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Data-driven segmentation of sharia-based SMEs digital readiness: Comparing K-means and fuzzy C-means for strategic transformation planning

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ABSTRACT

Quired to adopt digital technologies while preserving Islamic business principles such as transparency, fairness, trustworthiness, halal integrity, and ethical value creation. However, many sharia-based SMEs still lack clear diagnostic information regarding their digital readinesslevel, making it difficult for policymakers, business associations, and SMEs managers to design targeted digitaltransformation interventions. Prior studies on SMEs digitalisation have largely focused on technology adoption, digital marketing, or general readiness assessment, while limited attention has been given to data-driven segmentation models that can classify sharia-based SMEs into actionable readiness groups. Addressing this gap, this study compares K-means and Fuzzy C-means clustering to identify digital readiness patterns among sharia-based SMEs. The dataset consists of 314 SMES records collected through questionnaires and structured into two main perspectives, includes economic/business readiness and technological/digital readiness. The variables include business activity, transaction capability, management capability, market interaction, macro-environmental readiness, digital culture, digital education, financial resources, and technical infrastructure. Prior to clustering, the data were normalised to ensure comparability across indicators. K-means was used as a hard clustering benchmark because of its computational simplicity and ability to produce clear readiness groups, while Fuzzy C-means was applied as a soft clustering method because SMEs readiness boundaries are often overlapping and gradual rather than strictly separated. The clustering process was designed to generate three readiness categories viz., low, moderate, and high digital readiness. Model evaluation was conducted using silhouette index, Davies–Bouldin index, accuracy, F1-score, computational stability, and principal component analysis-based visualisation. The results show a trade-off between cluster separation quality and classification-oriented performance. Fuzzy C-means achieved a higher silhouette index of 0.1362 and a lower Davies–Bouldin index of 2.6126, indicating better internal cluster quality and stronger ability to represent overlapping readiness characteristics. In contrast, K-means produced higher accuracy of 0.6033 and F1-score of 0.3202, and more clearly formed three practical readiness categories. These findings suggest that Fuzzy C-means is more suitable for exploratory readiness profiling where SMEs may belong partially to more than one readiness stage, whereas K-means is more useful for managerial decision-making requiring crisp classification into low, moderate, and high readiness groups. This study contributes to SMEs digital transformation literature by demonstrating that sharia-based digital readiness should be analysed not only through aggregate scores, but also through segmentation models that reveal heterogeneous readiness patterns. Practically, the proposed comparative

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clustering framework provides a diagnostic basis for policymakers, Islamic business institutions, and SMEs development agencies to design differentiated digital capability-building programmes.

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1. INTRODUCTION

Small, and medium enterprises (SMEs) play a strategic role in economic development, employment creation, poverty reduction, and community-based entrepreneurship. In emerging economies, SMEs are not only economic actors but also social institutions that sustain local livelihoods and strengthen inclusive growth. The acceleration of digital transformation has created new opportunities for SMEs to expand market access, improve operational efficiency, strengthen customer engagement, and participate in digital business ecosystems. Digital platforms, e- commerce, mobile payment systems, data analytics, and social media marketing have enabled SMEs to overcome geographical limitations and interact more directly with customers. However, digital transformation also creates new managerial challenges because many SMEs still face limited infrastructure, inadequate digital skills, weak financial capability, low organisational readiness, and fragmented digital strategies. The challenge becomes more complex in the context of Sharia-based SMEs. Unlike conventional SMEs, Sharia-based SMEs are expected to adopt digital technologies while maintaining Islamic business values, including fairness, transparency, trustworthiness, halal assurance, ethical transactions, and social responsibility. Digital transformation in this sector should therefore support not only efficiency and competitiveness, but also halal value-chain integrity and Sharia-compliant business conduct. A digital transaction system, for example, may improve speed and market reach, but it must also preserve transparency, trust, and compliance with Islamic principles. Similarly, digital marketing may improve visibility, but it should not compromise ethical communication and consumer protection. This dual requirement makes Sharia-based SMES digital readiness a multidimensional issue involving economic capability, technological capability, managerial capability, and ethical business orientation.

The uploaded manuscript positions this problem around the absence of clear grouping or classification of Sharia-based SMEs according to their digital readiness level. The study uses 314 SMEs records collected through questionnaires and evaluates readiness based on economic/business and technological/digital perspectives. The economic/business perspective includes indicators such as business activity, transaction capability, management capability, market interaction, and macro-environmental readiness, while the technological/digital perspective includes digital culture, digital education, financial resources, and technical infrastructure. This structure shows that digital readiness is not a single-dimensional construct. Rather, it reflects the interaction between business capability and digital capability. Therefore, a data-driven segmentation approach is needed to identify whether SMEs are not ready, moderately ready, or highly ready for digital transformation. Recent literature on SME digitalisation confirms that digital readiness cannot be reduced to technology ownership alone [1] argue that SME readiness for Industry 4.0 depends on people, resources, security, strategy, and organisational capability [2] show that SME digitalisation barriers are shaped by infrastructure, financial capacity, and human resources [3] further emphasise that workforce skills and employability are critical for successful digital transformation, especially in developing regions. These studies demonstrate that digital readiness is a multidimensional organisational condition rather than a simple indicator of whether a firm uses technology. However, many studies still focus on adoption determinants, maturity models, or general digital transformation frameworks, while fewer studies provide empirical segmentation of SMEs into practical readiness groups that can be used for targeted intervention. From a management perspective, segmentation is important because SMEs at different readiness levels require different support strategies. SMEs with low readiness may need basic digital literacy, infrastructure access, and managerial awareness. SMEs with moderate readiness may need digital process integration, financial support, and structured digital training. SMEs with high readiness may require advanced digital tools, analytics capability, halal traceability systems, and innovation-oriented support. Without segmentation, policy programmes may treat SMEs as homogeneous entities, resulting in inefficient resource allocation. This is especially problematic for Sharia-based SMEs because intervention strategies must consider not only technological capacity but also halal integrity, Sharia-compliant transactions, and ethical business governance.

