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CLUSTERING ANALYSIS AND HEALTHCARE FINANCING: A SECONDARY DATA STUDY OF BPJS KESEHATAN ON TUBERCULOSIS AND DIABETES MELLITUS IN INDONESIA

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ABSTRACT

The increasing burden of infectious diseases such as Tuberculosis (TB) and non-communicable diseases such as Diabetes Mellitus (DM) places significant pressure on the National Health Insurance (JKN) financing system. This study aims to analyze the healthcare financing patterns of TB and DM using BPJS Kesehatan secondary data from 2022 through a clustering analysis approach. This quantitative study employs BPJS Kesehatan Sample Data, covering 34 provinces in Indonesia. Data processing was performed using Stata 14.2 for case proportion calculations and RStudio for cluster analysis with the K-Means algorithm. The optimal number of clusters was determined using the Gap Statistic and Within-Cluster Sum of Squares (WCSS) methods. The results indicate three regional clusters: a moderate-burden cluster (Sumatra), a high-burden cluster (Java), and a low-burden cluster (other provinces).

Keywords: BPJS Kesehatan, Tuberculosis, Diabetes Mellitus, Healthcare Financing

INTRODUCTION

The healthcare financing system in Indonesia continues to face complex challenges due to the increasing burden of communicable and non-communicable diseases. The primary concern regarding JKN funding is its long-term financial viability, particularly as the prevalence and treatment costs of chronic diseases continue to rise.[1,2] This financial pressure is largely driven by expenditures associated with two priority illnesses: Diabetes Mellitus (DM) and Tuberculosis (TB). Two diseases that consistently receive significant attention in the national healthcare system are Tuberculosis (TB) and Diabetes Mellitus (DM). Tuberculosis is an infectious disease caused by the bacterium Mycobacterium tuberculosis.[3,4] The spread of this pathogen occurs through sputum droplets (droplet nuclei); with a single cough producing approximately 3.000 droplets. These airborne pathogens are then inhaled into the lungs of healthy individuals, leading to infection.[5] Indonesia ranks among the countries with the highest number of TB cases, making it a serious public health problem. This disease not only causes high morbidity and mortality rates but also impacts household productivity and economy, especially among the productive-age group.

On the other hand, Diabetes Mellitus (DM) is a group of metabolic diseases characterized by hyperglycemia due to abnormal insulin secretion, impaired insulin action, or both. Insufficient insulin production by the pancreas disrupts blood sugar balance leading to elevated glucose level.[6] This condition causes in various chronic complications affecting the eyes, kidneys, nerves, and blood vessels. DM is classified into several types: type 1 diabetes, type 2 diabetes, other specific types, and gestational diabetes.[7] The disease is progressive and often requires long-term management, involving lifestyle control, regular medication, and continuous monitoring.

The BPJS Health claim data constitute an extensive secondary database with significant strategic value for both health research and policy formulation.[8,9] Leveraging the BPJS Health Sample Data has become a key method for assessing the burden of chronic diseases, service utilization patterns, and direct medical expenditures, thereby offering crucial insights into the operational implementation of the JKN program.[10,11]

Furthermore, the analysis of these claims extends beyond cost examination. Hospitals can utilize those data to evaluate service quality and identify challenges in their claim management processes. This multifaceted application ultimately contributes to enhancing the efficiency and quality of the entire healthcare system.[12]

Within the context of the National Health Insurance (JKN) administered by BPJS Kesehatan, financing for TB and DM constitutes a significant proportion of total healthcare service claims. This financial burden is primarily driven by high visit frequency, management complexity, and prolonged therapy duration. Furthermore, the presence of these conditions as multimorbidity (TB-DM) is strongly correlated with increased healthcare utilization and costs within the UHC scheme[2]. Specifically, the high direct medical costs of DM, especially in cases with severe complications, often surpass the INA-CBGs tariffs reimbursed by BPJS Health[13,14]. Therefore, understanding the distribution of financing for these diseases and the characteristics of participants accessing these services is essential for-developing more efficient and equitable financing strategies.

One approach for describing the diversity of healthcare financing data is clustering analysis. Clustering analysis is a statistical method used to group data based on similar characteristics. It is an important tool in statistical data processing for data analysis. Cluster analysis encompasses methods that group objects into clusters based on information in the data.[15] In this context, clustering can help BPJS Kesehatan identify participant groups with similar financing patterns, enabling more effective intervention planning and budget allocation. By applying clustering, we can identify dense areas, discover overall distribution patterns, and find relationships between data attributes. In data mining, emphasis is placed on methods that discover clusters in large databases effectively and efficiently.

