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Exploring the Association between Mobility Fluctuations andSocioeconomic Indicators Using Data Mining Techniques in Indonesia and Malaysia

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Abstract: *Human mobility has become a global issue during the Covid-19 pandemic and is believed to be a critical factor in the transmission of Covid -19. The timetable for the government's movement control has stimulated the fluctuation of national mobility. However, the characteristics of variations between regions of the country are not yet understood. The purpose of this study was to characterise community mobility fluctuations in Indonesia and Malaysia and identify the association between socioeconomic indicators and mobility fluctuations in regions. This secondary and exploratory research investigated 34 Indonesian provinces and 14 Malaysian states. Data mining approaches using the CRISP-DM framework and the Knime Analytics platform was used. As a result, Indonesia and Malaysia show the strength of mobility fluctuations in decreasing order: transit stations, workplaces, and residential areas. Malaysia shows higher mobility fluctuations than Indonesia, which may indicate the community's response to the Covid-19 pandemic. As socioeconomic indicators, Human Development Index (HDI), poverty rate, and labor force participation are associated with the fluctuation of mobility. Therefore, regions with high fluctuation in mobility will likely have high HDI, high labour force participation rates, and low poverty rates. High-mobility areas include capitals and other cities with high-density populations. This study provides evidence that socioeconomic indicators are determinants of mobility fluctuation during the pandemic. Regional governments may use the findings to anticipate community mobility and planning policies when similar pandemic conditions occur.*

Keywords: Covid-19, Data mining, Indonesia, Malaysia, Socioeconomic

1. Introduction

The Director of the World Health Organization (WHO) on 14 September 2022 said that the end of the Covid-19 pandemic was approaching (Nations, 2022).

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Most countries have lifted movement control and resumed normal activities. The pandemic that started in early 2020 has negatively impacted the world. However, some life lessons were often quoted, such as the human capacity for resilience, vaccine effectiveness, mental health concerns, and the importance of supporting education/work/social activities (Katella, 2021). In terms of academics, some studies have resulted from the pandemic. This paper discusses the theoretical understanding that can be drawn from the Covid-19 pandemic.

During the first year of the Covid-19 pandemic, numerous studies emerged to propose solutions to deal with the situation and stop the pandemic. One example was modelling and understanding the virus spread, providing information on suppressing outbreak growth (Lanteri et al., 2021). Human mobility is considered a critical factor for the transmission of Covid-19 in general. The observable phenomenon during the pandemic is the decrease in community mobility worldwide, as the impact of community mobility control imposed by each country's government, including the limitation of international mobility. Google has released daily data on community mobility for 135 countries since February 2020 (Google, 2020). The data presented the change or fluctuation from the baseline, which was the median value of the five weeks, 3 January - 6 February 2020. The overall data presented were taken from each country's region, such as a province or a state.

Google’s community mobility data has helped observe whether specific government-imposed movement control has an impact on reducing community mobility. The impact was observed in Japan, Hongkong, Singapore, and Australia (Hakim et al., 2021). In Malaysia, the Movement Control Order also reduced human mobility (Aziz et al., 2020). Similarly, the social restriction policy in Indonesia reduced people's mobility (Djalante et al., 2020). Those cases indicated that the government-imposed movement control policy mainly affected mobility fluctuation within a country (Mendolia et al., 2021). Conversely, the time of government policy varies among countries. Therefore, the pattern of fluctuation in mobility among countries will likely differ.

In a country, government-imposed mobility control tends to affect all regions. Therefore, the mobility fluctuation might indicate a similar pattern of variation among regions. The timing of movement control implementation could explain a country's mobility fluctuation. However, the fluctuation among regions within a country is less understood. The question is what factors might be associated with the variation of fluctuations between regions.

Google's mobility data could be considered a dependent variable from the effect of independent variables. Among regions within a country, the independent variables that affect the variation of mobility fluctuations are unknown. Governments regularly publish socioeconomic indicators to present the successful economic development implemented and to be used for programme planning. The available socioeconomic indicators could be used as potentially independent variables. A previous study found a correlation between human mobility patterns and socioeconomic indicators (Pappalardo et al., 2015).

This study aims to investigate the fluctuation of community mobility and its association with socioeconomic indicators at the country level. Two neighbouring countries - Indonesia and Malaysia - were chosen for comparison. The study's specific objectives were: (1) characterising community mobility fluctuations in Indonesian provinces and Malaysian states; (2) identifying the association between socioeconomic indicators and the intensity of mobility fluctuations across regions. The subjects of this study were 34 Indonesian provinces and 14 Malaysian states/federal regions.

Understanding the characteristics of mobility fluctuations between regions within a country and the potential effect of socioeconomic indicators could provide helpful information to local governments. Prior studies focused on mobility across countries (Hakim et al., 2021) rather than across regions in a country. This study aims to fill the gap. Furthermore, this study used Google's mobility data for about one year, longer than previous studies with months (Saha et al., 2020a). Finally, this study attempted to find the determinants of community mobility during the pandemic, other than the apparent government-imposed movement control order (Mendolia et al., 2021), by proposing socioeconomic indicators.

The paper was organised as follows. Section 2 reviews associated studies focussing on community mobility during the pandemic, socioeconomic indicators, and the government's response to the pandemic. Section 3 presents a detailed research framework and data mining process. Furthermore, Section 4 discusses the results to answer the research objectives. Finally, Section 5 concludes this work with an outline of the main findings.