Although several digital readiness frameworks have been developed, most are not specifically designed for Sharia-based SMEs. General Industry 4.0 and Industry 5.0 readiness models usually emphasise technology infrastructure, organisational maturity, digital capability, human resources, or supply-chain digitalization [4], for example, developed an Industry 4.0 maturity model using data envelopment analysis and the Best– Worst Method, while [5] reviewed Industry 5.0 implementation from human, technological, and sustainability perspectives. [6] examined Supply Chain 5.0 digitalisation and risk assessment, and [7] discussed the role of digital technologies in food supply chains. These studies are highly relevant for understanding digital transformation, but they do not fully address the specific conditions of Sharia-based SMEs, where halal assurance, ethical transactions, and Sharia-oriented business conduct are central to organisational legitimacy. The framework used in this study is therefore grounded in previous work on Sharia-based SMEs digital readiness. The Mahyarni and Okfalisa research report conceptualises Sharia SME preparedness toward Digital Industry 5.0 through economic, technological, and Sharia-oriented perspectives, and proposes a model that connects business activities, transaction capability, management, macro-environmental factors, IT culture, IT competence, IT financial resources, IT infrastructure, and Sharia values. The same report also states that the development of the conceptual model was based on systematic literature review using keywords related to halal, supply chain, maturity, readiness, industry, and SMEs, with resources retrieved from Scopus and ACM databases and filtered into 99 relevant articles. This provides a stronger theoretical foundation than using a generic digital maturity model because it explicitly links digital readiness with Sharia-based business preparedness. However, the present paper should not merely repeat the previous framework. Its contribution lies in transforming the readiness framework into a clustering- based diagnostic model. While Mahyarni and Okfalisa's framework provides the conceptual basis for measuring readiness, this study operationalises the framework using unsupervised learning to identify readiness patterns among SMEs. In other words, the novelty is not only in measuring readiness, but in segmenting SMEs into data-driven readiness groups that can inform strategic digital intervention. This is important because readiness scores alone may not reveal whether SMEs naturally form distinct groups or whether their characteristics overlap across readiness levels. Clustering is an appropriate method for this research because the objective is to discover hidden patterns in SMES readiness data without relying on predefined class labels. In the uploaded manuscript, clustering is used to group SMEs based on similarity among readiness indicators, and the process is conducted using K-Means and Fuzzy C- Means. K-Means is selected because it is one of the most widely used hard clustering methods, offering simplicity, interpretability, and computational efficiency. It partitions observations into mutually exclusive clusters by minimising the distance between data points and cluster centroids. For managerial purposes, K-Means is useful because it produces clear readiness categories, such as not ready, ready, and highly ready. This makes it easier for policymakers and SMEs development agencies to design group-specific intervention programmes.

Nevertheless, K-Means also has limitations. It assumes that each SME belongs to only one cluster, even though digital readiness is often gradual and overlapping. An SME may have strong digital marketing capability but weak financial resources; another may have good infrastructure but low digital culture or limited managerial readiness. Such cases are difficult to represent through strict cluster membership. This limitation justifies the use of Fuzzy C- Means. Unlike K-Means, Fuzzy C-Means allows each observation to have a degree of membership in multiple clusters. This is methodologically relevant because SME digital readiness is not always sharply separated into low, moderate, and high categories. Instead, readiness may exist along a continuum, where some SMEs show transitional characteristics between clusters. The use of both K-Means and Fuzzy C-Means therefore strengthens the analytical design of the study. K-Means provides a crisp segmentation model that is useful for direct managerial classification, while Fuzzy C-Means provides a soft clustering model that better captures uncertainty and overlapping readiness characteristics. Recent applications of clustering in digital transformation and organisational analytics show that hard and soft clustering can provide complementary insights. [8], for example, applied Fuzzy C-Means in analysing sustainable retail performance and digital transformation, showing that fuzzy membership can capture heterogeneous digital behaviour. Machine learning studies in manufacturing and Industry 5.0 also recognise K-Means and Fuzzy C-Means as relevant techniques for discovering patterns in complex organisational and technological datasets [9, 10]. Thus, comparing both methods is justified because the research problem involves both practical classification and uncertainty-sensitive readiness profiling. The evaluation strategy also needs to be understood critically. The uploaded manuscript evaluates clustering performance using Silhouette Index, Davies–Bouldin Index, accuracy, F1-score, and PCA-based visualisation. Silhouette Index and Davies–Bouldin Index are internal validity measures that assess cluster cohesion and separation. A higher Silhouette Index indicates stronger within-cluster similarity and between-cluster separation, while a lower Davies–Bouldin Index indicates better cluster compactness and separation. Accuracy and F1-score, on the other hand, are classification- oriented metrics that require comparison with a reference structure or labelled interpretation. PCA visualisation is used to reduce the multidimensional readiness data into two dimensions for interpretability and visual inspection. The combination of these metrics is useful because clustering quality should not be assessed from a single perspective. Internal validity explains structural clustering quality, while accuracy and F1-score provide additional insight into how well the clustering output aligns with practical readiness categories [11].

The empirical results show an important methodological trade-off. Fuzzy C-Means produced a higher Silhouette Index of 0.1362 and a lower Davies–Bouldin Index of 2.6126 than K-Means, indicating better internal cluster separation and stronger ability to capture overlapping data structures. This supports the argument that Fuzzy C-Means is more suitable when the boundaries between readiness categories are not rigid. However, K-Means achieved higher accuracy of 0.6033 and F1-score of 0.3202, indicating stronger alignment with crisp classification- oriented evaluation. PCA visualisation further shows that K-Means formed three practical clusters—Not Ready, Ready, and Highly Ready—whereas Fuzzy C-Means produced two dominant visual groups—Not Ready and Ready. These results indicate that neither method is universally superior. Instead, each method offers different analytical value depending on the decision objective. This trade-off is central to the contribution of the paper. If the objective is exploratory diagnosis and understanding overlapping readiness characteristics, Fuzzy C-Means is preferable because it captures gradual membership and transitional readiness patterns. If the objective is managerial classification and direct policy targeting, K-Means is more practical because it produces clearer readiness categories and stronger classification-oriented performance. This distinction is important for high-quality journal positioning because the paper should not simply state that one algorithm is better than the other. Instead, it should explain when and why each method is useful. By doing so, the study moves beyond technical comparison and contributes to strategic SME digital transformation management.

The research gap addressed in this study can therefore be formulated in three ways. First, existing SME digitalisation studies often discuss adoption, barriers, or maturity but provide limited clustering-based diagnosis of readiness levels. Second, existing digital readiness models are generally designed for conventional firms and do not fully incorporate the Sharia-based business context. Third, previous clustering studies often compare algorithmic performance but do not sufficiently translate clustering outcomes into managerial and policy implications. This study responds to these gaps by applying and comparing hard and soft clustering methods to Sharia-based SMES readiness data, evaluating the results using multiple metrics, and interpreting the findings as a basis for evidence-based digital transformation strategy. Accordingly, the objective of this study is to compare K-Means and Fuzzy C-Means in identifying digital readiness patterns among Sharia-based SMEs. Specifically, this study aims to classify SMEs into readiness groups, evaluate clustering quality using internal and classification-oriented metrics, analyse the trade-off between hard and soft clustering, and explain the managerial implications of the resulting readiness segmentation. The dataset consists of 314 questionnaire-based SME records structured according to economic/business and technological/digital readiness indicators. The analysis includes data normalisation, clustering simulation using K- Means and Fuzzy C-Means, evaluation using Silhouette Index, Davies–Bouldin Index, accuracy, and F1-score, and PCA-based visualisation. The expected contribution of this study is both methodological and practical. Methodologically, it provides a comparative hard–soft clustering framework for analysing Sharia-based SME digital readiness. Practically, it offers a diagnostic model that helps policymakers, halal business institutions, Islamic economic development agencies, and SME managers identify which groups of SMEs need basic digital literacy, infrastructure support, business process digitalisation, or advanced transformation assistance. By linking clustering results to readiness strategy, this study supports more targeted, efficient, and ethically aligned digital development programmes for Sharia-based SMEs.

