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INVESTIGATING THE FEASIBILITY OF ISLAMIC EDUCATION FACTORS THROUGH A MULTIATTRIBUTE FUZZY C-MEANS BASED SPATIAL APPROACH

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ABSTRACT
Education plays a vital role in human resource development and national progress. Madrasahs contribute significantly to character formation and religious education in Indonesia; however, many continue to face challenges related to facilities, infrastructure, teacher availability, educational quality, governance, and public perceptions. Therefore, evaluating the feasibility of Islamic education is essential to support educational equity and improve national educational outcomes. This study investigates the feasibility of Islamic education across Indonesia's 34 provinces using a spatial Multiattribute Fuzzy C-Means (FCM) clustering approach. Secondary data from the Ministry of Religious Affairs in 2023 were utilized, covering educator availability, Islamic educational institution units, and student enrollment. The results indicate that these factors are predominantly classified in the low category, particularly at the Madrasah Aliyah level, where 91 percent of provinces fall into the low group. FCM clustering identified three education-quality categories, namely low quality ranging from 26 percent to 32 percent of provinces, medium quality ranging from 59 percent to 65 percent, and high quality accounting for only 9 percent. Spatial analysis further revealed considerable regional disparities in Islamic education quality across Indonesia. Model evaluation using the Akaike Information Criterion showed that Teacher Availability was the best-performing model with an AIC value of 444.96, followed by Institution Units with 451.13 and Students with 474.48. These findings highlight substantial disparities in Islamic education quality and emphasize the need for targeted policies, equitable resource allocation, continuous monitoring, stakeholder collaboration, and sustainable interventions to improve educational quality nationwide.

I. INTRODUCTION

Education significantly influences the development of science and technology. According to the National Education System Law Number 20 of 2003, the purpose of national education is to cultivate individuals who are devoted to God Almighty, possess noble character, and have knowledge, skills, physical and spiritual health, a stable and independent personality, and a sense of responsibility towards society and the nation. Education plays a crucial role in promoting development across all fields, particularly in the era of regional autonomy that demands accelerated progress in the regions [1]. Moreover, education aims to enhance the competence of human resources, enabling them to compete with resources from other countries. Therefore, schools and educators play a strategic role in organizing education [2].

The development of educational programs should not only be limited to general education but also include madrasahs. It is undeniable that the progress of madrasas will have an impact on the overall education system in

Indonesia, particularly with the increasing number and quality of madrasas. Given the current moral crisis and the inability of public education to adequately address the character and morals of the nation, the role of madrasas in national education cannot be underestimated. Madrasas play an important role in building education towards a better direction for the realization of a smart and noble nation [3]. Madrasahs are expected to produce graduates who are qualified in both general and religious knowledge, under national education standards. This is regulated by Law Number 20 of 2003 concerning the National Education System and Government Regulation Number 55 of 2007 concerning Religious Education and Religious Education in the form of Raudhatul Athfal (RA), Madrasah, and Religious Universities, as well as Religious Education [4], [5], [6].

Most Madrasahs were private from the beginning and established with limited capabilities based on the circumstances. The facilities, infrastructure, learning facilities, teaching staff, and requirements of PP No. 19 of 2005 concerning SNP are minimal [7]. Most public Madrasahs still lack the facilities, infrastructure, and teaching staff stipulated in the National Education Standards (SNP). Public Madrasahs differ from public schools in that they were originally private institutions established and built by the community. Public schools, on the other hand, are usually built directly by the government and involve education, teaching staff, and infrastructure from the bottom up [8]. However, the general public still tends to undervalue madrasas, often regarding them as the second choice to formal education organized under the auspices of the Ministry of Education and Culture. This perception is often accompanied by the belief that madrasas lack quality and are less competitive than equivalent public institutions, and that their governance is inadequate. Therefore, it is unsurprising that some individuals still consider madrasahs as a last resort for education, leading to a divide between general education and madrasahs [9].

The Ministry of Religious Affairs and the Ministry of Education and Culture play crucial roles in the implementation of education in madrasahs and in bridging the gap between public and private education in Indonesia by finding common ground between public education and Madrasahs and incorporating religious education into the public curriculum [10]. According to Law No. 20 of 2003 on the National Education System and Law No. 22 of 1999 on Regional Autonomy, the Ministry of Education and Culture is responsible for overseeing the implementation of Islamic education in both public schools and Madrasahs [5], [11] . Local governments are responsible for providing training and financial support. However, many local governments have not yet recognized that religious education is their responsibility. This lack of recognition is detrimental to education providers and students within the ministry of religion. To achieve common goals that will benefit all Indonesian people, policymakers must develop solutions to these problems, it is necessary to assess the feasibility of madrasahs in Indonesia.

Several studies have applied data-driven approaches to evaluate educational quality and institutional performance using clustering, spatial analysis, and multi-criteria decision-making techniques. Fuzzy clustering methods, particularly Fuzzy C-Means (FCM), have been widely employed because they allow an institution to belong to multiple clusters simultaneously, thereby accommodating uncertainty and overlapping characteristics in educational data [12]. Previous studies have utilized FCM to classify school quality, identify educational disparities, and support educational planning based on infrastructure, teacher qualifications, and student achievement. Meanwhile, spatial analysis has been extensively applied to reveal regional disparities in educational accessibility, resource allocation, and school distribution by considering geographical relationships among administrative region [13]. Other studies have also integrated multi-criteria evaluation methods, such as AHP, TOPSIS, and PROMETHEE, to assess school feasibility and educational performance. These approaches have demonstrated the importance of data-driven decision support for educational policy; however, they generally treat clustering, spatial dependency, and multiple educational indicators separately.

Despite these advances, several limitations remain. Existing studies generally employ conventional FCM without considering the heterogeneous contribution of multiple educational attributes or the spatial interaction among neighboring regions. As a result, schools located in geographically adjacent areas with similar educational characteristics may be assigned to different clusters, reducing the interpretability of clustering results for regional policy formulation [14]. Furthermore, previous studies rarely integrate infrastructure, teacher availability, student conditions, institutional management, and spatial proximity into a unified clustering framework for evaluating madrasah feasibility. To address these limitations, this study proposes a MV-FCM that combines multiattribute weighting with spatial information to produce more robust and geographically consistent clustering results. The proposed framework is expected to provide a more comprehensive assessment of madrasah feasibility and to support evidence-based educational planning and resource allocation by the Ministry of Religious Affairs and local governments.