One of the most well-known clustering methods is K-Means. K-Means is a non-hierarchical clustering algorithm that partitions objects into clusters based on characteristics, grouping similar objects together while separating those with differing characteristics.[15]

Previous studies have successfully applied clustering analysis to segment JKN participant data based on medical records and service utilization[16], especially for cost-intensive non-communicable diseases (NCDs) such as DM[17]. This segmentation is crucial for planning efficient resource allocation and re-evaluating the JKN benefits package. However, few studies have simultaneously analyzed the regional variability (clustering) of both TB (communicable) and DM (non-communicable) case burdens and directly link them to healthcare financing patterns across Indonesian provinces. This study addresses this gap by applying a dual-disease clustering approach to BPJS Kesehatan data to inform more granular, geographically specific financing strategies. The major costs in most healthcare systems from human resource, hospital care, and drug provision. In many tropical countries, healthcare is financed through government expenditure, private spending (primarily out-of-pocket), and external aid. Financing healthcare services in low- and middle-income countries remains a significant challenge.

This study aims to analyze the segmentation of JKN participants based on the burden of TB and DM healthcare financing using a clustering approach with BPJS Kesehatan secondary data. The research is expected to contribute to the utilization of big data to support evidence-based decision-making in the JKN system, particularly for financing control and healthcare service prioritization.

METHOD

This study employed a quantitative research design and utilized a single primary data source: the 2022 Social Security Administering Body Sample Data Report, with the unit of analysis being all 34 provinces in Indonesia, providing information on TB and DM cases. Data collection began with a request submitted to BPJS Kesehatan via the official website: https://data.bpjs-kesehatan.go.id/bpjs-portal/action/datasampel.cbi. The proportion of Tuberculosis (TB) and Diabetes Mellitus (DM) cases was calculated using Stata version 14.2. Subsequently, RStudio with the K-Means algorithm was used for clustering analysis to group participants based on financing and service patterns.

RESULTS AND DISCUSSION

Based on the collection and analysis of BPJS Kesehatan secondary data for 2022, the geographical distribution of JKN participants diagnosed with Tuberculosis (TB) and Diabetes Mellitus (DM) across all Indonesian provinces, by province of residence, is illustrated in Table 1.

Table 1. Data Overview of Place of Residence

No	Province	TB		DM	
		N	%	N	%
1	Aceh	4,510	4.75	5,084	3.58
2	North Sumatera	6,462	6.80	7,235	5.04
3	West Sumatera	3,930	4.14	4,185	2.92
4	Riau	2,766	2.91	3,235	2.25
5	Jambi	1,937	2.04	1,869	1.30
6	South Sumatera	3,336	3.51	3,529	2.46

7	Bengkulu	1,591	1.68	1,289	0.90
8	Lampung	2,763	2.91	3,234	2.25
9	Bangka Belitung Islands	1,107	1.17	1,341	0.93
10	Riau Island	1,153	1.21	1,388	0.97
11	DKI Jakarta	1,654	1.74	9,742	6.79
12	West Java	7,493	7.89	15,922	11.10
13	Central Java	9,002	9.48	20,734	14.45
14	Special Region of Yogyakarta	1,109	1.17	3,760	2.62
15	East Java	9,495	10.00	23,422	16.32
16	Banten	2,145	2.26	4,504	3.14
17	Bali	1,580	1.66	3,251	2.27
18	West Nusa Tenggara	2,015	2.12	2,249	1.57
19	East Nusa Tenggara	2,909	3.06	1,866	1.30
20	West Kalimantan	2,697	2.84	2,294	1.60
21	Central Kalimantan	1,958	2.06	1,645	1.15
22	South Kalimantan	2,476	2.61	2,523	1.76
23	Kalimantan Timur	2,036	2.14	3,045	2.12
24	East Kalimantan	740	0.78	684	0.48
25	North Sulawesi	1,968	2.07	2,467	1.72
26	Central Sulawesi	2,029	2.14	1,919	1.34
27	South Sulawesi	4,481	4.72	4,888	3.41
28	Southeast Sulawesi	2,066	2.18	1,434	1.00
29	Gorontalo	897	0.94	941	0.66
30	West Sulawesi	1,010	1.06	718	0.50
31	Maluku	1,267	1.33	683	0.48
32	North Maluku	996	1.05	699	0.49
33	West Papua	1,227	1.29	614	0.43
34	Papua	2,155	2.27	1,023	0.71
	Undefined	6	0.01	80	0.06
	TOTAL	**94,966**	**100.00**	**143,496**	**100.00**