2. RESEARCH METHODS

2.1. Research Design

This study employs a quantitative, data-driven comparative clustering design to segment the digital readiness of Sharia-based micro, small, and medium enterprises (SMEs). The main objective is to compare K-Means and Fuzzy C-Means in identifying readiness groups that can support strategic digital transformation planning. This design follows the methodological structure of the original study, which begins with problem identification, continues with the use of questionnaire-based SMES data, applies K-Means and Fuzzy C-Means clustering, evaluates the models, and compares the final clustering results.

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2.2. Methodological Framework

The overall research process is illustrated in Figure 1.

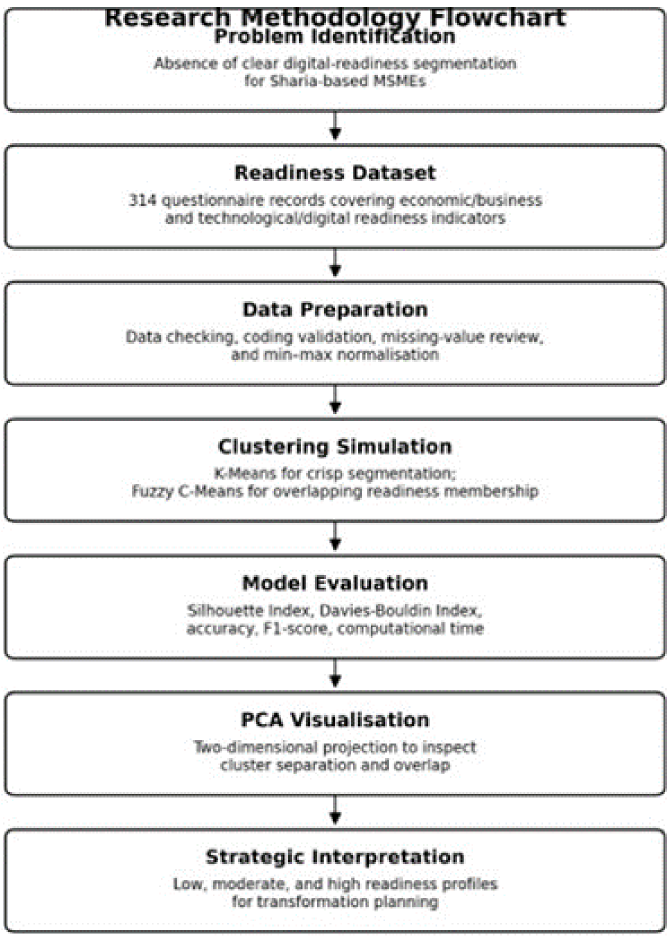

Figure 1. Research methodology flowchart.

Figure 1 shows that the research begins with problem identification, namely the absence of a clear segmentation model for Sharia-based SMES digital readiness. The second stage involves the use of 314 questionnaire-based SMES records, consistent with the dataset described in the original manuscript. The third stage is data preparation, including data checking, coding validation, missing-value review, and normalisation. This step is essential because both K-Means and Fuzzy C-Means are distance-based algorithms, and distance-based clustering is sensitive to scale differences among [12, 5]. The fourth stage is clustering simulation using K- Means and Fuzzy C-Means. K-Means is used to generate crisp readiness categories, while Fuzzy C-Means is applied to capture overlapping readiness membership. The fifth stage evaluates model performance using Silhouette Index, Davies–Bouldin Index, accuracy, F1-score, and computational time. The sixth stage uses Principal Component Analysis (PCA) to visualise multidimensional clustering results in two-dimensional space. Finally, the clustering outputs are interpreted strategically to explain which method is more suitable for exploratory readiness profiling and which is more appropriate for direct policy or managerial classification. This framework is designed to ensure that the study does not stop at algorithmic comparison. Instead, it connects clustering performance with practical transformation planning. This is important because clustering results are only useful for management research when they can be translated into actionable decision categories. [12] emphasise that clustering and dimensionality reduction are useful in smart system analysis when they improve interpretability and decision support. In the same direction Kaur, Kumar, and [5] argue that clustering evaluation should involve both methodological validity and practical interpretability, especially when clustering is applied to real-world decision problems.

2.3. Data Source and Readiness Indicators

The study uses 314 Sharia-based SMES records collected through questionnaires. The original manuscript states that the data were obtained from questionnaire responses and used to analyse digital readiness based on economic/business and technological/digital perspectives. Questionnaire-based data are appropriate because digital readiness includes internal organisational conditions that cannot be fully captured through secondary records, such as digital culture, management capability, digital education, perceived transaction readiness, and infrastructure support. In SME transformation studies, survey-based data remain relevant because they allow researchers to capture firm-level capability, organisational perception, readiness conditions that are not always available in formal databases [1, 2].

The readiness indicators are organised into two main perspectives. The economic/business perspective captures the extent to which SMEs possess the business capability required to benefit from digitalisation. It includes indicators related to business activity, transaction capability, management capability, market interaction, and macro- environmental readiness. These indicators are important because digital transformation is not only about adopting.

Digital tools, but also about whether the business model, management practices, and transaction processes are ready to absorb digital innovation. The technological/digital perspective captures the extent to which SMEs possess the digital culture, digital education, financial resources, and technical infrastructure required for transformation. This perspective is essential because digital readiness requires organisational willingness, employee competence, funding capability, and infrastructure availability. The use of these two perspectives is grounded in the Sharia-based SME readiness framework developed by Mahyarni and Okfalisa, which conceptualises SME preparedness toward Digital Industry 5.0 through economic, technological, and Sharia-related perspectives. However, the present clustering study focuses on the economic/business and technological/digital indicators used in the attached paper because its analytical purpose is to segment SMEs according to operational and digital readiness characteristics. This focus improves methodological clarity and avoids mixing broader Sharia compliance assessment with clustering objectives. At the same time, the Sharia-based context remains central because the SMEs are expected to adopt digital tools while maintaining Islamic business principles such as fairness, transparency, trustworthiness, and halal integrity.