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II. METHOD

A. Multiattribute Fuzzy C-Means

The commonly utilized clustering algorithms, specifically k-means and FCM, are extensively favored for managing single-view data. It is widely recognized that FCM functions as a fuzzy expansion of the k-means clustering method [15]. However, the majority of multiview clustering algorithms necessitate prior knowledge such as the cluster count and parameter choice. Consequently, there exists a critical necessity for an algorithm capable of addressing these issues and autonomously determining the optimal cluster count for multiview data clustering [16]. To address this significant gap in research, a novel U-MV-FCM algorithm is introduced aimed at overcoming the constraints of existing algorithms. The efficacy of this algorithm has been demonstrated as detailed below. Consider a multiview dataset $X = \{x_1, \dots, x_n\}$, where each x_i is composed of s views denoted as $x_i = \{x_i^h\}_{h=1}^{s}$, with $x_i^h \in \mathbb{R}^{d_h}$ for $i = 1, \dots, n$. Let $V = [v_h]_{1\times s}$ represent the weights assigned to each view, where v_h denotes the weight of the hth view. Additionally, let $A^h = \{a_1^h, \dots, a_c^h\}$ denote the set of c cluster centers in the hth view, with $a_k^h = \{a_{kj}^h\}$ for $j = 1, \dots, d_h$. Define $U = [\mu_{ik}]_{n\times c}$ as the fuzzy c-membership matrix, where $\mu_{ik} \in [0,1]$ and $\sum_{k=1}^{c} \mu_{ik} = 1 \forall i$ for all μ_{ik} indicating the degree of membership of the ith data point in the k th cluster center shared across different views h. Drawing from the approach outlined by Hussain et al. [17], we formulate the following unsupervised multiview FCM objective function:

$$J_{U-MVFCM}(U, A^h, V, \alpha) = \left[\sum_{h=1}^{s} v_h^{\beta} \sum_{i=1}^{n}\sum_{k=1}^{c} \mu_{ik} \left\|x_t^h - a_k^h\right\|^2 - \eta_1 \sum_{i=1}^{n}\sum_{k=1}^{c} \mu_{ik} \ln \alpha_k + \eta_2 \sum_{i=1}^{n}\sum_{k=1}^{c} \mu_{ik} \ln \mu_{ik} - \eta_3 \sum_{i=1}^{n}\sum_{k=1}^{c} \alpha_k \ln \alpha_k\right] \quad (1)$$

In compliance with:

$$\sum_{k=1}^{c} \mu_{ik} = 1 \; for \; \forall i, \mu_{ik} \in [0,1] \quad (2)$$

$$\sum_{h=1}^{s} v_h = 1 \; for \; v_h \in [0,1] \quad (3)$$

$$\sum_{k=1}^{c} \alpha_k = 1 \; for \; \alpha_k \in [0,1] \quad (4)$$

In the context where $\left\|x_i^h - a_k^h\right\|^2 = \sum_{j=1}^{d_h} \left(x_{ij}^h - a_{kj}^h\right)^2$, is represented as the summation over j from 1 to d_h of the squared differences between corresponding elements of x_i^h and a_k^h, where $\eta_1, \eta_2, \eta_3 > 0$ and β serves as the exponent for the view weights, multiview data serves as a pivotal asset for informed decision-making. Within the multiview data framework, comprehensive insights at a granular level are leveraged to discern the interconnections among diverse attributes across the h th view. This strategic approach facilitates a nuanced understanding of the underlying data structure, enabling more informed analyses and decision-making processes.

B. Spatial Weighted

In the realm of spatial data modeling, the spatial weight matrix assumes a pivotal role in capturing the spatial interrelations among units of observation. This matrix serves to represent spatial contiguity, elucidating the degree of proximity or interconnectedness between individual units within a geographical context. Among the various types of spatial weight matrices, such as Queen Contiguity, Rook Contiguity, and Bishop Contiguity, each serves to delineate different facets of spatial adjacency [18]. Typically, denoted as W, the spatial weight matrix is an n x n non-negative array, with n denoting the count of spatial observation units, outlining the spatial adjacency relationships among these units. For instance, within the framework of Queen Contiguity, the weight matrix W delineates the adjacency of edges and corner points between one region and another, encapsulating both Rook and Bishop Contiguity. Mathematically, the weight matrix W can be represented as an n x n array, where the entry w_{ij}signifies the adjacency weight between unit i and unit j. These values are determined based on the specific type of contiguity considered (Queen, Rook, or Bishop Contiguity). For example, $w_{ij} = 1$ if unit i and unit \ j are adjacent, and $w_{ij} = 0$ if they are not adjacent.

C. Spatial Autocorrelation Test

Spatial autocorrelation refers to the assessment of correlation between the values of observations associated with spatial positions on a given variable. Positive spatial autocorrelation suggests a likeness in values among

neighboring locations, resulting in clustering tendencies. Conversely, negative spatial autocorrelation implies that adjacent locations exhibit varying values and tend to be more dispersed [19]. The calculation of spatial autocorrelation through Moran's Index method can be executed in two manners: utilizing Moran's Index with a non-standardized spatial weight matrix and employing Moran's Index with a standardized spatial weight matrix. One of these methods involves:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} * (x_j - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (5)$$

Subsequently, hypothesis testing is conducted on the Moran's Index statistical test value using the following equation:

$$Z(I) = \frac{I - E(I)}{\sqrt{Var(I)}} \approx N(0,1) \quad (6)$$

Additionally, Moran's I statistic can be calculated using both non-standardized and standardized spatial weight matrices. The choice of spatial weight matrix depends on the specific characteristics of the spatial data and the research question at hand. Non-standardized spatial weight matrices preserve the original data scale, while standardized spatial weight matrices ensure that the spatial weights sum up to one, making interpretation and comparison across different datasets more straightforward [20]. In summary, Moran's I statistic is a powerful tool for quantifying spatial autocorrelation and understanding the spatial structure of datasets. Its application extends across various disciplines, providing insights into spatial patterns, processes, and relationships that underlie spatial phenomena. Through its formula and interpretation, researchers can gain valuable insights into the spatial characteristics of their data and make informed decisions in spatial analysis and decision-making processes.

D. Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is a widely used statistical measure for model selection, particularly in the context of regression analysis. It provides a balance between goodness of fit and model complexity, allowing researchers to choose the most appropriate model among a set of candidate models. The AIC is based on information theory principles and was developed by Hirotugu Akaike in 1974. It is derived from the Kullback-Leibler information criterion, which measures the relative amount of information lost when a given model is used to approximate the true data-generating process. The formula for calculating the AIC is as follows [21]:

$$AIC = -2\ln(L) + 2k \quad (7)$$

Where $\boldsymbol{L}$ is represents the likelihood of the model given the observed data. This likelihood quantifies how well the model fits the data, essentially measuring the probability of observing the data under the assumed model. $\boldsymbol{k}$ denotes the number of parameters in the model. Parameters are the coefficients or variables that the model estimates from the data. The inclusion of this term penalizes models for their complexity, discouraging overly complex models that may fit the data well but are less interpretable or generalizable.

In practice, researchers compare the AIC values of different models fitted to the same dataset. The model with the lowest AIC value is considered the best-fitting model among the candidates. This approach allows researchers to identify the most parsimonious model that adequately explains the observed data without being overly complex [22]. The AIC is widely used in various fields such as econometrics, biology, ecology, and engineering, where researchers often encounter the need to select the most appropriate model from a set of competing models. Its simplicity, effectiveness, and ability to balance goodness of fit and model complexity make it a valuable tool in statistical modeling and inference.

