Building of Informatics, Technology and Science (BITS)
Volume 7, No 4, March 2026 Page: 2789−2799
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i4.9512

Comparison of Clustering Algorithms for Analyzing the Impact of Conflict on Poverty and Inflation

M Raykah Alam Ramadan*, Dhio Pratama Wiransyah, Satria Ramadhani, Rayya Ramadhan Simangunsong, Ken Dhita Tania, Alsella Meiriza, Ahmad Rifai

Faculty of Computer Study, Information System Study Program, Universitas Sriwijaya, Palembang, Indonesia
Email: [1,*]rakapalembang2004@gmail.com, [2] dhiopratama0507@gmail.com, [3] satriaramadhani2005@gmail.com,[4] rayyaramadhans9@gmail.com, [5] kenditha@ilkom.unsri.ac.id, [6] allsela_meiriza@yahoo.co.id , [7]rifai.bae@gmail.com
Correspondence Author Email: rakapalembang2004@gmail.com
Submitted: **09/03/2026**; Accepted: **31/03/2026**; Published**: 31/03/2026**

Abstract−Armed conflict can have significant impacts on the social and economic conditions of a region, particularly on poverty levels and inflation. This study aims to analyze the impact of conflict on key economic indicators using a Knowledge Management System (KMS) approach and to compare the performance of clustering algorithms in identifying underlying data patterns. The research applies clustering analysis by comparing K-Means, DBSCAN, and Hierarchical Clustering algorithms to group data based on similarities in economic characteristics. The dataset used in this study consists of several indicators, including poverty levels before and during conflict, extreme poverty rates, inflation rates, GDP changes, and currency devaluation. Data preprocessing techniques such as normalization are applied to ensure comparability among variables. The evaluation of clustering performance is conducted using Silhouette Score and Davies–Bouldin Index to determine the most effective algorithm. The results show that clustering methods are able to identify distinct grouping patterns of regions based on the level of conflict impact on economic conditions. Among the evaluated algorithms, DBSCAN demonstrates superior performance in handling complex and uneven data distributions. The analysis also indicates a consistent tendency for poverty and inflation to increase during periods of conflict, highlighting the economic vulnerability of affected regions. Furthermore, the integration of clustering results into a Knowledge Management System enables the transformation of analytical outputs into structured knowledge that can support data-driven decision making. These findings are expected to contribute to the development of more effective economic policies and analytical frameworks in conflict-affected areas.

Keywords: Clustering Algorithms; DBSCAN; Poverty; Inflation; Knowledge Management System

1. INTRODUCTION

Social and economic conflict can disrupt macroeconomic stability through declines in production, distribution, and consumption activities. These conditions often lead to increasing poverty levels, inflationary pressure, and income inequality that affect public welfare [1]. In many developing and transitional economies, conflict not only weakens institutional capacity but also reduces investor confidence and limits access to essential goods and services. As a result, the economic system becomes more vulnerable to shocks, which further amplifies instability across regions.

Poverty in conflict situations tends to be multidimensional because it is influenced by various economic and social factors. Conflict may worsen these conditions through declining income, rising prices of basic goods, and limited access to productive resources [2]. In addition, social disruptions such as displacement, reduced educational access, and weakened labor markets contribute to long-term poverty persistence. Therefore, understanding the interaction between conflict, poverty, and inflation requires a comprehensive analytical approach that is capable of capturing complex and nonlinear relationships among variables.

To address this complexity, data-based analysis becomes essential. Data mining techniques such as clustering allow data to be grouped according to similarities in characteristics, enabling researchers to identify hidden patterns within socio-economic datasets. The K-Means algorithm is widely used for numerical data analysis due to its computational efficiency and simplicity in implementation [3], [4]. Several previous studies have successfully applied K-Means in regional economic analysis, particularly in grouping areas based on poverty indicators and development levels. However, despite its advantages, K-Means is highly sensitive to uneven data distribution and the presence of outliers, which may reduce clustering accuracy and interpretability [5].

As an alternative approach, DBSCAN (Density-Based Spatial Clustering of Applications with Noise) applies a density-based method that allows the model to identify clusters while simultaneously detecting noise within the dataset [6], [7]. This capability makes DBSCAN more robust in handling datasets with irregular shapes and varying densities. Previous research has demonstrated that DBSCAN can outperform partition-based clustering methods in identifying meaningful structures in complex socio-economic data, especially when noise and anomalies are present. However, DBSCAN also has limitations, particularly in determining optimal parameter values such as epsilon (ε) and minimum points (MinPts), which significantly influence clustering results.

Hierarchical Clustering, on the other hand, provides insight into relationships between data points through a hierarchical structure that can be visualized using a dendrogram [6]. This method has been widely used in exploratory data analysis because it does not require pre-specification of the number of clusters. Prior studies have utilized hierarchical clustering to analyze regional disparities and socio-economic segmentation, offering more interpretable results compared to other clustering techniques. Nevertheless, hierarchical methods are computationally expensive for large datasets and may produce less stable clusters when data variability is high.

