for teacher profile mapping (Rodiatun & Lestari, 2025). The approach used is agglomerative, grouping data in stages, starting with the most detailed level, generating a hierarchical structure in the shape of a dendrogram (Sarfraz et al., 2021). Hierarchical clustering provides the benefit of creating a visual depiction of group structure and identifying the optimal number of clusters based on the data. This approach is highly effective for exploratory analysis of complex educational data when the original grouping structure is unclear.

Furthermore, teacher profile information is often heterogeneous, comprising both numerical variables (e.g., age and years of teaching experience) and categorical attributes (e.g., educational background or certification status). Gower distance is used to measure the similarity of teachers based on these mixed attributes (Vagni et al., 2021). Gower distance calculates distances between components of data with both numeric and categorical factors (Liu et al., 2024), making it suitable for use in hierarchical clustering research. It is expected that combining hierarchical clustering and Gower distance approaches can yield more reliable and meaningful teacher profile groups for Balangan Regency education policy planning.

The gap between this research and previous research, Jalal et al. (2023) and Zhang et al. (2024), are that most existing studies on teacher profiling and clustering emphasize general competencies, training needs, or technology adoption at national or multiregional levels, while limited attention has been given to localized, district-level analyses that simultaneously integrate demographic, professional, and economic characteristics, particularly income satisfaction.

The difference between this research and another previous research (Witter & Hattie, 2024) is that this study applies hierarchical clustering combined with Gower distance to mixed-type teacher data at the regency level, enabling the identification of teacher groups based on age, length of service, income, economic class, and income satisfaction through a fully data-driven approach. The objective of this research is to identify and analyze distinct clusters of teachers in Balangan Regency based on their demographic, professional, and economic characteristics using hierarchical clustering with Gower distance. The contribution of this research extends teacher career-stage theory by empirically incorporating financial well-being into teacher profiling and by providing practical, data-driven insights to support more targeted teacher development and welfare policies at the local government level.

B. RESEARCH METHOD

1. Flowchart

The research process is broken down into three major phases: collecting data, analyzing the data, and interpreting the results.

a. Data Collecting

At this step, data were gathered by distributing surveys to teachers in Balangan Regency. The survey was designed to collect data on teacher characteristics, both numerical (e.g., age and number of relatives) and categorical (e.g., education and economic status). The survey responses were then collated and prepared for data analysis.

b. Data Analysis

The analytical stage began by calculating distances among respondents using the Gower distance, which is designed specifically to handle mixed data (numerical and categorical). The Gower distance matrix served as the basis for hierarchical clustering, employing an agglomerative approach. A dendrogram, or tree diagram, was constructed to visually evaluate the optimal number of clusters. Once the optimal number of clusters was determined, each teacher's answer was assigned to a single cluster. Each cluster was further investigated by examining the centroid values and the distribution of key variables within it. This helped me learn the general characteristics of each teaching group. All analytical procedures were implemented in Python using Google Colab.

c. Analysis of Results

The third stage was interpreting the clustering results. In this phase, the characteristics of each cluster are carefully analyzed to identify similarities and differences among teacher groups. The data is analyzed to conclude the various teacher profiles in Balangan Regency. Figure 1 shows a summary of the whole procedure.

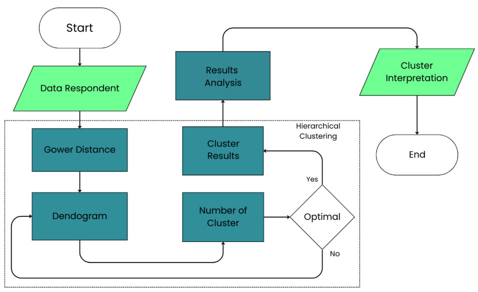

Figure 1. Flowchart

2. Data

The data consisted of a survey completed by 376 teachers in Balangan Regency, representing 18% of the region's total teacher population. Teachers asked questions from elementary school to high school. The survey contained 10 main questions, which were subsequently grouped into 10 features, as shown in Table 1.

Table 1. Questions and Features

Questions	Feature
Age	Age
Gender	Gender

Questions	Feature
Marital Status	Marital Status
Highest Level of Education	Highest Education Level
Number of Dependents	Number of Dependents
Length of Service as a Teacher	Length of Service
What is the range of income you receive per month?	Income Level
Are you satisfied with your current income?	Income Satisfaction
Which economic class do you consider yourself to belong to?	Economic Class
How interested are you in using technological advancements in teaching and learning activities?	Interest in Technological Development for Teaching and Learning

3. Visualization

a. Age Distribution

Figure 2 depicts the age distribution of teachers in Balangan Regency, which follows a normal curve. The majority of instructors are between 30 and 45 years old, as evidenced by the large number of teachers in this age range. In contrast, the distribution shows a slight rightward shift, indicating the presence of teachers older than 50, though the number is small. These data indicate that most of the teaching staff are of productive age, yet the presence of senior professors is equally significant and warrants consideration.

