Data Mining for Revealing Relationship Between Google Community Mobility and Macro-Economic Indicators

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***Abstract*—Google community mobility reports have helped to evaluate the effectiveness of government-imposed movement control among countries. However, the relationship between the mobility data and the characteristic of regions is less reported. This study aims to reveal hidden information from Google community mobility reports and relate them to all 34 Indonesian provinces' macro-economic indicators. This secondary research implements a data mining approach using the CRISP-DM process framework and Knime Analytics Platform. The community mobility data of residence and workplace are collected as a time series covering Feb 16, 2020, to Jan 31, 2021. Macro-economic indicators are collected from the website of the Indonesian national statistics agency. The clustering method has grouped provinces into three based on their mobility. The findings indicate the relationship between mobility fluctuation during the COVID-19 pandemic and macro-economic indicators, namely human development index and labor force participation rate. In the theoretical aspect, this study has been initiating the investigation of community mobility and macro-economic. Policymakers in dealing with post-pandemic recovery planning might consider the cluster characteristics for better planning.**

Keywords—mobility, covid-19, data mining, macro-economics, Indonesia

I. INTRODUCTION

Post-pandemic recovery issues have been addressed in many forums (e.g., Indonesian Economic Outlook 2021 on Feb 8, 2021) and planned by the government and international organizations. Google community mobility reports (CMR) provide information that can be used to predict whether a country could recover its economic activity sooner or later. For example, UNDP's report on planning a post-pandemic recovery in Latin America described that Latin America might need longer time to resume economic activity than Europe by analyzing Google community mobility data [1]. As reported by Google in time series since Feb 16, 2020, the mobility data is essential to look for post-pandemic recovery planning.

Given the vastly spread of COVID-19, lowering social interaction and people movement's intensity becomes the main premise to reduce the transmission rate of COVID-19 [2]. The study of community mobility patterns is a crucial factor in understanding the diffusion of the currently COVID-19 pandemic and the effectiveness of the government-imposed social distancing mandates. The government of each country responded varies with rigid lockdown mandates to less social distancing measures. The effectiveness of such a social movement policy has been reported in Germany [3], U.S. [4], and India [5]. The general conclusion is that those movement control orders constitute the primary decrease in community mobility [6]. In addition to government mandates, the contribution of voluntary social distancing in mobility reduction is also confirmed [7]. In general, both government-imposed and voluntary social distancing impact community mobility during the COVID-19 pandemic.

The Indonesian national statistics agency (Badan Pusat Statistik/ BPS) published a report concerning big data analysis in the context of the COVID-19 pandemic. The report presents the effect of government-imposed social distancing order from Mar 15, 2020, to May 31, 2020, using Google community mobility reports [8]. A paper from BPS also identified the different effects between the social distancing mandate (PSBB) and a new-normal policy toward increasing COVID-19 cases [9]. Both reports deliver valuable information in evaluating government policy at the national level. However, the report offers no detailed information and recommendation to provinces. In data mining, more opportunities can be revealed from the Google community mobility reports. This study was intended to fill the gap.

This study, in general, aims to reveal hidden information from Google community mobility reports and relate them to macro-economic indicators of Indonesian provinces. Each province has different geographic, demographic, and economic characteristics. These characteristics are, in general, described as macro-economic indicators, regularly published by the national statistics agency (BPS). This study departs from the proposition that the fluctuation of community mobility of each province relates to the province's characteristics specified by some macro-economic indicators. None of the published studies and BPS reports has linked Google community mobility with macro-economic indicators. If the relationship exists, it will open the possibility to understand and manage the movement control order based on the province's characteristics.

During the current Covid-19 pandemic period, the number of patients, deaths, and survivors was updated and published in a time-series format. The data represent big data for further analysis with data mining or machine learning methods. Data mining aims to reveal hidden information from a set of data. The use of data mining in economic research, especially in the Indonesian economy, is still emerging. This research adopts a data mining method to discover information that links mobility fluctuation to some macro-economic indicators of each province. This study takes a position to focus on the appropriate use of data mining for a better understanding of the real social-economic aspect of the community and region.