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Although many previous studies have applied clustering techniques in socio-economic analysis, most of them rely on a single algorithm without conducting a comparative evaluation using performance metrics such as Silhouette Score or Davies–Bouldin Index [8]. This limitation reduces the reliability of clustering outcomes, as different algorithms may produce significantly different results depending on data characteristics. Furthermore, research findings are rarely integrated into a Knowledge Management System (KMS), which limits the practical application of analytical results in supporting data-driven decision making [9], [10].

In the context of knowledge management, a Knowledge Management System plays a crucial role in managing information and transforming it into actionable knowledge that supports organizational and policy decision making [9], [10]. The integration of clustering techniques into information systems has been shown to improve data analysis efficiency and enhance the quality of decisions by providing structured and accessible insights [11]. However, the implementation of such integration in the context of conflict, poverty, and inflation analysis remains limited.

Several related studies have attempted to analyze poverty and economic instability using clustering approaches. For instance, previous research utilizing K-Means has focused on classifying regions based on poverty levels and development indicators [3], [4]. Other studies have explored density-based approaches such as DBSCAN to detect anomalies in economic data and identify regions experiencing abnormal economic conditions [6], [7]. Additionally, hierarchical clustering has been used to understand regional disparities and visualize socio-economic structures [6]. Despite these contributions, these studies generally lack a comprehensive comparative framework that evaluates multiple algorithms simultaneously using standardized metrics. Moreover, the integration of analytical results into a Knowledge Management System to support decision-making processes has not been adequately addressed.

Based on this review, there are clear research gaps that need to be addressed. First, there is a lack of comparative studies that systematically evaluate the performance of different clustering algorithms in analyzing the relationship between conflict, poverty, and inflation. Second, existing studies rarely incorporate evaluation metrics to validate clustering quality, leading to potential bias in interpretation. Third, the integration of clustering results into a Knowledge Management System framework is still underexplored, limiting the usability of research findings in real-world policy and decision-making contexts.

Therefore, this study aims to fill these gaps by proposing a comprehensive analytical framework. The objectives of this research are: (1) to analyze the impact of social and economic conflict on poverty and inflation using clustering techniques; (2) to compare the performance of K-Means, DBSCAN, and Hierarchical Clustering algorithms using evaluation metrics such as Silhouette Score and Davies–Bouldin Index; and (3) to integrate the clustering results into a Knowledge Management System framework that supports data-driven decision making. By achieving these objectives, this study is expected to contribute both theoretically and practically, particularly in improving the understanding of socio-economic dynamics and enhancing the effectiveness of policy formulation based on data-driven insights.

2. RESEARCH METHODOLOGY

2.1 Research Type

This research uses a quantitative approach based on data analysis to examine the relationship between social and economic conflict, poverty, and inflation. The methodology emphasizes systematic stages that include dataset collection, data preprocessing, implementation of clustering algorithms (K-Means, DBSCAN, and Hierarchical Clustering), evaluation of clustering performance, and integration of analytical results into a Knowledge Management System (KMS). The use of a quantitative approach allows for objective measurement and comparison of clustering performance based on numerical indicators.

The clustering methods used in this study are selected based on their characteristics and previous applications in socio-economic data analysis. K-Means is widely recognized for its efficiency in handling numerical data and its simplicity in partitioning datasets into clusters [3], [4]. However, its sensitivity to outliers and dependency on the number of clusters require careful consideration [5]. DBSCAN is employed as an alternative method due to its ability to identify clusters based on data density and detect noise automatically, making it suitable for complex data distributions [6], [7]. Meanwhile, Hierarchical Clustering is used to provide a structured representation of relationships among data points through a dendrogram, enabling deeper interpretation of clustering structures [6].

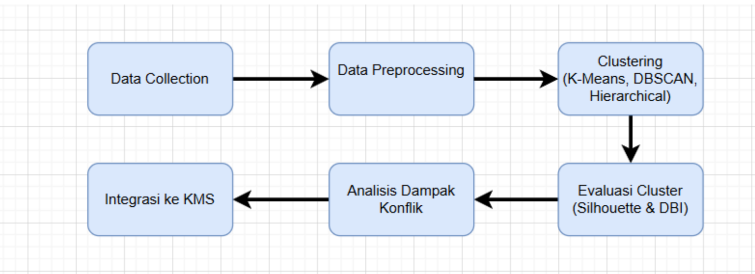

Figure 1. Research Method Stages

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Based on Figure 1, the research methodology is carried out through several sequential stages. The process begins with data collection, followed by data preprocessing to ensure data quality and consistency. The next stage is the implementation of clustering algorithms, including K-Means, DBSCAN, and Hierarchical Clustering. After clustering is performed, the results are evaluated using cluster validation metrics, namely Silhouette Score and Davies–Bouldin Index. The final stage involves analyzing the impact of conflict on poverty and inflation based on clustering results and integrating these findings into a Knowledge Management System to support decision-making.