2.4. Data Preparation and Normalisation

Before clustering, the dataset is prepared through data checking, coding validation, missing-value review, and transformation into numerical readiness indicators. This stage is necessary because clustering algorithms are sensitive to inconsistent values and scale differences. Poorly prepared data can produce misleading cluster assignments, especially when indicators are measured using different scales or have different numerical ranges. Recent clustering reviews emphasise that preprocessing is a fundamental stage in partitional clustering because distance-based algorithms can be distorted when variables are not made comparable [5, 13].

The study applies min–max normalisation to transform each readiness indicator into a comparable scale. The normalisation formula is expressed as:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{1}$$

where x'_{ij} represents the normalised value of SME i on indicator j, x_{ij} represents the original value, min (x_j) is the minimum value of indicator j, and max (x_j) is the maximum value of indicator j. Min–max normalisation is used because it preserves the relative position of each SMES while ensuring that all indicators contribute proportionally to distance calculations. This is critical because K-Means and Fuzzy C-Means both use distance-based similarity measures. Without normalisation, indicators with larger numerical ranges may dominate the clustering result, reducing the validity of the readiness segmentation. [12] also highlight the importance of preprocessing and dimensional transformation when clustering high-dimensional decision data.

2.5. K-Means Clustering

K-Means is used as the hard clustering benchmark in this study. It partitions SMEs into mutually exclusive clusters by minimising the within-cluster distance between observations and their assigned centroids. The objective function of K-Means is formulated as:

$$J = \sum_{i=1}^{n} \sum_{k=1}^{K} r_{ik} \|x_i - c_k\|^2 \tag{2}$$

where, J is the total within-cluster sum of squares, x_i is the readiness vector of SME i, c_k is the centroid of cluster k, K is the number of clusters, and r_{ik} equals 1 if SME i is assigned to cluster k, otherwise 0. The Euclidean distance used to assign SMEs to the nearest centroid is:

$$d(x_i, c_k) = \sqrt{\sum_{j=1}^{p} \left(x_{ij} - c_{kj}\right)^2} \tag{3}$$

where p is the number of readiness indicators. After assignment, the centroid is updated using:

$$c_k \frac{1}{n_k} \sum_{i \in C_k} x_i \tag{4}$$

where n_k is the number of SMEs in cluster k, and c_k is the set of SMEs assigned to cluster k.

K-Means is selected because it is computationally efficient, easy to interpret, and suitable for producing clear readiness categories. These characteristics are important for strategic transformation planning because policymakers and SME development agencies often need crisp classifications to decide which SMEs should receive basic digital literacy support, infrastructure assistance, transaction-system training, or advanced digital integration support. [5] identify K-Means as one of the most common partitional clustering baselines because of its simplicity and scalability. [10] also note that machine learning methods, including clustering algorithms, are increasingly relevant for discovering patterns in complex industrial and organisational datasets.

However, K-Means has limitations that must be acknowledged. It assumes that each SME belongs to one cluster only, even though digital readiness may be gradual. For example, an SME may show high readiness in digital transactions but low readiness in IT infrastructure, or strong management support but weak digital culture. K-Means may force such transitional cases into a single group, which can oversimplify the real readiness condition. This limitation justifies the inclusion of Fuzzy C-Means as a comparative method.

2.6. Fuzzy C-Means Clustering

Fuzzy C-Means is used as the soft clustering method because it allows each SME to have partial membership in multiple clusters. This is methodologically relevant for Sharia-based SME digital readiness because readiness does not always form sharply separated categories. Some SMEs may be between low and moderate readiness, while others may be between moderate and high readiness. Fuzzy membership enables the model to represent this uncertainty more realistically.

The Fuzzy C-Means objective function is expressed as:

$$J_m = \sum_{i-1}^{n} \sum_{k=1}^{K} u_{ik}^{m} \|x_i - c_k\|^2 \tag{5}$$

where J_m is the fuzzy objective function, u_{ik} is the degree of membership of SMES i in cluster k, m is the fuzziness coefficient, x_i is the readiness vector of SME i, and c_k is the centroid of cluster k. The fuzzy centroid is calculated as:

$$c_k = \frac{\sum_{i=1}^{n} u_{ik}^{m} x_i}{\sum_{i=1}^{n} u_{ik}^{m}} \tag{6}$$

The membership degree is updated using:

$$u_{ik} = \frac{1}{\sum_{h=1}^{k} \left(\frac{\|x_i - c_k\|}{\|x_i - c_h\|} \right)^{\frac{2}{m-1}}} \tag{7}$$

The algorithm iterates until convergence. In the original manuscript, the clustering process was configured using a maximum iteration parameter and a minimum error threshold of 0.0000010.0000010.000001, with three digital readiness clusters. Fuzzy C-Means is justified because it provides richer diagnostic information than hard clustering when the data contain overlapping readiness characteristics. Kaur et al. (2024) explain that fuzzy clustering is useful when strict boundaries are not appropriate, while [8] show that Fuzzy C-Means can support digital transformation analysis by capturing heterogeneous patterns through membership degrees. In the context of this study, the fuzzy approach is valuable because SME digital readiness is not only a technical condition but also a managerial and organisational transition. Therefore, Fuzzy C-Means can identify SMEs that are not fully low, moderate, or high readiness but are moving between stages.

2.7. Cluster Formation and Readiness Interpretation

The clustering process is designed to form three readiness groups: low, moderate, and high digital readiness. This classification follows the original study, which aims to generate readiness groups for Sharia-based SMES digitalisation. The use of three clusters is justified because it provides a balance between analytical simplicity and managerial usefulness. Too few clusters may oversimplify readiness differences, while too many clusters may make policy interpretation and intervention planning difficult.

Low-readiness SMEs are interpreted as firms that require basic digital literacy, access to infrastructure, managerial awareness, and introductory digital transaction support. Moderate-readiness SMEs are interpreted as firms that already possess partial digital capability but still require process integration, financial support, digital education, and stronger management commitment. High-readiness SMEs are interpreted as firms that are more prepared for advanced digital transformation, including platform integration, data-driven decision-making, digital transaction expansion, and potentially halal traceability systems. This interpretation links clustering results directly to strategic transformation planning, which is necessary for management-oriented research. Fernández et al. (2024) argue that readiness assessment should support organisational transformation decisions rather than merely describe technological adoption status.

