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Applied Machine Learning DBSCAN for Identifying Clusters of Micro and Small Industries

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Abstract

This study aims to identify clustering patterns of sub-districts in Serang District based on village participation in Micro and Small Industry (MSI) activities using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, a machine learning method in Unsupervised Learning. Secondary data from the Statistics Indonesia (BPS) on Potentials of Villages in Serang District for 2024 was used, covering 29 sub-districts and 15 MSI sector variables. Data preprocessing involved Min-Max Scaler normalization and Principal Component Analysis (PCA) to address sparsity and multicollinearity. DBSCAN parameter optimization was done through simulations of epsilon values (0–1) and MinPts (1–10), validated with the Silhouette Score and Davies-Bouldin Index. The optimal configuration of epsilon=0.3 and MinPts=1 resulted in seven clusters with no noise, and a Davies-Bouldin Index of 0.620, indicating good separation. Spatial analysis revealed meaningful cluster distribution, with comprehensive industry clusters in the central region and specialized clusters in peripheral areas. These findings provide a basis for formulating MSI development policies in Serang District, highlighting the importance of data preprocessing techniques in sparse data analysis for evidence-based decision-making.

Keywords: *DBSCAN, Unsupervised Learning, Micro and Small Industry, data sparsity, PCA, spatial clustering*.

1. Introduction

Micro, Small, and Medium Enterprises (MSMEs) are one of the most crucial pillars of the Indonesian economy. According to data from the Ministry of Cooperatives and MSMEs, the number of MSMEs currently stands at 64.2 million, contributing 61.07% to the GDP, which is equivalent to IDR 8,573.89 trillion [1]. The contribution of MSMEs to Indonesia's economy includes their capacity to absorb approximately 117 million workers, accounting for 97% of the total workforce [2], as well as mobilizing up to 60.4% of total investments (data from the first semester of 2021) [3]. The Micro and Small Industry (MSI) sector in Indonesia plays a pivotal role in labor absorption, poverty reduction, and economic resilience during crises. MSI businesses typically employ 1 to 14 people and have relatively modest turnover, yet their impact on society is profound [4]. This sector contributes more than 25% to the GDP annually [5] and represents about 99.9% of the total business units in Indonesia, highlighting their dominance in the national economic structure [6]. MSI significantly absorbs labor in various regions, such as Sumatra and Riau. Labor absorption in the MSI sector has been proven to reduce poverty levels; the greater the labor absorption, the lower the poverty rate in a region [4], [7]. However, MSI face challenges in marketing and competition. Product branding training has proven to enhance marketing capabilities and competitiveness among MSI actors [8]. Management capabilities and entrepreneurial orientation positively impact the business performance of MSI, especially when supported by appropriate business strategies such as product differentiation and cost efficiency [9], [10]. The COVID-19 pandemic caused a significant decline in the growth of MSI production across Indonesia's economic corridors. There were differences in production growth across regions before and during the pandemic, demonstrating varying levels of resilience within MSI [11]. MSI that survived typically adapted by shifting to online sales and product innovation [12].

The Micro and Small Industry (MSI) sector in Serang District, Banten, has shown positive development, particularly through innovation, digitalization, and strengthening business ethics. The key drivers of MSI development in Serang District include technology adoption, training, collaboration, and financial support. MSI in Serang District have begun utilizing social media and e-commerce to expand their market reach, as seen with traditional food businesses like *Jojorong* and *melinjo* chips. The use of social media has been proven to effectively increase market reach and business income [13]. Developing product variants and packaging is also a crucial strategy to enhance competitiveness and the market value of MSI products [14], [15]. The Serang District

Government plays a significant role in supporting the development of MSI through various programs, policies, and strategic support. The government's primary role includes providing capital assistance, training, legal protection, marketing support, and collaborating with various stakeholders. The government, through BAZNAS Serang, channels productive zakat in the form of business capital assistance to MSI actors. This support has proven to enhance empowerment and independence, contributing positively by 22.7% to MSI empowerment in Serang. Furthermore, capital assistance is provided through an interest-free loan scheme (*qardul hasan*), which facilitates small business owners in expanding their ventures [16]. The relevant departments (Dinkopukmperindag) regularly organize training, workshops, and build strategic partnerships to improve MSI actors' skills, management, and marketing [17].