E. Islamic Education Factor

In this investigation, cluster analysis has been employed to delve into the myriad factors influencing the feasibility of Islamic education in Indonesia. Among the key variables scrutinized are the number of Islamic educational institutions, the enrollment figures of students (known as Santri), and the qualifications of educators. Islamic educational establishments serve as focal points for both religious and secular learning, offering an enriching milieu for students to delve into Islamic teachings while also receiving a comprehensive academic curriculum. These institutions typically adhere closely to Islamic principles and values, fostering a holistic approach to education that seamlessly integrates religious doctrines with contemporary pedagogical methodologies [23] [24] [25].

The enrollment numbers of Santri, representing the student body in Islamic institutions, emerge as a pivotal factor in gauging the viability and efficacy of Islamic education. A higher influx of students often signifies robust

community support and a burgeoning demand for Islamic education, underscoring the significance and relevance of these educational entities within the societal fabric. Moreover, the number of Santri can exert considerable influence on resource allocation, classroom dynamics, and overall educational outcomes, thereby shaping the educational landscape and its responsiveness to the needs of learners [26] [27] [28].

Equally instrumental in shaping the educational landscape are the qualifications and expertise of educators within Islamic institutions. Educators possessing robust Islamic knowledge and pedagogical acumen are aptly equipped to impart religious teachings and academic subjects with efficacy and finesse. Their credentials, spanning educational backgrounds, specialized training, and practical experience, bear profound implications for the learning journey of students and contribute substantially to the success and efficacy of Islamic education programs. Consequently, the qualifications of educators serve as a cornerstone in cultivating an enriching and intellectually stimulating learning environment within Islamic educational institutions, fostering the holistic development of students and nurturing a generation well-versed in Islamic principles and values [29] [30].

F. Identify Subsections

The introduction to the Multiattribute Fuzzy C-Means (FCM) based spatial approach acquaints readers with its core principles and applications. It elucidates the fusion of fuzzy clustering and spatial analysis, underscoring how this methodology amalgamates diverse attributes and spatial dimensions to navigate intricate datasets. Furthermore, it underscores the pertinence of such an approach in educational research, particularly in probing the feasibility of Islamic education factors, where intricate interrelations demand sophisticated analytical techniques. The factors under scrutiny encompass the number of Islamic educational institutions, the enrollment figures of students (known as Santri), and the qualifications of educators, each bearing unique significance in shaping the educational landscape within Islamic institutions.

Moving forward, the discussion delves into the application landscape of Multiattribute FCM in educational research, encompassing the aforementioned factors. This segment delves into prior studies and instances where Multiattribute FCM has been harnessed. It traverses diverse educational facets like student performance, teacher effectiveness, and school quality, illustrating the versatility and adaptability of this method. Emphasizing its capacity to navigate uncertainty and complexity, this exploration underscores Multiattribute FCM's prowess in dissecting intricate educational phenomena, including the dynamics surrounding Islamic educational institutions, Santri enrollment, and teacher qualifications. Transitioning to the incorporation of Islamic education factors into Multiattribute Fuzzy C-Means analysis, the discourse intricately weaves the unique intricacies of Islamic education into the analytical framework. Delving into the selection rationale and representation nuances of factors like the number of Islamic institutions, Santri enrollment, and teacher qualifications, this section unravels the methodological intricacies. It further broaches potential challenges and nuances in integrating Islamic education dynamics, presenting a comprehensive view of the analytical landscape.

As the study progresses, attention shifts towards the meticulous methodology employed in investigating the feasibility of Islamic education factors through the Multiattribute FCM based spatial approach. Here, a systematic breakdown of data collection, preprocessing, model formulation, parameter selection, and analysis techniques unfolds. This methodological elucidation not only offers transparency but also ensures the robustness and validity of the findings, reinforcing the study's scholarly integrity. The inclusion of factors such as the number of Islamic educational institutions, Santri enrollment, and educator qualifications underscores the thoroughness and comprehensiveness of the methodology.Subsequently, the subsection unravels the crux of the investigation, presenting the results and analysis gleaned from the Multiattribute Fuzzy C-Means approach applied to Islamic education factors. It unravels spatial patterns and interrelations entrenched within the data, offering insights into the feasibility and dynamics of Islamic education. This segment culminates in a comprehensive exploration of the implications of these findings, spotlighting their potential to inform Islamic education policy and practice.

G. Participant Characteristics

Participant Characteristics in the context of the Multiattribute Fuzzy C-Means (FCM) based spatial approach play a pivotal role in shaping the scope and direction of research endeavors. This approach, which combines fuzzy clustering and spatial analysis, relies heavily on understanding the attributes and demographics of the participants involved in educational research. By elucidating the intricate fusion of fuzzy clustering and spatial analysis, researchers can navigate complex datasets, extracting meaningful insights that shed light on the feasibility of Islamic education factors.

Within the realm of educational research, participant characteristics assume heightened significance, particularly when investigating the feasibility of Islamic education factors. The nuanced interplay between various attributes and spatial dimensions necessitates a sophisticated analytical framework, such as the Multiattribute FCM based spatial approach. Here, the focus extends beyond conventional demographic factors to encompass elements specific to Islamic educational settings.

The factors under scrutiny encompass a triad of crucial elements: the number of Islamic educational institutions, the enrollment figures of students (commonly referred to as Santri), and the qualifications of educators. Each facet holds unique significance in shaping the educational landscape within Islamic institutions. The number of Islamic educational institutions serves as a foundational pillar, reflecting the institutional infrastructure and capacity to deliver Islamic education. Concurrently, the enrollment figures of Santri offer insights into the demand and accessibility of Islamic education within the community, signifying the relevance and impact of these institutions. Moreover, the qualifications of educators emerge as a pivotal determinant of educational quality, influencing the pedagogical approaches and learning outcomes within Islamic educational settings.

Understanding these participant characteristics is paramount for researchers utilizing the Multiattribute FCM based spatial approach. By delving into the intricacies of Islamic education factors, researchers can glean valuable insights into the feasibility and efficacy of educational interventions. Moreover, by integrating participant characteristics into the analytical framework, researchers can ensure the relevance and applicability of their findings to the broader Islamic education landscape. Thus, participant characteristics serve as a cornerstone in shaping the trajectory of research endeavors, enriching our understanding of Islamic education feasibility and fostering meaningful advancements in educational practice and policy.

H. Research Design

This study aims to analyze the spatial distribution of education quality in Indonesia using a Multi-View Fuzzy C-Means (MV-FCM) approach. Three educational dimensions are considered as independent data views, namely teacher availability, Islamic educational institution units, and students of Islamic educational institutions. The study utilizes secondary data published by the Ministry of Religious Affairs of the Republic of Indonesia for the year 2023, covering all 34 provinces in Indonesia. The research framework consists of several sequential stages. First, data preprocessing is conducted to ensure data quality through missing-value inspection, verification of variable types, and Min–Max normalization to transform all numerical variables into a common range of 0–1. This normalization reduces the influence of differences in measurement scales and improves the stability of the clustering process.