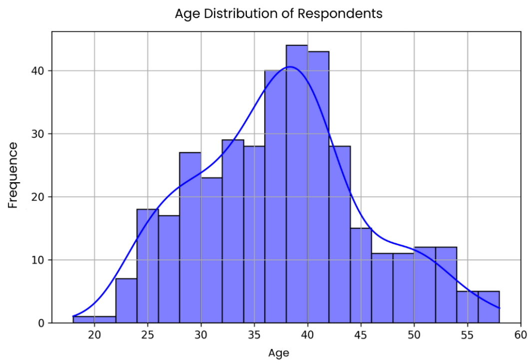

Figure 2. Age Distribution of Respondents

b. Length of Service

Figure 3 presents a violin plot that illustrates the association between length-of-service categories and the age distribution of Balangan Regency teachers. A consistent trend emerges: teachers with more than 10 years of experience had an older age distribution, with the 40-55 age group dominating. The age distribution for the group with 6-10 years of service is normally between 35-50. Groups with 4-5 years of experience and 1-3 years of experience had younger age distributions (25-40 years). Meanwhile, teachers with less than a year of experience are primarily aged 20-35. This trend confirms the association between age and teaching experience: the longer the service period, the more diverse the age group.

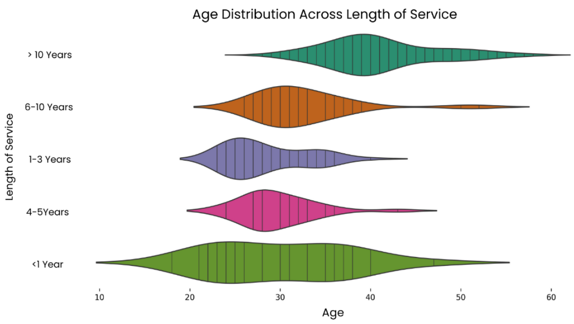

Figure 3. Age Distribution Across Length of Service

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c. Economic Class

Figure 4 depicts a violin plot of the age distribution of teachers in Balangan Regency by income level. In general, a pattern of age variation is observed within each financial class: the middle class has a relatively even age distribution, with a peak between ages 35-45. The lower middle class is slightly younger, with most people around the ages of 30-40. The upper middle class has a broader age range, although it also peaks between ages 35-45. The lower class is concentrated among individuals aged 25-40. The upper class is quite narrow in the graph, reflecting a small number of respondents and an underrepresentation of older age groups. These studies show that age composition varies across economic classes. Lower-income teachers are often younger, whereas middle- and upper-income teachers span a wider age range. This data is critical for developing competency development programs that consider both teachers' ages and economic circumstances.

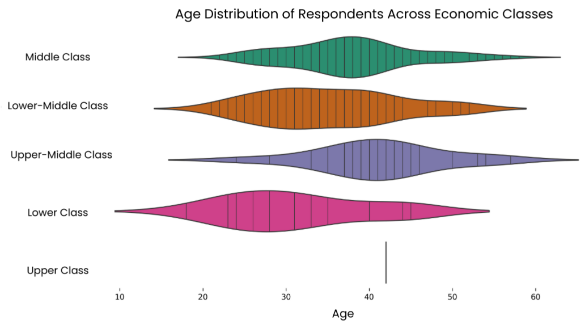

Figure 4. Comparation Age and Financial Class

C. RESULT AND DISCUSSION

1. Data Respondent and Descriptive Statistics

Descriptive statistics were used to summarize the participants' demographics. Descriptive statistics were used depending on the type of data provided. Indicators for numerical variables included the mean, standard deviation, minimum, and maximum. This revealed information about the distribution and central tendency of the data. Meanwhile, for the categorical variables, descriptive statistics focused on estimating the mode (the most frequently occurring value) and the frequency distribution within each category.

Table 2 presents descriptive statistics from the survey data. Based on these results, the average age of teachers is 37.24 years (SD = 7.9), with a range of 18 to 58 years. The average family had 2-3 dependents. A majority of respondents were female (265), and the majority were married (324). A total of 343 respondents achieved a D4/S1 education level. Work experience was dominated by a group of 247 people with more than ten years of service. The highest income category was above 4 million rupiah, with 242 respondents. Additionally, 287 teachers were satisfied with their current salaries. This also aligned with the distribution of economic class, with the majority of respondents (261 persons) falling into the medium category. On a scale of 1-4, interest in the growth of technology in learning was rated 2.93.