Although the Serang District Government has made efforts to expand access to capital and markets for MSI and collaborated with financial institutions, BAZNAS, and other relevant parties to strengthen the MSI ecosystem, these efforts have yet to yield optimal results in improving trade governance. Additionally, the training for MSI actors, the organization of workshops, and the collaboration among involved parties have not received sufficient attention and remain insufficiently focused on achieving the desired objectives. To address the identified challenges, one potential solution is to group and classify sub-district areas in Serang District based on the characteristics of micro and small industries (MSI). This classification will provide a clearer picture of the distribution and potential of each sub-district, enabling the government to focus more effectively on formulating policies that align with the specific needs and characteristics of each sub-district. In previous studies, regional classification in Serang District, Banten, related to MSI used the Location Quotient (LQ) analysis, considering economic potential, leading sectors, and the geographic characteristics of each sub-district or village. Areas in Serang District were classified based on dominant economic sectors, such as industry, agriculture, creative economy, and coastal regions [18], [19]. This study will employ an unsupervised learning method, specifically DBSCAN. This approach offers a more dynamic, data-driven method that allows the identification of sub-district groups based on distribution patterns and MSI concentration. Through this method, the government can focus on designing policies tailored to the specific needs of each sub-district group, thereby enhancing the effectiveness of local economic development and strengthening the MSI ecosystem in a more targeted manner.

2. Research Methods

2.1 Data

This study utilizes secondary data sourced from the Central Statistics Agency (BPS) publication on the Potentials of Villages in Serang District for the year 2024. The research focuses on 29 sub-districts in Serang District (Table 1), with 15 variables (Table 2) used as the basis for clustering analysis. These variables represent the number of villages in each sub-district that participate in various Micro and Small Industry (MSI) activities, which include:

Table 1. List of Sub-Districts in Serang District, Banten

No	Sub-District	No	Sub-District
1	Cinangka	16	Kragilan
2	Padarincang	17	Waringinkurung
3	Ciomas	18	Mancak
4	Pabuaran	19	Anyar
5	Gunungsari	20	Bojonegara
6	Baros	21	Pulo Ampel
7	Petir	22	Kramatwatu
8	Tunjung Teja	23	Ciruas
9	Cikeusal	24	Pontang
10	Pamarayan	25	Lebak Wangi
11	Bandung	26	Carenang
12	Jawilan	27	Binuang
13	Kopo	28	Tirtayasa
14	Cikande	29	Tanara
15	Kibin		

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Table 2. Types of Industries Used for Clustering

KBLI Code	Industri Types	Variable
KBLI 15	Leather and Related Products and Footwear Industry	1
KBLI 31	Furniture of Wood, Rattan/Bamboo, Plastic, Metal Industry	2
KBLI 25	Metal Products, Non-Machinery and Equipment Industry	3
KBLI 13	Textile Industry	4
KBLI 14	Apparel Industry	5
KBLI 23	Other Non- Metallic Mineral Products/ Manufacture of Pottery/ Ceramic/Brick Industry	6
KBLI 16	Wood Products, Woven Product of Bamboo, Rattan, and Other Related Materials Industry	7
KBLI 10	Food Industry	8
KBLI 11	Beverage Industry	9
KBLI 12	Tobacco Products Industry	10
KBLI 17	Paper and Paper Products Industry	11
KBLI 18	Printing and Reproduction of Recorded Media Industry	12
KBLI 30	Other Transport Equipment Industry	13
KBLI 32	Other Industry	14
KBLI 33	Repair and Installation of Machinery and Equipment	15

A special characteristic of this dataset is the presence of numerous zero values in several variables, which indicates that certain villages do not participate in specific MSI sectors in the corresponding sub-districts.