The specific objectives of this study are: (1) to present graphs and to identify a correlation between a residential area and workplace mobility across all 34 Indonesian provinces; (2) to cluster provinces based on the community mobility fluctuation; (3) to investigate the characteristics of each cluster against macro-economic indicators. The achievement of these objectives provides information for a better understanding of each province and making policy.

II. Methods

A. Research approach

This study applies secondary research, because of using existing (secondary) data. Secondary research also requires a method with systematic steps [10]. This study adopts the data mining method, which requires a systematized process for its implementation. One of the popular process frameworks in data mining is CRISP-DM. The CRSP-DM method, which stands for Cross-Industry Standard Process for Data Mining, consists of 6 phases: Business understanding - Data understanding - Data preparation - Modeling - Evaluation - Deployment. The first phase, business understanding, for research could be renamed with research understanding. Research objectives as described in the previous section represent the research understanding. Data understanding covers activity to gather, describe, and verify data quality, while data preparation includes an activity to select, clean, construct, and format data [11]. Based on research objectives, modeling techniques adopted are clustering methods and supported with linear correlations and ANOVA. The evaluation phase was to evaluate the model's appropriateness and whether the result meets the research objectives. Finally, the deployment phase is performed by analyzing the result and make recommendations.

B. Data sources

Data are collected from the Community Mobility Reports released by Google (www.google.com/covid19/mobility/) for 135 countries and their regional area, e.g., province, state. The reports are created with accumulated and anonymized data sets from mobile device users who activate the Location History setting. The reports differentiate six places: residential, workplaces, retail-and-recreation, grocery-and-pharmacy, parks, and transit stations. This study selected Indonesian residence and workplace data as a daily time series from Feb 16, 2020, to Jan 31, 2021. The data represent the percent change of baseline data, which is the median value, for the corresponding day of the week, during the five weeks Jan 3–Feb 6, 2020. The time-series data cover all 34 provinces.

The second data source is the national statistics agency's official site (BPS), which is bps.go.id. Some macro-economic indicators are selected to characterize each province. In line with the mobility data with relative values (percent of change), the macro-economic indicators selected are those with relative values. Three variables are chosen: human development index, labor participation rate, and poverty level.

The Human Development Index (HDI) is a composite indicator of a human-oriented country's development achievements. HDI consists of 3 dimensions with four indicators, namely: the health dimension (life expectancy), the education dimension (the expected length of schooling, the average length of schooling), and the expenditure dimension (per capita expenditure) [12]. The poverty rate is defined as the percentage of the population who live below the poverty line. The labor force participation rate is a measure of an economy’s active workforce, which is the sum of all employed workers divided by the total civilian working-age population.

C. Data mining tool

This study uses Knime as a data mining tool. The first reason relates to Knime as open-source software with a large number of users. Second, Knime offers visualization of the data analysis process (workflow) for simple to complex tasks with no need for coding language expertise [11]. Microsoft Excel is used in some parts of the data preparation phase, for example, to format data, to rename variables, and to calculate root mean square (RMS) values.

III. Results

A. Graph and correlation

Knime workflows were designed to plot residential and workplace mobility data. The daily data are group weekly for better visualization, then the mean scores of mobility fluctuation per week were calculated. Fig. 1 presents the workflow.

Fig. 2 exhibits the graph with x-axis plotting date (in weekly) and y-axis plotting the percent of change (in mean scores) from the baseline for residential data. Each line plot represents a time series of each province. The fluctuation of residential data is positive, indicating the increase of civilian stay at home.

Furthermore, Fig. 3 exhibits plots of workplace mobility data for all 34 provinces. In contrast with residential data plots, the workplace has a negative direction. It means that fewer people appear at the workplace than in the baseline period.

The correlation between residential and workplace data is performed to explore their relationship. As residential data is positive and workplace negative, all correlation scores are negative. Fig. 4 shows the absolute correlation scores, which extend from 0.028 to 0.918. Among 34 provinces, 31 have significance values p<0.001, one (Papua Barat) p<0.005, and 2 provinces (Aceh and Maluku Utara) indicate non-significant with p>0.05.

