Community Mobility during Covid-19 Pandemic and Tourism Performance: Data Mining Approach

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Abstract. The movement control policy imposed by the government worldwide has changed the community mobility during the Covid-19 pandemic. In addition, the limitation of flights and the visiting policy has nearly stopped visitors to tourist destinations. This study contends that the community mobility change in a region during a pandemic relates to the region's tourism-related performance before the pandemic. Data mining approach with CRISP-DM as a framework and Knime Analytics Platform as a tool are used to analyze data on 34 Indonesian provinces. The study aims (1) to present the nature of community mobility fluctuation at the tourism-related area, (2) to group provinces based on the similarity in mobility fluctuation and tourism-related performance, and (3) to characterize provinces across the tourism-related performance. Data are collected from Google's community mobility covering mobility change in retail-and-recreation areas, parks, and transit-and-station as a time series for all provinces. In addition, tourism-related indicators are collected from the Indonesian statistics agency covering length-of-stay and occupancy rates for starred and non-starred hotels. Among three tourism-related areas, transit-and-station experience the highest mobility fluctuation in a decreasing direction. The main finding shows that six provinces with higher visitor length-of-stay and hotel occupancy rates experience greater mobility change. Bali, Yogyakarta, and Jakarta are well-known as domestic and international tourist destinations; North Sulawesi with Bunaken National Marine Park, West Papua with Raja Ampat, and Riau Islands are also popular tourist spots. The result implies that those regions may suffer a higher impact on tourism. This study contributes to the application of data mining to reveal information on publicly available socio-economic indicators.

Keywords: data mining, covid-19, mobility, tourism, Indonesia

INTRODUCTION

According to the European Central Bank, the term innovation explains the development and application of ideas and technologies that enhance goods and services or improve production efficiency. Several studies indicate the relationship between innovation (e.g., patents, R&D expenditure) and economic growth [1], [2]. Furthermore, disruptive technological innovations such as steam engines, electricity, automotive, and computer have brought impact to create new economic activities.

At the macroeconomic level, technological innovation has permeated all economic sectors: primary, secondary, tertiary, and quaternary. Hospitality and leisure industries within the tertiary sector experienced a significant impact of technological innovation. Travel booking technology is evident in how the tourism industry is growing around the world. Some technologies, such as mobile technology, augmented reality, recognition technology, the internet of things, and big data, continuously affect tourism trends.

The use of big data in tourism industries is still potential among businesses. The accumulated big data such as the travel itinerary, the country origins, the amount of money spent, the length of stay, and the motive for the trip can be analyzed to compose a better segmentation and its promoting channels. Currently, emerging passive mobile data (PMD) recorded by mobile network operators about visitors' activity offers opportunities [3]. Big data could provide a better understanding of the actual tourism condition for the government, and better policy could be made. However, the analysis has not been much conducted.

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Before the pandemic, extreme weather or climate change is considered a critical factor to influence tourism, especially in island countries such as Indonesia [4]. However, to what extent climate change influences tourism in island countries with tropical weather has not been fully understood. The critical factor falls to the Covid-19 pandemic, which has brought unprecedented impact. The movement control policy and limitation of flights have nearly stopped visitors to tourist destinations. The World Tourism Organization reported that international tourist arrivals in the Asia Pacific regions suffer a 94% drop between January – March 2021, compared to the same first quarter of 2020 [5]. The report states that the global plunge is 83%. The impact of this pandemic is different from the other prior pandemics. While the average recovery period of other pandemics to the tourism industry is about ten months, this Covid-19 pandemic is predicted to make a recovery longer [6].

To solve the global tourism problem impacted by the outbreak of Covid-19, the role of tourism academia is significant [7]. Four research areas on tourism were suggested: the impact of the pandemic, post-pandemic recovery, resilience and sustainability, and technological solution [8]. Some studies have investigated the impact of the pandemic on the tourism sector. Studies in China found that small-sized tourism-related businesses are vulnerable to the pandemic [9]. A study among provinces in Spain signified that the preferred tourist destinations have a higher vulnerability to pandemic among [10]. Considering the complexity of the tourism sector impacted by the pandemic, system thinking might be adopted as an approach to understand a system's behavior and identify measures for changing the system [11]. A better understanding of the actual condition will be an input for government and businesses to formulate strategy.

The World Tourism Organization defines tourism as "a social, cultural and economic phenomenon which entails the movement of people to countries or places outside their usual environment for personal or business/professional purposes" [12]. It emphasizes that tourism and people's movement or mobility are intertwined. This research departs from this basic notion. During the over one-year pandemic, starting March 2020, the movement control policy and social distancing campaign have changed the community mobility. Google published Community Mobility Report, with daily time series data starting from 16 February 2020, covering six areas: residential, workplace, grocery-and-pharmacy, retail and recreation, transit-and-station, and park. Among them, the last three (retail-and- recreation, transit-and-station, park) could be considered as tourism-related places. The question is whether the community mobility change (fluctuation) relates to tourism indicators from years before. The answer might add understanding about the independent (tourism-related) variables explaining the mobility fluctuation during the pandemic.