2.2 Data Collection

The data used in this research is a secondary dataset obtained from the Kaggle platform. The dataset contains economic and social indicators related to conflict, poverty, and inflation. The use of publicly available datasets ensures transparency and reproducibility of the research process [12]. Data collection is an essential stage because the quality of the dataset directly affects the validity of the analysis. The data collection process begins with dataset retrieval from Kaggle, followed by initial exploration to understand the structure, variable types, and distribution patterns. This exploration helps identify potential issues such as missing values, inconsistencies, and outliers. Understanding these characteristics is crucial before proceeding to the preprocessing stage.

2.3 Data Analysis Technique

The data analysis technique in this study consists of several main stages, including preprocessing, clustering, and evaluation. Each stage is supported by relevant theoretical foundations and previous studies. First, data preprocessing is conducted to prepare the dataset for analysis. This stage includes data cleaning, handling missing values, and normalization. Normalization is particularly important in clustering because it ensures that all variables have comparable scales, preventing bias in distance-based calculations [13]. Without normalization, variables with larger scales may dominate the clustering process.

Second, the study implements three clustering algorithms: K-Means, DBSCAN, and Hierarchical Clustering. K-Means works by partitioning data into a predefined number of clusters by minimizing the distance between data points and cluster centroids [3], [4]. This method is efficient and suitable for structured numerical data but requires prior determination of the number of clusters and is sensitive to initial centroid selection [5]. DBSCAN, on the other hand, groups data based on density by identifying core points, border points, and noise [6], [7]. This method does not require specifying the number of clusters in advance and is effective in detecting outliers. However, it requires careful parameter selection, particularly epsilon (ε) and minimum points (MinPts), which influence clustering results.

Hierarchical Clustering builds a hierarchy of clusters either through agglomerative (bottom-up) or divisive (top-down) approaches [6]. The results are typically visualized using a dendrogram, which helps interpret relationships between clusters. This method is advantageous for exploratory analysis but can be computationally intensive for large datasets.

Third, cluster evaluation is performed to assess the quality of clustering results. This study uses Silhouette Score and Davies–Bouldin Index as evaluation metrics. Silhouette Score measures how similar a data point is to its own cluster compared to other clusters, while Davies–Bouldin Index evaluates cluster separation and compactness [8]. These metrics provide an objective basis for comparing the performance of different algorithms.

Finally, the clustering results are integrated into a Knowledge Management System (KMS) framework. This integration aims to transform analytical results into structured knowledge that can support data-driven decision making [9], [10]. The use of KMS allows stakeholders to access, interpret, and utilize clustering insights effectively, thereby improving the overall impact of the research.

3. RESULT AND DISCUSSION

3.1 Dataset Description

This study uses the War Economic & Livelihood Impact Dataset obtained from Kaggle, which contains indicators describing the economic conditions of communities before and during conflict. The variables used in this study encompass several key economic and social indicators to capture the multidimensional impact of crisis conditions. These include the poverty rate before and during war, as well as the extreme poverty rate to reflect severity levels. Additional variables involve estimates of households falling into poverty, inflation rate, and currency devaluation. The analysis also considers GDP changes and food insecurity rates, providing a comprehensive framework to examine economic instability and its broader societal consequences. These variables were selected because they represent changes in the economic conditions of communities during periods of conflict [2]. The selection of these variables is also based on their strong theoretical relevance in representing macroeconomic and socio-economic instability during conflict situations. For instance, poverty-related indicators capture welfare degradation, while inflation and currency devaluation reflect macroeconomic instability. GDP change represents overall economic performance, and food insecurity highlights the direct impact of conflict on basic human needs. By combining these variables, the dataset provides a multidimensional perspective that allows for a more comprehensive clustering analysis. Furthermore, the inclusion of both pre-war and during-war indicators enables a comparative analysis that can reveal the magnitude of economic deterioration caused by conflict.

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3.2 Data Preprocessing

Preprocessing was conducted to ensure data quality before performing the clustering process. This stage includes variable selection, data cleaning, and normalization using StandardScaler so that all variables are measured on comparable scales. Normalization is necessary because differences in variable scales can influence clustering results, particularly for distance based algorithms such as K-Means [4]. In addition, preprocessing also plays a crucial role in improving the reliability of clustering results. Data cleaning ensures that missing values, inconsistencies, or extreme outliers do not distort the clustering structure. The use of StandardScaler transforms the data into a standard normal distribution with a mean of zero and standard deviation of one, which is particularly important for algorithms that rely on distance calculations. Without this transformation, variables with larger ranges such as GDP change or household poverty estimates could dominate the clustering process, leading to biased results. Therefore, preprocessing serves as a foundational step that directly affects the validity and interpretability of the analysis.