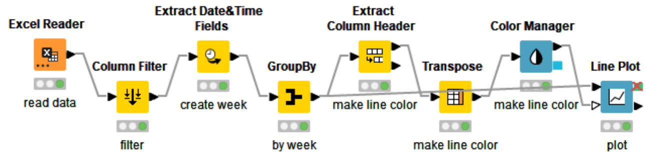

Fig. 1. Workflow for line plot

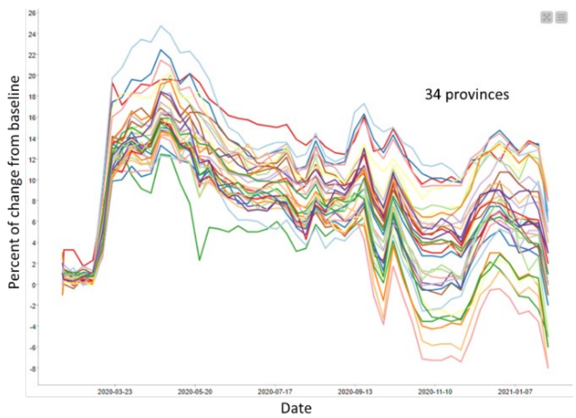

Fig. 2. Mobility in residential area

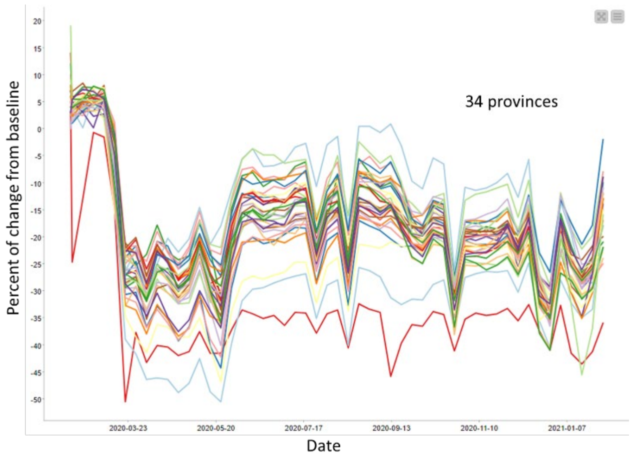

Fig. 3. Mobility in workplaces

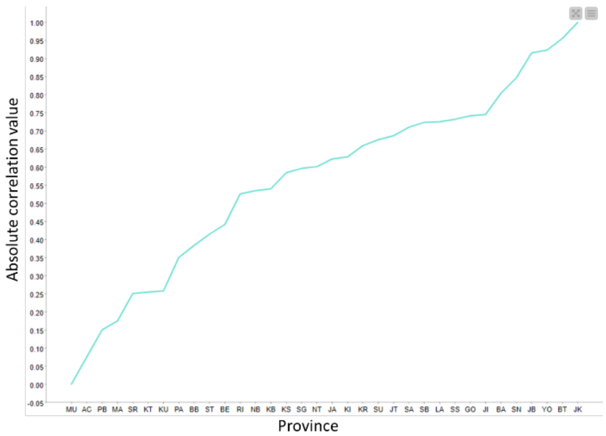

Fig. 4. Correlation of workplace and residential area mobility

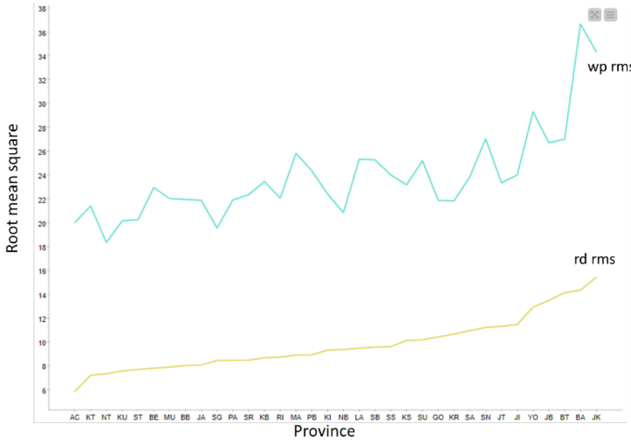

Fig. 5. RMS of workplace and residential area mobility

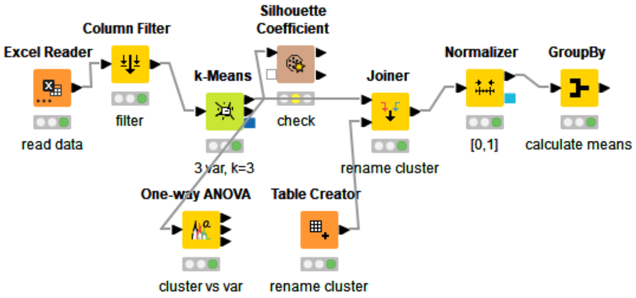

Fig. 6. Workflow for clustering

B. *Clustering*

Clustering was aimed to group 34 provinces based on their residence and workplace mobility. Variables for clustering were developed. The first is the absolute correlation scores as presented above. Furthermore, the root means square of residence and workplace mobility for each province were calculated. The root mean square (RMS) is defined as the square root of the mean values x_i^2, where x_i is daily mobility. RMS's score can be interpreted as the strength of residence or workplace mobility fluctuation within the dataset period.

Fig. 5 exhibits root mean squares of residential and workplace mobility, presented in ascending order of RMS residence. The graph indicates that the fluctuation of the workplace is bigger than the residence. The mean of RMS workplace is 23.8, while RMS residence 9.8.

Furthermore, the k-means algorithm's clustering method was performed through the Knime workflow shown in Fig. 6. The choice of the k-means algorithm relates to its advantages documented in the literature, such as simplicity, wide use, and scalability to a large data set. The weakness of k-means is sensitive to the outliers. The outlier detection was performed using the Numeric Outliers node. The result found only three outliers (above upper bound) among the whole data set. Therefore, the data set is considered appropriate for k-means clustering.

