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Application of the LSE (longevity, scale, employee) framework for characterizing MSMEs with the k-means algorithm: a case study in semarang city

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ABSTRACT

The diversity of characteristics among Micro, Small, and Medium Enterprises (MSMEs) often poses a challenge for effective policy formulation, where a one-size-fits-all approach fails to distinguish the specific needs of each business. This study aims to overcome the limitations of administrative segmentation by applying a new behavior-based framework, namely LSE (Longevity, Scale, Employment), to characterize the typology of MSMEs in the city of Semarang. The research method adapts the principles of Recency, Frequency, Monetary (RFM) into business metrics: Longevity (resilience), Scale (maturity), and Employment (socio-economic impact). Using data sourced from the Semarang City Cooperative and MSME Office, this study analyzed 8,804 valid MSME data points through a K-Means Clustering algorithm optimized with the Elbow Method. The results identified three distinct clusters: Sustainable Businesses, Accelerative Businesses, and Stagnant Micro Businesses. These findings validate the effectiveness of the LSE model in mapping business heterogeneity and recommend a paradigm shift in policy towards targeted and relevant interventions for each segment.

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1. INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) have long been recognized as the backbone of Indonesia's economy. Their contribution to the national Gross Domestic Product (GDP), which has consistently been reported to exceed 60%, and their remarkable ability to absorb more than 97% of the total national workforce, underscore their role as a vital driving force for macroeconomic growth and social stability (Karavasilis, Vrana, & Karavasilis, 2024). At the regional level, such as in the city of Semarang, which is one of the strategic economic hubs on the island of Java, MSMEs play an equally important role, not only as job creators but also as pillars of regional economic resilience and catalysts for financial inclusion.

However, despite this collective significance, MSMEs are not a monolithic or homogeneous entity. In reality, the MSME landscape is characterized by extreme heterogeneity, including differences in operational scale, technology adoption, management capacity, and growth ambitions(Kumar, Kumar, & Verma, 2024). A fundamental problem then arises when stakeholders, especially local governments and financial institutions, design interventions or development programs using a one-size-fits-all approach. This policy paradox, where uniform programs are applied to diverse target audiences, often leads to inefficiency, waste of resources, and program failure to deliver significant impact (Saxena, 2025). An SME that has been operating for 20 years but remains stagnant at the micro level clearly requires a different intervention from a two-year-old start-up that is showing aggressive employee growth.

Traditionally, SME segmentation in research and policy has often been limited to static and administrative one-dimensional classifications. General classifications based on business sector are too broad because they fail to distinguish between street vendors and medium-scale catering businesses even though both are in the same sector. Similarly, legal classifications based on business scale are often based on unverified or self-reported turnover data, thus failing to capture the actual operational dynamics and business capacity. In the field of marketing and customer management, segmentation models such as RFM have proven to be very effective in grouping customers based on their transactional behavior, enabling companies to design targeted marketing strategies(Laga et al., 2023). However, there is a significant research gap in adapting these behavior-based segmentation principles from the customer side to the business unit or MSME side itself.

This study aims to fill the literature gap by proposing and operationalizing a new segmentation framework, namely LSE (Longevity, Scale, Employment), which conceptually reconstructs the principles of the RFM model to capture the core profile and operational behavior of MSMEs more accurately. The theoretical contribution of integrating these three specific indicators lies in their synergistic ability to deconstruct MSME heterogeneity through a multi-dimensional evolutionary lens. By combining longevity, scale, and employment, this framework provides a comprehensive developmental diagnostic that links a firm's historical resilience with its current organizational maturity and real-world economic impact. Longevity as the main proxy for resilience, market experience, and business endurance (Carayannis, 2025); Scale—objectively derived from the number of employees—as an indicator of business maturity and successful business escalation (Touijer, 2025); Employment as a quantitative measure of socio-economic impact and operational complexity (Samputra, 2025). This integration allows the model to transcend statutory labels, revealing hidden archetypes—such as 'stagnant resilient' or 'accelerative growth' firms—that remain invisible in traditional administrative models. To validate this research framework, the K-Means algorithm was applied to the MSME dataset in Semarang City, given that this method has proven to be robust for business segmentation (Schroth, 2024). Through the identification and visualization of these fundamentally different segments, this study aims to provide nuanced data-based insights as a basis for stakeholders in designing more precise, effective, and targeted policy interventions for each unique MSME typology (Lu, 2024).