2. Review of the Literature

This study focuses on community mobility during the pandemic and socioeconomic indicators. This short review of the literature addresses three aspects: community mobility during the Covid-19 pandemic, socioeconomic indicators, and government response during the pandemic, as follows.

2.1 Community Mobility during the Covid-19 Pandemic

Since the early spread of Covid-19 in Wuhan – China, data analytics has been used to nowcast to predict the spread of Covid-19 in the near future (Wu et al., 2020). The term nowcasting, from the merging of 'now' and 'forecasting,' refers to predicting certain conditions (e.g., economic indicators, weather) at present and in the immediate future. Due to the urgent condition, the prediction could be made with minimal data and a limited number of parameters (Zhong et al., 2020). Therefore, nowcasting is intended to predict the Covid-19 spread and envisage the execution of the lockdown policy and its economic impact. Furthermore, a simulation could be made to implement the movement control order and its potential mobility and economic aspects (Rahman et al., 2020).

The immediate measure to mitigate the pandemic is through movement control and physical-social distancing policies imposed by governments. Lowering social interaction and the intensity of people's movements become the main argument for lowering the spread rate of Covid-19 (Sulyok & M. Walker, 2020). The government policy varies among countries, ranging from a rigid lockdown decree to less social distancing actions. The success of such a policy has been reported, such as in the US (Brzezinski et al., 2020) and

India (Saha et al., 2020b). These cases confirm that movement control policies have decreased community mobility (Mendolia et al., 2021). Furthermore, the influence of voluntary social distancing on mobility decrease is also proven (Maloney & Taskin, 2020).

Google's community mobility reports have been used with the Stringency Index, a measure of how a country takes strict action against the Covid-19 pandemic, such as in a study in Latin America (Zhu et al., 2020). Similarly, the investigation of Google's community mobility and stringency index among countries across the globe verifies that government-imposed movement control explains the primary reduction in community mobility (Mendolia et al., 2021). Another study on cases in Japan, Hongkong, Singapore, and Australia confirms the impact on government movement control policy and community mobility (Hakim et al., 2021). Moreover, Google's community mobility data is modelled using a partial differential equation to predict Covid-19 cases in Arizona-US (Wang & Yamamoto, 2020). Finally, a study in Germany reported that the face mask mandate does not impact community mobility change (Kovacs et al., 2020). In general, Google community mobility reports have been analysed with other indicators to forecast Covid-19 cases or justify the effectiveness of the social distancing policy.

Limited studies have linked Google's mobility database to economic indicators. One example is a report from the World Bank, which indicates that Google's mobility data is a leading indicator in predicting the industrial production growth rate (Sampi & Jooste, 2020). Furthermore, by mapping Google's mobility data and economic activity in the Australian context, it appears that mobility could represent economic activity (Faulkner, 2020). A similar result is observed in Ireland, where Google's mobility data supplement economic indicators (McGrath, 2020). Therefore, Google's mobility database, linked with economic and social indicators, is essential to understand the pandemic situation better.

2.2 Socio-economic Indicators

The Encyclopaedia of Quality of Life and Well-Being Research defines economic and social (or socioeconomic) indicators as "statistics that measure different aspects of development and performance of the economy and society" (Wong, 2014). The data are commonly produced and published by the official statistics agency. Analysts and governments use it to assess the growth of economic and social conditions in the population.

The term socioeconomic indicator is related to indicators of sustainable development. Sustainability is defined as having three interrelated aspects: environmental, economic, and social. The term socioeconomic environment also emerges to cover those three pillars of sustainability. Referring to the 17 Sustainable Development Goals (SDGs), the goals related to socioeconomic indicators, for example, are poverty, hunger, good health and well-being, education, decent work and economic growth, and inequality.

A study investigating Covid-19 case fatalities and socioeconomic aspects used the unemployment rate and household income as socioeconomic indicators (Sen-Crowe et al., 2021). Furthermore, education, population density, and the number of tenants, as socioeconomic indicators, were used to investigate the impact of the Covid-19 outbreak (Bashir et al., 2020). Finally, social-cultural indicators were associated with the pandemic growth rate, in which individualistic societies experience a lower growth rate (Messner, 2020).

2.3 Government Response to Pandemic

The Indonesian government's initial formal response to the Covid-19 pandemic was the Ministry of Health stating Covid-19 as a disease that can cause the plague and its response measures on 4 February 2020. During February-March 2020, 15 regulations / decrees of the President of Indonesia, the Ministry of Health, the Ministry of Finance, the Ministry of Information and Communication, the Ministry of Village, Regional Disadvantage and Transmigration, the National Police and National Disaster Management Agency were published (Djalante et al., 2020). However, instead of a full lockdown policy, Indonesia implemented a large-scale social restriction policy for economic activity concerns. The main goal of that restriction was to limit human mobility. Implementing the policy covered school and workplace closure, restriction of religious/social/cultural activities, and limitation of public transport operations (Health, 2020).

In Malaysia, the Ministry of Health responded early to the Covid-19 pandemic by imposing health screening at all entry points into Malaysia and increasing the number of hospitals treating Covid-19 patients (Shah et al., 2020a). The most severe action to limit human mobility was the nationwide implementation of the Phase 1 Movement Control Order from 18 March to 31 March 2020, as Phase 1. This mobility control included staying at home, banning social assemblies, health screening and quarantine for international visitors, and closing some public facilities (Aziz et al., 2020). The worst conditions of the pandemic forced the Malaysian government to implement a total lockdown between 1 and 28 June 2021.