In k-means, the number of clusters must be determined in advance. Literature indicates that the number of clustering variables and the number of clusters should consider the number of objects [13], 34 provinces in this study. The number of clusters (k) was set as 2,3, or 4. The model was evaluated using the Silhouette coefficient (value range -1 to 1). Table I presents Silhouette coefficients and the cluster size. Both coefficient and cluster size were considered in determining the number of k. While the Silhouette coefficient of k=3 is not the highest, it has a more comparable cluster size than k=2.

Further analysis in the next section has been applied for clusters with k=2 and k=3. It appears that grouping provinces into three (k=3) provides better information than two (k=2). Therefore, this study selected k=3. The clustering groups 34 provinces into three, named Low, Medium, and High mobility, as presented in Table II.

Furthermore, the GroupBy node was applied to calculate the means of five significant variables across three clusters. This analysis was aimed to obtain a clearer picture characterizing each cluster. Table IV depicts the result.

TABLE I. EVALUATION OF CLUSTER NUMBER

k	Cluster size	Mean Silhouette Coefficient [-1 to 1]
2	6, 28	0.613
3	5, 14, 15	0.402
4	2, 8, 10, 14	0.359

TABLE II. CLUSTERED PROVINCES

Cluster	Provinces
Low mobility	Aceh, Kep. Bangka Belitung, Bengkulu, Jambi, Kalimantan Tengah, Kalimantan Utara, Maluku Utara, Nusa Tenggara Barat, Nusa Tenggara Timur, Papua, Riau, Sulawesi Tenggara, Sulawesi Barat, Sulawesi Tengah
Medium mobility	Gorontalo, Jawa Timur, Jawa Tengah, Kalimantan Barat, Kalimantan Timur, Kep. Riau, Kalimantan Selatan, Lampung, Maluku, Papua Barat, Sulawesi Utara, Sumatera Barat, Sulawesi Selatan, Sumatera Selatan, Sumatera Utara
High mobility	Bali, Banten, Jawa Barat, DKI Jakarta, DI Yogyakarta