Second, descriptive statistical analysis is performed to summarize the characteristics of each educational view. The variables representing teacher availability, Islamic institution units, and student enrollment are transformed into fuzzy membership values and categorized into low, moderate, and high levels to provide an initial overview of educational conditions across provinces. Third, the optimal number of clusters is determined using the Elbow Method based on the Within-Cluster Sum of Squares (WSS). The elbow point is selected as the optimal number of clusters because it provides the best trade-off between cluster compactness and model simplicity before implementing the MV-FCM algorithm. Fourth, the Multi-View Fuzzy C-Means (MV-FCM) algorithm is applied separately to the three educational views. The algorithm generates fuzzy membership values that assign each province to one of three education-quality clusters (low, moderate, and high), while preserving the uncertainty inherent in educational data. Cluster visualization is then performed using two-dimensional projections (Dim1 and Dim2) to examine the similarity patterns among provinces. Fifth, spatial mapping is conducted by integrating the clustering results with the geographic locations of Indonesian provinces. This stage visualizes the spatial distribution of education quality clusters and identifies regional disparities based on teacher availability, Islamic institution units, and student enrollment. Finally, model performance is evaluated using the Akaike Information Criterion (AIC). The AIC values obtained from the three educational views are compared to identify the clustering model that provides the best balance between goodness of fit and model complexity.

III. RESULTS AND DISCUSSION

A. Desciptive Analyze

The initial stage of this study is data preprocessing, which aims to improve data quality before performing clustering using the Multi-View Fuzzy C-Means (MV-FCM) method. At this stage, a missing value check is conducted to ensure that the dataset is complete and that all variables can be included in the analysis. In addition,

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the data structure and variable types are examined to verify that the dataset is suitable for further processing. Subsequently, all numerical variables are normalized using the Min–Max normalization method to transform their values into a common range of 0–1. This normalization is essential because variables with different scales may dominate the distance calculations in the MV-FCM algorithm, potentially leading to suboptimal clustering results. Therefore, the preprocessing stage produces a more consistent and balanced dataset, ensuring that the data are well-prepared for the subsequent clustering analysis.

Following the preprocessing stage, a descriptive analysis is conducted to provide an initial overview of the characteristics of each data view, the categorization of each factor will be conducted, namely teacher availability, Islamic institution units, and students of Islamic institutions. This categorization will be divided into three levels: low, moderate, and high, based on the degree of membership from the transformation into the fuzzification process. The table for each factor is presented as follows:

TABLE 1.
DESCRIPTIVE STATISTICS TEACHER AVAILABILITY IN 2023

Category	Teacher MI		Teacher MTs		Teacher MA	
	Number of Provinces	(%)	Number of Provinces	(%)	Number of Province	(%)
Low	22	65%	13	38%	31	91%
Medium	2	6%	2	6%	0	0%
High	10	29%	19	56%	3	9%
Total of Provinces	34	100%	34	100%	34	100%

The table presents a detailed analysis of teacher availability in 2023 across different types of Islamic schools: MI (Madrasah Ibtidaiyah), MTs (Madrasah Tsanawiyah), and MA (Madrasah Aliyah). The data is categorized into three levels: Low, Medium, and High. For MI teachers, the analysis reveals that 65% of provinces experience low availability, with 22 provinces falling into this category. Medium availability is observed in 6% of provinces, while high availability is noted in 29% of provinces, totaling 34 provinces considered. In the case of MTs teachers, 38% of provinces exhibit low availability, while 56% have high availability, with 6% experiencing medium availability. Finally, for MA teachers, a substantial 91% of provinces face low availability, while 9% exhibit high availability, totaling 100% of provinces assessed. This comprehensive analysis provides valuable insights into the distribution of teacher availability across provinces, highlighting the varying degrees of availability among different types of Islamic schools.

TABLE 2.
DESCRIPTIVE STATISTICS OF UNIT ISLAMIC INSTITUTION IN 2023

Category	Unit Institution MI		Unit Institution MTs		Unit Institution MA	
	Number of Provinces	(%)	Number of Provinces	(%)	Number of Provinces	(%)
Low	21	62%	11	32%	31	91%
Medium	4	12%	5	15%	0	0%
High	9	26%	18	53%	3	9%
Total Province	34	100%	34	100%	34	100%

Table 2 provides a detailed analysis of the distribution of Islamic institution units across provinces in 2023, focusing on MI (Madrasah Ibtidaiyah), MTs (Madrasah Tsanawiyah), and MA (Madrasah Aliyah) institutions. Categorized into three levels Low, Medium, and High the data reveals the following trends. In terms of MI institution units, 21 provinces, representing 62% of the total, exhibit a low number of units, while 4 provinces (12%) have a moderate number, and 9 provinces (26%) boast a high number. For MTs institution units, 11 provinces (32%) have a low count, 5 provinces (15%) a medium count, and 18 provinces (53%) a high count. As for MA institution units, a significant majority of 31 provinces (91%) demonstrate a low number, with no provinces reporting a medium count, and only 3 provinces (9%) showing a high count. These findings underscore the disparities in the availability of Islamic institution units across provinces, providing crucial insights into the distribution of educational infrastructure within the Islamic education sector.

TABLE 3.
DESCRIPTIVE STATISTICS STUDENTS OF ISLAMIC INSTITUTION IN 2023

Category	Students MI	Students MTs	Students MA

	Count of Province	(%)	Count of Province	(%)	Count of Province	(%)
Low	21	62%	13	38%	31	91%
Medium	4	12%	3	9%	0	0%
High	9	26%	18	53%	3	9%
Total Province	34	100%	34	100%	34	100%

Table 3 provides a detailed breakdown of student distribution across various types of Islamic institutions in 2023, including MI (Madrasah Ibtidaiyah), MTs (Madrasah Tsanawiyah), and MA (Madrasah Aliyah) institutions. The data is categorized into three levels: Low, Medium, and High. For MI students, the analysis indicates that 21 provinces, representing 62% of the total, have a low student count, while 4 provinces (12%) report a medium count, and 9 provinces (26%) have a high count. Regarding MTs students, 13 provinces (38%) have a low count, 3 provinces (9%) have a medium count, and 18 provinces (53%) have a high count. For MA students, the majority of provinces, specifically 31 (91%), exhibit a low student count, with no provinces reporting a medium count, and only 3 provinces (9%) indicating a high count. These findings shed light on the distribution of student enrollment across different types of Islamic institutions and provide valuable insights into educational access and enrollment trends within the Islamic education sector.