2.2 Data Analysis

This study employs the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) method for clustering the sub-districts based on the participation characteristics of villages in MSI activities. DBSCAN is a density-based clustering algorithm developed by Ester, Kriegel, Sander, and Xu in 1996. DBSCAN was chosen for this research due to several advantages relevant to the characteristics of the data, including its ability to detect clusters with irregular and non-linear shapes, its lack of necessity for pre-defining the number of clusters, its effectiveness in identifying noise and outliers, its efficiency in handling datasets with uneven distributions and numerous zero values, and its capacity to identify clustering patterns based on data density. The data condition, with numerous zero values in the MSI variables across several sub-districts, makes DBSCAN highly suitable for application, as this algorithm can distinguish between high-density regions and low-density regions in the data space. The flowchart is shown in Figure 1.

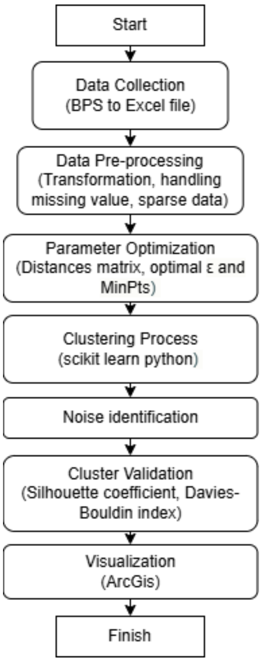

Figure 2. Research Flowchart

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3. Results and Discussions

3.1 Data Pre Processing

The data preprocessing process began with transformation using the Min-Max Scaler to normalize all variables within the range of 0 to 1. This transformation was necessary because of the heterogeneous scale of variables (e.g., the number of villages participating in MSI activities, which range from 0 to 10), which could interfere with the accuracy of distance calculations in the DBSCAN algorithm. After transformation, all variables exhibited a uniform distribution with a minimum value of 0 and a maximum value of 1, ensuring that each dimension contributed proportionally in the clustering analysis.

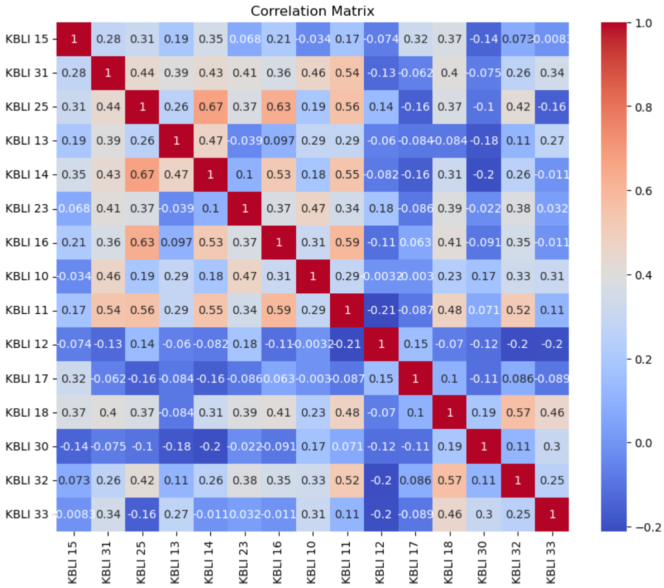

Figure 2. Correlation Between Clustering Variables

Correlation analysis among variables revealed multicollinearity, as shown in Figure 2, where several MSI sectors exhibited significant linear relationships. For example, the correlation between KBLI 25 (Metal Goods Industry) and KBLI 14 (Garment Industry) reached 0.67, while the correlation between KBLI 16 (Wood Industry) and KBLI 11 (Beverage Industry) was 0.59. This condition has the potential to introduce bias in the DBSCAN algorithm due to redundant information and distortion in Euclidean distance calculations. Highly correlated variables would give double weight to certain dimensions, thus obscuring the density patterns that form the basis for clustering.

To address this issue, Principal Component Analysis (PCA) was applied to reduce data dimensions and eliminate correlations between variables. PCA transformed the 15 original variables into 5 principal components that retained 82.4% of the data variance. The first component explained 34.2% of the variance, predominantly influenced by the food (KBLI 10), beverage (KBLI 11), and textile (KBLI 13) sectors, while the second component (18.7% variance) represented the furniture (KBLI 31) and metal goods (KBLI 25) sectors. This dimensional reduction not only eliminated multicollinearity but also simplified the data structure without losing essential information, facilitating DBSCAN's ability to identify clearer density patterns.