3.3 Determining the Number of Clusters Using the Elbow Method

The optimal number of clusters in the K-Means algorithm was determined using the Elbow Method by calculating the Within Cluster Sum of Squares (WCSS) value. Based on the generated graph, the optimal number of clusters is k = 3.

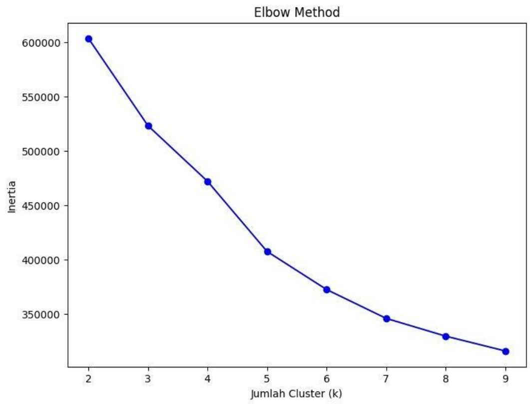

Figure 2. Elbow Method

Based on Figure 2, the Elbow Method graph shows a significant decrease in WCSS values from k = 1 to k = 3, after which the rate of decrease becomes more gradual. This pattern indicates that adding more clusters beyond k = 3 does not significantly improve the compactness of the clusters. Therefore, k = 3 is considered the optimal number of clusters because it represents a balance between model simplicity and clustering accuracy. The identification of the elbow point is critical because selecting too few clusters may oversimplify the data structure, while too many clusters may lead to overfitting and reduced interpretability.

3.4 Clustering Results Using K-Means

The clustering results show that the K-Means algorithm is able to group the dataset into three clusters representing different levels of conflict impact on the economic conditions of communities.

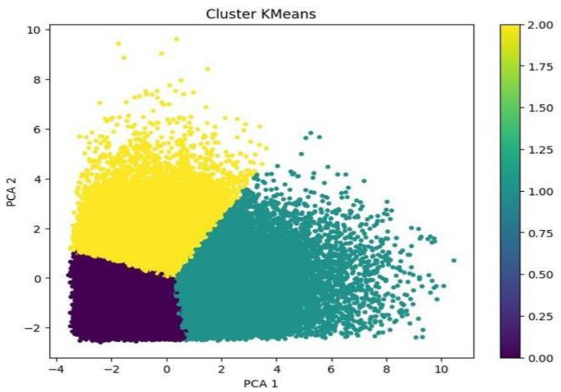

Figure 3. K-Means Clustering

Based on Figure 3, the visualization illustrates how the dataset is partitioned into three distinct clusters. Each cluster represents a different level of economic impact caused by conflict, ranging from low to high severity. The separation between clusters indicates that K-Means is able to identify general patterns in the data, particularly in grouping regions with similar economic characteristics. However, some overlap between clusters can still be observed, suggesting that the boundaries between clusters are not entirely distinct. This limitation is consistent with the nature

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of K-Means, which assumes spherical cluster shapes and may struggle with complex data distributions. The DBSCAN algorithm is able to detect clusters based on data density and identify outliers that do not belong to any specific cluster. Hierarchical Clustering, on the other hand, provides visualization of relationships among data through a dendrogram structure that illustrates the gradual merging process of clusters.

This comparison highlights the fundamental differences between partition-based, density-based, and hierarchical clustering approaches. While K-Means focuses on minimizing intra-cluster variance, DBSCAN emphasizes density connectivity, and Hierarchical Clustering focuses on the relationships among data points. These differences justify the need for a comparative analysis to determine which method is most suitable for the dataset used in this study.

3.5 Clustering Results Using DBSCAN

Evaluation was conducted using Silhouette Score and Davies-Bouldin Index. The evaluation results indicate that the DBSCAN algorithm achieves the best performance with the highest Silhouette Score and the lowest Davies-Bouldin Index compared with the other algorithms.

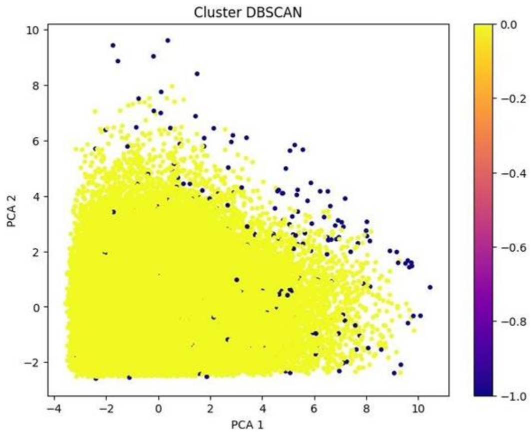

Figure 4. DBSCAN Clustering

Based on Figure 4, the DBSCAN clustering results show clearly separated clusters with several points identified as noise or outliers. These outliers represent data points that do not fit into any cluster, which is an important advantage of DBSCAN compared to K-Means. The ability to detect noise allows DBSCAN to produce more accurate and meaningful clusters, especially in datasets with irregular distributions. The clear separation between clusters indicates that DBSCAN is effective in capturing the underlying structure of the data. These findings indicate that density based algorithms are more effective in identifying patterns within socio economic data that have uneven distributions [6]. This result is particularly relevant for socio-economic datasets, which often exhibit non-linear relationships and heterogeneous distributions. The superior performance of DBSCAN suggests that density-based approaches are better suited for analyzing complex real-world data compared to traditional partition-based methods.