B. Determination of the Optimal Number of Clusters

Before performing the clustering process, it is essential to determine the optimal number of clusters to ensure that the resulting partition accurately represents the underlying structure of the data. In this study, the Elbow Method based on the Within-Cluster Sum of Squares (WSS) was employed to identify the most appropriate number of clusters. The optimal cluster number corresponds to the point where the reduction in WSS begins to diminish, indicating that adding more clusters provides only marginal improvement in cluster compactness. The visualization of the Elbow Method for the three data views is presented in Fig. 1.

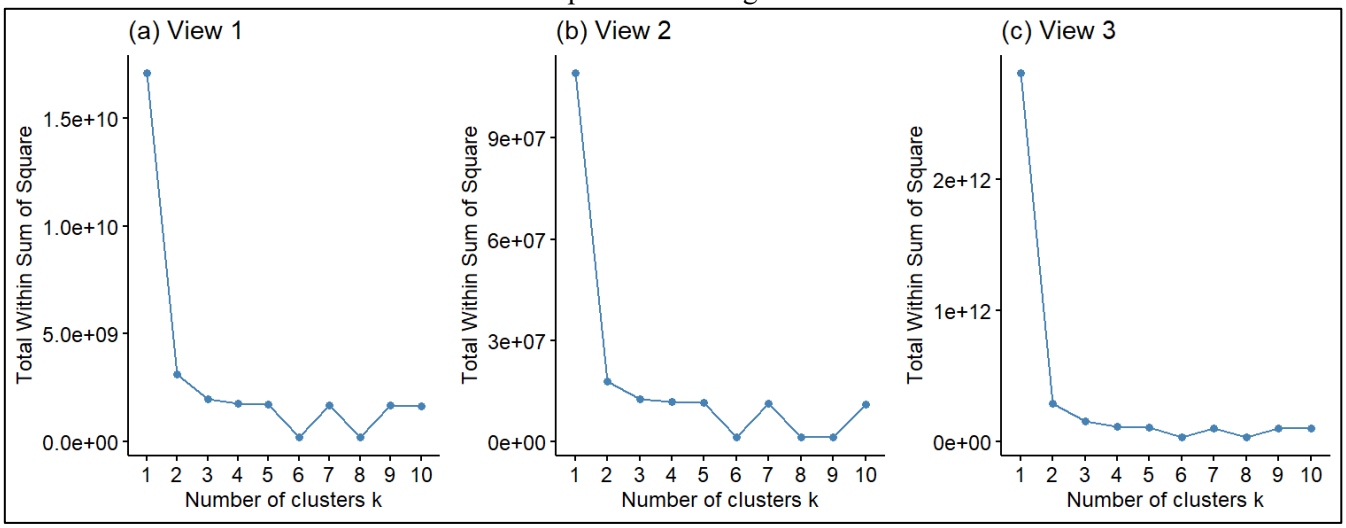


Fig 1. Elbow Plot for Determining the Optimal Number of Clusters in (a) Teacher Availability (View 1), (b) Islamic Institution Units (View 2), and (c) Students of Islamic Institutions (View 3).

Figure 1 presents the Elbow plots for the three data views used in this study, namely teacher availability (View 1), Islamic institution units (View 2), and students of Islamic institutions (View 3). The Elbow Method was employed to determine the optimal number of clusters by examining the pattern of the Within-Cluster Sum of Squares (WSS) as the number of clusters increased. Across all three views, a substantial reduction in WSS is observed from $k = 1$ to $k = 3$, after which the curves begin to flatten, indicating that additional clusters provide only marginal improvements in cluster compactness. Although minor fluctuations appear for $k > 3$, these changes are relatively small and do not significantly improve the clustering structure. Therefore, the elbow point is consistently identified at $k = 3$ for all views, suggesting that three clusters provide the best balance between cluster homogeneity and model simplicity. Accordingly, the subsequent Multiattribute Fuzzy C-Means analysis adopts three clusters, representing low, moderate, and high levels of educational quality, to ensure meaningful and interpretable clustering results across the three educational dimensions.

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C. *Level of Education Quality Clustering*

The following subsection will discuss Education Quality Clusters. Its aim is to conduct a comprehensive analysis of educational data with a focus on identifying patterns or hidden patterns in educational quality at various levels. Through cluster formation, the goal is to group educational institutions based on factors under scrutiny, such as teacher availability, Islamic institution units, and Islamic institution students, in hopes of gaining valuable insights into the influence levels of these factors on educational quality. With specific objectives, such as identifying variations in educational quality, developing cluster profiles, identifying determining factors, developing improvement strategies, and providing information to stakeholders, this discussion is expected to make a meaningful contribution to efforts to enhance education for all individuals and communities as a whole. As for the results of the cluster analysis, they are presented as follows:

TABLE 4.
CLUSTERING LEVEL OF EDUCATION QUALITY BASED ON EACH FACTOR

Category	Cluster					
	Teachers		Unit Institution		Students	
	Count	(%)	Count	(%)	Count	(%)
Low	11	32%	9	26%	11	32%
Medium	20	59%	22	65%	20	59%
High	3	9%	3	9%	3	9%
Total Province	34	100%	34	100%	34	100%

Table 4 provides a detailed breakdown of the clustering of education quality levels, categorized based on three key factors: Teachers, Unit Institution, and Students. Within the Teachers category, it is revealed that 32% of the clusters are classified as low quality, 59% as medium quality, and only 9% as high quality. Similarly, in the Unit Institution category, 26% of clusters exhibit low quality, 65% medium quality, and 9% high quality. As for the Students category, 32% of clusters are identified as low quality, 59% as medium quality, and again, 9% as high quality. This comprehensive analysis offers valuable insights into the distribution of education quality clusters across different factors. It sheds light on areas where improvements are needed and can inform policymakers and educators in developing targeted interventions to enhance education quality effectively.



Fig 2. Cluster Visualization Education Quality Based on Teacher Availability in 2023

Based on Figure 2, which presents the cluster visualization of education quality based on teacher availability in 2023, the distribution of clusters can be analyzed to identify different patterns among institutions. The visualization consists of two dimensions, Dim1 and Dim2, explaining 98.4% and 1.5% of the total variance, respectively. Three clusters are identified, representing different characteristics of teacher availability and education quality. Cluster 3 is located in the region with the most negative Dim1 values and shows a wider distribution compared with other clusters, indicating a distinct pattern associated with lower education quality characteristics based on teacher availability indicators. Meanwhile, Clusters 1 and 2 are positioned closer to the positive side of Dim1, indicating relatively similar characteristics associated with higher education quality patterns.

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Overall, the clustering results reveal that variations in teacher availability contribute to the differentiation of education quality characteristics among clusters. These findings represent the similarity patterns identified by the MV-FCM method and do not indicate a direct causal relationship between teacher availability and education quality.