Based on the collection and analysis of BPJS Kesehatan secondary data for 2022, the geographical distribution of JKN participants with claimed Tuberculosis (TB) and Diabetes Mellitus (DM) cases across all provinces in Indonesia, by province of residence is illustrated in Table 1. The tabulation of 2022 BPJS Kesehatan data shows that East Java Province had the highest number of participants with claimed Tuberculosis (TB) and Diabetes Mellitus (DM) cases. Recording 9,495 claimed TB cases (10.00% of the national) and 23,422 claimed DM cases (16.32% of the national total).

Cluster Number Determination Process

The initial cluster determination process involves defining the value of k (number of groups/clusters) and the number of randomly assigned cluster centroids corresponding to the k value. In the clustering simulation shown in Figure 1, the optimal number of centroids (k value) was determined using the Gap Statistic. The results obtained from this method are presented in Figure 1.

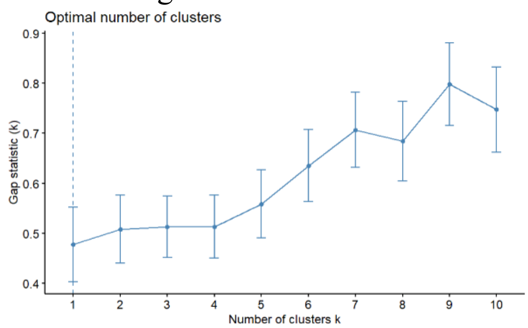

Figure 1. Gap Statistic

Analysis using the Gap Statistic method indicates that the optimal number of clusters is one (k=1). The Gap Statistic measures the difference between the clustering quality of the original data and that of random data, with higher values indicating better separation or cluster structure.

Although the Gap value increases with the number of clusters, the difference is not significant due to high variation between values (as shown by the error bars), indicating that the data do not form distinct groups. Subsequently, as shown in Figure 2, the analysis continued using the WCSS method to re-evaluate the optimal number of clusters and identify a more representative cluster structure.

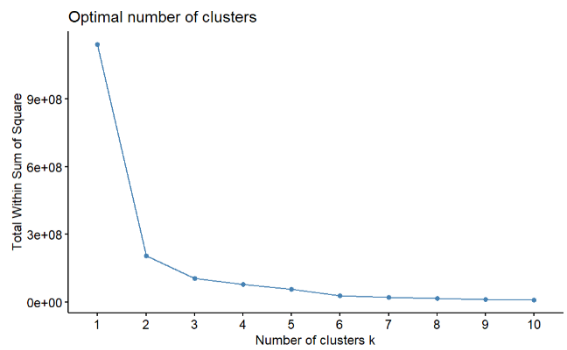

Figure 2. WCSS

Based on analysis using the Within-Cluster Sum of Squares (WCSS) method, the highest WCSS value occurred at k = 1 and sharply decreased as the number of clusters increased. The most significant decrease was from k = 1 to k = 2 and continued until k = 3, after which the graph began to flatten. In the elbow method, the point where the graph flattens is considered the optimal number of clusters, as additional clusters beyond this point, adding provide only a small reduction in within-cluster variation. The elbow point was identified at k = 3, indicating that the optimal number of clusters in this analysis is three.

Clustering Results

Based on the determination of the optimal number of clusters using the Within-Cluster Sum of Squares (WCSS) method, the optimal number of clusters is three (k = 3). From these clustering results, Indonesia provinces are divided into three groups based on the similarity of TB and DM case prevalence, as shown in Table 2.

Table 2. Clustering Results

Provinces			
Cluster 1	**Cluster 2**	**Cluster 3**	
Aceh	West Java	Riau	West Kalimantan
North Sumatera	Central Java	Jambi	North Kalimantan
West Sumatera	East Java	Bengkulu	South Kalimantan
South Sumatera		Lampung	Kalimantan East
South Sulawesi		Bangka Belitung Islands	Central Kalimantan
		Riau Island	North Sulawesi
		DKI Jakarta	Central Sulawesi
		Special Region of Yogyakarta	Sulawesi Southeast
		Banten	Gorontalo
		Bali	West Sulawesi
		West Nusa Tenggara	Maluku
		East Nusa Tenggara	North Maluku
		Papua	West Papua

The table above presents the results of grouping 34 Indonesia provinces into three clusters based on the proportion of claimed Tuberculosis (TB) and Diabetes Mellitus (DM) cases. Cluster 1 comprises five provinces: Aceh, North Sumatra, West Sumatra, South Sumatra, and South Sulawesi, which exhibit a moderate claimed case burden.