Table 2. Descriptive Statistic

Feature	Data Type	Unique	Top	Freq	Mean	Std	Min	25%	50%	75%	Max
Age	Num	-	-	-	37.24	7.91	18	32	37	45	58
Gender	Var	2	Female	265	-	-	-	-	-	-	-
Marital Status	Var	3	Married	324	-	-	-	-	-	-	-
Highest Education Level	Var	5	D4/S1	343	-	-	-	-	-	-	-
Number of Dependents	Num	-	-	-	2.33	1.08	1	1	2	3	5
Length of Service	Var	5	>10 Years	247	-	-	-	-	-	-	-
Income Level	Var	5	>4 mil.	242	-	-	-	-	-	-	-
Income Satisfaction	Var	2	Yes	287	-	-	-	-	-	-	-
Economic Class	Var	5	Middle Class	261	-	-	-	-	-	-	-
Interest in Technological Development for Teaching and Learning	Num	-	-	-	2.93	0.72	1	3	3	3	4

2. Gower Distance and Dendrogram

During this phase of the analysis, teachers were grouped according to several factors, using hierarchical clustering with the Gower distance. This approach was selected because it can handle mixed data, both numerical and categorical, which relates to the variables in this study. Figure 8 shows the dendrogram obtained from hierarchical clustering. The vertical axis shows the Gower distance, which quantifies the degree of dissimilarity between objects or groups. The more branches in the dendrogram, the greater the differences between the merged groups. Referring to the dendrogram shown in Figure 5, the Gower distance axis indicates an increase in distance (hierarchy) between values 4 and 5. This serves as the base for calculating the number of clusters. Figure 5 illustrates that the optimal number of clusters = 2.

To accomplish hierarchical clustering, we began with the Linkage Method. We computed the average Gower Distance for the linkages. We generated two clusters by applying hierarchical clustering with the Gower distance. The first cluster comprised 318 teachers, and the second 58. A descriptive analysis was conducted on each cluster to identify the primary characteristics that appeared from hierarchical clustering.

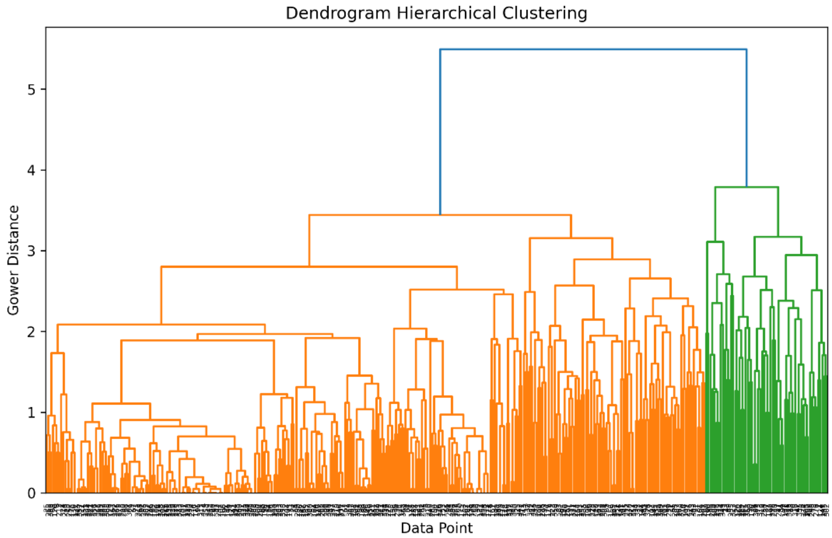

Figure 5. Dendogram

3. Cluster Results and Analysis

Each cluster was summarized using the mean values of the numerical variables “age”, “number of dependents”, and “interest in technological development for teaching and learning.” For the categorical variables, the mode value was used for “gender,” “marital status,” “highest education level,” “length of service,” “income level,” “income satisfaction,” and “economic class.” Table 3 presents a representative view of the fundamental profile of each teacher cluster.