3. Research Methodology

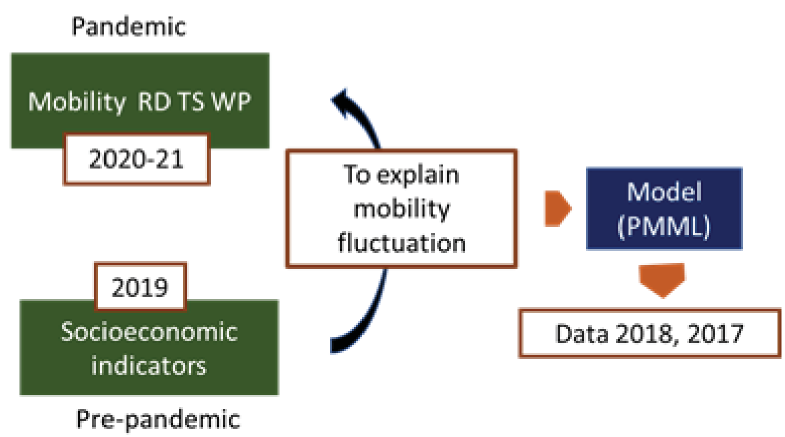
This section presents the research framework and the framework of the data mining process framework. This study belongs to secondary and exploratory research. The case covers Indonesia and Malaysia. The unit of analysis is a country's region covering all Indonesian provinces and Malaysian states/federal territories. There are 13 states and one federal territory in Malaysia. The federal territory consists of three regions: Kuala Lumpur, Putra Jaya, and Labuan. Statistics for these three regions are presented separately. Therefore, this study considers Malaysia to have 16 regions for data analysis.

3.1 Research Framework

The research framework of this study is shown in Figure 1. The first element is community mobility. Community mobility areas are related to people's activities at home, transportation, and the workplace. Therefore, three areas of human mobility were selected: residential place (rd), transit station (ts), and workplace (wp). Google's mobility data supplied the percentage of community mobility change. The second element is the socioeconomic indicators that represent social and economic performance. Socioeconomic indicators are the result of people's activities, and activities denote daily mobility. Therefore, the level of mobility change during a pandemic could be related to socioeconomic indicators before the pandemic. Regions with a better performance of socioeconomic indicators are expected to show a greater fluctuation in mobility. The analysis was carried out through the modelling of mobility and socioeconomic indicators.

The model produced could be saved as a predictive model in a Predictive Model Markup Language (PMML) format and then applied to a new data set to predict the behaviour of the regions. The model was then applied to the dataset year 2018 and 2017. The purpose was to examine the difference from the results of the year 2019.

Figure 1: A Research Framework



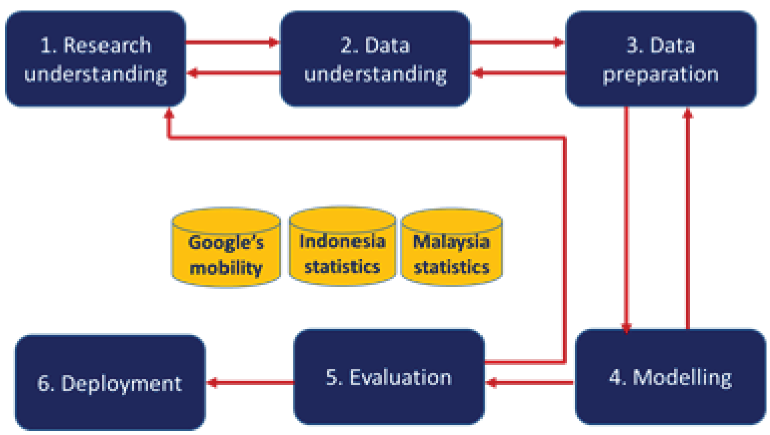
Source: Authors' Compilation

3.2 Data Mining Process

This secondary research implemented a data mining method, where data mining aims to reveal hidden information from secondary data. The implementation of data mining uses a process framework, where popular ones are CRISP-DM, KDD, and SEMMA (Azevedo & Santos, 2008). This study adopted CRISP-DM, which stands for Cross Industry Standard Process for Data Mining, as a broad industry standard used by academia and practitioners.

Figure 2 presents the CRISP-DM framework with its six steps. First, the research understanding was modified from its original term to business understanding. The data understanding phase refers to exploring data needs and their availability for access. Data preparation was aimed at cleaning and formatting data to be ready for further modelling. The modelling step was the primary analysis to find an appropriate model from the data. Fourth, the evaluation phase was to examine the goodness and reflect on whether the research goal was achieved. Finally, the deployment phase refers to the use of the model for the new data set.

Figure 2: CRISP-DM Methodology



Source: Authors' Graph by Adapting the Crisp-Dm Framework

An analysis tool or software was needed to implement data mining. This study used the Knime Analytics Platform as open-source software. Knime offers an advantage to non-coding software people because it is code-free software.

The implementation of CRISP-DM is elaborated in this methodology section for the research understanding, data understanding, and data preparation phases, and in the next section for the modelling, evaluation, and deployment phases. The research understanding refers to the research objectives in this data analysis to plot and correlate mobility fluctuations and cluster provinces/states based on community mobility and socioeconomic indicators.