Cluster 2 includes three provinces: West Java, Central Java, and East Java, with the highest national burden of claimed

TB and DM cases. Provinces within this group are considered top priorities for health intervention planning. Cluster 3 comprises the remaining 26 provinces, which have a relatively low case burden. Nevertheless, regions within this cluster still require attention through preventive efforts and early detection to prevent future increases in cases.

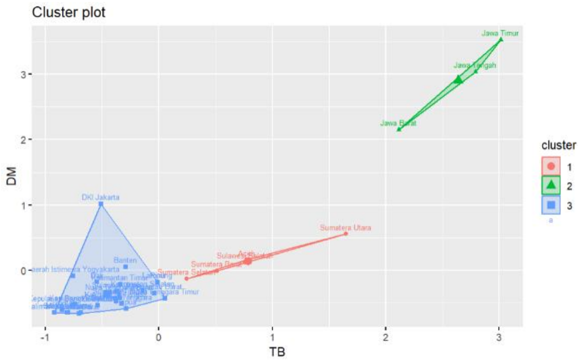

Figure 3. Cluster Grouping Results Based on Visualization

The visualization of clustering results based on Tuberculosis (TB) and Diabetes Mellitus (DM) prevalence in Indonesia demonstrates the division of provinces into three groups. Cluster 1, marked with a red circle symbol, includes areas in Sumatra with moderate prevalence, where some provinces, such as North Sumatra show a dominance of TB cases. Cluster 2, represented by a green triangle symbol, comprises provinces on Java Island with the highest national prevalence of TB and DM. Cluster 3 indicated by a blue square, encompasses most other provinces, including DKI Jakarta and Papua, with lower or near-national average prevalence levels. Overall, the disease burden is higher on Java Island compared to other regions.

Relationship of Clustering in TB and DM Diseases

Analysis of BPJS Kesehatan secondary data in Indonesia, shows that the clustering pattern of Tuberculosis (TB) and Diabetes Mellitus (DM) diseases are closely related to regional variations in healthcare financing. Claim data indicate that areas with a high burden of TB and DM tend to (cluster together) exhibiting similar financing characteristics, specifically high expenditures for curative care and health services. Conversely, regions with a lower disease burden form clusters with smaller financing patterns.

Clustering analysis revealed three groups of provinces based on the burden of TB and DM diseases. Cluster 1 includes five provinces, such as Aceh and North Sumatra, with a moderate disease burden, requiring strengthened prevention and early detection efforts. Cluster 2 comprises West Java, Central Java, and East Java, which have the highest burden due to large populations and urbanization, thus necessitating prioritization for control. Cluster 3 involves 26 provinces with a lower disease burden but face challenges in healthcare access, particularly in Eastern Indonesia, although some areas, such as DKI Jakarta still report high DM rates.

These findings align with research conducted at the Mojokerto Community Health Center, titled "Cluster Analysis of Diabetes Patient Data for Identifying Patient Patterns and Characteristics," which performed per-cluster analysis to identify the five most common sub-districts and ten most frequent diagnoses in each cluster. In Cluster 1, the most prevalent sub-districts were Modopuro, Kebondalem, Ngimbangan, Pekukuhan, and Kedunggempol, while in Cluster 2, they were Kebondalem, Modopuro, Menanggal, Pekukuhan, and Ngimbangan, with Modopuro and Kebondalem dominant in both clusters. The "ideal" BMI category was most common in both clusters, though the "underweight" category was more frequently in Cluster 2. The most common diagnosis in both clusters was E11.8 (type 2 diabetes mellitus with unspecified complications), with unique diagnoses in both Cluster 1 being M13.9 and I15, and for Cluster 2, A15 and E11.6. This per-cluster approach helps identify more specific health pattern differences between regions.[18]

Numerous studies have successfully applied the K-Means Clustering technique to segment inpatient data for JKN participants based on medical records and service indicators.[16] Clustering is vital for identifying groups of patients with similar spending patterns and healthcare needs. Such segmentation is indispensable for BPJS and health facilities to plan efficient resource allocation.

