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# Mitigating Indonesia's Financial Market Risk: A Cluster-Based Approach to Payment System Infrastructure

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ABSTRACT

An analysis of Indonesia's payment systems and financial market infrastructure (FMI) reveals a landscape in the midst of a fundamental shift toward digitalization. The study defines the regional disparities in this transformation and their respective risks. We clustered provinces using Euclidean distance and average linkage. The highest quality analysis resulted in a 3-cluster solution, with clusters reflecting low, moderate, and high risk profiles. Our findings indicate that the high-risk cluster (DKI Jakarta) is characterized by a concentration of financial activity to level up the systemic risk and cyber threat. Meanwhile, the moderate-risk cluster, which includes provinces such as West and Central Java, has a relatively high level of digital adoption but is not as extreme compared to the concentration in the first cluster. Last but not least, the large-volume, low-risk cluster with little transactions high level of digitalisation. This cluster is also the most exposed to economic marginalization, but sees less cyber risks than all of the other groups. Based on these results, the study argues that gaining a deeper knowledge of these distinct cluster-specific risk profiles is imperative in tailoring bespoke targeted risk mitigation strategies which can ultimately help steer Indonesia's financial ecosystem towards greater stability and inclusivity for all its citizens alike.

## INTRODUCTION

Indonesia's economy is currently being reshaped by a massive wave. There has been a fundamental shift in the payments and financial market infrastructure landscape. In a great wave of digitalization, we are watching the electrification of virtually everything and traditional cash is losing its mighty dominion. This paves the way for democratic digital payment in Indonesia, not only in malls and hypermarket but also small shops, including street vendors. On the backend, Bank Indonesia is continuing to upgrade its infrastructure in opening BI-FAST (Indonesian National FAST Retail Payment System) which is a cross platform real-time, secure and efficient payment system made available for retail businesses 24/7 developed by the central bank. This system allows the transfer of funds to process much quicker and with a high level of cost-effectiveness. But all those facts of success hide another: inequality. Not everyone in the country has had a chance to partake in the acceleration of digitization. A few provinces have leapfrogged into the lead with digital adoption and developed infrastructure, whereas many other states are still stuck in low/ no access and lower level of literacy on this front. This variance builds different risk profiles. In the digital sphere, there could be a high level of cyber risks in one jurisdiction due to vast scale-digital transactions whereas another state/territory could face exclusion from formal financial economy on account of very low access to modern services.

In line with the digital transition and tokenization (Kurniasari et al., 2023). By narrowly focusing on technology, attention is often diverted from the financial accessibility and inclusion implications of digital models as well as doubts about the efficacy of digital innovations over existing infrastructure (Falaiye et al., 2024; Ababio et al., 2023). The current research has also failed to look in depth into challenges that hinder Small and Medium-sized Enterprises (SMEs) from securing finance, which are lack of financial Know-how or market links (Huong & Anh, 2024; Gbatu, 2022). One big gap is understanding how to coordinate traditional institutions and digital services to increase financial inclusion without sacrificing stability (Ababio et al., 2023). A focus on understanding the geopolitical and social drivers, incentives, and levers that impact payment system development as well as how to measure effectiveness of public-private partnerships and their economic sustanability (Anguelov, 2024; Langenohl, 2024; Hall et al., 2023). All these gaps point towards a further research required to make sure Financial Innovation is not just being technologically superior but also inclusive and stable and complimentary to prevailing social economic order.

However, a fundamental understanding is lacking in the area of payment system and financial market infrastructure (FMI) research, specifically on their role in different segments. Given the fact that prolonged studies on how financial infrastructure affects the expansion and stability of Small- and Medium-sized Enterprises (SMEs) are limited, it is imperative to investigate this phenomenon in a more urgent manner (Huong & Anh, 2024). Moreover, studies on green finance are very few that could support developing efficient solutions for financing sustainable projects (Desalegn & Tangl, 2022). The pandemic has also magnified the importance of broadening knowledge around public-private partnerships (PPPs) related to risk management and infrastructure resilience (Casady & Baxter, 2020). In addition, we must pay attention to the impact of fintech integration on financial inclusion and resilience in marginalized communities (Kurniasari et al., 2023). Future research should consider the influence of strong risk management systems on the performance of different financial structures (Akomea-Frimpong et al., 2023). The last knowledge gap, which is identified in the dynamics of cloud-based accounting and big data tools can improve risk management inside existing infrastructure (Zou, 2023). It is expected that bridging these gaps will offer important insights for dealing with the challenges and opportunities in the contemporary financial ecosystem.