The data understanding phase first addressed the data source. Mobility data for Indonesia and Malaysia were collected from Google's community mobility reports (Google, 2020). These data began from 15 February 2020 to 31 January 2021. Furthermore, socioeconomic data were collected from the Indonesian Statistics Agency and the Department of Statistics, Malaysia.
The percentage of change (fluctuation) in community mobility is a relative measure that does not indicate the number of people or mobility. It is a relative measure that is independent among regions. Therefore, socioeconomic indicators should have that characteristic. Absolute measures such as the size of the population, the area, and the amount of regional GDP may not be used. Some appropriate socioeconomic indicators selected were the Human Development Index, poverty rate, and labor force participation rate. The choice of these indicators also depends on the data available in both Indonesia and Malaysia.

The data preparation phase refers to acquiring, formatting, and determining the appropriate measures for data analysis. As the unit of analysis was a province, the mobility change should be one value per province/state. For this purpose, the root mean square (RMS) of daily mobility fluctuation was calculated for each province/state.

The period of socioeconomic data was 2019, 2018, and 2017. The Indonesian data per province for socioeconomic indicators: The Human Development Index (HDI), the poverty rate (PR), and the labor force participation rate (LFPR) were complete. Malaysia’s Statistics Agency does not report the yearly data, so interpolation and extrapolation techniques were applied. Furthermore, the mobility data cover three areas, namely, residential area (rd), transit-and-station (ts), and workplace (wp). The data are in daily time series. The root means square (RMS) was calculated.

4. Data Analysis and Discussion

This section presents data analysis for answering the research objectives by implementing the CRISP-DM modelling, evaluation, and deployment phases. The analysis covers the characteristics of community mobility and the link between community mobility and socioeconomic indicators.

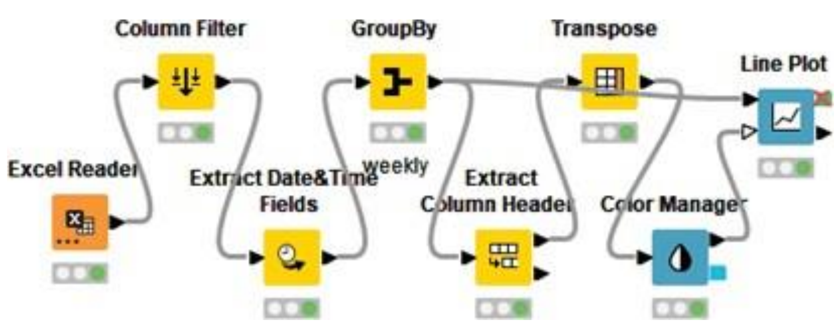
4.1 Characteristics of Community Mobility

Characteristics of community mobility are explored by mapping mobility fluctuation, finding an association between mobility areas, and calculating the strength of mobility.

4.1.1 The Plot of Mobility Fluctuation

The pattern of mobility fluctuation in daily time series does not indicate a good presentation. Therefore, the Knime workflow (Figure 3) was created to convert the daily data into weekly data and then plot them as a line plot.