Furthermore, a comprehensive strategy for Tuberculosis elimination requires integration of funding between the National Program and BPJS Health. Cost clusters derived from BPJS Health data can guide BPJS in formulating improved strategic purchasing policies, particularly to ensure adequate tariffs for healthcare facilities managing complex TB-DM cases.[19]

Relationship of Healthcare Financing In TB and DM Diseases

Based on BPJS Kesehatan secondary data in Indonesia, there is a clear relationship between healthcare financing patterns and the burden of Tuberculosis (TB) and Diabetes Mellitus (DM). Regions with higher TB and DM incidence require larger funding allocations, especially for curative services such as routine treatment, laboratory examinations, complication management, and hospitalization. Conversely, areas with lower disease burden allocate a greater proportion of financing to preventive measures, including early screening, education, and prevention programs. This pattern indicates that BPJS Kesehatan financing is responsive to the epidemiological characteristics of diseases in each region.

These results align with the research "Non-communicable Comorbidities in Pulmonary Tuberculosis And Healthcare Utilization: a 2021 Cross-Sectional Study," which showed a clear relationship between pulmonary tuberculosis (pulmonary TB) and non-communicable diseases (such as diabetes mellitus, COPD, and cardiovascular diseases). Patients with these comorbidities showed relatively high prevalence, particularly in the elderly and participants funded through government subsidies. Areas with a high comorbidity burden have different patterns of healthcare utilization and financing characterized by a significant increase in inpatient services. This condition can add to the financial burden on the National Health Insurance (JKN) financing system. Therefore, integrating TB and NCD healthcare services through bidirectional screening is crucial to ensure comprehensive and efficient case. Strengthened integrated prevention and treatment efforts are necessary to sustain the JKN scheme while improving the quality of care for patients with dual disease burden.[20]

The INA-CBGs provider payment system under JKN necessitates improvements for BPJS Health to function as a more effective strategic purchaser. A key strategy for achieving spending efficiency involves utilizing data to manage expenditures and ensure that resource allocation is allocatively and technically efficient. Specifically, research on cost clustering for Diabetes Mellitus (DM) and Tuberculosis (TB) can provide essential information to re-evaluate the JKN benefits package and payment system, particularly for chronic, cost-intensive cases such as Non-Communicable Diseases (NCDs).[17]

Research consistently indicates that Type 2 DM, especially complicated such as renal failure, cardiovascular issues, and diabetic gangrene, imposes a substantial medical cost burden. These costs frequently surpass the INA-CBGs tariffs reimbursed by BPJS Health.[13,14] Direct comparison between actual hospital costs and INA-CBGs rates routinely reveal a significant cost deficit from the healthcare provider's perspective.[13] Furthermore, Cost of Illness (COI) analysis for DM highlight the considerable expenses associated with prescriptions and indirect costs at the primary care level.[21]

While TB financing is typically supported by the National Program, funding for hospital-based TB services and comorbid cases increasingly overlaps with the JKN system.[10] TB-DM comorbidity introduces a dual cost burden, as DM notably impacts service utilization and the overall TB treatment outcomes.[8] This underscores the need for a comprehensive evaluation of the financing model for patients with these dual conditions.

Increased multimorbidity (the existence of two or more chronic conditions, such as TB-DM) is strongly correlated with higher healthcare utilization and costs within the UHC scheme.[2] Key factors including advanced age and severe complications have been identified as major contributors to mortality among inpatient DM patients.[8]

Relationship of Clustering with Financing in TB and DM Diseases

Observing the distribution patterns of Tuberculosis (TB) and Diabetes Mellitus (DM) in Indonesia reveals differences in BPJS Kesehatan claim costs across provincial groups. In Cluster 1, comprising provinces in Sumatra, the claim cost burden is moderate. As the TB and DM prevalence in these areas is not excessively high, claim financing tends to be more stable. In Cluster 2, consisting of large provinces on Java Island such as West Java, Central Java, and East Java, BPJS claim costs are significantly higher, reflecting high number of TB and DM cases, and leading to a heavier financing burden. In Cluster 3, which includes DKI Jakarta, Bali, Nusa Tenggara, Kalimantan, Sulawesi, and Papua, claim costs are lower than on Java Island. Although some areas face challenges in service access, the overall claim burden remains smaller.