2.8. Model Evaluation

The clustering results are evaluated using internal validity measures, classification-oriented measures, computational performance, and visual interpretation. This multi-metric strategy is necessary because clustering quality cannot be fully assessed using a single metric. A model may generate compact clusters but weak practical classification, or it may generate managerially clear categories but weaker internal separation. Kaur, Kumar, and Sidhu (2024) emphasise that clustering evaluation requires multiple metrics because each index captures a different aspect of cluster quality.

The Silhouette Index is used to evaluate cohesion and separation at the observation level. It measures whether an SMES is closer to other SMEs in the same cluster than to SMEs in different clusters. The formula is:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{8}$$

where $a(i)$ is the average distance between SME i and other members of the same cluster, and $b(i)$ is the smallest average distance between SME i and members of another cluster. The average Silhouette Index is:

$$SI = \frac{1}{n}\sum_{i=1}^{n} s(i) \tag{9}$$

A higher Silhouette Index indicates better clustering quality. This metric is used because it provides insight into whether the readiness groups are internally cohesive and externally separated. [12, 14] use the Silhouette Index to assess the quality of clustering outputs in complex data environments. The Davies–Bouldin Index is used to evaluate compactness and separation at the cluster level. It is formulated as:

$$DBI = \frac{1}{K}\sum_{k=1}^{k} \max_{h \neq k} \left(\frac{S_k + S_h}{M_{kh}}\right) \tag{10}$$

where S_k and S_h are the average within-cluster distances of clusters k and h, and M_{kh} is the distance between their centroids. A lower DBI indicates better cluster separation and compactness. DBI complements the Silhouette Index because it evaluates the overall relationship between cluster dispersion and centroid separation. Recent clustering studies frequently combine Silhouette and DBI to obtain a more reliable evaluation of clustering performance [5, 15].

Accuracy is used as an additional classification-oriented evaluation when the clustering results are compared with interpreted or reference readiness categories. It is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

where, TPTPTP represents true positives, TNTNTN represents true negatives, FPFPFP represents false positives, and FNFNFN represents false negatives. Accuracy is useful for assessing how well the clusters align with practical readiness labels. However, it is interpreted critically because clustering is unsupervised; a higher accuracy does not necessarily mean better internal cluster structure. It only indicates stronger alignment with a reference classification scheme.

The F1-score is used to balance precision and recall. Precision is formulated as:

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

Recall is formulated as:

$$Recall = \frac{TP}{TP + FN} \tag{13}$$

The F1-score is calculated as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{14}$$

F1-score is included because readiness categories may not be evenly distributed. When the number of SMEs in one readiness group is larger than another, accuracy alone may overstate performance. F1-score provides a more balanced measure of classification-oriented performance. This is particularly relevant for SMES readiness segmentation because low-, moderate-, and high-readiness groups may not contain equal numbers of firms. Computational time is also considered because a readiness segmentation model should be feasible for repeated use in policy dashboards, institutional monitoring, or SMES development programmes. K-Means is expected to be computationally faster because it assigns each observation to one centroid, while Fuzzy C-Means requires iterative membership updates across clusters. The original manuscript also includes computation time as part of the comparative evaluation. This is important because a model that is statistically strong but computationally inefficient may be less practical for large- scale implementation.

2.9. PCA-Based Visualisation

Principal Component Analysis is used to visualise the clustering results in two-dimensional space. Since the SMES readiness dataset contains multiple indicators, direct visual inspection is difficult. PCA reduces the dimensionality of the normalised dataset while retaining the largest variance structure. The first principal component can be expressed as:

$$PC_1 = X_{W1} \tag{15}$$

where X is the normalised data matrix and $W1$ is the eigenvector corresponding to the largest eigenvalue of the covariance matrix. More generally, PCA projection is formulated as:

$$Z = XW \tag{16}$$

where Z is the transformed data matrix and W is the matrix of selected eigenvectors.

PCA is justified because it supports interpretability. In clustering research, visualisation is not used to replace quantitative validation, but to complement it by showing whether clusters appear separated, overlapping, or transitional. The original manuscript uses PCA-based visualisation to compare how K-Means and Fuzzy C-Means form readiness clusters. Barbierato and Gatti (2024) also show that PCA can support clustering interpretation by reducing complex multidimensional patterns into interpretable visual structures. For this study, PCA is especially useful because it helps explain the difference between crisp segmentation produced by K-Means and overlapping readiness membership produced by Fuzzy C- Means.

2.10. Integrated Analytical Procedure

The analysis begins with the collection of 314 questionnaire-based records from Sharia-based SMEs. The indicators are derived from economic/business and technological/digital readiness perspectives, reflecting the ability of SMEs to adopt digital tools while maintaining business capability and Sharia-oriented values. After the dataset is checked and transformed, all indicators are normalised using min–max normalisation to ensure comparability across variables. The clustering simulation is then conducted using K-Means and Fuzzy C-Means with three readiness groups: low, moderate, and high digital readiness. K-Means assigns each SMES to a single readiness cluster based on the closest centroid, making it suitable for crisp managerial classification. Fuzzy C-Means then calculates the degree of membership of each SMES across clusters, making it suitable for identifying overlapping or transitional readiness profiles. Both models are evaluated using Silhouette Index and Davies–Bouldin Index to assess internal cluster quality, while accuracy and F1-score are used to assess alignment with practical readiness categories. Computational time is measured to determine implementation feasibility, and PCA visualisation is used to support interpretation of cluster separation and overlap. The final stage translates the clustering outcomes into strategic transformation planning by identifying whether each algorithm is better suited for exploratory diagnosis or direct intervention classification.

This integrated procedure ensures methodological rigor in several ways. The dataset is grounded in a readiness framework rather than arbitrary variables, which strengthens construct relevance. The comparison between K-Means and Fuzzy C-Means is theoretically meaningful because it contrasts crisp and fuzzy segmentation logics, a distinction that is especially relevant when readiness levels are gradual and uncertain. The use of multiple metrics prevents overreliance on a single evaluation criterion, while PCA improves interpretability for decision-makers. Finally, the analytical outputs are connected to managerial implications, ensuring that the study contributes not only to computational clustering but also to evidence-based digital transformation planning for Sharia-based SMEs

3. RESULTS AND DISCUSSIONS

3.1. Analytical Overview

This chapter presents the empirical results of Sharia-based SMES digital readiness segmentation using K-Means and Fuzzy C-Means. The analysis follows the methodological flow developed in the previous chapter: data preparation, normalisation, K-Means clustering, Fuzzy C-Means clustering, comparative evaluation, PCA-based interpretation, and strategic transformation analysis. The dataset consisted of 314 questionnaire-based Sharia-based SMES records, measured through economic/business and technological/digital readiness indicators, including business activity, transaction capability, management capability, market interaction, macro-environmental readiness, digital culture, digital education, financial resources, and technical infrastructure. The main objective of the analysis is not merely to determine which clustering algorithm produces better numerical performance, but to explain how each method supports different strategic purposes. K-Means is evaluated as a hard clustering method that produces clear readiness categories, while Fuzzy C-Means is evaluated as a soft clustering method that captures overlapping and transitional readiness profiles. This distinction is critical because digital transformation readiness among SMEs is rarely binary. Many SMEs may be digitally ready in one dimension but weak in another, making segmentation more complex than a simple ready–not ready classification. This analytical positioning is consistent with recent clustering and digital transformation studies, which argue that data-driven segmentation should support both statistical validity and managerial interpretability [1, 2, 5].