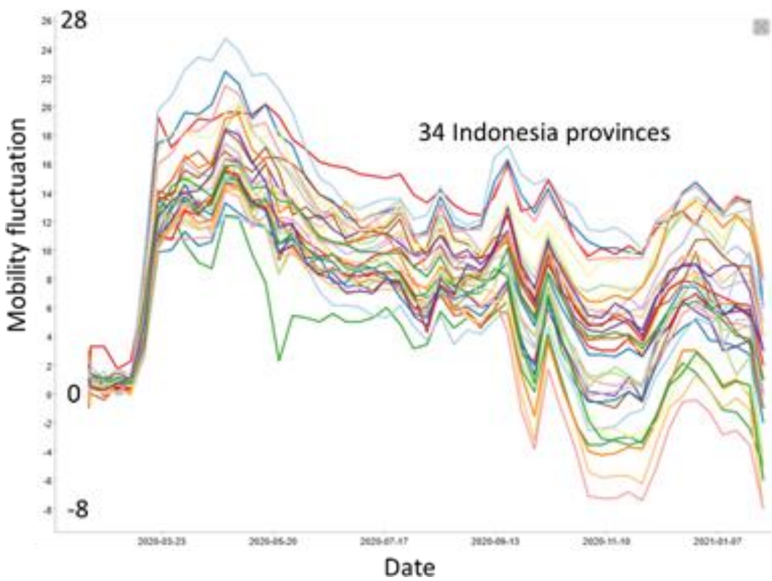
Figure 3: Knime Workflow



Source: Authors' Diagram Created Using Knime

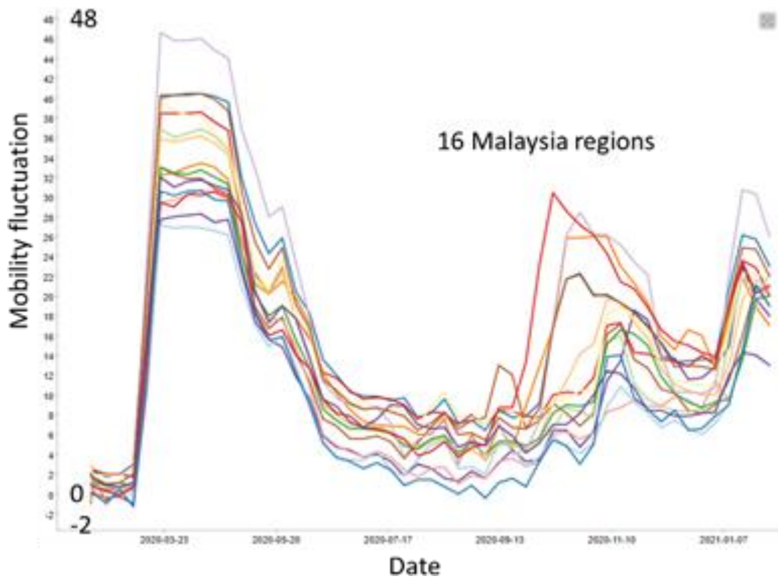
First, the fluctuation of the residential area mobility for Indonesia (Figure 4) and Malaysia (Figure 5) indicated a pattern in which the provinces/states in each country had a similar pattern. Second, the Indonesia and Malaysia plots indicated positive mobility fluctuation. It implies an increase in mobility in residential areas during the pandemic. Therefore, it was reasonable that the stay-at-home or work-from-home policy showed its impact. Third, the fluctuation pattern between Indonesia and Malaysia indicated the difference. It is logical as both countries had their timing of the government-imposed policy. Finally, an increase in mobility in residential places was also reported in a study in other countries, such as India (Saha et al., 2020b).

Figure 4: Indonesian Mobility in a Residential Area



Source: Authors' Graph Created Using Knime

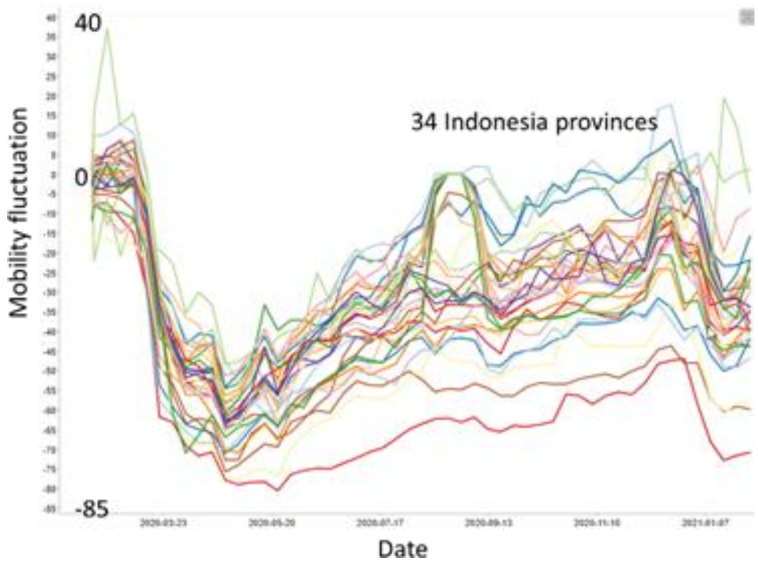
Figure 5: Mobility in a Residential Area in Malaysia



Note: 16 regions represent 14 states/federal territories.
Source: Authors' Graph Created Using Knime

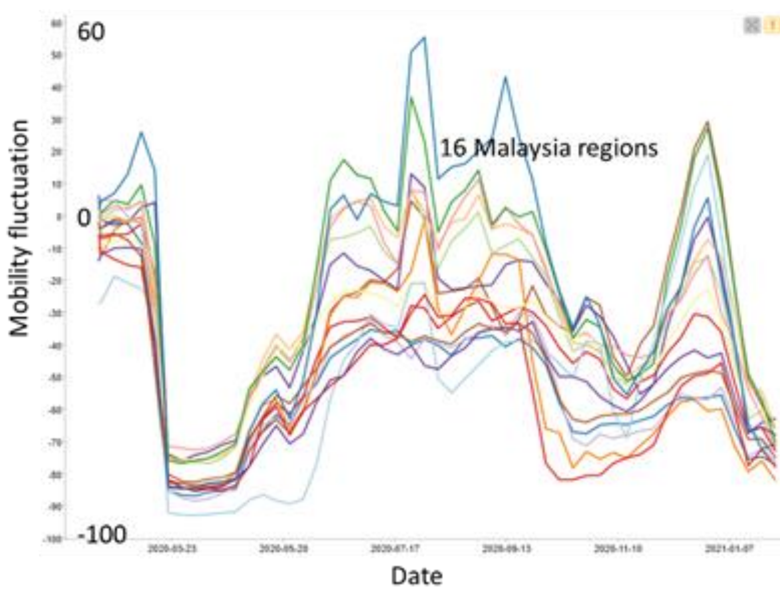
Second, the transit-station fluctuation for Indonesia (Figure 6) and Malaysia (Figure 7) shows negative fluctuation. This means that all provinces/states tend to experience a decrease in mobility during the pandemic. Mobility restriction orders and restricted public transport reduced the number of people travelling. Like residential places, a similar pattern was observed within a country but not across the country.