These findings align with the study "Implementation of K-Means Clustering for Optimizing Non-Communicable Disease Budget," which applied the k-means clustering method to 2021 health budget data from 33 provinces in Indonesia. This study yielded four clusters with good separation based on average budget allocation for non-communicable diseases, including diabetes, hypertension, obesity, and emotional mental disorders. Cluster 0 included five provinces with medium budget allocation. Cluster 1 only included North Sumatra Province, which had a relatively high budget allocation for diabetes sub-activities, despite low prevalence. Cluster 2 contained 28 provinces with the lowest budget allocation, while cluster 3 only included East Java Province, which received the highest allocation, consistent with the high prevalence of hypertension in that region.[22]

The identification of high-cost clusters among Tuberculosis (TB) and Diabetes Mellitus (DM) patients suggests potential technical inefficiencies or operational funding gaps. Identifying these clusters is crucial for establishing targeted, differentiated intervention strategies. For instance, high-burden regions (Cluster 2) require a comprehensive approach to strengthen primary healthcare (PHC) and the referral system, emphasizing improved case management, bidirectional screening, and prevention efforts[20]. This finding also aligns with SMERU's recommendations which emphasize addressing policy fragmentation and improving JKN data governance to ensure that future tariff policies reflect actual patient expenditure patterns[23].

Furthermore, cost clustering identifies very high-cost segments of TB-DM patients can guide the government to rebalance fund allocation. Although BPJS Health manages substantial curative funding, these findings highlight the comparatively smaller expenditure on preventive services.[24] This underscore the needs for greater investment in preventive measures, such as DM screening for TB patients, which could ultimately mitigate the long term curative burden.

CONCLUSION

Based on the analysis of BPJS Kesehatan secondary data for 2022, claimed TB and DM cases are distributed across all Indonesian provinces, with the highest numbers in East Java, Central Java, and West Java. Clustering results divided provinces into three groups: moderate claimed case burden (Cluster 1), high (Cluster 2), and low (Cluster 3).

The clustering pattern demonstrates an uneven geographical distribution influenced by socioeconomic factors and health infrastructure. High disease burden correlates with high BPJS financing, especially for curative services and inpatient care. Cluster 2 exhibited the highest claim costs, followed by Cluster 1 and Cluster 3. These findings underscore the importance of incorporating clustering patterns into BPJS financing planning to enhance efficiency and targeting. It is therefore, suggested that BPJS Kesehatan implement differentiated financing models and focused intervention strategies: prioritizing resource allocation to strengthen primary care and prevention in high-cost Cluster 2 regions, while improving service access and early detection programs in lower-cost Cluster 3 regions.

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REFERENCES

1. Collins D, Hafidz F, Mustikawati D. The economic burden of tuberculosis in Indonesia. *Int J Tuberc Lung Dis* 2017; 21: 1041–1048.
2. Mahmudah NA, Tessma MK, Mahendradhata Y. Multimorbidity and its associated factors in Indonesia through universal health coverage scheme: A cross-sectional study based on national claims data. *medRxiv*. Epub ahead of print September 2022. DOI: 10.1101/2022.09.19.22280100.
3. Kristini T, Hamidah R. Potensi Penularan Tuberculosis Paru pada Anggota Keluarga Penderita. *J Kesehat Masy Indones* 2020; 15: 24.
4. Janan M. Faktor-faktor Risiko Yang Berhubungan Dengan Peningkat Prevalensoi