Current development worldwide indicates that business decisions and government policy require comprehensive information from analyzing a large volume of data. As a result, big data analysis has been of great interest among practitioners and academics. The terms data analytics, data mining, data science, machine learning, deep learning are popularly used. All of them refers to provide rich information that could not be exploited by prior conventional data analysis. This study uses a data mining approach to address tourism in Indonesia in the context of the Covid-19 pandemic.

This study focuses the analysis on all 34 Indonesian provinces. The specific objectives of this study are: (1) to present the nature of community mobility fluctuation at the tourism-related area, (2) to group provinces based on the similarity in mobility fluctuation and tourism-related performance, and (3) to characterize provinces across the tourism-related performance. The achievement of these objectives could explain whether the tourism-related performance contributes to the mobility fluctuation in that province.

METHODOLOGY

Research Framework

This study applies secondary research because of using existing (secondary) data. Secondary research also requires a method with systematic steps. Figure 1 presents the research framework. Time frame is differentiated into before pandemic and during pandemic for explaining the source of data. Mobility fluctuation at retail-and-recreation, transit-and-station, and parks are data during the pandemic period. Data of tourism-related indicators are for the year are data before the pandemic, the year 2019. Analysis of mobility fluctuation and tourism indicators among provinces is targeted to explain mobility fluctuation (Modelling and Evaluation Phase). The data mining process produces a clustering model that can be used as a predictive model for other data sets, which are 2018 and 2017. The application of the model (Deployment Phase) to the year 2018 and 2017 is aimed to observe whether there is a change in the grouping of provinces (cluster).

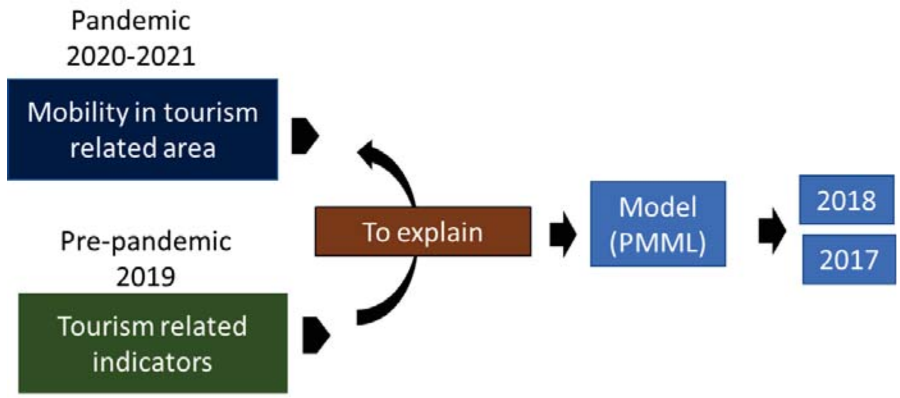

FIGURE 1. Research framework

This study adopts the data mining method, which requires a systematized process for its implementation. Two popular process frameworks in data mining are SEMMA and CRISP-DM. The SEMMA method consists of 5 phases, namely Sample - Explore - Modify - Model - Assess. The CRSP-DM method stands for Cross-Industry Standard Process for Data Mining. Their comparison indicated that CRISP-DM is a more comprehensive method than SEMMA [13], [14]. 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 (Fig. 2). The CRISP-DM is well performed if the data analysis project is goal-directed and process-driven [15]. The first phase, business understanding, for research could be renamed with research understanding. In this phase, research and data mining goals were clarified. Research goals have been presented in the Introduction section. Among the rest steps, data understanding, and data preparation are presented in this Methodology section and the Modelling, Evaluation, and Deployment in the Result and Discussion.

