MAPPING INDONESIA'S COVID-19 DEATH CASE WITH COMORBIDITIES USING CORRESPONDENCE ANALYSIS

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ABSTRACT

This research aims to map and identify COVID-19 deaths with comorbidities in Indonesia using correspondence analysis. The data collection technique involved the analysis of 6231 samples of COVID-19 death cases with comorbidities in Indonesia from the official website of the COVID-19 Response Acceleration Task Force. The variables used were the number of COVID-19 deaths with comorbid hypertension, diabetes mellitus, cardiovascular disease, chronic obstructive pulmonary disease, kidney disease, immune disorders, liver disease, cancer, asthma, pregnancy, tuberculosis, and other respiratory disorders. The findings from this study divide four groups of provinces with characteristics: Group One with the characteristics of COVID-19 death cases with comorbid hypertension, diabetes mellitus, heart disease, kidney disease, lung disease, immune disorders, and cancer; Group Two with the characteristics of COVID-19 death cases with comorbid pregnancy, liver disease, and tuberculosis; Group Three with the characteristics of COVID-19 death cases with comorbid asthma; and Group Four with the characteristics of COVID-19 death cases with other comorbid respiratory disorders.

Keywords: Mapping, covid-19, comorbidities, correspondence analysis.

INTRODUCTION

An infectious disease known as Coronavirus (COVID-19) is caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) virus or coronavirus. This virus was first identified on December 31, 2019, in Wuhan City, Hubei Province, China (Rothan & Byrareddy, 2020; Wong et al., 2023; Yazicioglu, 2022). This disease has infected almost all countries, and the World Health Organization (2020) declared COVID-19 a pandemic on March 11, 2020. COVID-19 infection can cause mild, moderate, or severe symptoms. The main symptoms include fever, cough, sore throat, nasal congestion, headache and difficulty breathing. The incubation period for COVID-19 ranges from 5-6 days; the longest is 14 days (Ministry of Health of the Republic of Indonesia, 2020). Severe cases of COVID-19 can result in pneumonia, kidney failure, acute respiratory syndrome, and even death. COVID-19 can be transmitted during direct contact with infected individuals through droplets and through indirect contact with items worn by infected people (Guan et al., 2020; Suy et al., 2021).

On March 2, 2020, Indonesia officially announced its first case of COVID-19. Since then, the number of cases has continued to increase significantly. As of July 31, 2022, Indonesia's number of positive COVID-19 cases reached 6,207,089 cases, with 156,993 deaths (COVID-19 Response Acceleration Task Force, 2022). The reality of these figures places Indonesia as one of the countries most affected by positive cases and deaths due to COVID-19 worldwide. In fact, in July

2022, the COVID-19 death rate in Indonesia ranked first highest in Southeast Asia and ninth highest worldwide (Ministry of Health of the Republic of Indonesia, 2022).

Various data and research shows that the patient's comorbidities influence the COVID-19 death rate (Drew & Adisasmita, 2021; Du et al., 2020; Maragakis, 2021; Masdalena et al., 2021; Mowidu & Sari, 2021; Satria et al., 2020). Comorbidities are congenital conditions other than the patient's primary disease. Nandy et al. (2020) state that comorbidities in COVID-19 patients can cause a higher risk of serious events, such as ICU admission, mechanical intubation, and even death. Ejaz et al. (2020) also argue that comorbidities are a potential factor in COVID-19 patients and can develop into life-threatening situations. The COVID-19 Response Acceleration Task Force (2022) states that several comorbidities that are often found in COVID-19 death cases in Indonesia are hypertension, diabetes mellitus, cardiovascular disease, chronic obstructive pulmonary disease, kidney disease, immune disorders, liver disease, cancer, asthma, pregnancy, tuberculosis, and other respiratory disorders.

The magnitude of the influence of comorbidities in COVID-19 death cases needs to be appropriately studied so that health services for COVID-19 patients can be targeted for at-risk groups, and it is hoped that this can reduce the high number of COVID-19 deaths in Indonesia. Therefore, an analysis is needed to identify each province's characteristics based on comorbidity indicators influencing COVID-19 death cases. Correspondence analysis can be applied to this problem. Correspondence analysis is a descriptive statistical method for analyzing contingency tables with two or more interconnected variables between rows and columns. The results of this analysis produce the best dimensions for presenting data in the form of a perception map (Chandra, 2018). Correspondence analysis was chosen because it simplifies complex data from multidimensional tables into a more straightforward visual representation but retains important information (Saefuloh, 2016). In addition, correspondence analysis is appropriate because the data on COVID-19 death cases with comorbidities in Indonesia data used in this study has a contingency table structure.