3.6 Clustering Results Using Hierarchical Clustering

The third clustering method used in this study is Hierarchical Clustering with the Ward Linkage approach. This method forms clusters gradually by merging data points or clusters with the closest distance.

Hierarchical clustering produces a cluster structure in the form of a dendrogram, which illustrates hierarchical relationships among clusters.

The clustering visualization results are presented in the following Figure 5.

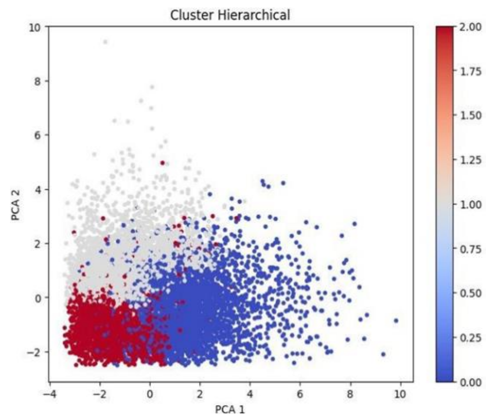

Figure 5. Hierarchical Clustering

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Based on Figure 5, the clustering visualization shows how data points are grouped step by step into larger clusters. Unlike K-Means, this method does not require a predefined number of clusters, allowing for more flexibility in exploratory analysis. However, the clusters formed may not be as compact as those produced by other methods, especially when the dataset contains high variability.

The hierarchical cluster structure can be observed in the following dendrogram.

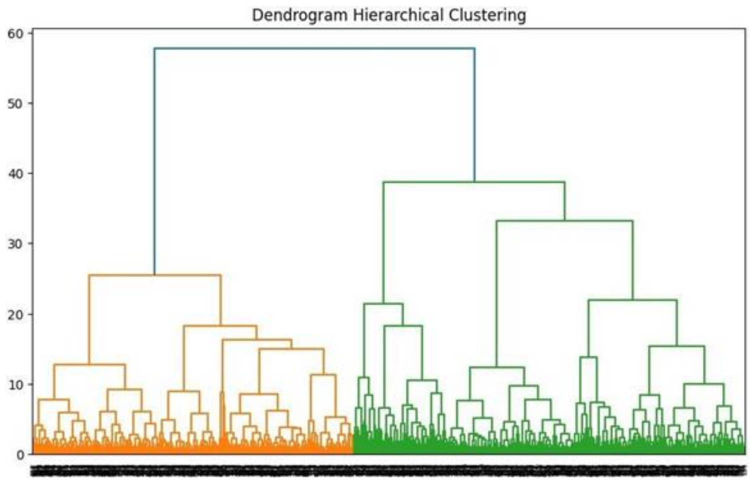

Figure 6. Hierarchical Clustering Dendrogram

Based on Figure 6, the dendrogram illustrates the hierarchical merging process of clusters, where data points are progressively combined based on their similarity. The height of the branches represents the distance between clusters, providing insight into the level of similarity among data points. This visualization is useful for understanding the structure of the data, although it may become difficult to interpret when dealing with large datasets. The dendrogram illustrates how data points are gradually merged to form larger clusters. This method provides a clear visual representation of the relationships among data points during the clustering process [7].

3.7 Evaluation and Comparison of Clustering Algorithms

To determine which clustering algorithm produces the best results, evaluation was conducted using two evaluation metrics:

a. Silhouette Score
b. Davies Bouldin Index

Silhouette Score measures how well each data point fits within its assigned cluster, while the Davies Bouldin Index measures the separation between clusters.

The following table presents the evaluation results of the three clustering algorithms used in this study.

Table 1. Evaluation Results

Algoritma	Silhouette Score	Davies Bouldin Index	Waktu Komputasi
K-Means	0.2036	1.4870	1 menit
DBSCAN	0.6902	1.3000	4 menit
Hierarchical	0.1405	1.6181	12 detik

Based on Table 1, the evaluation results indicate clear differences in clustering performance among the three algorithms. DBSCAN achieves the highest Silhouette Score, indicating strong intra-cluster similarity and clear separation between clusters. At the same time, it produces the lowest Davies-Bouldin Index, which confirms that the clusters are compact and well separated. In contrast, K-Means and Hierarchical Clustering show lower performance, suggesting that they are less effective in handling the complexity of the dataset.