2. RESEARCH METHOD

To ensure empirical validity and accuracy of analysis in mapping MSME heterogeneity, this study adopts a systematic data mining approach. Figure 1 visualizes the end-to-end research methodology architecture, which is designed to transform raw administrative data into strategic insights in the form of business segment typologies.

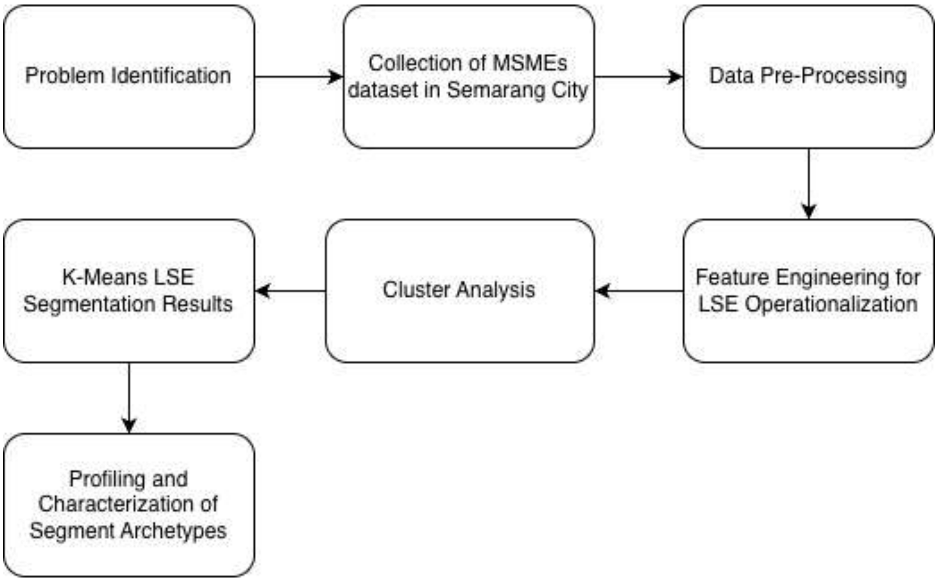

Figure 1. End-to-End Research Methodology

This workflow is arranged sequentially in seven critical, integrated stages. Beginning with problem identification as the basis for the urgency of the research, the process continues with data acquisition and pre-processing to ensure the integrity of the analysis input. The core of this framework lies in the feature engineering stage to operationalize the LSE model, which is then executed through the K-Means algorithm. This series of processes culminates in the profiling stage, where statistical results are translated into interpretable segment archetype characterizations for policy needs.

2.1 Problem Identification

The problem identification stage in this study is driven by fundamental issues hindering the effectiveness of MSME development, particularly within the context of regional economies such as Semarang City. The primary underlying issue is the paradox of one-size-fits-all policies applied amidst MSME heterogeneity. Although recognized as the backbone of the economy, MSMEs are often treated as monolithic or homogeneous entities in policy formulation (Strilets, 2022). In reality, this sector is extremely heterogeneous, encompassing a wide variation in operational scale, technology adoption, and growth ambitions (Ilahiane, 2025). Consequently, the application of uniform policies becomes ineffective and results in resource wastage, as the needs of fast-growing start-ups are often equated with those of micro-enterprises that have been operating for decades but remain stagnant or at a subsistence level (Dittmar, 2025).