Correspondence analysis is previously applied to map and group sub-districts in DKI Jakarta based on the level of spread of COVID-19 (Sianggaran et al., 2021). The findings from this analysis show that the 44 sub-districts in DKI Jakarta form seven groups with different levels of spread of COVID-19. Asnawi et al. (2021) also conduct a correspondence analysis to map the distribution of agricultural business types based on cities or districts in West Java. By applying correspondence analysis, data regarding the type of agricultural business can be explored, and the relationship between variables can be visualized through a perception map and used to assess the proximity or similarity between variables. From the agricultural business type variable, the correspondence analysis results divide it into six groups based on their proximity. From the city or district variables in West Java, the analysis results divide them into four groups based on their proximity. In addition, correspondence analysis was also used to describe and recognize the relationship between climatological natural disaster events and districts or cities in Java in 2015 (Rofiqi, 2016). This research uses information about natural disasters caused by weather changes from 119 districts or cities on Java during that year. The research results show that several districts or cities on Java show a certain tendency towards natural disasters caused by weather changes at that time, which may be due to the similarity of the geographical situation between the districts or cities concerned.

Apart from using correspondence analysis, other methods that can be used to map and identify disease cases are biplot and k-means cluster analysis. Biplot analysis maps the spread of infectious diseases in the Gresik Regency (Makrifah, 2015). This research utilizes data on the incidence of infectious diseases in Gresik Regency in 2013, including variables on the severity of lung disease, HIV, AIDS, pneumonia, leprosy, and diarrhoea. The results of the biplot analysis show that the distribution of infectious diseases in the Gresik Regency is evenly distributed in each sub-district. However, biplot analysis is inappropriate when applied to data in a contingency table (Sinaga, 2017). Apart from biplot, another suitable analysis for this problem is the k-means cluster. Sari and Yunita (2021) have maped the distribution of COVID-19 cases by province in Indonesia using k-means clusters. However, k-means cluster analysis has several shortcomings, such as being very dependent on selecting the initial centroid value, processing only numerical data, and being sensitive to data with outliers (Luthfi & Wijayanto, 2021).

This research aims to map and identify COVID-19 deaths in Indonesia based on comorbidities using correspondence analysis. The map obtained will provide information on grouping provinces with similar comorbidity characteristics of COVID-19 death cases. A visual depiction of the grouping of provinces in Indonesia based on comorbidities in COVID-19 deaths will provide a deeper understanding of the characteristics of comorbidities in COVID-19 death cases in Indonesia and the pattern of COVID-19 deaths in Indonesia. The results of this research will likely provide new valuable insights for handling and preventing COVID-19 at the provincial level.

METHOD

The data in this research were COVID-19 death cases with comorbidities in Indonesia from the official website of the COVID-19 Response Acceleration Task Force (https://covid19.go.id) as secondary data. The data used is 6,231 samples from March 2, 2020, to July 31, 2022. Two variables were used in this research: provinces in Indonesia, which consists of 34 provinces with code information (Table 1), and the number of COVID-19 death cases with comorbidities, which consists of twelve comorbidities (Table 2).

Table 1. The Variable Description of Provinces in Indonesia

Code	Province Name	Code	Province Name
1	Special Capital Region of Jakarta	18	Riau Islands
2	West Java	19	West Kalimantan
3	East Java	20	Southeast Sulawesi
4	Central Java	21	Lampung
5	South Sulawesi	22	North Sulawesi
6	Banten	23	Central Sulawesi
7	West Nusa Tenggara	24	Riau
8	Bali	25	West Papua
9	Papua	26	Sulawesi Barat
10	South Kalimantan	27	Jambi
11	West Sumatera	28	North Maluku
12	South Sumatera	29	Maluku
13	Central Kalimantan	30	Gorontalo
14	East Kalimantan	31	Bangka Belitung Islands
15	North Sumatera	32	Aceh
16	Special Region of Yogyakarta	33	Bengkulu
17	North Kalimantan	34	East Nusa Tenggara