The study of payment systems and financial market infrastructure (FMI) goes far beyond conventional monetary economics in an effort to fathom the contradictions that exist between transactions, technology and regulation. As digital payment systems in Indonesia are rapidly evolving, cluster analysis presents a felicitous approach to explore the numerous dimensions of digital transactions on the provincial scale. In theory, doing so can help establish where the user preferences and adoption behaviors in each province lie which we claimed would be enabling to customize digital adoption strategies (Poudel et al., 2023). In empirical terms, cluster analysis allows them to show the relationship between risk factors in different regions and how this correlates with payment system structure on which their research results are based (Трусова et al., 2021). Its deployment also holds substantial policy implications, helping policymakers understand how technologies like QRIS can be effective in fighting fraud and advancing financial inclusion across various demographic groups (Panya & Abuya, 2022). In addition, cluster analysis can also be a novel approach to study regional heterogeneities of cyber secure problems (Hassan et al., 2020), as well as customer behavioral pattern among electronic payment services (Armah et al., 2023). Through this multi-dimensional approach, we hope to address the scattered landscape in Indonesia and accelerate innovation towards a more inclusive and robust payment ecosystem which will evolve across all provinces.

Some important gaps emerge from a cluster analysis of different payment systems and financial market infrastructure (FMI) that exist with respect to user behaviour between distinct payment platforms. The literature continues to attempt to make sense of technology an opportunity structure, but this understanding is largely limited in terms of how users are able to cluster based on their tastes and location (Lai & Samers, 2020). Research on the use of cluster analysis in determining the factors that define success or failure for payment technologies and how they resist threats like competition and cyber risk are also lacking (Błach & Klimontowicz, 2021). Cluster analysis can also help to identify the challenges faced by under-served clusters of communities in access to financial infrastructure which may or may not promote financial inclusion (Jóia & Cordeiro, 2021). Further, the extant literature has a somewhat limited focus on international financial collaboration effects on infrastructure at the local level (Petry, 2020), and how changing regulations are affecting different stakeholder groups (Putrevu & Mertzanis, 2023) as well. Finally, further research can explore the innovation of new technologies such as blockchain (Karki et al., 2023) and its socioeconomic implications when it comes to payment systems´ functionality clusters (Bublyk et al., 2023). Cluster analysis can therefore be useful in identifying these gaps and driving innovation or equitability within the financial ecosystem.

The cluster analysis enables us to identify and group the provinces into number of payment system an financial infrastructure categories. A seemingly straightforward yet absolutely critical aim: to develop risk mitigation tactics which are no longer universalised. Instead, these can be adaptive and on-target to the specific circumstances in every area. This research can be beneficial in manifesting a clear path towards a firmer, safer and more inclusive financial ecosystem for all Indonesians.

## LITERATURE REVIEW

### Concept and Workflow Cluster Analysis

Cluster analysis is a type of multivariate technique used to classify objects into different groups in which each group has similar characteristics. In general, the closer objects in a group are to one another, while at the same time being farther from those in other groups, the more powerful and independent that group can be. Most characters in the same group share many similar features, while different groups are characterised by totally divergent type of characteristics. Cluster analysis follows the steps: (1) Data Standardization; (2) Determining Similarity Measures; (3) Choosing Clustering Procedures; (4) Determining the Number of Clusters, and (5) Interpreting Cluster Results Chapter Retrieved from (Simamora & Bagus Sumargo, 2019).

The central one is the distance and similarity when it comes to cluster analysis. Distance measures how different objects are while similarity quantifies the proximity between them. Similarity is crucial in the sense that cluster analysis bases its grouping on the proximity principle. Quantitative data can be measured using a distance measure whereas matching-type measures (similarity indices) are more appropriate for qualitative data. In practice, distance calculations frequently employ the Euclidean distance, which was devised for two-dimensional observations.

Several studies have found that Euclidean distance is often the most effective method for measuring similarity. For instance, (Mohibullah et al., 2015) found it to be particularly strong for smaller datasets. Similarly, Nishom (2019) concluded that Euclidean distance is more accurate than both Manhattan and Minkowski distances. Furthermore, Sinwar & Kaushik (2014) showed that Euclidean distance is also more efficient in terms of the number of iterations required to complete the clustering process.

Hierarchical clustering begins by grouping the two most similar objects. The process then iteratively merges the next closest objects or groups until all objects have been combined into a single hierarchical tree. This tree, known as a dendrogram, visually represents the relationships between all objects, from the most similar to the most distinct. Johnson (1967) describes this process in three main steps: Cluster Initialization, Cluster Merging, and Recalculating Distances.