Further impediments arise from the limitations of traditional segmentation, which is inherently static and administrative. Current MSME classification methods are generally based solely on legal definitions, such as annual turnover or total assets. This approach possesses fatal flaws, particularly regarding data unreliability, where classification is often based on self-reported data that is difficult to verify, thereby hindering evidence-based decision-making (Tawil, 2024). Moreover, this static classification fails to capture actual business dynamics as it does not distinguish between firm life cycle stages. This leads to "old" micro-enterprises and "new" micro-enterprises being grouped into the same category, even though their risk profiles and operational behaviors differ significantly (Aberkane, 2025).

A significant research gap remains in the domain of behavior-based segmentation. While the RFM model has proven successful in dynamically mapping customer behavior within marketing contexts (Sanjaya, 2023), there is a distinct lack of adaptation of these principles to the context of MSME business units. Currently, no established framework exists to measure MSME “behavior” using objective metrics—specifically business age as a proxy for resilience and labor absorption as a proxy for economic impact—simultaneously (Masenya, 2023). Consequently, the primary problem identified is the absence of a data-based segmentation method capable of accurately mapping the behavioral typology of MSMEs. This deficiency underscores the critical need to develop a new framework LSE and apply a K-Means clustering algorithm to deconstruct the heterogeneity of MSMEs in Semarang City into actionable segments (Vajjhala, 2024).

2.2 Collection of MSMEs Dataset in Semarang City

Following the problem identification, the research proceeds to the critical stage of data acquisition and preparation. This phase is designed to transform raw administrative records into a high-quality dataset suitable for computational analysis. Collection of MSMEs Dataset The study utilizes a secondary dataset obtained from the Department of Cooperatives and Micro Enterprises of Semarang City. The initial raw dataset comprised a snapshot of 30,423 MSME records, featuring 20 distinct attributes. To facilitate the specific requirements of the LSE framework, key variables were selectively extracted, including the Year of Establishment, Number of Male and Female Employees, Education Level, and Business District.

2.3 Data Pre-Processing

The validity of cluster analysis results is highly dependent on the quality of the input data. Therefore, a series of strict data preprocessing procedures were applied before modeling was performed. The first stage focused on standardizing categorical data, particularly the Education variable, which contained various inconsistent entries such as high school, vocational school, bachelor's degree, or master's degree. Through mapping techniques, these values were reduced and standardized into a standard category taxonomy ranging from ‘No Schooling’ and ‘Elementary School’ to ‘Doctorate’ to ensure label consistency.

Concurrently, missing values were handled in the numerical variable for labor force. Missing data in the variable was imputed with a value of zero, based on the logical assumption that the absence of a reported entry represents the absence of a labor force in the relevant business unit. The next step involved data type transformation and anomaly filtering. The Year of Business Establishment variable was converted from float to integer for temporal precision. Further investigation of the data distribution indicated the existence of extreme outliers in the year of business establishment, which resulted in unrealistic Longevity calculations. Given the sensitivity of the K-Means algorithm to outliers that can drastically distort the position of the centroid, a reasonable threshold was applied by filtering out business data established before 1980. After this series of cleaning, validation, and selection, a final dataset of 8,804 valid MSME entities was obtained for processing in the cluster analysis stage.