IV. DISCUSSION

The government-imposing movement control in Indonesia started on the mid of March 2020, while Google's community mobility reports start in mid of February. Therefore, graphs of workplace and residence mobility show that the fluctuation is low across all provinces during the first four weeks. This low fluctuation from baseline might indicate that during that period, voluntary social distancing was not noticeable. This finding opposes some cases in other countries (Maloney & Taskin, 2020).

Data analysis indicates the relationship between mobility in residential areas and workplace is observed for all provinces, except Aceh and Maluku Utara. Observing the strength of mobility fluctuation as measured by root mean square, both provinces indicate low mobility. The mobility fluctuation of a workplace is about 2.5 times of a residential area. The interpretation is borrowed from Google's community mobility site, which described that people already spend much of the day at residential places.

The clustering method has grouped 34 provinces into low, medium, and high mobility clusters. The low mobility cluster covers 14 provinces with less mobility fluctuation and a low correlation of residence and workplace mobility data. On the other side are five provinces with high mobility fluctuation and a high correlation between residence and workplace mobility. The other 15 provinces stay between both groups.

As shown in Table IV, the investigation of macro-economic indicators shows that the high mobility cluster tends to have high HDI and low labor force participation rate. This cluster consists of five provinces: Bali, Banten, Jawa Barat, DKI Jakarta, and DI Yogyakarta. Three provinces: Jawa Barat, DKI Jakarta, and Banten, have vital industrial sectors. Bali and DI Yogyakarta have a strong tourism sector, and DI Yogyakarta also has a strong education sector. These economic activities might explain their high mobility fluctuation. The development of those provinces is represented by high HDI as a composite index. Furthermore, a lower labor force participation rate means a lower ratio of the sum of all workers (who are employed or actively seeking employment) divided by the total civilian working-age population. A lower ratio implies more percentage of civilians currently not working but studying in higher education.

TABLE III. TABLE III.RESULT OF ANOVA

Test Column	F-ratio	p-value
Correlation workplace – residence	16.78	0.000
RMS workplace	40.54	0.000
RMS residence	88.19	0.000
HDI	8.20	0.001
Labor force participation rate	10.67	0.000
Poverty rate	1.48	0.242

TABLE IV. CLUSTERS WITH VARIABLE MEANS

Variable / Cluster	Low mobility	Medium mobility	High mobility
Correlation workplace-residence	0.38 (L)	0.62 (M)	0.92 (H)
RMS workplace	0.15 (L)	0.31 (M)	0.68 (H)
RMS residence	0.22 (L)	0.44 (M)	0.86 (H)
HDI	0.44 (L)	0.52 (M)	0.77 (H)
Labor force participation rate	0.81 (H)	0.59 (M)	0.33(L)

Note: L=Low, M=Medium, H-High

On the other side, the low mobility cluster inclines to have a lower Human Development Index (HDI) but a high labor force participation rate. The low mobility fluctuation might indicate fewer economic activities than the five provinces in the high mobility cluster. The low mobility provinces are likely to be less developed, as indicated by HDI. The high labor force participation rate might show fewer civilians continue their studies in higher education institutions.

The finding of this study should not be interpreted to confront the concept of macro-economic indicators, especially HDI and labor force participation rate. Instead, it enriches them by relating both indicators to community mobility.

V. CONCLUSION

This study has implemented a data mining approach using the CRISP-DM process framework and Knime Analytics Platform to explore Google's community mobility reports for Indonesian provinces. Based on the community mobility in the workplace and residential area, 34 provinces have been grouped. The analysis reveals the relationship between mobility fluctuation during the pandemic, and macro-economic indicators, namely human development index and labor force participation rate among provinces.