Table 3. Characterization of Each Cluster

Feature	**Cluster**	
	1	**2**
Age	38.54	30.25
Gender	Female	Male
Marital Status	Married	Married
Highest Education Level	D4/S1	D4/S1
Number of Dependents	2.4	1.8
Length of Service	>10 Years	1-3 Years
Income Level	>4 Million	1-2 Million
Income Satisfaction	Yes	No.
Economic Class	Middle Class	Lower-Middle Class
Interest in Technological Development for Teaching and Learning	2.94	2.89
Frequency of Data	318	58

4. Cluster Results Interpretation

The findings of this research indicate the existence of two teacher clusters with different features. The two clusters differ in demographic, professional, and socioeconomic attributes. These clusters were derived from hierarchical clustering based on the Gower distance and reflect meaningful variation in teachers' career stages and financial conditions. For clarity and ease of interpretation, the two groups are hereafter referred to as Cluster 1 and Cluster 2.

a. Cluster 1

Contains experienced and respected teachers. The average age in this cluster is higher (approximately 38.5 years), and the majority have more than ten years of service. This is also consistent with their higher income levels (typically above 4 million rupiah) and better financial condition (middle class). The majority of teachers in this cluster are satisfied with their salaries. In this regard, Cluster 1 comprises experienced teachers with more stable financial circumstances.

b. Cluster 2

contains inexperienced and young teachers. The average age is roughly 30.2 years, and they generally work for 1-3 years. Their annual salaries are likewise lower (between 1 and 2 million rupiah), and they are therefore considered lower-middle class. In this cluster, the majority of teachers were dissatisfied with their pay. Cluster 2 reflects a group of teachers that are still in the early phases of their careers and encounter significant financial challenges.

In general, the most significant differences among these two clusters are: "Age," "Length of Service," "Income Level," "Economic Class," and "Income Satisfacion." These results are essential for understanding the varied training requirements of senior and junior teachers. The more experienced group may require ongoing skill-development programs, whereas the younger group may benefit more from early-career support and welfare improvements. From a theoretical perspective, these findings extend career stage theory between junior and senior teachers are not limited to experience or pedagogical maturity, but are also strongly associated with financial well-being and income satisfaction. The empirical identification of these two clusters supports the conclusion that teachers' professional development trajectories evolve alongside changes in economic stability.

The results of this research are consistent with and supported by prior studies that show systematic differences across teacher career stages. For example, Admiraal et al. (2023) distinguished early-career teacher groups based on years of experience and found that career stage influences teachers' professional experiences and job-related outcomes, thereby reinforcing the importance of considering career stages in understanding teachers' needs and satisfaction.

The findings also align with and reinforce financial well-being and job satisfaction theories, particularly the work of Ecija (2020), which emphasizes that financial management practices and economic well-being are closely linked to educators' professional concentration and performance. Teachers in Cluster 2, who report lower satisfaction with income, may face greater economic pressures that could affect their long-term professional development. Overall, this study contributes by proposing a multidimensional, data-driven view of teacher stratification that integrates demographic, professional, and financial factors within a clustering framework. This approach enriches existing theoretical models of teacher development by demonstrating that teacher heterogeneity is shaped by the interaction between career stage and financial satisfaction, rather than by experience alone.

D. CONCLUSION AND SUGGESTION

The goal of the research is to show teacher clustering characteristics based on demographic, social, and financial factors using a hierarchical clustering method with Gower distance. This study applies Gower-based hierarchical clustering to mixed numerical and categorical data to reveal heterogeneity among teachers that is not captured by aggregate indicators. The analysis begins with descriptive statistics, providing a snapshot of the participant population. The descriptive statistics indicate that the majority of teachers are of productive age (average age 37.24 years), mostly female, married, hold a D4/S1 degree, have an average income of more than 4 million rupiahs, and are satisfied with their salaries.

This study identified two major clusters with distinct characteristics using hierarchical clustering. The majority of respondents are in Cluster 1, which is defined by their age (average 38.54 years), length of service (¿10 years), higher income levels (¿4 million rupiah), middle-class financial situation, and higher income satisfaction. Cluster 2 is defined by a younger age (average 30.25 years), shorter career duration (1–3 years), lower income levels (1–2 million rupiah), lower-middle economic status, and a tendency toward income dissatisfaction.

This disparity suggests a natural division within the teaching population based on career stage, economic conditions, and perceived financial satisfaction. The novelty of this research lies in integrating demographic, professional, and socioeconomic variables within a single Gower-based clustering framework to profile teachers more comprehensively. Substantively, the findings of this clustering can serve as the foundation for developing human resource development policies in the education sector. These findings imply that differentiated policy interventions are necessary, such as targeted professional development for early-career teachers and welfare or incentive schemes for economically vulnerable groups.

Despite its contributions, this study has several limitations. The analysis relies on cross-sectional survey data and does not incorporate performance-based or psychosocial indicators, which may further enrich teacher profiling. Future research is therefore encouraged to employ longitudinal data, include additional teacher performance or motivation variables, and conduct comparative analyses across different educational contexts to enhance the robustness and generalizability of the findings.

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DECLARATIONS

AUTHOR CONTRIBUTION

All authors contributed equally to this research, including problem identification, data collection, analysis, and manuscript writing.

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COMPETING INTEREST

The authors declare that there are no competing financial interests or conflicts of interest related to this research.

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