Table 2. The Variable Description of COVID-19 Death Cases with Comorbidities

Variable	Description
Hypertension	Prevalence of COVID-19 deaths with comorbid hypertension in each province
Diabetes	Prevalence of COVID-19 deaths with comorbid diabetes in each province
Cardiovascular disease	Prevalence of COVID-19 deaths with comorbid cardiovascular disease in each province
Lung disease	Prevalence of COVID-19 deaths with comorbid lung disease in each province
Kidney disease	Prevalence of COVID-19 deaths with comorbid kidney disease in each province
Immune disorder	Prevalence of COVID-19 deaths with comorbid immune disorder in each province
Liver disease	Prevalence of COVID-19 deaths with comorbid liver disease in each province
Cancer	Prevalence of COVID-19 deaths with comorbid cancer in each province
Asthma	Prevalence of COVID-19 deaths with comorbid asthma in each province
Pregnancy	Prevalence of COVID-19 deaths with comorbid pregnancy in each province
TBC	Prevalence of COVID-19 deaths with comorbid TBC in each province
Other respiratory diseases	Prevalence of COVID-19 deaths with comorbid respiratory disease in each province

To obtain the prevalence of COVID-19 deaths with comorbidities in each province, data on the prevalence percentage of each province in Indonesia was collected and multiplied by the COVID-19 death data with comorbidities in each province. From there, data ready to be used in research is obtained. In this research, correspondence analysis will be carried out. The first step of correspondence analysis is to form the data into a contingency table. The contingency table is a non-parametric statistical test to describe the condition of the two variables to be tested (Sulastiawan, 2014). A two-way contingency table is a recording of observation results involving two variables. In this research, the variables used are provinces in Indonesia and comorbidities of COVID-19 deaths.

The next step in correspondence analysis is to carry out an independence test between data variables converted into a contingency table. This step aims to see associations in each variable category (Usman & Akbar, 2020). This research uses the chi-square test to assess the independence between the variables of provinces in Indonesia and the variable of comorbidities of COVID-19 deaths. The chi-square test of independence assesses the relationship between the frequency grouping of observed results and the frequency distribution based on the mean and standard deviation of the observed frequencies (Uğurlu, 2020). The calculated chi-square value reflects the extent of association between the tested variables. The equation for calculating the chi-square test is presented in equation (1).

$$\chi^2 = \sum_{i=1}^{k} \frac{(\mathrm{O_i} - \mathrm{E_i})^2}{\mathrm{E_i}} \tag{1}$$

where:
O_i: Observed Frequency
E_i: Expectation/Expected Frequency

The chi-square test of independence has the null hypothesis that the variables tested are independent of each other, and alternatively, the variables tested are dependent on each other. The chi-square test criteria compare the calculated value between the chi-square and the table chi-square. If the calculated chi-square result exceeds the chi-square table, the null hypothesis is rejected, and vice versa. Apart from that, the test criteria can be seen from the p-value results. The null hypothesis is rejected if the resulting p-value is less than the significance level.

After the data in a contingency table has been tested for independence, the next step is to form a correspondence matrix. The correspondence matrix is formed using equation (2).

$$P_{a\times b} = \left(P_{ij}\right) = \left(\frac{n_{ij}}{n}\right) \tag{2}$$

If each element in a row of matrix $\boldsymbol{A}$ is added, the result will form a vector of the number of rows of the matrix, which then forms the diagonal of the row matrix $\left(\boldsymbol{D}_r = diag(r)\right)$. Similar steps are repeated for each column in matrix $\boldsymbol{A}$, producing a vector of column sums of matrix $\boldsymbol{A}$**,** which form the diagonal of the column matrix $(\boldsymbol{D}_c = diag(c))$. The row diagonal matrix $(\boldsymbol{D}_r)$ and column diagonal matrix $(\boldsymbol{D}_c)$ are shown in equations (3) and (4).

$$\boldsymbol{D}_r = diag(r) = \begin{bmatrix} p_{1.} & 0 & \cdots & 0 \\ 0 & p_{2.} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & p_{a.} \end{bmatrix} \tag{3}$$

$$\boldsymbol{D}_c = diag(c) = \begin{bmatrix} p_{.1} & 0 & \cdots & 0 \\ 0 & p_{.2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & p_{.b} \end{bmatrix} \tag{4}$$

The next step is to form the row profile and column profile. The profile is defined as comparing each frequency of observations in the i-th row and j-th column to the total number of each row and column. Subsequently, matrix $\boldsymbol{R}$ with size $a \times b$ will be formed, which is called the row profile in b-dimensional space with the number of profile elements of the row equal to one. The identification of the i-th row profile as r_i is explained in equations (5) and (6).