Based on the evaluation results, the DBSCAN algorithm shows the best performance with the highest Silhouette Score and the lowest Davies Bouldin Index compared with the other algorithms. These results indicate that DBSCAN produces clusters that are more clearly separated than those generated by the other methods. This finding is consistent with previous studies showing that density based algorithms such as DBSCAN perform well in identifying complex data patterns [6]. In addition, the computation time also provides insight into the efficiency of each algorithm. Although DBSCAN requires more computation time than K-Means, the improvement in clustering quality justifies its use in this context. Therefore, the selection of a clustering algorithm should consider both performance and computational cost, depending on the research objectives.

3.8 Analysis of the Impact of Conflict on Poverty and Inflation

Armed conflict can influence economic stability and public welfare. These impacts are often reflected in changes in poverty levels and inflation. For that reason, this study analyzes several economic indicators such as Pre War Poverty

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Rate, During War Poverty Rate, Extreme Poverty Rate, and Inflation Rate to observe changes in economic conditions before and during conflict.

This analysis is important because it connects the clustering results with real-world socio-economic implications. By examining these indicators, the study provides a deeper understanding of how conflict affects economic conditions beyond statistical patterns.

3.8.1 Comparison of Poverty Levels Before and During Conflict

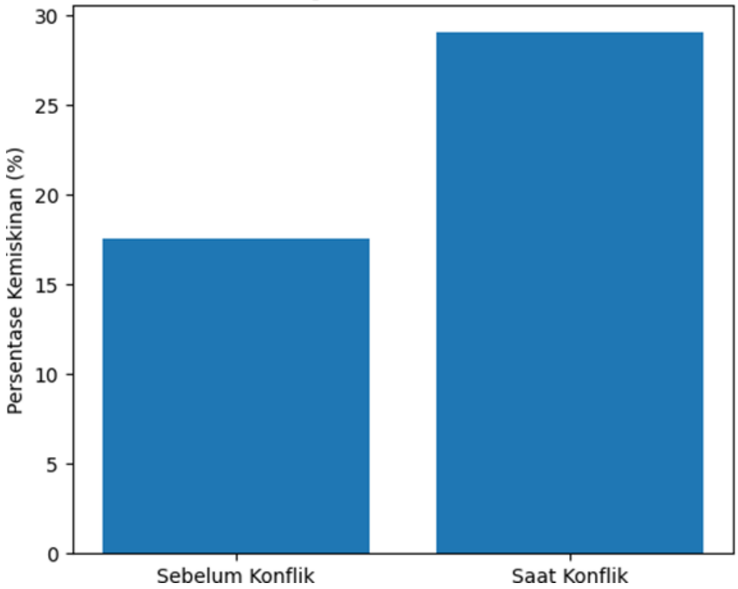

Figure 7. Average Poverty Comparison

Based on Figure 7, the comparison shows a clear increase in poverty levels during conflict compared to pre-conflict conditions. This trend indicates that conflict significantly disrupts economic stability and reduces income levels, leading to an increase in poverty rates. The visualization also highlights the magnitude of change, which can vary across regions depending on the intensity of conflict and economic resilience.

The visualization results show that poverty levels during conflict tend to be higher than those before conflict. This condition indicates that conflict can worsen public welfare and increase the number of people living in poverty [2].

3.8.2 Distribution of Inflation Rates During Conflict

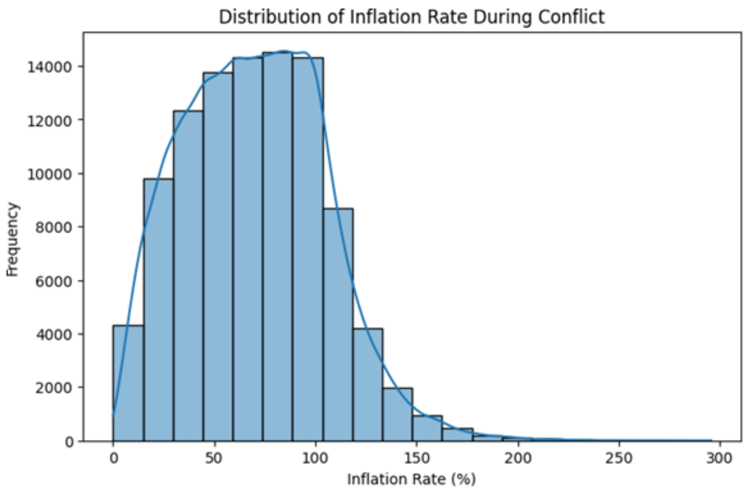

Figure 8. Distribution of Inflation Rates During Conflict

Based on Figure 8, the distribution of inflation rates shows a wide spread, indicating significant variation across different regions affected by conflict. Some regions experience moderate inflation, while others face extremely high inflation rates. This variation reflects differences in economic structure, government policies, and the severity of conflict.

The inflation distribution shows considerable variation across regions affected by conflict. This indicates that conflict can influence price stability due to disruptions in economic activity and the distribution of goods [1].