### Hierarchical Cluster Analysis

In the case of Hierarchical Clustering, it is a clustering technique which creates a tree data structure based on the distance between each pair. This approach is done by two major ways namely agglomerative (bottom-up) or divisive (top-down) methods (Nafisah & Chandra, 2017).

a. Agglomerative Method

The agglomerative method starts with each object as a separate cluster. At first, each object is a cluster. The merging process starts with most similar objects and continues based on the similarity between clusters. As the degree of similarity decreases, all subgroups ultimately merge into one very large cluster. It is again divided into Single Linkage, Complete Linkage, Average Linkage, Ward's Method and Centroid Method.

b. Divisive Method

The divisive method operates inversely. For this, the objects are put together and mushed into one large cluster that contains everything as shown in the above diagram, then divide that large blobby cluster into two subgroups where none of objects from one subgroup is close to each other: This process of splitting carries on recursively until each object has been its group. We also apply the Cophenetic correlation coefficient, which is a very common method for testing whether the clusters in this study are efficient to be used. The cophenetic correlation coefficient computes the correlation between elements of the original dissimilarity distance matrix to ones generated by the dendrogram. The cophenetic correlation coefficient takes values between -1 and 1. A high value of r coph close to 1 indicates that the clustering process is valid (Saraçli et al., 2013).

A dendrogram is, in fact a graph representation of how the hierarchical cluster analysis created those clusters. It is a kind of tree diagram showing branching points in terms of clusters and branch lengths displaying the distance at which objects are combined. The dendrogram will be changed as you can use different distance metric or linkage method. This task is then to find the optimal cutting point in a dendrogram where the two resulting clusters are farthest apart. This is built upon theory from Dillon & Goldstein (1984), in which integrations clusters emerge at the outskirts of distance-to-merging space, defining a 'rubber band' zone.

### The Payment Systems and Financial Market Infrastructure Environment

Modern financial markets require efficient and reliable banking payment systems viz Real-Time Gross Settlement (RTGS), clearing systems, electronic payments. The RTGS system enables the real-time settlement of high-value transactions, thereby reducing the risk profile and improving financial stability (Трусова et al., 2021). Central banks can manage liquidity and effect the transmission of monetary policy through RTGS (Xiong & Badarch, 2023). At the same time clearing systems assist with offsetting of bank-to-bank credits and debits for high-volume transactions, helping to support RTGS in liquidity management (Chen, 2022). The advent of electronic payment systems, in the form of digital wallets and mobile payments has revolutionized banking transactions by providing speed and ease to customers (Al-Sabaawi et al., 2021). This trend intensified during the COVID-19 pandemic, as it spurred and accelerated digitalization of services which in turn prompted requests for more secure security concepts (Srouji & Torre, 2022). These are also payment systems, thus it is essential for orderly liquidity management in central banker-supervised payment systems that any payment failure poses a systemic threat (Triepels et al., 2020) so these payments must be managed with a broad societal perspective. As such, grasping the inherent relationship between these two systems is central to innovation and infallibility at work in the digital landscape.

Foundational to smooth, secure financial transactions are modern banking payment systems including ATMs, EDC devices, debit cards and credit cards. ATMs serve as important customer touchpoints that enable customers to execute banking services outside of a physical branch in addition to helping banks with efficient liquidity management (Chunytska, 2020). By empowering a merchant to accept non-cash payments securely and efficiently, EDC devices can help in relieving the difficulty of handling cash as well as enhancing the shopping and post-shop experiences. As explained by Onyshchenko (2021) they can give customers a secure way to directly pay from their accounts, while Guggenheim et al. (2022) mention that other people use credit cards to increase spending/revive economic fires by issuing a line of credit. These technologies interact together seamlessly to form a holistic financial ecosystem that enables banks to deliver personalized services and create new business models (Mikryukov & Serebrennikova, 2020). Yet problems with cyber threats and interoperability remain as difficulties. With the advent of digital currencies, there is a need for the existing frameworks to evolve continually (Shabsigh et al., 2020), with an increasing importance in understanding how these systems are interconnected in order to achieve innovation and satisfy evolving consumer needs.

Payment systems and financial market infrastructure (FMI) are associated with the study of cluster analysis which provides a guide on what pertains these systems work and how users behave. The analysis is done grouping entities by common attributes, which allows us to understand recurring patterns and enables in developing payment solutions for business requirement & improve operational efficiency. A primary use case is user segmentation by payment methods preference and behavior (Rabbani et al., 2024). Cluster analysis is also able to help measure the impact of socioeconomic on payment behavior, e.g., during COVID-19 period, in order for policymakers to understand how their payment systems have responded to emerging needs (Ngo et al., 2021). Also, this technique allows for an advanced analysis of usages and performance trends to enhance fraud detection which results in strong control over the system too (Faizi et al., 2024). Cluster analysis is also used for examining the technology adoption studies considering the perspectives of diverse stakeholders (Hwang et al., 2022) and identifying customer preferences across different markets (Armah et al., 2023). Basically, cluster analysis provides an all-encompassing ability to make sense of the complex payment landscape for innovation and more effective systems.