3.2. Data Preparation and Normalisation Results

Before applying the clustering algorithms, the dataset was prepared by validating questionnaire responses, converting readiness indicators into numerical values, and normalising the variables. Normalisation was necessary because both K-Means and Fuzzy C-Means rely on distance-based calculations. If the indicators remain on different numerical scales, variables with larger ranges may dominate the distance calculation and distort the resulting clusters. Therefore, min–max normalisation was applied using Equation (1) in the methodology section. The normalisation process transformed all readiness indicators into comparable values while preserving the relative position of each SMES within each indicator. This ensured that economic/business readiness indicators and technological/digital readiness indicators contributed proportionally to the clustering process. This step is not merely technical; it is essential for methodological validity [5] emphasise that clustering performance is highly sensitive to feature scaling and preprocessing decisions, while [12] show that preprocessing and dimensional transformation improve the interpretability of clustering results in complex decision datasets. After normalisation, the dataset became suitable for both hard and soft clustering simulation. This preprocessing stage directly supports the research objective because the study aims to produce fair and comparable segmentation across heterogeneous SMES readiness indicators. Without this step, the clustering result could reflect scale bias rather than true readiness similarity.

3.3. K-Means Clustering Results

K-Means clustering was applied to generate crisp digital readiness categories. The algorithm assigns each SMES to one cluster by minimising the within-cluster sum of squares, as formulated in Equation (2). The Euclidean distance between each SMES and cluster centroid was calculated using Equation (3), while centroid updating was conducted using Equation (4). Through this iterative process, SMEs were grouped according to similarity in their normalised readiness profiles. The K-Means result produced three practical readiness categories: low readiness, moderate readiness, and high readiness. This output is managerially useful because each SMES is assigned to a single readiness group, making the segmentation directly applicable for policy intervention, business development programmes, and digital transformation planning. The K-Means model achieved an accuracy value of 0.6033 and an F1-score of 0.3202. These values indicate that K-Means produced stronger classification-oriented performance compared with Fuzzy C- Means, particularly when the objective is to assign SMEs into clear and actionable readiness categories.

Table 1. K-means execution results and analytical interpretation.

Analytical component	Result obtained	Interpretation for SMEs readiness segmentation
Input data	314 Sharia-based SMES records	Provides firm-level readiness observations for segmentation
Clustering type	Hard clustering	Each SMES is assigned to only one readiness cluster
Number of clusters	3	Represents low, moderate, and high digital readiness
Main computation basis	Equations (2), (3), and (4)	Uses centroid optimisation and Euclidean distance
Accuracy	0.6033	Indicates stronger alignment with practical readiness classification
F1-score	0.3202	Shows moderate classification balance across readiness categories
PCA-based visual pattern	Clearer three-group separation	Supports practical interpretability for intervention planning
Strategic function	Crisp policy classification	Suitable for assigning SMEs into direct support categories

The K-Means result shows that hard clustering is particularly effective when decision-makers require clear intervention categories. In the context of Sharia-based SMEs, this is important because support programmes are often implemented through categorical policy schemes. For example, low-readiness SMEs may require basic digital literacy, managerial awareness, and infrastructure access. Moderate-readiness SMEs may need business process digitalisation, digital transaction support, and structured digital training. High-readiness SMEs may be prepared for advanced digital platforms, data-driven business analytics, halal traceability systems, and wider participation in the Sharia-based digital ecosystem. However, the F1-score of 0.3202 indicates that K-Means still has limitations in capturing all readiness variations. This moderate score suggests that some SMEs may have mixed readiness characteristics that are difficult to represent through a single crisp category. This is theoretically important because it confirms that SMES digital readiness is not always sharply separated. A firm may have strong digital transactions but weak infrastructure, or good managerial support but limited digital financial resources. Thus, while K-Means is useful for managerial classification, it may oversimplify transitional readiness conditions. This supports [16], who argue that crisp clustering is useful for segmentation-based decision-making but may be less sensitive to overlapping behavioural or organisational patterns.

3.4. Fuzzy C-Means Clustering Results

Fuzzy C-Means was applied to capture the gradual and overlapping nature of SMES digital readiness. Unlike K- Means, Fuzzy C-Means does not force each SMES into one cluster. Instead, each SMES receives membership degrees across all clusters. The objective function was calculated using Equation (5), the fuzzy centroid was updated using Equation (6), and the membership degree was calculated using Equation (7). This approach is suitable for readiness analysis because firms may simultaneously show characteristics of more than one readiness group.

The Fuzzy C-Means model achieved a Silhouette Index of 0.1362 and a Davies–Bouldin Index of 2.6126. These results indicate that Fuzzy C-Means produced better internal cluster quality than K-Means. A higher Silhouette Index suggests better cohesion and separation among observations, while a lower Davies–Bouldin Index indicates better compactness and separation among clusters. Therefore, Fuzzy C-Means is stronger for exploratory profiling because it better captures the internal structure of SMES readiness data.

Table 2. Fuzzy C-means execution results and analytical interpretation.

Analytical component	Result obtained	Interpretation for SMES readiness segmentation
Input data	314 Sharia-based SMES records	Uses the same normalised readiness dataset as K-Means
Clustering type	Soft clustering	Each SMES has membership degrees across readiness clusters
Number of clusters	3	Represents gradual membership across low, moderate, and high readiness
Main computation basis	Equations (5), (6), and (7)	Uses fuzzy membership, fuzzy centroid updating, distance-based optimisation
Silhouette Index	0.1362	Indicates better internal cohesion and separation
Davies–Bouldin Index	2.6126	Indicates better cluster compactness and separation
PCA-based visual pattern	More overlapping membership structure	Reflects transitional readiness characteristics
Strategic function	Diagnostic readiness profiling	Suitable for identifying SMEs that require hybrid intervention strategies

The Fuzzy C-Means result is significant because it reveals that digital readiness among Sharia-based SMEs may exist as a continuum rather than as fixed categories. This has important implications for both theory and practice. Theoretically, it supports the argument that SMES digital transformation should be understood as a capability transition process, not merely as a binary adoption decision. Practically, it helps policymakers identify SMEs that are between readiness stages. For example, a firm may partially belong to both moderate- and high-readiness groups, indicating that it may not need basic digital literacy but may still require financial support, transaction system integration, or infrastructure upgrading.This finding aligns with [5], who explain that fuzzy clustering is more appropriate when cluster boundaries are uncertain, and with [8], who demonstrate that Fuzzy C-Means can reveal heterogeneous digital transformation patterns through membership-based interpretation. In the context of Sharia-based SMEs, this is particularly useful because transformation readiness includes not only technological factors, but also business capability, ethical transaction readiness, halal value-chain integrity, and managerial support.