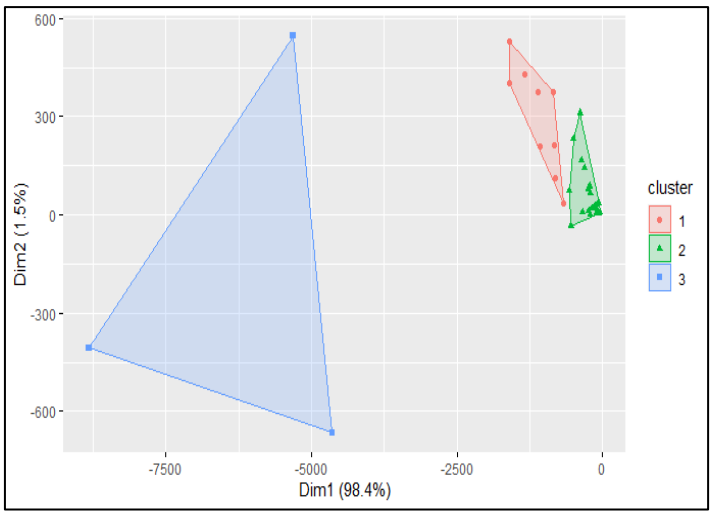


Fig 3. Cluster Visualization Education Quality Based on Unit Islamic Institution in 2023

Based on Figure 3, which illustrates the cluster visualization of education quality based on the number of Islamic institution units in 2023, the clustering structure demonstrates different patterns among institutions. The visualization consists of Dim1 and Dim2, accounting for 98.4% and 1.5% of the total variance, respectively. Three clusters are identified, where each cluster represents a different combination of Islamic institution unit characteristics and education quality indicators. Cluster 3 is positioned on the negative side of Dim1 and Dim2, representing a group with relatively different characteristics compared with other clusters. In contrast, Clusters 1 and 2 are located closer to the positive region, indicating a pattern associated with higher education quality characteristics based on institutional availability. The distribution of clusters suggests that differences in the number of Islamic institution units contribute to the formation of distinct education quality profiles. However, the interpretation should be understood as a clustering pattern generated by MV-FCM rather than a statistical correlation or causal relationship.

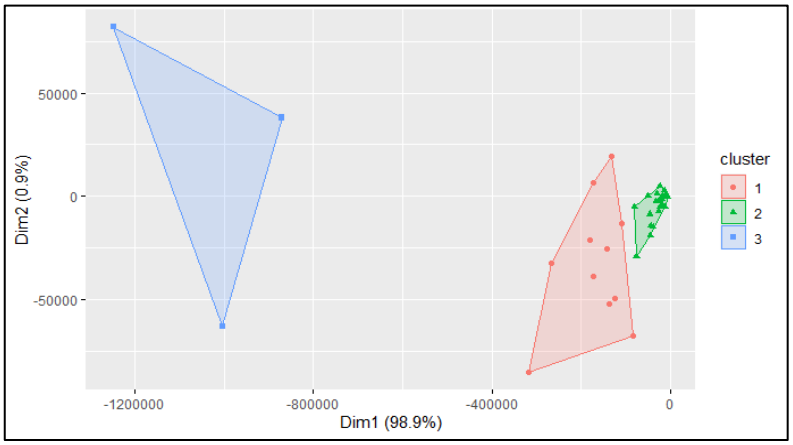


Figure 4. Cluster Visualization Education Quality Based on Students of Islamic Institutitution in 2023

Based on Figure 4, which presents the cluster visualization of education quality based on the number of students in Islamic institutions in 2023, the clustering results reveal distinct patterns among institutions. The visualization consists of Dim1 and Dim2, explaining 98.9% and 0.9% of the total variance, respectively. Three clusters are observed, representing different characteristics based on student numbers and education quality indicators. Cluster 3 is located on the negative side of Dim1 with a wider distribution, indicating a unique pattern associated with relatively lower education quality characteristics. Meanwhile, Clusters 1 and 2 are positioned closer to the positive region of Dim1, suggesting characteristics associated with relatively higher education quality patterns. The distribution indicates that institutions with different student population characteristics form distinct

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education quality clusters. Therefore, the results demonstrate that the number of students contributes to the differentiation of education quality profiles identified by the MV-FCM algorithm. This interpretation reflects the clustering structure and similarity patterns within the data, rather than implying a direct positive or negative correlation between student numbers and education quality.

D. Spatial Mapping

The subsequent section delves into the concept of Education Quality Clusters, aiming to conduct a comprehensive spatial analysis of educational data to uncover underlying patterns in educational quality across different geographic regions. By employing spatial mapping techniques, the objective is to discern spatial clusters or groupings of educational institutions based on key factors such as teacher availability, the presence of Islamic institution units, and the enrollment of students in Islamic institutions. This spatial approach allows for a deeper understanding of the geographical distribution of educational quality and the varying influences of these factors across different regions. The specific goals include identifying variations in educational quality, creating spatial cluster profiles, determining influential factors, formulating targeted improvement strategies, and disseminating pertinent information to stakeholders. Through spatial mapping and cluster analysis, this endeavor is anticipated to yield valuable insights that can inform policy-making and interventions aimed at enhancing educational outcomes for diverse populations and communities. The subsequent section will present the results of the spatial cluster analysis, providing a detailed overview of the identified clusters and their spatial distribution.



Fig 5. Spatial Visualization Education Quality Based on Teacher Availability in 2023

Figure 5 illustrates the spatial distribution of education quality in Indonesia based on teacher availability across various provinces and regions, including Sumatra, Java, Kalimantan, Sulawesi, and Papua. The clustering results identify three distinct groups that represent different levels of education quality associated with teacher availability. The low-quality cluster consists of regions with limited educational resources and lower teacher availability, the moderate cluster represents areas with intermediate educational conditions, while the high-quality cluster includes regions characterized by relatively better educational access and teacher distribution. The low cluster includes several regions such as Kupang in East Nusa Tenggara, Tulungagung in East Java, and several districts in Papua, including Mimika, Nabire, and Yapen. Meanwhile, the moderate cluster is predominantly composed of more developed and densely populated areas, including Jakarta, Banten, and several regions in Java, although Tulungagung exhibits a different pattern. In contrast, the high cluster comprises several urban and regional centers, such as Pontianak in West Kalimantan, Palu in Central Sulawesi, and areas in West Java, including Bandung, Cianjur, and Garut. The visualization highlights geographical disparities in educational conditions, with different colors representing the cluster membership of each region and providing an overview of spatial variation in education quality throughout Indonesia. These findings are consistent with previous studies reporting that regional clustering patterns in education are strongly associated with indicators such as teacher distribution, gross enrollment

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rate (GER), student participation, and access to educational services. Several studies have also identified a persistent disparity between western and eastern regions of Indonesia, where provinces in Papua, East Nusa Tenggara, and Maluku tend to demonstrate lower educational performance compared with Java–Bali and other western regions [31].