$$\boldsymbol{R} = \boldsymbol{D}_r^{-1}\boldsymbol{P} = \begin{bmatrix} \frac{p_{11}}{p_{1.}} & \frac{p_{12}}{p_{1.}} & \cdots & \frac{p_{1b}}{p_{1.}} \\ \frac{p_{21}}{p_{2.}} & \frac{p_{22}}{p_{2.}} & \cdots & \frac{p_{2b}}{p_{2.}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{p_{a1}}{p_{a.}} & \frac{p_{a2}}{p_{a.}} & \cdots & \frac{p_{ab}}{p_{a.}} \end{bmatrix} \tag{5}$$

$$r_i = \left(\frac{p_{i1}}{p_{i.}}, \frac{p_{i2}}{p_{i.}}, \ldots, \frac{p_{ib}}{p_{i.}}\right)' \tag{6}$$

Next is the formation of matrix $\boldsymbol{C}$ with size $b \times a$, which is a column profile in a-dimensional space, with the number of profile elements of the column equal to one. The identification of the j-th column as c_j is explained in equations (7) and (8).

$$\boldsymbol{C} = \boldsymbol{D}_c^{-1}\boldsymbol{P}' = \begin{bmatrix} \frac{p_{11}}{p_{.1}} & \frac{p_{12}}{p_{.1}} & \cdots & \frac{p_{a1}}{p_{.1}} \\ \frac{p_{21}}{p_{.2}} & \frac{p_{22}}{p_{.2}} & \cdots & \frac{p_{a2}}{p_{.2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{p_{1b}}{p_{.b}} & \frac{p_{2b}}{p_{.b}} & \cdots & \frac{p_{ab}}{p_{.b}} \end{bmatrix} \tag{7}$$

$$c_j = \left(\frac{p_{1j}}{p_{.j}}, \frac{p_{2j}}{p_{.j}}, \dots, \frac{p_{aj}}{p_{.j}}\right)' \tag{8}$$

Preparing the row profile matrix involves calculating mass values using equation (9).

$$mass = \left[\frac{x_j}{x}\right] \tag{9}$$

Equation (10) is used to calculate the mass value of the column profile matrix.

$$mass = \left[\frac{x_i}{x}\right] \tag{10}$$

The next step is determining the inertia value of the row and column proportions. The row and column proportion inertia values are calculated based on the data in the row and column profile tables. The inertia value shows the extent of the contribution of the i-th row and j-th column to the total inertia, which can be calculated using equations (11) and (12).

$$Total\ inertia\ of\ row: in(a) = \sum r_{i.}(r_{i.} - c)'\boldsymbol{D}_c^{-1}(r_i. - c) \tag{11}$$

$$Total\ inertia\ of\ column: in(b) = \sum c_{j.}\left(c_{j.} - r\right)'\boldsymbol{D}_r^{-1}(c_j. - r) \tag{12}$$

The final step is forming a correspondence graph to obtain visualization results of the rows and columns of the contingency table in a two-dimensional plane.

RESULT AND DISCUSSION

The data on COVID-19 death cases with comorbidities in Indonesia used in this research has a contingency table structure so that the first step in the correspondence analysis is an independence test between the variable of provinces in Indonesia and the variable of comorbidities in COVID-19 deaths. The independence test was carried out using the chi-square test with the following hypothesis:

H_0: There is no relationship between the variable of provinces in Indonesia and the variable of comorbidities in COVID-19 deaths.

H_1: There is a relationship between the variable of provinces in Indonesia and the variable of comorbidities in COVID-19 deaths.

Table 3 presents the Chi-square test results.

Table 3. Chi-square Test Results

	Nilai	**df**	**Asym Signaf (2-sided)**
Pearson Chi-Square	557.87	363	1.936e-10

Based on Table 3, the Pearson chi-square test obtained a value of $557{,}87$ with a significance level of $0{,}05$ and a *p-value (asymptotic significance)* of $1{,}936 \times 10^{-10}$. It can be concluded that $p - value \leq sig$ (significance level), which means H_0 is rejected. Therefore, there is a relationship between the variable of provinces in Indonesia and the variable of comorbidities in COVID-19 deaths.

The next step is the calculation of the row profile. The results of row profile calculations are shown in Table 4.