## RESEARCH METHODS

This research uses secondary data obtained from Bank Indonesia (BI), Indonesia's central bank, regarding a summary of the Indonesian Payment System and Financial Market Infrastructure Statistics by province for the 2024 period. The data was published by BI on January 20, 2025, via the Statistics menu on its website www.bi.go.id. The data comprises 14 variables, including the following:

**Table 1.** The Indonesian Payment System and Financial Market Infrastructure Statistics

| Variable | Variable Code | Unit |
|---|---|---|
| Regional Rupiah Deposit Transactions (Inflow) | $X_1$ | Billions of Rp |
| Number of ATM Debit Cards | $X_2$ | Millions of Unit |
| Number of ATM Cards + Debit Cards | $X_3$ | Millions of Unit |
| Debit Card Transaction Volume | $X_4$ | Millions of Transaction |
| Debit Card Transaction Value | $X_5$ | Billions of Rp |
| Number of Credit Cards/Instruments | $X_6$ | Millions of Unit |
| Credit Card Transaction Volume | $X_7$ | Millions of Transaction |
| Credit Card Transaction Value | $X_8$ | Billions of Rp |
| Number of Regional Payment Instrument Infrastructure Merchants and Electronic Money (EU) | $X_9$ | Unit |
| Number of EDC Machines Infrastructure Payment Instruments Using Cards and Electronic Money (EU) Regional | $X_{10}$ | Unit |
| RTGS Transaction Volume derived from | $X_{11}$ | Thousand Transaction |
| RTGS Transaction Value derived from | $X_{12}$ | Billions of Rp |
| Clearing Transaction Volume derived from | $X_{13}$ | Thousands of Transaction |
| Clearing Transaction Value derived from | $X_{14}$ | Billions of Rp |

Source: The processed secondary data (2025)

The financial data of The Indonesian Payment System and Financial Market Infrastructure Statistics was collected across 34 provinces in Indonesia are numbered as follows: Nangroe Aceh Darussalam (1), North Sumatra (2), West Sumatra (3), Riau (4), Riau Islands (5), Jambi (6), South Sumatra (7), Bengkulu (8), Lampung (9), Bangka Belitung Islands (10), DKI Jakarta (11), West Java (12), Central Java (13), DI Yogyakarta (14), East Java (15), Banten (16), Bali (17), West Nusa Tenggara (18), East Nusa Tenggara

(19), West Kalimantan (20), Central Kalimantan (21), South Kalimantan (22), East Kalimantan (23), North Kalimantan (24), North Sulawesi (25), Central Sulawesi (26), South Sulawesi (27), Southeast Sulawesi (28), West Sulawesi (29), Gorontalo (30), North Maluku (31), Maluku (32), Papua (33), and West Papua (34).

The research has used R software for the purposes of this Hierarchical Cluster Analysis. Data analysis includes the processing of the dataset, descriptive statistics for 9 variables, data standardization process to examine similarity measures (e.g., Euclidean distance) with clustering procedures (e.g., Single, Average, Complete, Centroid, and Ward's linkage method), and determine optima cluster number (e.g., dendrogram) to interpret the clustering results.

## RESULT AND DISCUSSION

Descriptive statistics in this study are used to provide an overview and summarize The Indonesian Payment System and Financial Market Infrastructure Statistics. The analyzed variables include Regional Rupiah Deposit Transactions (Inflow) ($X_1$), the number of ATM Debit Cards ($X_2$), and the number of ATM Cards + Debit Cards ($X_3$) are key variables. These are further detailed by Debit Card Transaction Volume ($X_4$) and Debit Card Transaction Value ($X_5$), as well as the Number of Credit Cards/Instruments ($X_6$), Credit Card Transaction Volume ($X_7$), and Credit Card Transaction Value ($X_8$). The infrastructure is measured by the Number of Regional Payment Instrument Infrastructure Merchants and Electronic Money (EU) ($X_9$) and the Number of EDC Machines Infrastructure Payment Instruments Using Cards and Electronic Money (EU) Regional ($X_{10}$). Finally, wholesale transactions are represented by the RTGS Transaction Volume ($X_{11}$) and Value ($X_{12}$), as well as the Clearing Transaction Volume ($X_{13}$) and Value ($X_{14}$). These descriptive statistics include measures such as mean, median, minimum, and maximum values for each variable, providing an initial understanding of the data distribution and characteristics.