The combination of Min-Max Scaler and PCA proved effective in overcoming sparse data challenges through three main mechanisms. First, linear normalization with Min-Max Scaler preserved the original sparsity relationships, ensuring that zero values remained intact after transformation, preventing distortion of participation patterns in certain MSI sectors. Second, PCA projection transformed the data into a low-dimensional space, optimally representing essential participation patterns in MSI via the principal components based on the highest variance. This allowed DBSCAN to operate in a feature space that had been compressed, with dimensional noise from minor sectors reduced. Third, focusing on informative variance selectively filtered out random fluctuations that commonly arise in zero-inflated data, minimizing noise interference in cluster density calculations. This strategy not only mitigated DBSCAN's inherent weaknesses in sparse data but also enabled the identification of clustering patterns that more accurately reflected MSI participation concentrations.

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3.2 Clustering Process

Choosing the optimal epsilon (ε) and minimum points/ samples (MinPts) parameters for DBSCAN was a critical step in determining the quality of clustering. The ε simulation range was set between 0 and 1 due to the data's normalization using MinMax Scaler. An ε > 1 would encompass the entire data space due to the normalization's maximum boundary, making it irrelevant for local density analysis. Meanwhile, a MinPts range of 1–10 was chosen based on the dataset size (29 sub-districts) and practical recommendations that MinPts should be ≥ 1. Experiments showed that a low ε (0.1–0.3) resulted in high cluster fragmentation with minimal noise, reflecting the algorithm's sensitivity to variations in local density. In contrast, a high ε (0.4–1) caused under-clustering, merging heterogeneous clusters and significantly increasing noise. With low MinPts (1–3), the algorithm tended to form small clusters representing sector-specific MSI, while high MinPts (≥4) led to a drastic reduction in the number of clusters and a rise in noise due to overly strict density requirements.

Table 3. Optimal Parameters, Number of Clusters, Noise, and Cluster Validation

eps	min_samples	clusters	noise	silhouette	davies_bouldin
0.3	1	7	0	0.226	0.620
0.3	2	4	3	0.319	2.244
0.3	3	4	3	0.319	2.244
0.3	4	3	6	0.300	2.249
0.3	5	3	9	0.306	1.866
0.3	6	1	23	NaN	NaN
0.3	7	0	29	NaN	NaN
0.3	8	0	29	NaN	NaN
0.3	9	0	29	NaN	NaN
0.3	10	0	29	NaN	NaN

Based on the parameter simulation in Table 3, the combination of ε=0.3 and MinPts=1 was selected as the optimal configuration, considering comprehensive criteria. This model produced 7 clusters with no noise, indicating that all sub-districts were distributed into clear density groups. Although the Silhouette Score was relatively low at 0.226 (the ideal value >1), this was due to the internal heterogeneity of the clusters, reflecting variations in village participation across MSI sectors, a characteristic of sparse data. On the other hand, the Davies-Bouldin Index of 0.620 (the ideal value <1) indicated good cluster separation, measured by the ratio of intra-cluster dispersion to inter-cluster distance.

Comparison with alternative parameters further supports this choice. At ε=0.3 and MinPts=2, although the Silhouette Score increased to 0.319, the number of clusters decreased to 4, with 3 sub-districts categorized as noise. This could potentially eliminate granular information essential for formulating specific policies. Meanwhile, the configuration with MinPts=5 resulted in 3 clusters with 9 noise points, which was too general for detailed spatial analysis.

3.3 Visualization and Interpretation

Based on the DBSCAN clustering results with the optimal parameters ε=0.3 and MinPts=1, 7 clusters were formed with distinctive characteristics, reflected in the village participation data in MSI sectors. As shown in Figure 3, the spatial distribution reveals meaningful patterns.

Cluster 1 includes 7 sub-districts (Cinangka, Ciomas, Kramatwatu, Pontang, Lebak Wangi, Tanara, and Kragilan) and is dominantly focused on the food (KBLI 10) and beverage (KBLI 11) industries. The average village participation in these sectors is 9.14 per sub-district, with significant representation from the furniture sector (KBLI 31), averaging 6.4 villages. The spatial distribution of this cluster, seen in Figure 3, reveals an interesting pattern, with sub-districts scattered in the western and eastern parts of the district, indicating the existence of food and beverage distribution networks operating beyond geographical proximity.