Kejadian TB MDR di Kabupaten Brebes Tahun 2011-2017. *J Kebijak Kesehat Indones* 2019; 08: 64–70.
5. Kemenkes RI. *PROFIL KESEHATAN INDONESIA TAHUN 2016 (Health Statistics)[Internet]*. Indonesia, 2016.
6. Silalahi L. Hubungan Pengetahuan dan Tindakan Pencegahan Diabetes Mellitus Tipe 2. *J PROMKES* 2019; 7: 223.
7. Imanuel Saputra S, Nisa Berawi K, Susanti, et al. Hubungan Diabetes Melitus dengan Kejadian Gagal Ginjal Kronik. *J Medula* 2023; 13: 787–791.
8. Darmawan ES, Permanasari VY, Nisrina LV, et al. Behind the Hospital Ward: In-Hospital Mortality of Type 2 Diabetes Mellitus Patients in Indonesia (Analysis of National Health Insurance Claim Sample Data). *Int J Environ Res Public Health* 2024; 21: 581.
9. Machrumnizar M, Bachtiar A, K. Kusumaratna R. The Double Burden: A Bibliometric Analysis on Tuberculosis with Diabetes Mellitus Comorbidity. *J Kesehat Masy* 2025; 21: 35–45.
10. Arini M, Sugiyo D, Permana I. Challenges, opportunities, and potential roles of the private primary care providers in tuberculosis and diabetes mellitus collaborative care and control: a qualitative study. *BMC Health Serv Res* 2022; 22: 215.
11. Nurwahyuni A, Soewondo P, Nadjib M, et al. Health Care Spending for Cardiovascular Disease under National Health Insurance Scheme in Indonesia Before and During COVID-19: Descriptive Analysis and PolicyRecommendations. *J Indones Heal Policy Adm*; 8. Epub ahead of print 25 May 2023. DOI: 10.7454/ihpa.v8i2.6851.
12. Rachmawaty R, Wahyudin E, Bukhari A, et al. Healthcare Quality Received by Insured Patients in Two Indonesian Regional Public Hospitals. *J Holist Nurs* 2024; 42: S126–S134.
13. Fadila R, Purnamasari AT, Dewiyani AAIC. Direct Medical Costs of Diabetes Mellitus Treatment for Patients with Cardiovascular and Renal Complications. *Kesmas J Kesehat Masy Nas (National Public Heal Journal)*; 20. Epub ahead of print 8 July 2025. DOI: 10.7454/kesmas.v20isp1.2124.
14. Hidayat B, Ramadani RV, Rudijanto A, et al. Direct Medical Cost of Type 2 Diabetes Mellitus and Its Associated Complications in Indonesia. *Value Heal Reg Issues* 2022; 28: 82–89.
15. Nur Afidah N. Penerapan Metode Clustering dengan Algoritma K-means untuk Pengelompokkan Data Migrasi Penduduk Tiap Kecamatan di Kabupaten Rembang. In: *PRISMA, Prosiding Seminar Nasional Matematika*. Semarang: Jurusan Matematika FMIPA UNNES, pp. 729–738.
16. Maryani H, Rizkianti A, Izza N. Classification of Healthy Family Indicators in Indonesia Based on a K-means Cluster Analysis. *J Prev Med Public Heal* 2024; 57: 234–241.
17. Meilissa Y. *Invest Wisely, Execute Strategically, Achieve More: Indonesia's Pursuit of Universal Health Coverage*. 2nd ed. Jakarta: CISDI, 2024.
18. Satriatama AE, Wibowo AP, Arnold IGN, et al. Analisis Klaster Data Pasien Diabetes untuk Identifikasi Pola dan Karakteristik Pasien. *J Teknol Dan Sist Inf Bisnis* 2023; 5: 172–182.
19. Antaria A. *Ending The Epidemic: A Comprehensive Strategy for Tuberculosis Eradication in Indonesia by 2029*. 1st ed. Kota Malang: Litrus, 2024.
20. Prasiska DI, Chapagain DD, Osei KM, et al. Non-communicable comorbidities in pulmonary tuberculosis and healthcare utilization: a cross-sectional study of 2021

Indonesian national health insurance data. *Arch Public Heal*; 82. Epub ahead of print 1 December 2024. DOI: 10.1186/s13690-024-01352-y.

21. Sulistyaningrum IH, Arbianti K, Santoso A, et al. PRESCRIPTION COST ANALYSIS IN PATIENTS WITH HYPERTENSION AND TYPE 2 DIABETES MELITUS AFTER THE IMPLEMENTATION OF INDONESIAN NATIONAL HEALTH INSURANCE. *J Farm Sains dan Prakt* 2022; 238–249.
22. Sujak GMM, Rofiq HN, Tawakal FI. Implementasi K-Means Clustering untuk Optimalisasi Anggaran Penyakit Tidak Menular. *MALCOM Indones J Mach Learn Comput Sci* 2024; 5: 67–74.
23. Saputri NS, Darmawan AB, Toyamah N, et al. *Political Economy Analysis of Health Financing Reforms in Times of Crisis: Identifying Windows of Opportunity for Countries in the SEA Region. Indonesia Case Study Report.* Jakarta, www.smeru.or.id. (2023).
24. Soewondo P, Nadjib M, Sari K, et al. *National Health Account Indonesia 2020*. Jakarta: Lembaga Penerbit Badan Kebijakan Pembangunan Kesehatan (BKPK), 2022.