**Table 2.** Descriptive Statistics

| Variable | Unit | Mean | Median | Minimum | Maximum |
|---|---|---|---|---|---|
| $X_1$ | Billions of Rp | 17.845 | 8.081,4 | 515,6 | 112.605,8 |
| $X_2$ | Millions of Unit | 0,1144 | 0,0227 | 0 | 0,6891 |
| $X_3$ | Millions of Unit | 9,304 | 4,639 | 0 | 53,778 |
| $X_4$ | Millions of Transaction | 197,25 | 86,64 | 0 | 1.155,61 |
| $X_5$ | Billions of Rp | 204.757 | 93.868 | 0 | 1.076.014 |
| $X_6$ | Millions of Unit | 0,5340 | 0,1143 | 0 | 5,9188 |
| $X_7$ | Millions of Transaction | 13,2751 | 1,2257 | 0 | 264,62 |
| $X_8$ | Billions of Rp | 12.500,2 | 1.245,7 | 0 | 245.520,8 |
| $X_9$ | Unit | 43.933 | 9.076 | 0 | 497.363 |
| $X_{10}$ | Unit | 64.033 | 14.629 | 0 | 715.457 |
| $X_{11}$ | Thousand Transaction | 207,97 | 31,97 | 0 | 4.558,91 |
| $X_{12}$ | Billions of Rp | 1.368.366 | 64.392 | 0 | 38.891.247 |
| $X_{13}$ | Thousands of Transaction | 4.013,93 | 183,41 | 0 | 121.303,52 |
| $X_{14}$ | Billions of Rp | 134.130 | 9.562 | 0 | 3.819.570 |

Source: The processed secondary data (2025)

According to the descriptive statistics table that you shared, Indonesia has a wide gap in its payment system and financial market infrastructure among 34 provinces The distribution of all 14 variables, from Rupiah deposit transactions ($X_1$) to high-value RTGS and Clearing transaction ($X_{11}$-$X_{14}$), was highly skewed. This is demonstrated by the major discrepancies between the mean and median values for just about every variable. This means it that financial activity and infrastructure is unevenly distributed or heavily centralized in a few provinces.

This concentration is further emphasized by the pervasiveness of the minimum and max values in the table. Many variables (transaction volumes, merchants, EDC machines) record a domestic minimum value for their meaning that some provinces have a very low or no penetration of these modern financial services. On the other end, the maximum values are very high which is often order of magnitudes greater than mean and median. This pattern implies that there exist only a handful of outlier Province, most likely major economic centre such as DKI Jakarta, which holds the highest shares of all transaction and dominate majority of the whole payment infrastructure.

Before clustering, the first thing we need to do is data standardization. It does not need standardization if all the data sets have same units. Nonetheless, if these attributes are measured in different units, normalization is needed to standardize the scale and minimize ranges of features. In this case, it is important to standardize data because variable having different units. Then, we do correlation test between independent variables after getting standardized data. Correlation summary of the December 2024 The Indonesian Payment System and Financial Market Infrastructure Statistics Standardized shown as Table 3.

**Table 3.** Coefisien Correlation Test

| **Method** | **Cophenetic Correlation** |
| --- | --- |
| Single Lingkage | 0,9834 |
| Average Lingkage | 0,9911 |
| Complete Lingkage | 0,9839 |
| Centroid | 0,9891 |
| Ward | 0,8503 |

Source: The processed secondary data (2025)

Another way to evaluate which method is best in cluster analysis, is to compare cophenetic correlation values of the hundreds methods. The method most impactful on the cluster analysis results was chosen according to the greatest cophenetic correlation value. In Table 3 it can be seen that if we look at cophenetic correlation value the highest is for Average method which is 0.9911. Hence, we used a hierarchical clustering method in the cluster analysis with the Euclidean distance and Average linkage. The optimal number of clusters in this case (3 clusters) is shown as Figure 1. Three clusters were identified from these data -a low-risk cluster, moderate-risk cluster, high-risk cluster. This way, groupings are always in tandem with the aim of classifying entities according to risk types. We chose 3 clusters in order to better bin entities into risk categories that where meaningful for analytical or decision making purposes.