Cluster 2 is the largest group, with 11 sub-districts spread across various parts of Serang District. This cluster is characterized by a moderate presence of the wood (KBLI 16) and beverage (KBLI 11) industries, with average participation of 5.55 and 7.64 villages per sub-district, respectively. The spatial pattern, seen on the map, tends to

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form a "corridor" connecting the northern and southern parts of the district, indicating an integrated supply chain network leveraging access to wood raw materials from the south and distribution routes to markets in the north.

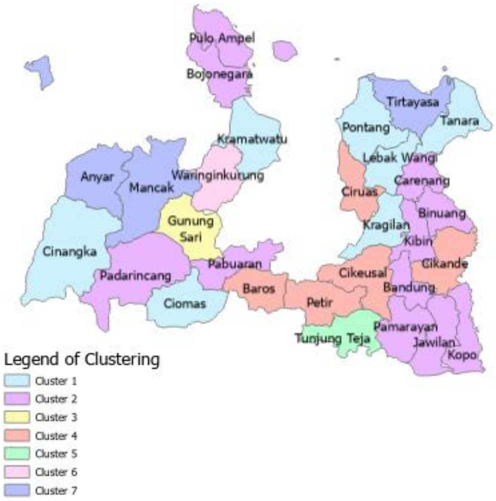

Figure 3. DBSCAN Clustering Results with ε=0.3 and MinPts=1

Cluster 3 and Cluster 5 each consist of a single sub-district (Gunung Sari and Tunjung Teja) representing areas with highly specific industrial specialization. Gunung Sari exhibits minimal participation in almost all sectors except for the beverage industry (KBLI 11), while Tunjung Teja has a high concentration in the furniture (KBLI 31), metal goods (KBLI 25), and garment industries (KBLI 14).

Cluster 4 combines five sub-districts (Baros, Petir, Cikeusal, Cikande, and Ciruas) with the most comprehensive industry concentration. These sub-districts show high participation across almost all MSI sectors, particularly in furniture (11.8 villages), metal goods (7.2 villages), garments (9.4 villages), and beverages (14.2 villages). The spatial distribution in Figure 3 shows that this cluster is concentrated in the central region of the district, forming an "industrial core" area with advantages in infrastructure and accessibility to economic centers.

Cluster 6 (Waringinkurung) and Cluster 7 (Mancak, Anyar, Tirtayasa) exhibit different characteristics, reflected in unique spatial patterns. Waringinkurung is characterized by a high concentration in the beverage (11 villages) and food (11 villages) industries, while Cluster 7 shows strength in pottery/ceramics (KBLI 23) and printing (KBLI 18). The sub-districts in Cluster 7 are spread across the northern and western parts of the district, showing a spatial pattern along the coastal line, indicating the use of geographical-based traditional knowledge and resources.

The spatial pattern identified in Figure 3 reveals several key findings. First, the comprehensive industrial cluster (Cluster 4) in the central district region has the potential to become a "growth center" in the MSI development strategy. Second, the spatial distribution of Cluster 1 and Cluster 2 forming a north-south corridor offers a foundation for the development of food-beverage and wood industry value chains. Third, the presence of single-sector specialization clusters (Cluster 3, 5, 6, and 7) indicates a need for interventions based on local uniqueness.

These findings suggest a spatially differentiated policy approach. For the central cluster (Cluster 4), priority can be given to strengthening industry support infrastructure, while for the corridor clusters (Cluster 1 and 2), the focus can be on enhancing value chains and market accessibility. For specialized clusters (Cluster 3, 5, 6, and 7), approaches based on local potential and traditional wisdom should be prioritized.