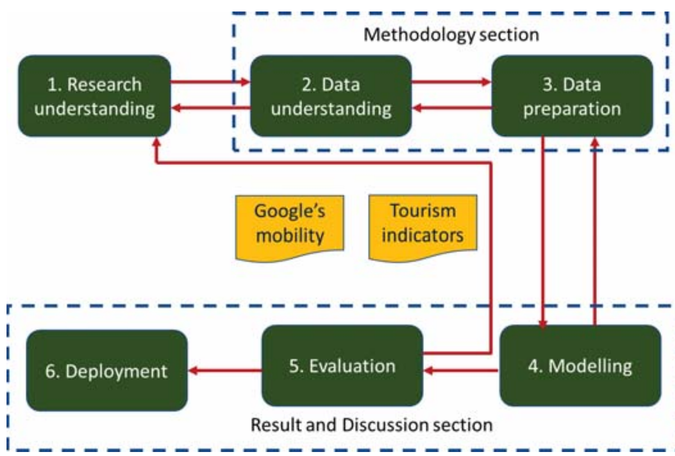

FIGURE 2. CRISP-DM methodology

Data source and variable identification

Finding data sources and understanding the data relates to the data understanding, as the second phase of CRISP-DM. Data are collected from the Community Mobility Reports released by Google (www.google.com/covid19/mobility/) for 135 countries and their regional areas. The reports were created with accumulated and anonymized data sets from mobile device users who activate the Location History setting. This study selected Indonesian data for all 34 provinces with mobility fluctuation at retail-and-recreation, transit-and-station, and park as a daily time series from 16 February 2020 to 31 January 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 03 January–06 February 2020.

The second data source is the national statistics agency's official site (BPS), which is bps.go.id. Among tourism-related indicators, four appropriate ones were identified: number of visitors, number of accommodations/ rooms/ beds, length of stay, and hotel occupancy rate. The number of visitors and length of stay are grouped into domestic and overseas visitors. The number of accommodations/ rooms/ beds and hotel occupancy rate are grouped into a starred hotel and a non-starred hotel. Mobility as a percent of change (fluctuation) could be considered as independent between provinces. However, the number of visitors and number of accommodations/rooms/beds are absolute measures. Some provinces might have a high number of visitors, such as Bali and Yogyakarta, while some others might below. Similarly with the number of accommodations. Investigation of descriptive statistics shows that both indicators with absolute values do not form a proper distribution. These data characteristics do not match with mobility fluctuation. Therefore, the number of visitors and accommodations/rooms/beds are removed from the analysis. Tourism indicators were extracted for the years 2019, 2018, and 2017.

Data mining requires a tool (software) for processing data. A large number of open-source analytic software is available for data mining. For example, Knime Analytic Platform is a popular open-source data mining software categorized as code-free software. Users do not need to master programming languages and create code [16]. This study uses Knime. As the third phase, data preparation mainly refers to the process of the data being ready for further analysis. In this CRISP-DM data mining process, considerable time was spent (1) to clean and format data so data can be read by Knime nodes; (2) to observe the pattern of variables about distribution, normality, (3) to select the suitable variables for next step, modeling. Figure 3 exhibit a Knime workflow to clean and normalized data.

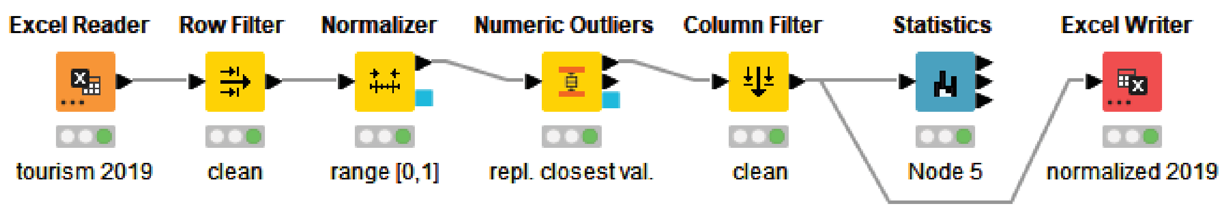

FIGURE 3. Knime workflow for data cleaning and normalization

The result of data preparation is a dataset of seven variables both with the original values and normalized form (range 0 to 1). Here are the variables with their notation:

1. Retail and recreation mobility (rr)
2. Park mobility (pa)
3. Transit and station mobility (ts)
4. Length of stay in starred hotels (s_ls)
5. Length of stay in non-starred hotels (n_ls)
6. The occupancy rate in starred hotels (s_or)
7. The occupancy rate in non-starred hotels (n_or)

RESULT AND DISCUSSION

Characteristics of mobility fluctuation

Mobility change of retail-and-recreation, park, and transit-and-station are plotted in weekly time-series. Daily data is collapsed into weekly by calculating mean values. Graph presentation is better using weekly data. Figure 4a, 4b, 4c presents the mobility fluctuation in retail-and-recreation, park, and transit-and-station. The fluctuation tends to the negative (decreasing) direction. In addition, a sample of two provinces: Bali and East Java, is presented in Fig 4d. It is apparent that transit-and-station was showing the biggest mobility change, followed by park and retail-and-recreation. Bali experienced a higher mobility decrease than East Java. It is realistic as Bali is a major tourist destination.