Figure 6: Mobility at Transit-station in Indonesia



Source: Authors' Graph Created Using Knime

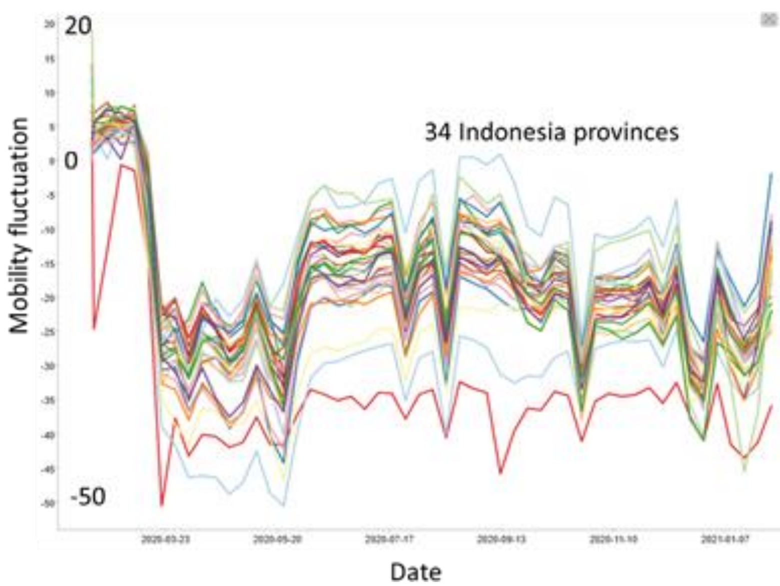
Figure 7: Mobility at Transit-station in Malaysia



Source: Authors' Graph based on Google's Community Mobility Data

Third, the fluctuations in mobility at the workplace in Indonesia (Figure 8) and Malaysia (Figure 9) also showed a similar pattern between the regions of the country. The fluctuation tended to be negative. It again indicated the visible impact of the work-from-home policy.

Figure 8: Mobility on the Workplace in Indonesia



Source: Authors' Graph based on Google's Community Mobility Data

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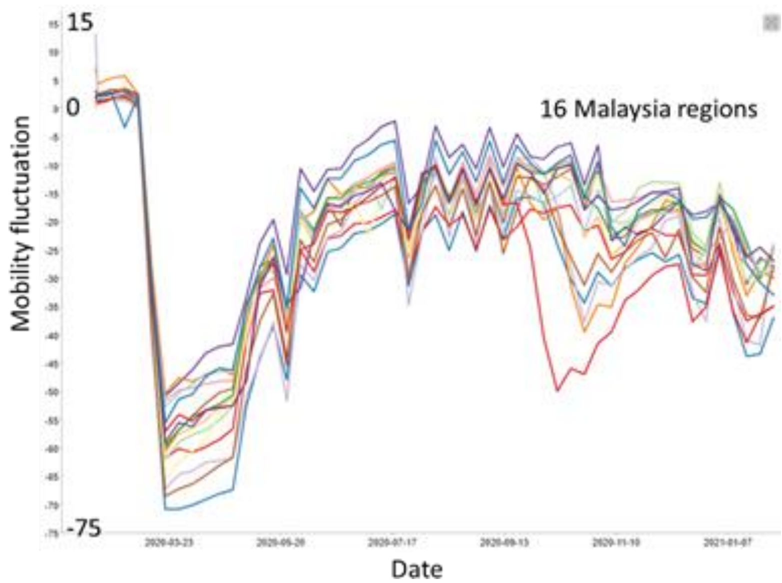
Figure 9: Mobility on the Workplace in Malaysia



Source: Authors' Graph based on Google's Community Mobility Data

4.1.2 Correlation of Mobility Fluctuation

Further investigation of mobility fluctuation was to find whether there was a correlation between the three areas: residential area, transit station, and workplace. A linear (bivariate) correlation was calculated among the three variables using transformed weekly data for each region. In addition, the analysis using Knime was performed and indicated a similar result. This paper presented Bali of Indonesia and Johor of Malaysia as a sample. Table 1 presents the linear correlation coefficients for Bali province and Johor state. The coefficients (in absolute values) extend from a minimum of 0.673 to a maximum of 0.915, and all correlations are statistically highly significant with a p-value < 0.001. As discussed earlier, the residential place had a positive mobility fluctuation, while the transit station and workplace were negative. Therefore, the negative and positive correlation values in Table 1 can be understood. The high correlation values could be interpreted as, for example, mobility restriction policy affected together on residential places, transit stations, and workplaces.

Table 1: Correlation of Mobility Area

Region	Corr. Value	p-value
Bali (rd - ts)	-0.837	0.000
Bali (rd - wp)	-0.743	0.000
Bali (ts - wp)	0.673	0.000
Johor (rd - ts)	-0.912	0.000
Johor (rd - wp)	-0.915	0.000
Johor (ts - wp)	0.806	0.000

Source: Authors' Analysis Results

The high correlation might indicate that the province/state likely had high (or low) mobility fluctuations in all three areas. Therefore, the variation in mobility fluctuation between provinces and states might be related to the characteristics of the province and state. Furthermore, the correlation analysis of the other provinces/states indicated similar characteristics of mobility fluctuation. Therefore, this finding could be generalised.

4.1.3 Strength of Mobility Fluctuation

The mobility fluctuation data do not indicate the number of people mobility, but only the percent change compared to the period before the pandemic. Therefore, the average root means square of the daily time series for each province/state was calculated. Table 2 presents Indonesia and Malaysia's average root mean square mobility, covering all regions. The values indicated the same order from the highest at the transit station to the lowest at the residential area for both countries. Furthermore, the mobility fluctuation in Malaysia was higher than in Indonesia.

Table 2: Average Root Mean Square Mobility

	residence	transit- station	workplace
Indonesia	9.75	37.18	23.81
Malaysia	16.93	48.63	39.96

Source: Authors' Analysis Results

In summary, the analysis indicates that:

1) Mobility fluctuation of each region within the country showed a similar pattern.
2) Mobility fluctuation in a residential area was positive, while the others were negative.
3) Correlation appeared among mobility fluctuations.
4) The strength of mobility fluctuation in the descending order was transit station, workplace, and residential area.
5) Malaysia showed higher mobility fluctuation than Indonesia.