3.5. Comparative Performance of K-Means and Fuzzy C-Means

The comparative evaluation reveals that K-Means and Fuzzy C-Means provide different analytical advantages. Fuzzy C-Means performs better in terms of internal cluster validity, while K-Means performs better in terms of classification- oriented interpretation. The Silhouette Index was calculated using Equations (8) and (9), the Davies–Bouldin Index using Equation (10), accuracy using Equation (11), and F1-score using Equations (12), (13), and (14).

The comparison shows that there is no single universally superior method. Instead, algorithm suitability depends on the strategic purpose of the analysis. Fuzzy C-Means is stronger when the objective is to understand the internal structure and overlapping characteristics of digital readiness. Its better Silhouette and Davies–Bouldin results show that it captures the readiness distribution more sensitively. This is important for research because it provides a more nuanced understanding of how Sharia-based SMEs transition across readiness stages.

K-Means, however, is stronger when the objective is to produce clear categories for decision-making. Its higher accuracy and F1-score indicate that it is more suitable when policymakers or business development agencies need to assign SMEs into practical intervention groups. This distinction is consistent with recent clustering literature, which emphasises that internal validity and practical interpretability do not always produce the same best model [5]. Therefore, the contribution of this study is not simply identifying which algorithm is “better”, but explaining when and why each algorithm is useful for Sharia-based SMES digital transformation planning. The PCA-based interpretation strengthens this conclusion. K-Means produced clearer visual grouping into three practical readiness categories, while Fuzzy C-Means produced more overlapping membership patterns. This supports the argument that K-Means is more suitable for policy classification, while Fuzzy C-Means is more suitable for diagnostic profiling. [12] note that PCA improves clustering interpretation by reducing complex multidimensional data into visual structures. In this study, PCA confirms that the two methods should be treated as complementary tools rather than competing substitutes. The PCA diagrams can be depicted in Figures 2 and 3.

Table 3. Comparative performance of K-means and Fuzzy C-means.

Evaluation criterion	K-means	Fuzzy C-means	Better-performing method	Analytical meaning
Silhouette index	Lower than FCM	0.1362	Fuzzy C-means	FCM provides better internal cohesion and separation
Davies–Bouldin index	Higher than FCM	2.6126	Fuzzy C-means	FCM produces more compact and better separated clusters
Accuracy	0.6033	Lower than k-means	K-means	K-Means better supports crisp readiness classification
F1-score	0.3202	Lower than k-means	K-means	K-means performs better for classification-oriented segmentation
Computational efficiency	Faster	Slower	K-means	K-means is more practical for repeated institutional use
PCA interpretability	Clearer three-group separation	More overlapping pattern	Depends on objective	K-means is clearer for policy categories; FCM is richer for diagnostic profiling
Strategic use	Direct intervention classification	Exploratory readiness diagnosis	Complementary	Both methods support different transformation planning needs

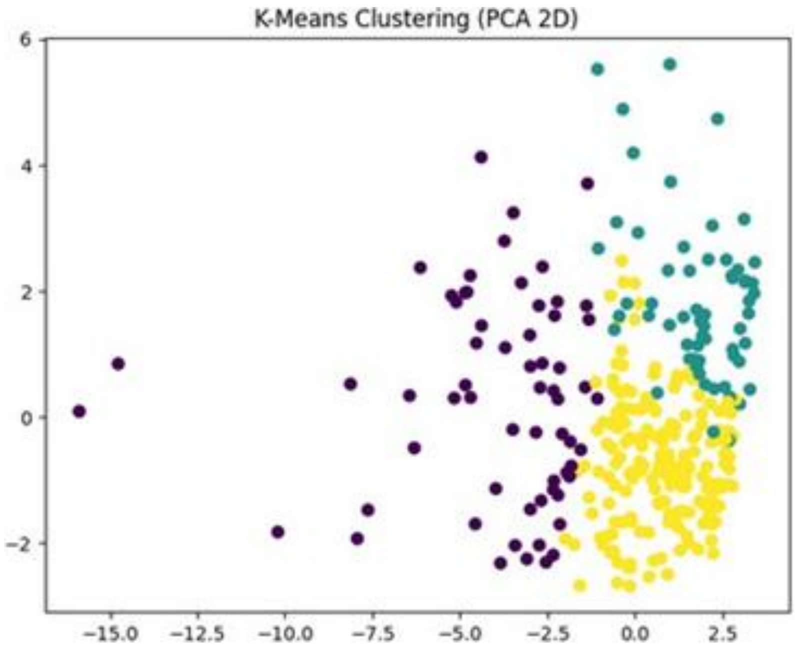

Figure 2. (a) PCA for K-mean.

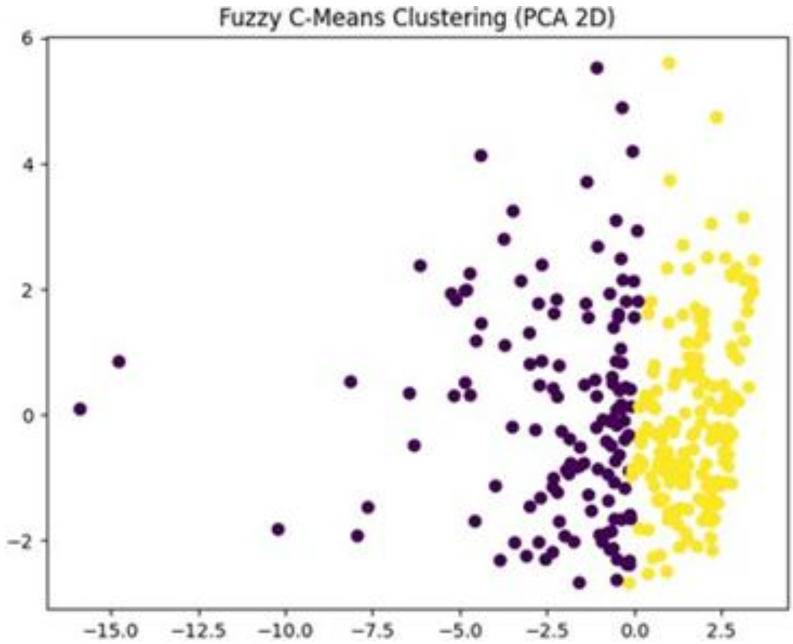

Figure 3. PCA for Fuzzy C-Means.