This study contributes to the theoretical aspect by finding the relationship between community mobility and macro-economic indicators and initiating a research topic on this area. This study has enriched the big data analysis report published by the national statistics agency/BPS [8], [9]. In dealing with post-pandemic recovery planning, policymakers might consider the cluster characteristics found in this study for better planning targeted to each province. From a data mining viewpoint, this study has initiated to apply the appropriate or 'less advanced' data mining tool and techniques for not-so-big data in the real social-economic context.

Some limitations should be noted. First, Google released the community mobility data when the pandemic began in the world. Time-series data in the 'normal years' before the pandemic was not available. This fact might have been limited the interpretation of the findings. Second, this study focused only on three macro-economic indicators: human development index, labor force participation rate, and poverty rate. Further studies might explore other indicators to get better knowledge how the mobility in a region relates to social-economic indicators.

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Greetings from the General Chair

On behalf of the Organizing and Program Committee, we warmly welcome you to the 9th International Conference on Information and Communication Technology (ICoICT) 2021 on August 3-5th, 2021. The 9th ICoICT 2021 is jointly organized by Telkom University Indonesia, Multimedia University Malaysia, and Universitas Gadjah Mada Indonesia, in association with The IEEE Indonesia Section, The IEEE Indonesia Section Computer Society Chapter, and The IEEE Signal Processing Society Indonesia Chapter. The previous ICoICT conferences have successfully served as a forum to bring together a diverse group of people from academics and industries to share and present the latest issues and recent developments in Information and Communication Technology (ICT). Papers from the previous ICoICT 2013 until 2020 have been published in IEEE Xplore and indexed in Scopus.

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The technical program of 9th ICoICT 2021 consists of eight keynotes, one knowledge transfer, five tutorials, and six tracks on "Digital Innovations for Post-pandemic Recovery." For the first time, the conference features social events that allow conference participants to meet and discuss with fellow researchers in the same field of interest. Competition for the Best Paper Award is also organized. The

9th ICoICT 2021 received 296 paper submissions from 20 countries, out of which 122 papers have been accepted - corresponding to an acceptance rate of 43.4%. All paper submissions have been subjected to a rigorous peer-review process that evaluates their significance, novelty, and technical quality. Each paper was reviewed independently by at least three experts.

Due to the COVID-19 pandemic, we have decided to hold the 9th ICoICT 2021 as a virtual conference. The organizing committee had been work hard to create a virtual conference that will be valuable and engaging for both presenters and attendees. The full conference format mixes pre-recorded and asynchronous engagement and lives engagement through Question-and-Answer (Q & A) and in-person video calls.

The 9th ICoICT 2021 has been organized due to the work and effort of colleagues, friends, and organizations. We wish to thank all who have participated and supported our work in many ways and all who helped us make this event possible and successful. We would like to express our gratitude to the Organizing Committee and Technical Committee members and all Telkom University colleagues who assisted us in planning and organizing this conference. We also wish to thank all the reviewers who worked very hard in reviewing papers and providing suggestions for the paper's improvements. We would like to express our sincere gratitude to the Keynote and Tutorial Speakers. We would also like to thank all of the sponsoring organizations for providing their generous financial support. Last but not least, we would like to give appreciation to the authors who have submitted their excellent works to this conference and all the attendees. We appreciate your virtual attendance at the 9th ICoICT 2021. We hope you enjoy all the keynote sessions, the technical sessions, and the social events and inspire your future research.

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Notification of Papes Acceptance	January 19, 2020
Paper Submission Deadline Round 2	March 01, 2021
Paper Submission Deadline Final Round	April 10, 2021
Notification of Papes Acceptance	May 03, 2021
Submission of Camera Ready Papers and Author Registration Deadline	May 21, 2021
Conference Date	August 03-05, 2021

ICoICT 2021 is co-sponsored by the IEEE Indonesia Section, the IEEE Indonesia Section Computer Society Chapter, and the IEEE Signal Processing Society Indonesia Chapter. All accepted papers in

ICoICT 2021 will be published in the conference proceedings and will be submitted for publication.

We look forward to seeing you in the virtual conference!

Dr. Warih Maharani

General Chair

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