Fig 6. Spatial Visualization Education Quality Based on Unit Islamic Institution in 2023

This map on Figure 6 illustrates three clusters representing the quality of education based on Islamic institution units in Indonesia. The low cluster comprises regions with the lowest education quality, the moderate cluster includes areas with average education quality, and the high cluster consists of regions with the highest education quality. The majority of regions in Indonesia fall into the moderate cluster, indicating that the education quality in Indonesia still requires further development. However, there are some regions in the high cluster, such as Pontianak and Palu, which exhibit relatively high education quality. This map can be utilized by local and central governments to understand education quality trends in Indonesia and to identify areas requiring educational development. Additionally, the map can also be utilized by the general public to comprehend the education quality in their regions and to make better educational decisions. The findings are consistent with Saiwanto et al. [32], who emphasized that mapping Islamic education provides a systematic basis for identifying regional disparities and supporting evidence-based educational planning across Indonesia.



Fig 7. Spatial Visualization Education Quality Based on Students of Islamic Institutitution in 2023

The map on Figure 7 illustrates three clusters of education quality based on the number of students of Islamic

institutions in Indonesia. The low cluster comprises regions with the lowest education quality, the moderate cluster includes areas with average education quality, and the high cluster consists of regions with the highest education quality. The majority of regions in Indonesia fall into the moderate cluster, indicating that the education quality in Indonesia still requires further development. However, there are some regions in the high cluster, such as Pontianak and Palu, which exhibit relatively high education quality.This map can be utilized by local and central governments to understand education quality trends in Indonesia and to identify areas requiring educational development. Additionally, the map can also be utilized by the general public to comprehend the education quality in their regions and to make better educational decisions. These findings are consistent with previous research highlighting the significant contribution of Islamic and informal educational institutions to lifelong learning and community-based education, while the predominance of the moderate cluster in the present study indicates that disparities in student distribution and educational capacity across regions still require targeted policy interventions [33].

E. Evaluation Model

The assessment of the models is carried out by employing the AIC derived from equation (7). The outcomes of the AIC computation pertaining to the clustering of three models are outlined below:

TABLE 5.
AIC RESULT FOR EACH FACTOR

Parameter	Model 1	Model 2	Model 3
AIC	444.96	451.13	474.48

The AIC values for three different models, namely Model 1 for FCM Teacher Availability, Model 2 for FCM Unit Islamic Institution, and Model 3 for FCM Student of Islamic Institution are 444.96, 451.13, and 474.48, respectively. The AIC, or Akaike Information Criterion, is a measure used for model selection, balancing goodness of fit with model complexity. In the context of these models, lower AIC values indicate better fits.Based on the AIC values, Model 1 (FCM Teacher Availability) has the lowest AIC value of 444.96, suggesting that it provides the best balance between goodness of fit and simplicity among the three models. Model 2 (FCM Unit Islamic Institution) follows with an AIC value of 451.13, indicating a slightly worse fit compared to Model 1. Lastly, Model 3 (FCM Student of Islamic Institution) has the highest AIC value of 474.48, implying the poorest fit among the three models. This comparison suggests that, in terms of AIC, Model 1 performs the best among the three in explaining the variation in the data, followed by Model 2, while Model 3 performs the poorest. However, it's important to consider other factors and conduct further analysis to determine the most appropriate model for the given dataset.

F. Discussion

The spatial clustering results indicate that policy interventions should be differentiated according to the characteristics of each cluster rather than applying a uniform national strategy. Regions classified in the low cluster, including Kupang (East Nusa Tenggara), Tulungagung (East Java), Mimika, Nabire, and Yapen (Papua), should be prioritized for programs addressing teacher shortages through incentive-based teacher deployment, rotational assignments, and distance-learning support to overcome geographical constraints. Considering that several of these regions are characterized by dispersed settlements and limited accessibility, strengthening digital learning infrastructure and providing internet-supported teaching resources are likely to be more effective than relying solely on the construction of new educational facilities. For regions remaining in the moderate cluster, particularly those located in Jakarta, Banten, and several parts of Java, policy efforts should focus on improving educational quality rather than merely increasing educational capacity. This can be achieved by strengthening teacher professional development, improving the management of Islamic educational institutions, and reducing disparities in educational services between urban and peri-urban areas. These interventions may facilitate the transition of moderate-cluster regions toward the high-quality cluster. Meanwhile, regions belonging to the high cluster, such as Pontianak, Palu, Bandung, Cianjur, and Garut, should be considered as reference regions for best practices. Instead of receiving identical interventions, these regions can function as mentoring hubs by sharing successful strategies in teacher management, institutional governance, and student services with neighboring low-cluster regions through inter-regional collaboration programs.

IV. CONCLUSION

In conclusion, the analysis of education quality clustering based on various factors such as teacher availability,

unit Islamic institution, and students of Islamic institutions has provided valuable insights into the current state of education in Indonesia. The clustering analysis has revealed distinct patterns and disparities in education quality across different regions, highlighting areas that require immediate attention and intervention. The findings suggest that a significant proportion of regions fall into the moderate cluster, indicating that there is still room for improvement in education quality across Indonesia. However, the presence of regions classified under the low and high clusters underscores the need for targeted interventions to address disparities and ensure equitable access to quality education.

Based on these findings, several recommendations can be proposed to stabilize and enhance education quality in Indonesia. These recommendations include the implementation of targeted intervention programs focused on regions classified under the low cluster, prioritization of resource allocation based on cluster classifications, fostering collaboration and knowledge sharing between regions, establishing continuous monitoring and evaluation mechanisms, engaging communities and stakeholders, and planning for long-term sustainability. By adopting these recommendations, the government can work towards stabilizing education quality levels across Indonesia, ensuring that all individuals have access to quality education and opportunities for socio-economic advancement. These efforts are crucial for building a skilled and knowledgeable workforce, promoting social mobility, and achieving sustainable development goals.

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REFERENCES

[1] A. Iman, I. A. Apzah, F. Aprianto, S. Sanam and B. Bohari, "Problematika Tenaga Pendidik dalam Pengembangan Profesionalitas Guru," *Vocational Education National Seminar (VENS),* pp. 55-58, 2022.

[2] F. Lafendry, "Kualifikasi dan Kompetensi Guru dalam Dunia Pendidikan," *Tarbawi: Jurnal Pemikiran dan Pendidikan Islam,* pp. 1-16, 2020.

[3] R. Risna and H. Pelu, "The Capacity of Islamic School Principals in Implementing The Merdeka Belajar (Freedom to Learn) Program," *Waiheru,* vol. 10, no. 2, p. 218–228, 2024.

[4] M. Hazin and N. W. D. Rahmawati, "KEBIJAKAN PENGEMBANGAN KURIKULUM PENDIDIKAN ISLAM (Studi Histori dan Regulasi di Indonesia)," *Journal Evaluasi,* vol. 5, no. 2, p. 293–310, 2021.

[5] P. P. Indonesia, "Undang-undang (UU) Nomor 20 Tahun 2003 tentang Sistem Pendidikan Nasional," Pemerintah Pusat Indonesia, Jakarta, 2003.