2.4 Feature Engineering for LSE Operationalization

To transform raw data into measurable performance indicators within the LSE framework, a systematic feature engineering procedure was carried out. The three core metrics were constructed operationally as follows: (a) Longevity (L): This metric captures the temporal dimension of the business to measure its operational duration and market resilience. The longevity value is calculated as the temporal difference between the reference year of the study, set at 2025, and the year of establishment of the business entity. (b) Scale (S): Unlike the two previous metrics, which are continuous, the business scale metric is constructed through a two-stage transformation procedure to ensure compliance with national regulatory standards and algorithmic computing requirements: (c) Stratification Stage: First, the continuous variable of total employees is classified into discrete strata categories that refer to Government Regulation of the Republic of Indonesia Number 7 of 2021. The stratification scheme is set as follows: Solo with 0 employees, Micro 1–4 employees, Small 5–19 employees, Medium 20–99 employees, and Large more than 100 employees (Pemerintah Republik Indonesia, 2021). (d) Ordinal Codification Stage: This stage facilitates numerical processing in the K-Means algorithm, where the qualitative categories are converted into ordinal numerical scores. This transformation maps each level of the scale to an integer value (Solo=0, Micro=1, Small=2, Medium=3, Large=4), which is then defined as the scale_score variable. (e) Employment (E): This metric serves as the main proxy for labor absorption capacity and socio-economic impact. This variable is constructed through the process of aggregating labor data disaggregated by gender, resulting in a composite variable of total labor.

2.5 Cluster Analysis

The K-Means algorithm requires determining the number of clusters. This study applies the Elbow Method heuristic approach to objectively identify the optimal k. This method evaluates the Inertia value at various k variations to find the centroid point, where the addition of new clusters no longer provides a significant decrease in data variance.

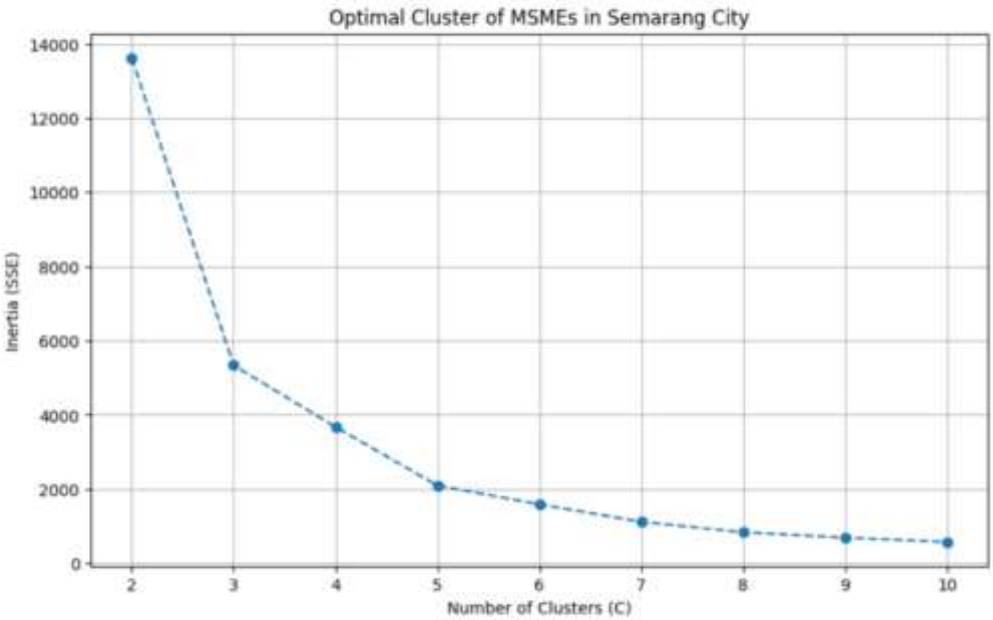

Figure 2. Elbow Graph in Determining the Number of Clusters

Based on the graph visualization in Figure 1 above, the vertical axis represents the Inertia (SSE) value, while the horizontal axis shows the variation in the number of clusters k tested, ranging from 2 to 10. The graph shows a sharp downward trend in SSE values as the number of clusters moves from 2 to 3. This drastic decrease indicates that separating the data into three groups provides a very significant increase in internal homogeneity. However, the pattern of SSE decline begins to level off significantly after passing the point of 3. The change in gradient that forms a right angle at this point indicates an inflection point. Referring to the principle of parsimony and the graphical interpretation, the optimal number of clusters for this study is set at 3 because it is considered the most efficient configuration for mapping the heterogeneity of MSMEs in Semarang City.