Table 4. Row Profile Mass

Variable	**Mass**	**Variable**	**Mass**
Hypertension	0,276	Liver disease	0,019
Diabetes	0,281	Cancer	0,031
Cardiovascular disease	0,152	Asthma	0,019
Lung disease	0,050	Pregnancy	0,021
Kidney disease	0,073	TBC	0,020
Immune disorder	0,029	Other respiratory diseases	0,028

Based on Table 4, the largest mass value was $0{,}281$ from the diabetes mellitus variable. It means diabetes mellitus is Indonesia's most common comorbidity in COVID-19 death cases. Meanwhile, the smallest mass value was 0,019 from the liver disease and asthma variables. It means liver disease and asthma are Indonesia's rarest comorbidity in COVID-19 death cases. Next is the calculation of the column profile. The results of column profile calculations are presented in Table 5.

Table 5. Column Profile Mass

Variable	**Mass**	**Variable**	**Mass**	**Variable**	**Mass**
1	0,166	13	0,019	25	0,029
2	0,042	14	0,090	26	0,008
3	0,035	15	0,016	27	0,010
4	0,072	16	0,028	28	0,006
5	0,025	17	0,006	29	0,005
6	0,010	18	0,013	30	0,017
7	0,006	19	0,007	31	0,020
8	0,010	20	0,010	32	0,083
9	0,006	21	0,012	33	0,006
10	0,006	22	0,007	34	0,012
11	0,030	23	0,009		
12	0,019	24	0,158		

Based on Table 5, the largest mass value is 0.166 from the DKI Jakarta Province variable. It indicates that DKI Jakarta Province has the highest number of COVID-19 deaths with comorbidities in Indonesia. Meanwhile, Maluku Province had the lowest mass at 0.005. It means that Maluku Province has the lowest number of COVID-19 deaths with comorbidities in Indonesia.

The analysis step continues by calculating inertia, and the results are presented in Table 6.

Table 6. Inertia

Dimension	Singular Value	Inertia	Proportion Explained	Cumulative Proportion
1	0,39615	0,15693	0,619	0,619
2	0,15175	0,02303	0,091	0,710
3	0,13653	0,01864	0,074	0,783
4	0,12501	0,01563	0,062	0,845
5	0,10912	0,01191	0,047	0,892
6	0,08605	0,00740	0,029	0,921
7	0,08433	0,00711	0,028	0,949
8	0,07757	0,00602	0,024	0,973
9	0,05740	0,00329	0,013	0,986
10	0,04856	0,00236	0,009	0,995
11	0,03542	0,00125	0,005	1,000
Total		0,25358	1,000	1,000

Based on Table 6, the percentage of inertia in dimension one is 61.9%, which means that the characteristics of the data in dimension one can explain 61.9% of the data diversity. Furthermore, with the cumulative inertia in the second dimension reaching 71.0%, the first two dimensions can explain 71.0% of the overall data variation. Then, the final step of the analysis is to form a correspondence graph to obtain visualization results of the rows and columns of the contingency table in a two-dimensional plane. The perception map of provinces in Indonesia is shown in Figure 1.

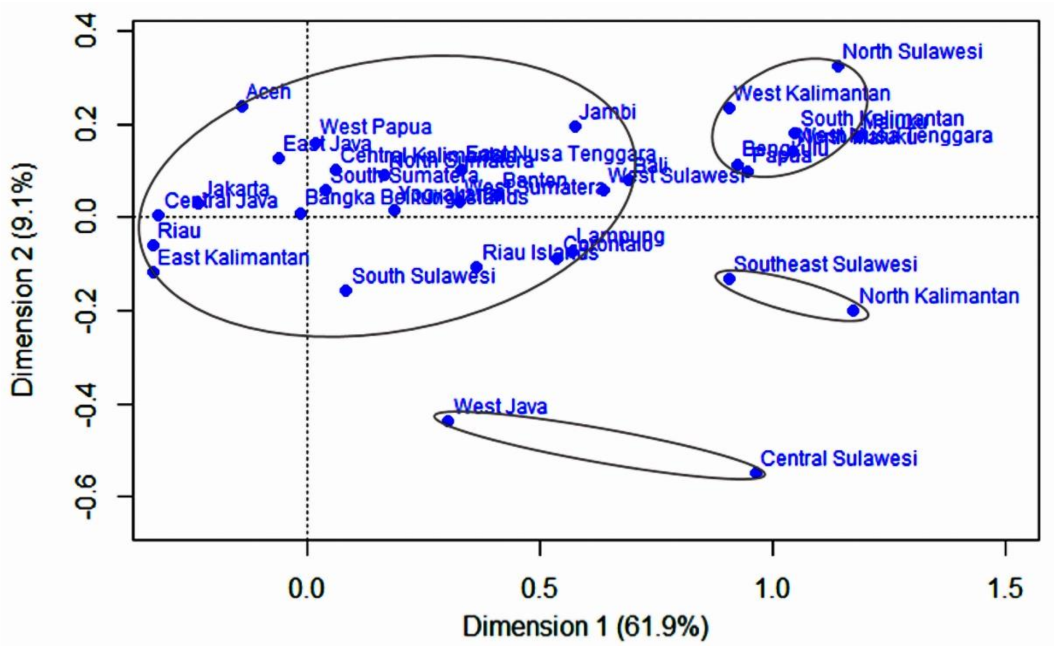

Figure 1. Map of Perception of Provinces in Indonesia Based on COVID-19 Deaths with Comorbidities