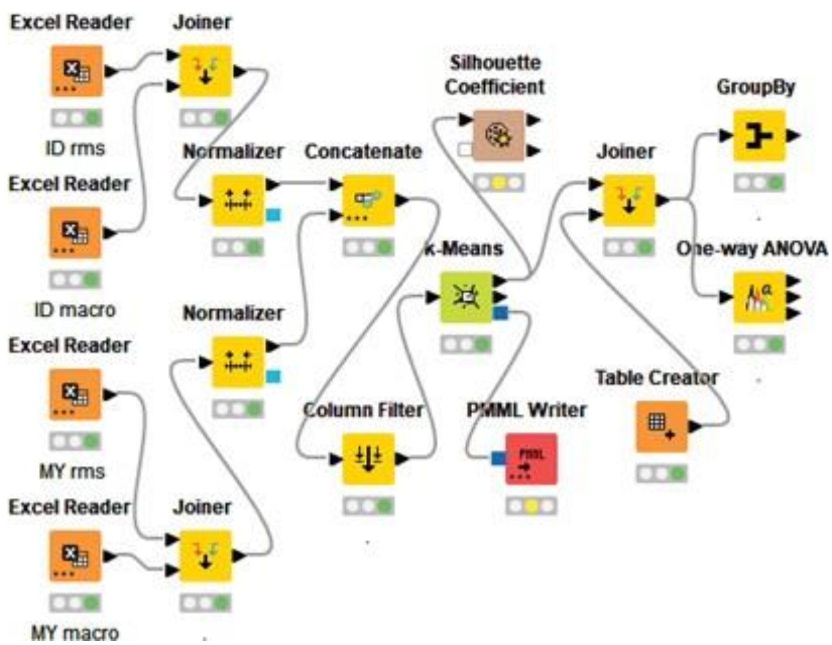
4.2 Community Mobility and Socioeconomic Indicators

The association between community mobility and socioeconomic indicators was analysed by clustering. Furthermore, this section explores the association between clusters and demographic indicators and the model deployment for the data years 2017 and 2018.

4.2.1 Clustering Method

The clustering method was implemented to group provinces/states with socioeconomic indicators. As data were exploratory, three mobility variables and three socioeconomic indicators (HDI, poverty rate, labour force participation rate) were performed. The ANOVA test was performed to identify which variables were not significant among the groups. Figure 10 shows the Knime workflow for clustering. Both Indonesia and Malaysia data were combined after normalisation was performed.

Figure 10: Knime Workflow For Clustering



Source: Author's Graph Created Using Knime

K-means clustering was implemented. K=2, 3, and 4 were examined to determine the value of k as the size of the cluster. The result is presented in Table 3. The silhouette coefficient, ranging from -1 to 1, was a metric applied to evaluate the goodness of a clustering technique (Řezanková, 2018). Table 3 shows that the highest mean of the silhouette coefficients was for k=2. To decide which k value, an ANOVA test was executed to examine which variables were significant in differentiating clusters. For k=3, all six variables were significant, but for k=2 and 4, one variable was not significant. For k=3, the silhouette coefficient was not the highest, but the difference between clusters for all six variables was significant. Therefore, the decision was to choose k=3.

Table 3: Evaluation of Cluster Size

k	cluster size	Silhouette Coef.	ANOVA p -value
2	8, 42	0.447	three s.v <0.001; one ns.v
3	6,21,23	0.212	six s.v <0.001
4	6,13,13,18	0.178	five s.v <0.001; one ns.v

s.v = significant variable; ns.v = non-significant variable

Source: Authors' Analysis Results

The characteristics of each group were analyzed using the GroupBy node to obtain the mean values of six variables. Table 4 exhibits the mean values of each variable across the three clusters. Three mobility variables were noticeably separated into low, medium, and high. Among the three socioeconomic indicators, only HDI shows a similar ascending trend. This means that regions with higher mobility fluctuations were likely to have higher HDI. The poverty rate (PR) indicates the reverse order. It implies that regions with higher mobility were likely to have lower poverty rates. The labour force participation rate (LFPR) did not indicate the same pattern as the others. However, it shows that regions with high labour force participation rates were likely to experience high mobility fluctuations during a pandemic.

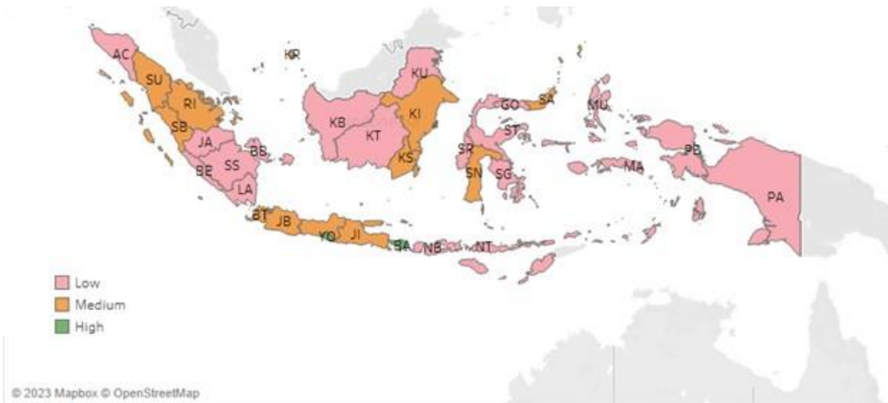
Table 4: Mean Values of Each Cluster

Variable	Cluster		
	Low	Medium	High
rd	0.266	0.476	0.894
ts	0.254	0.367	0.805
wp	0.216	0.316	0.861
HDI	0.378	0.598	0.907
PR	0.435	0.196	0.070
LFPR	0.565	0.357	0.773
Count	23	21	6