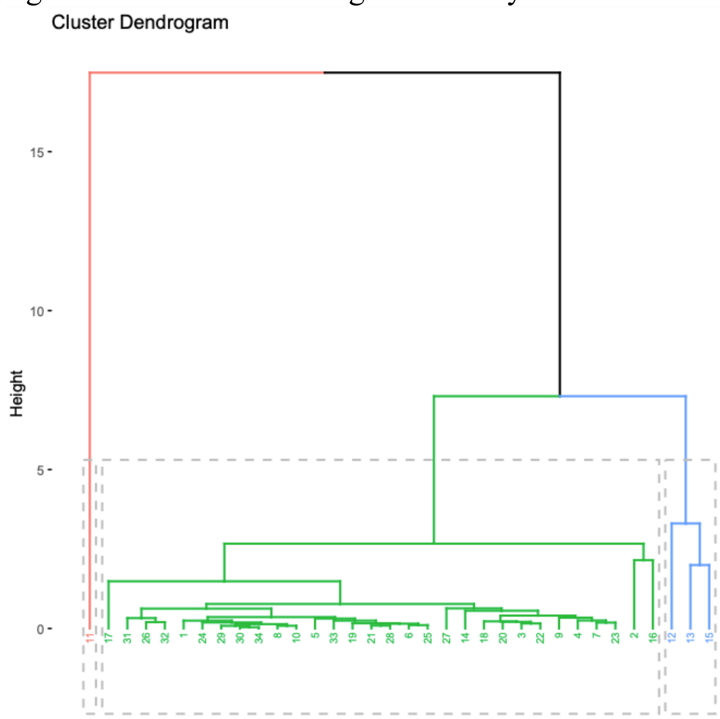


**Figure 1.** Cluster dendrogram
Source: The processed secondary data (2025)

By observing the longest gap in Figure 1, it can be seen that an appropriate cut will result in 3 clusters of The Indonesian Payment System and Financial Market Infrastructure, where Cluster 1 (red line) consists of 1 province, Cluster 2 (green line) consists of 30 provinces, and Cluster 3 (blue line) consists of 3 provinces. Based on the clustering results using R software, the members of each cluster are as follows:

**Table 3.** Cluster Segmentation

| Cluster | Entity |
|---|---|
| 1 | DKI Jakarta (11) |
| 2 | West Java (12), Central Java (13), East Java (15) |
| 3 | Nangroe Aceh Darussalam (1), North Sumatra (2), West Sumatra (3), Riau (4), Riau Islands (5), Jambi (6), South Sumatra (7), Bengkulu (8), Lampung (9), Bangka Belitung Islands (10), DI Yogyakarta (14), Banten (16), Bali (17), West Nusa Tenggara (18), East Nusa Tenggara (19), West Kalimantan (20), Central Kalimantan (21), South Kalimantan (22), East Kalimantan (23), North Kalimantan (24), North Sulawesi (25), Central Sulawesi (26), South Sulawesi (27), Southeast Sulawesi (28), West Sulawesi (29), Gorontalo (30), North Maluku (31), Maluku (32), Papua (33), and West Papua (34). |

Source: Processed secondary data (2025)

## Characteristics of Each Entity Cluster

To obtain the characteristics of each cluster, an analysis of the average values of the cluster members was conducted to understand the profile of each cluster for each variable, as presented in Table 4.

**Table 4.** Characteristics average of each entity cluster

| Variable (Unit) | Cluster 1 | Cluster 2 | Cluster 3 |
|---|---|---|---|
| Regional Rupiah Deposit Transactions (Inflow) (Billions of Rp) | 112.605,808 | 79.691,542 | 8.501,673 |
| Number of ATM Debit Cards (Millions of Unit) | 0,493 | 0,619 | 0,051 |
| Number of ATM Cards + Debit Cards (Millions of Unit) | 37,442 | 48,088 | 4,488 |
| Debit Card Transaction Volume (Millions of Transaction) | 999,810 | 938,647 | 96,361 |
| Debit Card Transaction Value (Billions of Rp) | 912.190,243 | 955.680,316 | 106.083,163 |
| Number of Credit Cards/Instruments (Millions of Unit) | 5,919 | 2,120 | 0,196 |
| Credit Card Transaction Volume (Millions of Transaction) | 264,620 | 31,395 | 3,085 |
| Credit Card Transaction Value (Billions of Rp) | 245.520,818 | 29.999,827 | 2.982,858 |
| Number of Regional Payment Instrument Infrastructure Merchants and Electronic Money (EU) (Unit) | 497.363,000 | 177.743,000 | 15.437,900 |
| Number of EDC Machines Infrastructure Payment Instruments Using Cards and Electronic Money (EU) Regional (Unit) | 715.457,000 | 256.749,667 | 23.046,867 |
| RTGS Transaction Volume derived from (Thousand Transaction) | 4.558,911 | 370,355 | 46,697 |
| RTGS Transaction Value derived from (Billions of Rp) | 38.891.246,836 | 1.194.881,923 | 134.952,124 |
| Clearing Transaction Volume derived from (Thousands of Transaction | 121.303,517 | 2.419,109 | 263,760 |
| Clearing Transaction Value derived from (Billions of Rp) | 3.819.570,207 | 114.410,490 | 13.253,997 |

Source: The processed secondary data (2025)

Cluster 1: High Risk, there is only one entity in this cluster, namely DKI Jakarta (11). Looking at the data, DKI Jakarta definitely wins by a big margin in virtually every metric. This cluster of High also recorded the highest values in Rupiah deposit transactions, debit and credit card transaction volume value, number of merchant EDC machines and RTGS Clearing transactions. Cluster 1 is at a high risk because all this heavy financial activity gets concentrated into such a small space. Due to its high digital transaction volume and large financial values, the region is exceptionally exposed to cyber-threats as well as systematic risk (where an operational pitfall in this area can initiate a triggering cascading process of failures across the national financial system).