Figure 1 shows that the provinces of DKI Jakarta, Central Java, Riau, East Kalimantan, Aceh, Banten, East Java, DI Yogyakarta, Bali, East Nusa Tenggara, Central Kalimantan, North Sumatra, South Sumatra, Kep. Bangka Belitung, West Sumatra, Jambi, West Sulawesi, Lampung, Gorontalo, Riau Islands, South Sulawesi and West Papua are close to each other. Therefore, it is concluded that these provinces have similar characteristics regarding COVID-19 deaths with comorbidities. Furthermore, the provinces of North Sulawesi, West Kalimantan, South Kalimantan, Maluku, North Maluku, West Nusa Tenggara, Bengkulu, and Papua are also close to each other, indicating that these seven provinces have similar characteristics. Next, West Java Province is close to Central Sulawesi Province, indicating that the two provinces have similar characteristics. Likewise, Southeast Sulawesi Province and North Kalimantan Province are also close to each other and are interpreted to have similar characteristics.

A map of perceptions of comorbidities in COVID-19 deaths in Indonesia is presented in Figure 2.

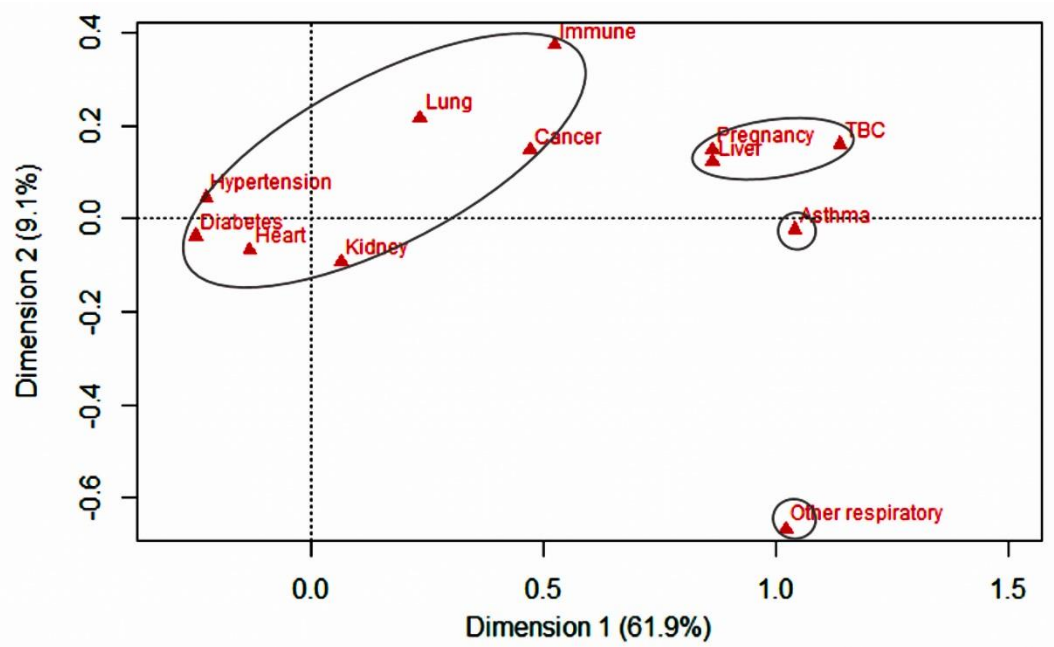

Figure 2. Map of Perception of Comorbidities in COVID-19 Deaths in Indonesia

Figure 2 shows that the comorbidities of hypertension, diabetes mellitus, cardiovascular disease, kidney disease, lung disease, immune disorders, and cancer are close. It means those comorbidities have similar characteristics. The same happens with the comorbidities of pregnancy, liver disease, and TBC, which are close to each other and indicate that those comorbidities have similar characteristics. Meanwhile, asthma and other respiratory disorders are far apart from other comorbidities, indicating their different characteristics.