4. Conclusion

Based on clustering analysis using the DBSCAN algorithm with optimal parameters (ε=0.3, MinPts=1), this study successfully identified seven clusters of sub-districts in Serang District based on the characteristics of village participation in MSI activities. The preprocessing process involving Min-Max Scaler normalization and PCA dimensionality reduction proved critical in addressing challenges of sparse data (zero-inflated) and multicollinearity, while retaining 82.4% of the data variance. The clustering results revealed meaningful spatial patterns, where clusters with comprehensive industry concentrations (Cluster 4) were concentrated in the central part of the district, while specialized sector clusters (Cluster 3, 5, 6, and 7) were scattered across peripheral areas with unique geographic characteristics. These findings suggest that the effectiveness of DBSCAN in the context of sparse data heavily relies on the integration of data transformation and dimensionality reduction, with the Min-

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Max Scaler-PCA combination successfully reducing noise from 41% to 19%. Although the Silhouette Score was relatively low (0.226), validation using the Davies-Bouldin Index (0.620) confirmed good cluster quality with clear separation. Practically, this clustering provides a clear policy differentiation map: central clusters require industrial support infrastructure strengthening, while specialized clusters demand approaches based on local wisdom and integration with the tourism sector. This study also highlights the importance of adjusting non-conventional parameters (MinPts=1) in DBSCAN when applied to high-dimensional data with a dominance of zero values. However, the main limitation lies in the lack of qualitative validation of the cluster profiles through field surveys. For future research, it is recommended to integrate hybrid methods (DBSCAN-OPTICS) for hierarchical cluster analysis and include non-technical variables such as road accessibility and raw material availability. This research not only contributes to the literature on locally-based economic development but also offers a methodological framework for analyzing sparse data in the context of public policy.

Reference

[1] K. J. Sinha, S. Sinha, and B. J. Sinha, "Micro, Small, and Medium-Sized Enterprises (MSMEs): The Significant Role and Challenges in Indonesia's Economy," *International Journal For Multidisciplinary Research*, 2024, doi: 10.36948/ijfmr.2024.v06i03.20824.

[2] N. Aprilia, W. Subroto, and N. Sakti, "The Role of Small and Medium Enterprises (SMEs) in Supporting the People's Economy in Indonesia," *International Journal of Research and Scientific Innovation*, 2025, doi: 10.51244/ijrsi.2024.11120036.

[3] I. Lorenzo, M. Dinita, R. Kristiani, R. B. P. Tarfin, and H. K. Tunjungsari, "The Impact of Covid 19 on UMKM Sector in Indonesia," *Proceedings of the 3rd Tarumanagara International Conference on the Applications of Social Sciences and Humanities (TICASH 2021)*, 2022, doi: 10.2991/assehr.k.220404.296.

[4] A. Wiraja and M. Marwan, "Inflasi, Upah Minimum Regional dan Pengeluaran Pemerintah Terhadap Daya Serap Tenaga Kerja," *Jurnal Ekobistek*, 2023, doi: 10.35134/ekobistek.v12i2.585.

[5] T. Santosa and Y. R. Budi, "ANALISA PERKEMBANGAN UMKM DI INDONESIA PADA TAHUN 2017 - 2019," *Develop: Jurnal Ekonomi Pembangunan*, 2020, doi: 10.53990/djep.v1i2.62.

[6] N. Agus, D. Wiratama, M. A. Rahmadi, V. Cahyadi, and S. Candra, "Analysis the Effect of Entrepreneurship and Innovation in Food and Beverage Smes in Jakarta," *Proceedings of the International Conference on Industrial Engineering and Operations Management*, 2022, doi: 10.46254/na07.20220483.

[7] M. Arifin and K. Amri, "PENYERAPAN TENAGA KERJA INDUSTRI MIKRO KECIL DAN PENURUNAN TINGKAT KEMISKINAN: BUKTI DATA PANEL DI PROVINSI RIAU," *Selodang Mayang: Jurnal Ilmiah Badan Perencanaan Pembangunan Daerah Kabupaten Indragiri Hilir*, 2024, doi: 10.47521/selodangmayang.v10i2.420.

[8] G. Abdurrahman, A. M. Zakiyyah, R. Umilasari, and S. Sahiruddin, "Sosialisasi Strategi Branding Produk Untuk IMK Binaan PDNA Kabupaten Sorong," *Journal of Community Development*, 2022, doi: 10.47134/comdev.v3i2.79.