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3.8.3 Relationship Between Inflation and Poverty During Conflict

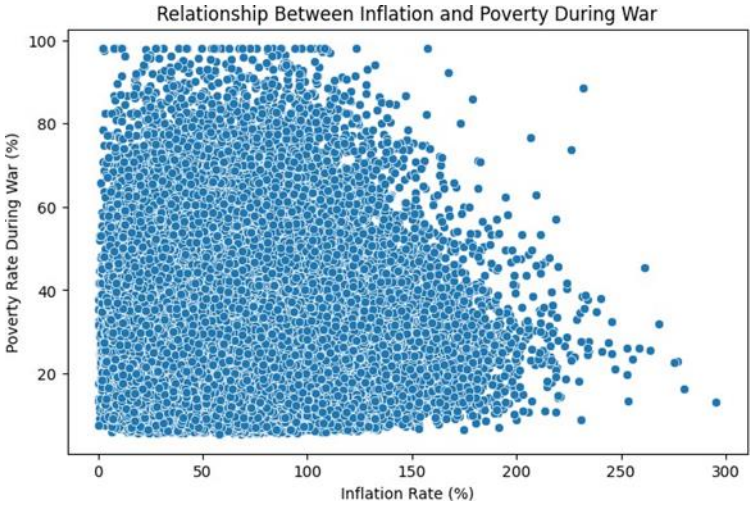

Figure 9. Relationship Between Inflation and Poverty During Conflict

Based on Figure 9, the scatter plot shows a positive relationship between inflation and poverty levels. As inflation increases, poverty levels also tend to rise. This relationship suggests that rising prices reduce household purchasing power, making it more difficult for people to meet basic needs.

The visualization shows a tendency for poverty levels to increase along with rising inflation. This occurs because increases in the prices of goods and services reduce the purchasing power of households [1].

3.8.4 Correlation of Economic Indicators During Conflict

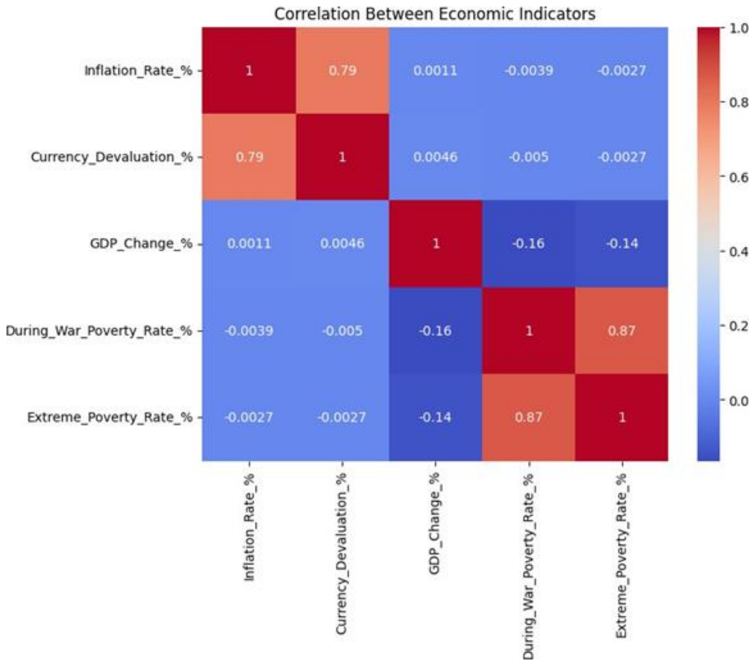

Figure 10. Correlation of Economic Indicators During Conflict

Based on Figure 10, the correlation matrix reveals significant relationships among key economic indicators, including inflation, GDP change, and poverty rates. Positive and negative correlations indicate how these variables interact during conflict conditions. For example, a negative correlation between GDP change and poverty suggests that economic decline is associated with increased poverty levels.

The correlation analysis indicates relationships among inflation, currency value changes, GDP changes, and poverty levels during conflict. This suggests that economic instability during conflict can simultaneously affect several economic indicators [14].

3.8.5 Interpretation of the Impact of Conflict on Economic Conditions

The analysis results indicate that conflict has a significant impact on the economic conditions of communities. Conflict not only increases poverty levels but also triggers price instability, which is reflected in rising inflation.

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Higher inflation during conflict can worsen economic conditions because the prices of goods and services increase while economic activity and household income tend to decline. This situation may lead to an increase in the number of households falling into poverty.

Therefore, analyzing poverty and inflation indicators becomes important to understand the socio economic impact of conflict in a more comprehensive way.

These findings emphasize that conflict creates a multidimensional economic crisis that affects both macroeconomic stability and household welfare. The simultaneous increase in poverty and inflation highlights the need for integrated policy interventions that address both income support and price stability.