3. RESULTS AND DISCUSSIONS

3.1 Spatial and Educational Heterogeneity as a Catalyst for Behavioral Modeling

Preliminary data analysis reveals that MSMEs in Semarang are not a unified entity, but rather a fragmented landscape characterized by significant operational disparities. Rather than viewing geospatial and educational data as mere statistics, this study leverages these disparities to justify the need for an LSE insight model. As shown in Figure 3, MSME activity is highly polarized, with dense clusters exceeding 1,000 units in centers such as Tembalang and Pedurungan, in contrast to only 200–400 units in peripheral areas such as Mijen. This spatial concentration proves that MSMEs are not a monolithic block; their operating environments vary drastically based on local market access and infrastructure, indicating that administrative data such as location alone is not sufficient to capture the actual operational health of a business.

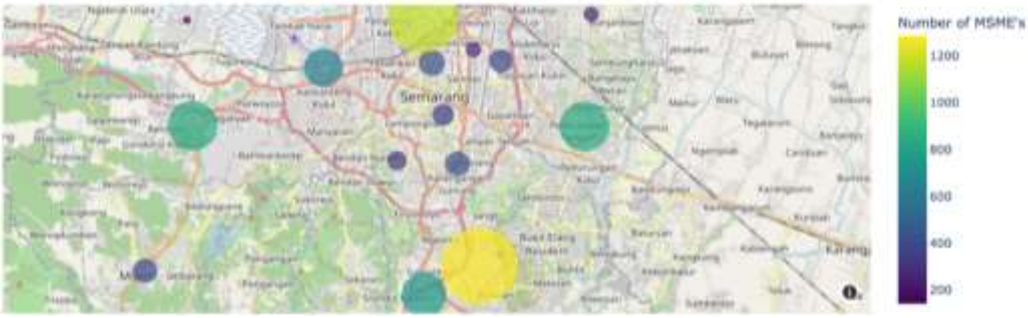

Figure 3. Map of the Distribution of MSMEs per District in Semarang City

This spatial polarization is mirrored in the human capital analysis in Figure 4 which identifies a distinct "managerial ceiling" where high school graduates dominate at 50.2% while higher education holders remain a minority at less than 25% . Such disparity suggests that traditional scale-up policies frequently fail by neglecting the diverse managerial literacy and technological absorptive capacities inherent within the sector. These spatial and educational gaps validate the transition from statutory-administrative labeling toward behavioral-operational metrics, enabling the LSE framework to align policy interventions with a business's actual evolutionary stage rather than its administrative category.

Figure 4. Proportion of Education Level of MSMEs in Semarang City

These findings confirm that traditional, static-administrative segmentation fails to capture the underlying operational dynamics . Consequently, the observed spatial and educational gaps necessitate a shift toward behavioral-operational metrics that prioritize business behavior over statutory labels.

3.2 Cohort Analysis of Business Scale Stagnation

To validate the relevance of the Longevity dimension in the LSE framework, this study conducted empirical testing of the assumptions of Firm Life Cycle Theory, which traditionally postulates a positive linear correlation between business age and organizational growth. The cohort analysis approach was applied to dissect the business scale structure longitudinally based on the year of establishment of the entity. This analysis aimed to detect whether there was a significant trend of vertical mobility in businesses that had been operating for a long time compared to new entrants.