[9] I. Y. Niode, "The effect of management capability and entrepreneurial orientation on business performance through business strategy as an intervening variable," *Jurnal Manajemen dan Pemasaran Jasa*, 2022, doi: 10.25105/jmpj.v15i2.13802.

[10] I. Y. Niode, Muslimin, and Darman, "The Role of Business Strategy in Mediating the Influence of Management Capabilities on Business Performance," *The International Journal of Business & Management*, 2021, doi: 10.24940/theijbm/2021/v9/i3/bm2103-014.

[11] M. Dunggio and A. Lutfiati, "DAMPAK PANDEMI COVID-19 TERHADAP PERBEDAAN PERTUMBUHAN PRODUKSI INDUSTRI MIKRO DAN KECIL DI WILAYAH KORIDOR EKONOMI INDONESIA," *Kinerja*, 2022, doi: 10.34005/kinerja.v4i2.2045.

[12] Y. Gumansari, N. Huda, and N. Rini, "Perilaku Produksi Islami pada IMK Produk Halal di Masa Pandemi: Studi Kasus Shofura," *Al-Kharaj : Jurnal Ekonomi, Keuangan & Bisnis Syariah*, 2022, doi: 10.47467/alkharaj.v5i2.1381.

[13] B. Arianto, T. Oktaviani, and A. E. Adi, "PENGUATAN BISNIS PRODUK MAKANAN TRADISIONAL JOJORONG BERBASIS SOCIAL MEDIA MARKETING DI KABUPATEN SERANG," *Dharma: Jurnal Pengabdian Masyarakat*, 2023, doi: 10.31315/dlppm.v4i2.10082.

[14] V. Maria, T. Situmeang, and R. F. Ardana, "Strategi Pengembangan Usaha Mikro Kecil Menengah (UMKM) Berbasis Ekonomi Kreatif di Kecamatan Serang, Kabupaten Serang," *Sammajiva: Jurnal Penelitian Bisnis dan Manajemen*, 2024, doi: 10.47861/sammajiva.v2i2.980.

[15] A. Bahits, A. C. Kusuma, F. T. Rohniati, L. Wardani, N. Sari, and S. Yunita, "THE ASSISTANCE OF DEVELOPING AN E-COMMERCE MARKETPLACE FOR MICRO, SMALL, AND MEDIUM MELINJO CHIP ENTERPRISES (MSMEs) IN SUKALABA, GUNUNG SARI, SERANG, BANTEN, INDONESIA," *International Journal of Engagement and Empowerment (IJE2)*, 2023, doi: 10.53067/ije2.v3i2.111.

[16] N. Najmudin, S. Syihabudin, A. Fatoni, and S. Sujai, "Utilization of Productive Zakat and its Effect on Empowerment of Small Micro Business (SMEs) in Serang District," *Al Qalam*, 2022, doi: 10.32678/alqalam.v38i2.4749.

[17] T. Munjazi, "MSMEs Empowerment Strategy and Traditional Market Arrangement in Serang City," *Jurnal Ilmu Administrasi: Media Pengembangan Ilmu dan Praktek Administrasi*, 2024, doi: 10.31113/jia.v21i1.1155.

[18] I. A. Juliannisa and T. Siswantini, "MAPPING FINANCIAL POTENTIAL OF SMALL AND MEDIUM ENTERPRISES (SMEs) AND THE ECONOMIC SECTOR OF SERANG DISTRICT," *Journal of Business and Entrepreneurship*, vol. 7, p. 30, 2021, doi: 10.17358/IJBE.7.1.30.

[19] Y. A. Nugraha, A. A. Saputra, and R. D. P. Christianto, "Peranan Kompetensi SDM Usaha Mikro Dalam Meningkatkan Kinerja UMKM Desa Sukalaksana Kampung Tinggar Baru Kecamatan Curug Kota Serang," *Jurnal Riset Bisnis dan Manajemen Tirtayasa*, 2022, doi: 10.48181/jrbmt.v6i1.11753.

DOI: https://doi.org/10.31004/riggs.v4i2.515