3.9 Discussion

The clustering results provide an overview of regional groupings based on similarities in economic characteristics during conflict. This grouping helps identify patterns of conflict impact on economic indicators such as poverty, inflation, and GDP change. These findings indicate that regions experiencing similar conflict intensities tend to exhibit comparable economic vulnerabilities, suggesting that conflict-driven economic disruptions follow identifiable patterns across different contexts. Such clustering-based segmentation enables a more structured understanding of how economic instability manifests under conflict conditions.

Through the Knowledge Management System (KMS) approach, clustering results can be utilized as a foundation for managing and using knowledge related to the economic impacts of conflict. Information generated from the clustering process can help researchers and policymakers understand economic patterns that occur during conflict. In this context, KMS serves as a bridge between raw analytical outputs and actionable insights, ensuring that data-driven findings are systematically organized and easily accessible for decision-making processes. Recent studies highlight that integrating data mining outputs into knowledge systems enhances organizational learning and improves the effectiveness of policy analysis [15], [16].

The analysis results can also support decision making in the formulation of economic and social policies in conflict affected regions. Previous studies show that the use of data and knowledge through KMS can improve analytical effectiveness and support data driven decision making [13]. In addition, the combination of clustering techniques and knowledge management enables policymakers to identify priority areas, allocate resources more efficiently, and design targeted interventions that address specific economic challenges in conflict-affected regions. Empirical research also suggests that data-driven policy frameworks supported by intelligent systems can significantly improve response strategies in complex socio-economic environments [17].

Furthermore, the integration of clustering results into KMS enhances the accessibility and usability of analytical insights. This approach ensures that the knowledge generated from the analysis is not only stored but also effectively utilized in strategic planning and policy formulation. By transforming clustering outputs into structured knowledge assets, organizations can continuously refine their understanding of socio-economic dynamics during conflict. This aligns with recent advancements in knowledge-based systems, which emphasize the importance of integrating analytics with knowledge repositories to support adaptive and evidence-based decision making [18].

3.10 Integration of Clustering Results into a Knowledge Management System (KMS)

The clustering results obtained from the K-Means, DBSCAN, and Hierarchical Clustering algorithms can be integrated into a Knowledge Management System (KMS) framework as part of a data based knowledge management process. This integration allows patterns produced from clustering analysis to function not only as statistical outputs but also as knowledge resources that can be stored, managed, and reused for decision making. The transformation of analytical results into knowledge assets is essential for ensuring that insights derived from data analysis can be effectively utilized beyond the research context.

In this study, information regarding the grouping of economic conditions based on the level of conflict impact can be represented as a knowledge base that supports economic policy analysis. Through this approach, the KMS functions to transform analytical results into strategic knowledge that can assist policymakers in developing more appropriate strategies for poverty reduction and inflation control in conflict affected regions. The structured representation of clustering results within a KMS also enables comparative analysis across regions and time periods, facilitating more comprehensive policy evaluation and planning. Recent literature emphasizes that integrating machine learning outputs into knowledge management frameworks can significantly enhance the quality of decision support systems [19].

In addition, the KMS framework enables continuous knowledge updating and sharing among stakeholders. This ensures that the insights derived from clustering analysis remain relevant and can be adapted to different contexts. The collaborative nature of KMS allows multiple stakeholders, including researchers, policymakers, and practitioners, to contribute to and benefit from shared knowledge resources. This continuous knowledge exchange is particularly important in dynamic environments such as conflict-affected regions, where economic conditions can change rapidly.

The integration of data mining techniques with knowledge management systems represents an important step toward developing intelligent decision support systems in the field of socio-economic analysis. By combining analytical capabilities with knowledge management processes, organizations can enhance their ability to respond to complex challenges and make informed decisions. Recent studies confirm that the convergence of data analytics and

KMS plays a critical role in improving organizational agility, innovation, and evidence-based policymaking in complex socio-economic systems [20].

4. CONCLUSION

This study demonstrates that the application of multiple clustering algorithms provides a more comprehensive understanding of the relationship between conflict, poverty, and inflation, particularly when supported by systematic evaluation and knowledge integration. The comparative analysis highlights that algorithm selection significantly influences the interpretation of socio-economic patterns, where DBSCAN proves to be more adaptive in capturing complex structures within unevenly distributed data. This indicates that density-based approaches offer a methodological advantage in analyzing real-world economic conditions that are often non-linear and heterogeneous. Beyond the technical findings, this study also confirms that conflict contributes to structural economic vulnerability, reflected in simultaneous pressures on household welfare and price stability. These conditions emphasize the importance of multidimensional analysis in identifying regions with higher risk levels and prioritizing policy interventions accordingly. Furthermore, the integration of clustering outputs into a Knowledge Management System transforms analytical results into structured and reusable knowledge, enabling more effective dissemination and utilization of insights. This approach bridges the gap between data analysis and decision-making by providing a framework that supports evidence-based policy formulation. Overall, this study contributes not only to methodological development in data mining applications but also to practical implications in managing socio-economic challenges in conflict-affected areas through informed and data-driven strategies.

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