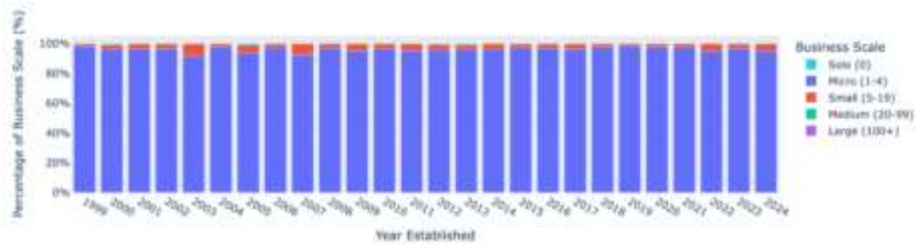

Figure 5. Distribution of MSME Segments in LSE 3D Space

The visualization diagram in Figure 5 reveals a crucial empirical phenomenon: the existence of scale invariance in terms of operational duration. The graph shows the absolute dominance of the Micro segment. Statistically, the proportion of micro-enterprises consistently remained above 90%, not only among new businesses in the 2020–2024 period but also among established businesses established between 1999 and 2005. The minimal proportion of red and green businesses in this group indicates structural growth stagnation.This finding refutes the assumption that business age automatically guarantees business scale escalation. Instead, the data shows that the majority of MSMEs in Semarang City are stuck at a low scale, where they are able to survive for decades but without significant organizational capacity expansion. This fact further reinforces the urgency of separating the Longevity and Scale dimensions in the segmentation process, as both have been proven to be independent variables.

3.3 K-Means LSE Segmentation Results

After identifying the membership of each segment, the next analytical step is to define the business archetypes or ‘personas’ of each cluster. For this purpose, a multivariate comparative analysis was conducted by visualizing the centroid values of the standardized Longevity, Scale, and Employment variables. The visualization approach was adopted to map the divergence of characteristics between groups simultaneously, so that the pattern of variable dominance in each segment could be identified intuitively.

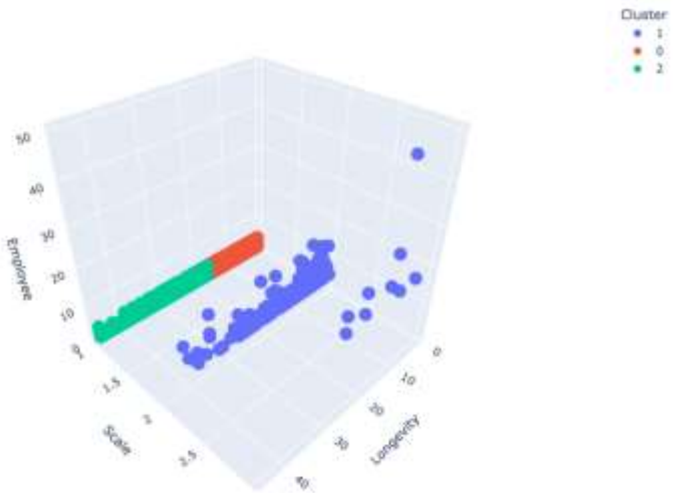

Figure 6. Distribution of MSME Segments in LSE 3D Space

The radar diagram visualization in Figure 5 demonstrates a clear geometric divergence between segments, which effectively validates the discriminatory ability of the L-S-E model in separating entities based on their performance typology.

Cluster 1 (Orange Line) forms an asymmetrical polygon pattern with significant area expansion towards the Scale and Employee axes. The visual dominance on the left side of this graph, contrasted with a sharp retraction on the Longevity axis, provides empirical evidence for the existence of the ‘High-Growth Stars’ segment: young business entities that show high aggressiveness in operational capacity escalation. Conversely, Cluster 2 (Green Field) displays the opposite orientation with strong elongation on the temporal dimension (Longevity). This profile is balanced by moderate area coverage on the operational dimension, reflecting the characteristics of ‘Established Champions’—a group of veteran businesses that have achieved market maturity and stability. Finally, Cluster 0 (Blue Line) is isolated at the center of the coordinate axis with a very minimal polygon area. The concentration of values close to zero on the Scale and Employee dimensions, despite having a fairly long operational duration, accurately describes the profile of ‘Established Micros’. This pattern confirms the finding that the majority of the sample population is trapped in a state of structural stagnation, where business longevity does not translate into tangible scale growth.

3.4 Profiling and Characterization of Segment Archetypes

As a final validation of the partitioning generated by the K-Means algorithm, this study projects each MSME data point into a 3D feature space constructed by the Longevity, Scale, and Employment axes.