[6] P. Indonesia, "Peraturan Pemerintah Republik Indonesia Nomor 55 Tahun 2007 tentang Pendidikan Agama dan Pendidikan Keagamaan," Kemenag, Jakarta, 2007.

[7] M. Frandani, A. M. Tamam and A. Ahmad, "Internal Quality Management Model in Islamic Boarding School-Based Madrasah," *Qalamuna Jurnal Pendidikan Sosial Dan Agama,* vol. 16, no. 1, p. 219–240, 2024.

[8] H. Susanto, R. N. Sasongko and M. Kristiawan, "Teachers 'Professionality in Improving the Quality of Madrasah Education in The Era of Globalization," *Jurnal Studi Guru Dan Pembelajaran,* vol. 4, no. 1, p. 135–141, 2021.

[9] M. Iqbal, M. R. Sirait, D. M. Sari, E. P. Khairani and M. S. Harahap, "Pengamatan Kebijakan Pendidikan pada Madrasah di Indonesia," *Journal of Education,* pp. 9173-9182, 2023.

[10] I. Yuniarti, N. khodijah and E. Suryana, "Analisis Kebijakan Pendidikan Agama Islam di Sekolah dan Madrasah," *Modeling: Jurnal Program Studi PGMI,* pp. 182-207, 2022.

[11] P. P. R. Indonesia, "Undang-Undang Republik Indonesia Nomor 22 Tahun 1999 tentang Pemerintahan Daerah," Pemerintah Pusat Republik Indonesia, Jakarta, 1999.

[12] G. R. Apsari, M. S. Pradana and N. E. Chandra, "Implementasi Fuzzy C-Means dan Possibilistik C-Means Pada Data Performance Mahasiswa," *UJMC,* vol. 6, no. 2, p. 39–48, 2020.

[13] A. A. Muhaimin, A. Gamal, M. A. Setianto and W. L. Larasati, "The Spatial Justice of School Distribution in Jakarta," *Heliyon 8,* vol. 8, no. e11369, 2022.

[14] S. Gamsu and H. Forsberg, "A typology of schools across the four nations of the United Kingdom: Class, race and geography," *British Educational Research Journal,* vol. 52, no. 1, p. 310–339, 2025.

[15] R. C. G. I. Kembaren, O. S. Sitompul and Sawaluddin, "Analysis clustering using Normalized Cross Correlationin Fuzzy C-Means Clustering Algorithm," *Sinkron :Jurnal dan PenelitianTeknik Informatika,* pp. 2262-2271, 2022.

[16] R. Manidatta, A. Banaitis, K. Muduli and A. K. Bandrana, "INTEGRATED APPROACH OF FUZZY MULTI-ATTRIBUTE DECISION MAKING AND DATA MINING FOR CUSTOMER SEGMENTATION," *E+M Ekonomie a Management,* pp. 174-188, 2021.

[17] I. Hussain, K. P. Sinaga and M. S. Yang, "Unsupervised Multiview Fuzzy C-Means Clustering Algorithm," *Electronics,* pp. 1-30, 2023.

[18] Y. Chen, "Spatial autocorrelation equation based on Moran's index," *Scientific Reports,* pp. 1-14, 2023.

[19] M. Sobari, A. Desiyanti, D. Yanti, P. Monika, A. S. Abdullah and B. N. Ruchjana, "Comparison of Spatial Weight Matrices in Spatial Autoregressive Model: Case Study of Intangible Cultural Heritage in Indonesia," *JTAM (Jurnal Teori dan Aplikasi Matematika),* pp. 244-261, 2023.

[20] S. Sun and H. Zhang, "Flow-Data-Based Global Spatial Autocorrelation Measurements for Evaluating Spatial Interactions," *International Journal of Geo-Information,* pp. 1-18, 2023.

[21] S. Potret, "A primer on model selection using the Akaike Information Criterion," *Infectious Disease Modelling,* pp. 111-128, 2020.

[22] Q. Liu, M. A. Charleston, S. A. Richards and B. R. Holland, "Performance of Akaike Information Criterion and Bayesian Information Criterion in Selecting Partition Models and Mixture Models," *Systematic Biology,* pp. 92-105, 2023.

[23] A. Zamroni and Wakidi, "Quality Development of Islamic Education in the Era of Society 5.0: Oppurtunities and Challenges," *Jurnal Al – Mau'izhoh,* pp. 326-334, 2023.

[24] I. A. Saputra and Ahmadi, "Paradigm Of Islam Religious Education In Responding To The Challenges Of The Times," *Proceedings,* pp. 66-76, 2022.

[25] M. Umar, F. Ismail, S. Rahmi and Z. Arifin, "Transforming of Moderate Character Education in Islamic Educational Institutions," *Nazhruna: Jurnal Pendidikan Islam,* pp. 171-188, 2024.

[26] Q. Yu, "Factors Influencing Online Learning Satisfaction," *Frontiers in Psychology,* pp. 1-8, 2022.

[27] M. Zuhdi and K. Syarief, "Constructing the Concept of Student Well-Being within Indonesian Islamic Higher Education," *Religions,* pp. 1-12, 2023.

[28] T. A. Syukur, T. P. Anhary, H. S. J. Rieuwpassa, G. Megan and S. Limei, "Factors Influencing Islamic Education: Government Policy, Principals and Teachers," *AL-FIKRAH: Jurnal Manajemen Pendidikan,* pp. 130-140, 2023.

[29] N. K. R. Putri and C. Setiawan, "What Islamic Education Teachers Need To Know and Be Able To Do To Teach Students Higher-Order Thinking Skills?," *Jurnal AFKARUNA,* pp. 308-323, 2022.

[30] I. Anshori and E. E. Sahara, "INTERNATIONALIZATION OF ISLAMIC EDUCATION INSTITUTIONAL CHARACTERS THROUGH THE ENGLISH ACCULTURATION STRATEGY," *Humanities & Social Sciences Reviews ,* pp. 140-157, 2020.

[31] K. Muttaqin, R. Nurhidayah, N. Novianda, A. K. Ariffin, J. Sultan and F. Rifqiyah, "Implementation of K-Means Clustering in Mapping Teacher Distribution Using Geographic Information System," *Elinvo (Electronics Informatics and Vocational Education),* vol. 9, no. 1, p. 187–196, 2024.

[32] S. Saiwanto, M. A. Alwlid, A. Haris and S. R. Yazid, "Kurikulum Pendidikan Islam," *Jurnal Sosial Dan Sains,* vol. 2, no. 9, p. 1039–1050, 2022.

[33] A. Hasib., "Changes and Continuity of Islamic Educational Institution Models," *DIROSAT: Journal of Education, Social Sciences & Humanities,* vol. 2, no. 1, p. 50–62, 2024.

[34] P. Pusat, "Peraturan Pemerintah (PP) Nomor 19 Tahun 2005 tentang Standar Nasional Pendidikan," Pemerintah Pusat Indonesia, Jakarta, 2005.