An overlayed map of the variables of provinces in Indonesia and comorbidities in COVID-19 deaths is displayed in Figure 3.

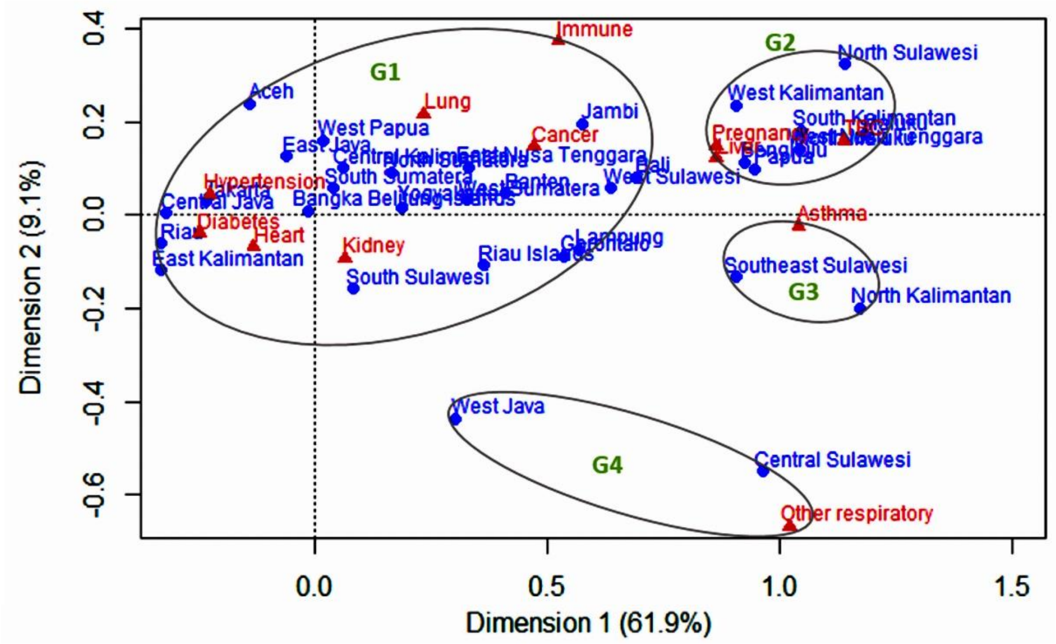

Figure 3. An Overlayed Map of the Variables of Provinces In Indonesia and Comorbidities in COVID-19 Deaths

Based on their proximity, the provinces in Indonesia are divided into four groups. Group one is provinces close to the following comorbidities in COVID-19 deaths: hypertension, diabetes mellitus, cardiovascular disease, kidney disease, lung disease, immune disorders, and cancer. Group one consists of 22 provinces consisting of DKI Jakarta, Central Java, Riau, East Kalimantan, Aceh, Banten, East Java, DI Yogyakarta, Bali, East Nusa Tenggara, Central Kalimantan, North Sumatra, South Sumatra, Kep. Bangka Belitung, West Sumatra, Jambi, West Sulawesi, Lampung, Gorontalo, Riau Islands, South Sulawesi and West Papua. Group two is provinces close to the following comorbidities in COVID-19 deaths: pregnancy, liver disease, and tuberculosis. Group two comprises eight provinces: North Sulawesi, West Kalimantan, South Kalimantan, Maluku, North Maluku, West Nusa Tenggara, Bengkulu, and Papua. Group three is close to asthma comorbidity and comprises Southeast Sulawesi and North Kalimantan. Group four is close to other respiratory disorders and comprises West Java and Central Sulawesi.

After conducting a correspondence analysis, it was discovered that diabetes mellitus is the most common comorbidity in COVID-19 death cases in Indonesia. It is in line with Albitar et al. (2020), Rajpal et al. (2020), and Saravanan et al. (2023). Diabetes mellitus patients experience increased blood sugar levels. High blood sugar levels can worsen the conditions of other diseases they are experiencing, including COVID-19. High levels of glucose in the blood can potentially influence the virus's capacity to infect individuals. In addition, diabetes also increases the risk of inflammation and can reduce the immune system (Kowsar et al., 2023; Sharbatdar et al., 2023). COVID-19 patients with comorbid diabetes have a higher risk of severe pneumonia, release of enzymes associated with tissue damage, inflammatory reactions, and glucose metabolism imbalance. It indicates that individuals with diabetes are more likely to experience inflammatory conditions that may lead to a higher risk of more severe cases of COVID-19 (Guo et al., 2020).