Figure 7. Characterization of the MSME Segment: LSE Cluster Analysis

Based on the quantitative profile in Figure 6 and the LSE average table, the three archetypes can be described as follows:

a. Cluster 0: Sustainable Business

Theoretically, this segment represents the Resilient Stagnation archetype. The high Longevity score indicates that entities in this cluster have proven market resilience with an estimated operational duration of 10 to 15 years. However, this operational persistence does not translate into vertical business expansion. Businesses in this segment experience a micro-scale trap phenomenon, where they are able to survive in the long term but continue to operate at minimal capacity and with very low labor absorption. This profile is highly correlated with the concept of subsistence entrepreneurship, where the main focus of the business is the sustainability of the owner rather than aggressive corporate growth.

b. Cluster 1: Accelerative Businesses

This segment represents the Growth Accelerator archetype, often referred to in entrepreneurship literature as Gazelles. This profile challenges the linearity of the traditional business life cycle. Despite their very young age, entities in this cluster exhibit aggressive growth kinetics. They have successfully leapfrogged the micro phase and directly occupied the Small or Medium scale. The high Employment score indicates that the business model adopted is labor-intensive or has high operational scalability, making them vital contributors to the creation of new jobs despite their minimal historical experience in the market.

c. Cluster 2: Stagnant Micro

This segment represents the Sustainable Incumbent archetype. Theoretically, entities in this group have successfully navigated all critical phases in the company life cycle, transforming from start-ups into established market players with an operational duration exceeding 15–20 years. Unlike Cluster 0, which is experiencing stagnation, Cluster 2 demonstrates success in converting market experience and accumulated capabilities into tangible organizational growth. They have successfully achieved vertical mobility from micro to small or medium scale. Operational stability and a moderate but consistent business scale make this segment function as vital economic anchors in sustainable regional employment.

4. CONCLUSION

This study successfully applied the K-Means algorithm to 8,804 valid MSME data in Semarang City to test the new LSE (Longevity, Scale, Employment) framework. Based on the Elbow Method analysis, three optimal clusters were found that represent significantly different SME behavior typologies within the studied dataset, namely businesses with high longevity but stagnant scale (subsistence), young businesses with accelerated growth (gazelles), and established businesses that have successfully scaled up. Additionally, empirical evidence from cohort analysis revealed the phenomenon of scale stagnation within this sample, where the majority of MSMEs remain stuck at the micro scale regardless of their business age, This findings suggest that in the specific context of Semarang City, operational duration does not automatically correlate linearly with business scale growth.

In summary, these findings address the primary research objective of deconstructing MSME heterogeneity within the scope of the analyzed data, which is often overlooked by conventional administrative policy approaches. The formation of clear spatial demarcations between clusters in the three-dimensional LSE space validates the hypothesis that MSMEs in this study are not monolithic entities, but rather have diverse life cycle dynamics. The LSE framework has proven to be effective as a behavior-based segmentation tool, where the Longevity variable successfully serves as a proxy for resilience, Scale as an indicator of maturity, and Employment as a measure of socio-economic impact.

The implications of these research findings contribute theoretically by filling a research gap through the adaptation of customer segmentation principles (RFM) to the business unit context. Practically, the resulting typology provides crucial insights for stakeholders to abandon a one-size-fits-all approach and explore targeted intervention design; for example, differentiating support for businesses that are merely surviving from those with aggressive growth ambitions could make local resource allocation more efficient and relevant.

Nevertheless, these findings must be interpreted within the boundaries of the study's limitations, including its use of snapshot secondary data from one administrative region of Semarang City and the application of a filter to business data prior to 1980. Therefore, further research is recommended to expand the geographical coverage to test the external validity of the LSE model on a broader scale, as well as to integrate additional dynamic variables such as financial transaction data or technology adoption to enrich the profiles of the segments formed.

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