Cluster 2: Moderate Risk, this cluster includes West Java (12) and Central Java (13); East Java is represented by a lone district, 15. This is a modest level of financial behavior, far away from Cluster 1. These provinces have high amount of Debit and Credit Card transactions, merchants, EDC Machines etc as shown in the data. This group has a low to moderate digital risk profile because it displays both high digital adoption and has a large population size. While being subject to substantial cyber risks due to the volume of transactions, they fall short from the end-to-end risks of Cluster 1. They also need to mitigate risks of rural exclusion for the sake financial inclusion.

Cluster 3: Low Risk, this cluster is the most numerous group and it contains other 30 provinces around Indonesia. According to the results, all examined metrics have their lowest values corresponding to Cluster 3. Compared to Clusters 1 and 2 the volume of transactions within this cluster and the usage of digital payment infrastructure is quite low. Low-risk pockets from a cyber and operational perspective, attributable to lower transactional volumes and lesser digital footprint. But they are at the highest risk of economic marginalization, in which residents and businesses have little or no access to contemporary financial services that are necessary for advancing credit as a form of capital to accelerate economic growth and improve comprehensive financial inclusion.

**Payment Systems and Financial Market Infrastructure (FMI) affect economic performance and financial risks**

The relationship between payment systems, financial market infrastructure (FMI), and economic performance in Indonesia is complex, influenced by geographic differences between provinces. These differences significantly impact economic resilience, financial inclusion, and addressing regional disparities. Within Indonesia, provinces exhibit significant variation in infrastructure development and digital adoption. Urban areas such as Jakarta and Surabaya boast developed fintech ecosystems and robust payment systems, which support economic growth and access to financial services, particularly for Small and Medium Enterprises (SMEs) (Wicaksana, 2023). Conversely, rural provinces often face challenges such as inadequate technological infrastructure and low levels of financial literacy, which limit the potential of payment systems to drive economic growth (Mata et al., 2023). Consequently, regions with less developed financial systems are more vulnerable to economic shocks, demonstrating a direct link between payment system effectiveness and the financial risks faced by each province.

Financial inclusion is also unevenly distributed across Indonesian provinces. Research by Ahmad et al. (2024) shows that financial inclusion positively contributes to economic growth, particularly in previously underserved areas. With improved payment networks, poverty rates decrease and economic activity increases, as individuals gain access to credit and savings options. This increased participation in the financial ecosystem also strengthens economic resilience to financial risks. However, provinces with low levels of financial inclusion tend to experience economic stagnation and higher vulnerability. The regulatory framework, managed by the Financial Services Authority (OJK), plays a crucial role in shaping economic sustainability. In regions with effective regulatory enforcement, trust in digital finance is generally higher, which stimulates economic activity (Sutikno et al., 2023). However, regulatory and bureaucratic challenges in less developed provinces can hinder fintech adoption and exacerbate economic disparities.

Uneven integration of financial technology can also exacerbate regional disparities. Successful fintech implementation in Jakarta, for example, can support the growth of MSME businesses, while in provinces like Papua, adoption of this technology is hampered by inadequate infrastructure and low digital literacy (Quatrini, 2021). This gap directly impacts economic performance, as rural areas often lack the technological tools necessary to effectively utilize modern payment systems. Therefore, regional support targeting education and infrastructure investment is crucial to ensure financial innovation can strengthen inclusiveness and economic vitality across all Indonesian provinces. Ultimately, by considering socio-economic sustainability and unique regional characteristics, tailored policies can mitigate financial risks and promote inclusive growth.

The dynamics of payment systems and financial market infrastructure (FMI) significantly influence economic performance and risk profiles. High-risk FMI often stems from technological and regulatory deficiencies, which can trigger systemic failures and financial crises (Guo & Zhou, 2023). The performance of Small and Medium Enterprises (SMEs) is significantly affected by the robustness of financial infrastructure; their inability to access funding due to inefficient systems places them in the high-risk category (Huong & Anh, 2024; Kurniasari et al., 2023). Medium-risk payment systems are generally efficient but vulnerable to economic stress, which can hamper growth potential (Guggenheim et al., 2022). On the other hand, low-risk payment systems are characterized by a strong regulatory framework, technological resilience, and efficient market operations. These systems successfully minimize financial risks, adapt quickly to market changes, and positively contribute to economic growth (Manzoor et al., 2021). Therefore, a thorough understanding of this risk categorization is crucial for policymakers and businesses to formulate strategies that strengthen economic stability. Efforts to improve FMI must consider regulatory, technological, and market behavioral dimensions (Vyas et al., 2020), to move towards a low-risk framework in which economic activity can thrive.