3.6. Strategic Interpretation of Readiness Segments

The clustering results can be translated into three strategic readiness profiles. Low-readiness SMEs are characterised by limited digital culture, weak infrastructure, low digital education, and limited transaction readiness. These firms require foundational support, including basic digital literacy, access to digital infrastructure, managerial awareness programmes, and introductory digital transaction training. For this group, digital transformation strategy should focus on reducing adoption barriers and building basic capability. Moderate-readiness SMEs show partial digital capability but still lack integration across management, transaction systems, financial resources, and infrastructure. This group requires digital process integration, business transaction strengthening, digital financial access, and structured training. The strategic priority is not merely introducing digital tools, but helping SMEs integrate those tools into business processes and managerial routines. High-readiness SMEs demonstrate stronger digital culture, better transaction capability, more adequate infrastructure, and stronger management capability. This group is suitable for advanced transformation strategies, such as platform integration, digital analytics, halal traceability systems, innovation support, and participation in broader Sharia-based digital ecosystems. For this group, the strategic objective is to move from digital adoption to digital competitiveness.

This segmentation directly addresses the research problem. Sharia-based SMEs should not be treated as a homogeneous group because they have different readiness levels and therefore require different forms of intervention. Uniform digitalisation programmes may be inefficient because they may provide advanced support to firms that still need foundational assistance, or basic training to firms that are already ready for advanced transformation. [2] similarly argue that SME digitalisation barriers differ across infrastructure, finance, and human resources [5, 17] also emphasise that Industry 5.0 transformation requires human-centred, capability-based, and resilient strategies rather than technology-driven programmes alone. For Sharia-based SMEs, the implication is even stronger. Digital transformation must preserve Islamic business values, including transparency, trustworthiness, fairness, halal assurance, and ethical transactions. Therefore, readiness segmentation should not only guide technology adoption but also support ethical and Sharia- aligned transformation. The Okfalisa- [18] readiness framework provides a relevant foundation for this interpretation because it conceptualises Sharia SME readiness as a multidimensional construct involving economic, technological, and Sharia-oriented preparedness. This study extends that framework by operationalising readiness into data-driven segmentation.

Overall, the findings demonstrate that the proposed clustering framework successfully addresses the main research objective: identifying digital readiness patterns among Sharia-based

SMEs and comparing the suitability of K-Means and Fuzzy C-Means for strategic transformation planning. The results show a clear methodological trade- off. Fuzzy C-Means achieves better internal cluster validity, indicating stronger ability to capture the natural structure and overlapping readiness characteristics of SMEs. K-Means achieves stronger classification-oriented performance, indicating better suitability for direct intervention classification. This dual finding is important because it moves the paper beyond a conventional algorithm comparison. The study does not claim that Fuzzy C-Means or K-Means is universally superior. Instead, it demonstrates that each method serves a different strategic function. Fuzzy C-Means is more appropriate for diagnostic readiness profiling, while K-Means is more appropriate for policy classification and intervention planning. This interpretation strengthens the contribution of the study because it links computational results to managerial decision-making. The findings also answer the practical problem identified in the introduction: Sharia-based SMEs lack clear segmentation for digital readiness. Without segmentation, digital transformation programmes may treat all firms similarly, even though their capability gaps differ. The proposed framework provides a data-driven basis for differentiating support. Low-readiness firms need foundational capability development, moderate-readiness firms need integration support, and high-readiness firms need acceleration strategies. This allows policymakers, Islamic business associations, halal ecosystem institutions, and SMES managers to allocate resources more effectively. The significant contribution of this study lies in combining Sharia-based readiness measurement with comparative hard–soft clustering analysis. The study contributes methodologically by comparing K-Means and Fuzzy C-Means using multiple evaluation metrics. It contributes theoretically by showing that SMES digital readiness is heterogeneous and transitional. It contributes practically by translating readiness clusters into strategic business transformation recommendations. Therefore, the study advances digital transformation research from general readiness assessment toward evidence-based readiness segmentation for Sharia-based SMEs.

4. CONCLUSION

This study developed a data-driven segmentation framework to classify the digital readiness of Sharia-based SMEs using K-Means and Fuzzy C-Means. Based on 314 questionnaire-based SMES records, the findings show that Sharia- based SMEs should not be treated as a homogeneous group because their readiness differs across business capability, transaction readiness, managerial support, digital culture, financial resources, and technical infrastructure. K-Means produced stronger classification-oriented performance, making it more suitable for assigning SMEs into clear low, moderate, and high readiness groups. In contrast, Fuzzy C-Means produced better internal cluster validity, making it more appropriate for identifying overlapping and transitional readiness profiles. Thus, the study answers its main objective by demonstrating that K-Means is more practical for policy classification, while Fuzzy C-Means is more useful for diagnostic readiness profiling. The novelty of this study lies in integrating Sharia-based SMES readiness assessment with comparative hard–soft clustering to support evidence-based digital transformation planning. Theoretically, the study extends SMES digital transformation literature by showing that readiness is heterogeneous, gradual, and context-sensitive. Methodologically, it demonstrates that clustering algorithms should be selected based on strategic purpose rather than statistical superiority alone. Practically, the framework helps policymakers, halal business associations, Islamic economic institutions, and SMES development agencies design differentiated interventions: low-readiness SMEs require basic digital literacy and infrastructure support; moderate-readiness SMEs need process integration and transaction strengthening; and high-readiness SMEs can be directed toward advanced digital platforms, halal traceability, and analytics-based business development. This supports a more targeted, efficient, and Sharia-aligned transformation strategy in line with human-centred Industry 5.0 development.

Future research should extend the model by incorporating more Sharia-specific indicators, such as halal certification readiness, Islamic financial inclusion, Sharia governance maturity, and halal supply-chain traceability. Further studies may also combine clustering with multi-criteria decision-making methods, such as Fuzzy AHP, DEMATEL, TOPSIS, or Best–Worst Method, to identify the weighted drivers behind each readiness cluster. Longitudinal research is also recommended to examine how SMEs move across readiness levels after receiving digital transformation interventions. In addition, future work may compare K-Means and Fuzzy C-Means with other clustering methods, such as DBSCAN, Gaussian Mixture Models, hierarchical clustering, self-organising maps, or ensemble clustering, to test the robustness and scalability of the proposed segmentation framework.

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