Source: Authors' Analysis Results

The clustering produced 23 low-mobility regions, 21 of medium mobility, and six high mobility. The 34 provinces of Indonesia were divided into three clusters, with 19 (low mobility), 12 (medium mobility), and 3 (high mobility) provinces. The three provinces with high mobility are Bali, Yogyakarta, and Jakarta. In Malaysia, the 16 regions were classified into 4 (low mobility), 9 (medium mobility), and 3 (high mobility) states. Those in high mobility clusters are Kuala Lumpur, Putrajaya, and Selangor. Figures 11 and 12, respectively, show the Indonesia and Malaysia cluster members.

Figure 11: Mobility Cluster Map of Indonesia



Source: Author's Graph Created Using Tableau

Figure 12: Mobility Cluster Map of Malaysia

Source: Authors' Graph Created Using Tableau

4.2.2 Cluster and Demographic Indicators

Furthermore, the characteristics of the clusters were explored with demographic indicators. As demographic indicators, the number of populations and the area of regions are absolute values. Therefore, both are incompatible with the relative measure of mobility fluctuation. Population density (people per sq. km) is a relative measure; therefore, it is appropriate. Group node was performed. Table 5 shows that in Indonesia and Malaysia, the high mobility cluster had a high median population density value, far from the values of the others. It means that provinces/states with higher mobility fluctuation tending had higher population density.

Table 5: Population Density among Clusters

Cluster	Median population density	
	Indonesia	Malaysia
Low mobility	72	50
Medium mobility	195	231
High mobility	1227	2222

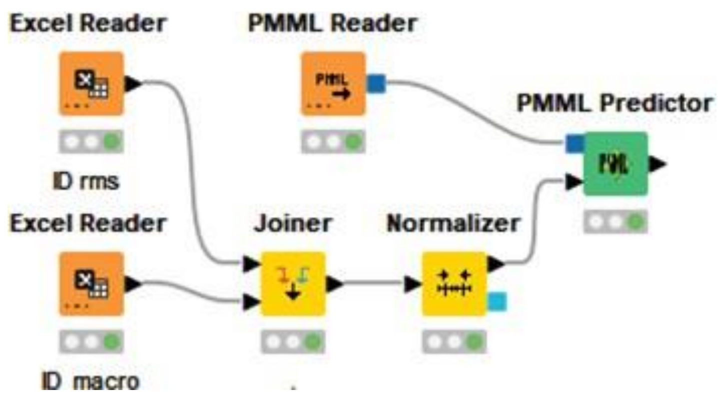
Source: Authors' Analysis Results

In Indonesia and Malaysia, the capital city belongs to this high-mobility cluster. The result was reasonable as the region with a high population density is likely to experience a higher decrease in mobility due to the mobility control policy. This argument might lead to a preliminary conclusion that the strength of mobility fluctuation is related to population density.

4.2.3 Model Deployment

The clustering process produces a model in PMML format that can be deployed (applied) to other datasets. Figure 13 presents the Knime workflow for model deployment. This deployment of the PMML model was applied to previous years' data. In this study, data from 2018 and 2017 were used.

Figure 13: Deployment of Model



Source: Authors' Graph Created Using Knime

The result indicates that the cluster membership position for Indonesia's data years 2018 and 2017 was the same as in 2019. It means that no province experienced a significant change in socioeconomic indicators. However, a shift of membership occurred for Malaysia data for the data set in the year 2017. Kedah, which belonged to a low mobility cluster, moved to the medium mobility cluster in 2018 and maintained its position in 2019. This shift was likely to represent better socioeconomic indicators.

5. Conclusion

This study has investigated the characteristics of mobility fluctuation at a residential place, transit station, and workplace to address the first study objective. The findings support previous studies that mobility fluctuation is affected by the government-imposed movement control order. The mobility pattern between regions within a country shows similarities but not mobility between countries. Indonesia and Malaysia showed the strength of mobility fluctuation in descending order: transit station, workplace, and residential area. Malaysia showed a higher fluctuation in mobility than Indonesia, which might indicate the level of community response to the Covid-19 pandemic.

This study has revealed that socioeconomic indicators determine mobility fluctuations during the pandemic. Regions with high mobility fluctuations are likely to have high HDI and labour force participation rates. Furthermore, regions with high mobility fluctuations are likely to have low poverty rates. High-mobility regions cover the capital city and other cities with high-density populations.

The novelty of this study is to discover that socioeconomic indicators such as HDI, poverty rate, and labour force participation rate are determinants of mobility fluctuation during the pandemic. These determinants add a primary factor in which government-imposed movement control is a significant determinant of fluctuation in mobility. Furthermore, this study contends that the strength of mobility fluctuation during a pandemic could be predicted. Therefore, regional governments (provincial or state) could use the findings to anticipate community mobility and plan related policies when similar pandemic conditions occur.

The findings should be interpreted under some limitations. First, this study focused on two neighbouring countries. Therefore, the generalisation of the finding was limited. Further studies might extend to neighbouring countries. Second, this study only covered three socioeconomic indicators. Further study might extend to other indicators to find a more comprehensive understanding.

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