**The implications for financial and economic sustainability in Indonesia**

The impact of payment systems and financial market infrastructure (FMI) on the sustainability and resilience of the Indonesian economy is crucial, especially in an era of increasingly digital globalization. As Indonesia's economy advances, modernizing the financial system through digital innovation offers a unique opportunity to address long-standing challenges and unlock new capabilities for economic development. A crucial element in this regard is the adoption of digital payment systems such as the Quick Response Indonesian Standard (QRIS). Research shows that QRIS is crucial for advancing Indonesia's digital economy, providing instant payment mechanisms and improving overall transaction security (Saputro et al., 2022). This contributes to economic sustainability by simplifying business operations, increasing economic activity, and expanding consumer access to financial services, enabling Micro, Small, and Medium Enterprises (MSMEs) to thrive (Metri, 2024).

However, as Indonesia embraces these technological advancements, attention must be directed to addressing potential vulnerabilities. The risks associated with over-reliance on digital systems can undermine economic stability if not effectively managed. Without consistent oversight of financial transactions and the implementation of robust compliance mechanisms, the rapid adoption of innovative payment solutions could exacerbate financial instability (Afifah & Kurniawan, 2024). Furthermore, the socio-economic dimension of sustainability should not be overlooked. Economic policies must not only promote financial growth but also ensure equity and environmental protection (Saleh et al., 2024), as demonstrated by the increasing emphasis on green finance initiatives. Regional cooperation, such as the integration of QRIS with ASEAN countries, is also a significant strategic step to improve trade efficiency and connectivity (Metri, 2024), which will ultimately strengthen Indonesia's position in the regional economic landscape.

The implications also extend to the realm of public policy. With fiscal and monetary policies playing a crucial role during the crisis, there is a strong case for tightening the regulatory framework (Al-Mujaddid & Suwito, 2024). Continuous adjustments in monetary policy can support sustainable economic growth while maintaining macroeconomic stability. Furthermore, investment in education and technological infrastructure is crucial to address the challenges posed by low digital literacy and consumer awareness (Najib & Fahma, 2020). Strategies to improve financial education are crucial to ensuring a broad transition, enabling consumers and businesses to effectively utilize this technology. Therefore, the path to economic sustainability in Indonesia is closely linked to the development and optimization of its payment systems and FMIs. By leveraging technological innovation while addressing regulatory challenges and promoting financial inclusion, Indonesia can enhance its economic resilience.

## CONCLUSIONS

From a cluster analysis perspective, Indonesia's provinces can be represented as distinct risk categories in terms of payment systems and financial market infrastructure. The specifics can be represented as High Risk – Cluster 1, where only DKI Jakarta is represented. This province dominates every financial and fintech zone, indicating a very high concentration of financial activity in daily economic transactions. Medium Risk is Cluster 2, which includes West Java, Central Java, and one district in East Java. These regions exhibit significant financial activity but are not as highly concentrated as in Cluster 1. Finally, Low Risk is Cluster 3, consisting of 30 other provinces that show the lowest scores across all metrics. It represents the lowest transaction volume and use of digital infrastructure in payment systems. High Risk refers to the susceptibility to systemic failure and financial crises. This cluster is characterized by technological deficiencies and an over-focus on financial outcomes. Medium Risk is generally efficient but has implicit vulnerabilities, which can restrain potential economic growth. Low Risk is characterized by a robust regulatory framework, technology, and centrality to market processes. These provinces have the lowest levels of risk exposure but are also vulnerable to the most economic harm through marginalization.

Therefore, payment systems and financial market infrastructure are fundamental not only to growth but also to internal prosperity and sustainable economic growth in Indonesia. Indeed, with the introduction of various digital innovations, including QRIS, the government is focusing on efficient transactions, enabling the growth of MSMEs, and the increasingly important aspect of inclusion: these are the keys to any industrial economy's survival. However, innovation also presents significant challenges, such as the risk of developing dependence on systems that defy management and could threaten economic doom. These issues must be addressed through a strengthened regulatory framework, oversight, and investments in our citizens' competitive literacy. Specifically, policies that support socioeconomic sustainability are needed. It should be noted that increased collaboration with countries in the region will strengthen the focus on FMI. Therefore, the path to economic sustainability in Indonesia is closely tied to optimal FMI development.

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