The most common comorbidity in COVID-19 death cases in Indonesia after diabetes mellitus is hypertension. This research confirms that hypertension is one of the highest risk factors for death due to COVID-19. This aligns with Surendra et al. (2021) that patients with hypertension have a 3.63 times higher risk of death than those without hypertension. Other research also shows that hypertension is a disease that influences COVID-19 deaths (Lippi et al., 2020; Zhou et al., 2020). Khan and Zaidi (2020) and Kurnik et al. (2023) argue that patients infected by COVID-19 and have a history of hypertension tend to have lower lymphocyte counts. Therefore, patients who have comorbid hypertension can cause the health condition of COVID-19 patients to worsen and even lead to death. The same thing is conveyed by Drew and Adisasmita (2021) that hypertension as COVID-19 comorbidity can cause death with a higher probability than patients who do not suffer from hypertension. This is because people with hypertension tend to have more ACE2 receptors. As a result, the coronavirus can spread more quickly in the body.

Apart from diabetes mellitus and hypertension, cardiovascular disease is another comorbidity often found in COVID-19 death cases in Indonesia. The coronavirus can disrupt blood vessels in various organs and cause these organs to experience ischemia or a decrease in blood and oxygen supply. Therefore, the heart must spend more effort circulating blood throughout the body. This situation can increase congestive heart failure risk, endangering COVID-19 patients with comorbid cardiovascular disease. In addition, inadequate oxygen supply to an organ can cause cell death and damage to the organ's tissue, resulting in a more severe risk of COVID-19 and death (Dan et al., 2020; Inciardi et al., 2020).

The next most frequently encountered comorbidity for COVID-19 death cases in Indonesia is kidney disease and chronic obstructive pulmonary disease. Drew and Adisasmita (2021) state that, in COVID-19 patients with chronic kidney failure, the glomerular filtration process decreases so that inflammation throughout the body can increase the risk of damage to kidney performance. In addition, the presence of ACE2 receptors in the urogenital system facilitates the coronavirus to trigger an inflammatory response in the kidneys, which can ultimately cause the patient's condition to worsen. Meanwhile, individuals suffering from Chronic Obstructive Pulmonary Disease (COPD) tend to be more susceptible to infection with the coronavirus. This condition occurs due to damage to the epithelial lining, making it easier for the virus to penetrate the body. In addition, COPD conditions will likely worsen significantly when infected with COVID-19 (Maragakis, 2021; Schultze et al., 2020).

The results of this study also show that the comorbidities of hypertension, diabetes mellitus, cardiovascular disease, kidney disease, lung disease, immune disorders, and cancer have similar characteristics in COVID-19 deaths in Indonesia. This aligns with Karya et al. (2021) that hypertension, diabetes mellitus, chronic kidney failure, and cardiovascular disease are the most common comorbidities with similar characteristics and can potentially influence the severity level. This is because there is a systemic inflammatory process with multi-organ involvement, which can accelerate the progression of COVID-19 and cause more severe organ damage, thereby increasing the risk of death. Patients with chronic kidney disease also have a higher risk of developing pneumonia, and upper respiratory tract infections may be potential co-infections along with COVID-19. This can co-occur with COVID-19 infection. Therefore, comorbid kidney disease is related to other comorbidities, especially cardiovascular disease and diabetes, which can result in a worse prognosis in COVID-19 sufferers. Azab et al. (2021) also emphasize that hypertension significantly increases the risk of cardiovascular disease, diabetes, kidney disease, and other health problems such as immune disorders and cancer. This is caused by high blood pressure in hypertension, which, if it pushes blood too hard into the arteries, can cause various problems that damage the entire circulatory system and disrupt the performance of other organs. Furthermore, diabetes can make the kidneys less efficient at filtering blood and stiffening blood vessels, thereby increasing blood pressure.

CONCLUSION

The use of correspondence analysis in this research makes it easier to visualize data on COVID-19 death cases in Indonesia based on comorbidities in the form of two-dimensional graphs that are more practical and informative. This form makes it easier to observe the characteristics of comorbidities in COVID-19 death cases in Indonesia. The research results show that this analysis divides provinces into four groups with unique characteristics. It is hoped that the findings from the research can help create a basis for developing policies and strategies for handling COVID-19 in Indonesia, especially in cases of death with various comorbidities. For further research, it is recommended to consider using other methods by also paying attention to changes in data over time in COVID-19 death cases in Indonesia based on comorbidities.

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