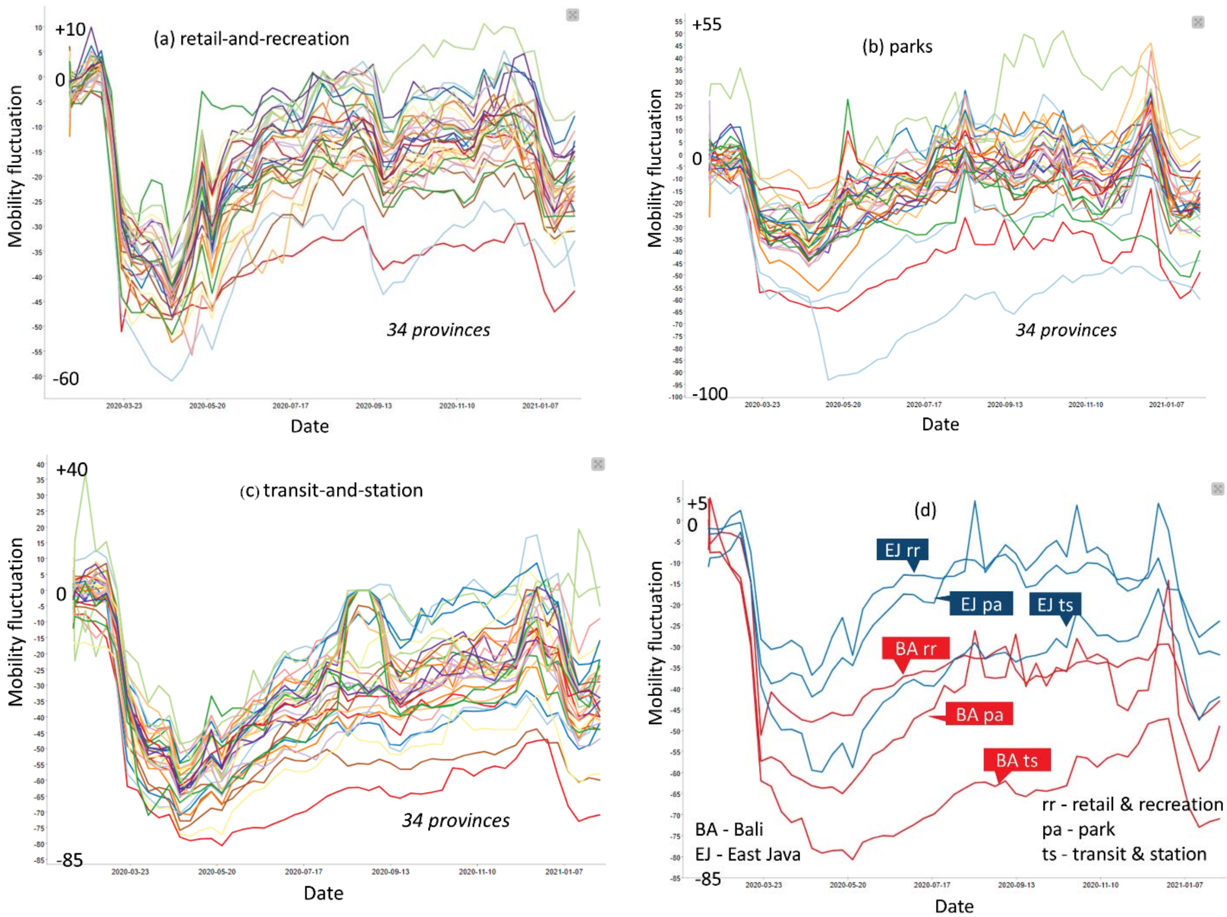

FIGURE 4. Mobility fluctuation

As the unit of analysis for further modeling is a province, the mobility fluctuation in the time series was transformed into a single value for each province. The root means square of mobility fluctuation for each province was calculated. Descriptive statistics were performed using the Statistics node. Table 1 shows that transit-and-station has the highest fluctuation and mean value. It implies that during the pandemic, this area category experiences a higher decline in mobility. This result is reasonable as the limitation of public transport operation and movement control policy in general.

TABLE 1. Descriptive statistics of mobility fluctuation

Mobility	Min	Max	Mean	Std. dev.
Transit-and station (ts)	26	63	37	8
Park (pa)	10	61	22	10
Retail-and-recreation (rr)	14	37	22	5

Characteristics of cluster

Based on the type of seven variables, the modeling belongs to unsupervised learning. Data is a numeric scale; thus clustering method is the appropriate one. Knime provides various clustering methods include k-means, k-medoid, fuzzy c-means, hierarchical clustering, and DBSCAN. Every method has its requirements. In this study, k-means is selected by considering the number of objects is not big, and it is simple, easy to understand, and widely used. The workflow is shown in Fig. 5.

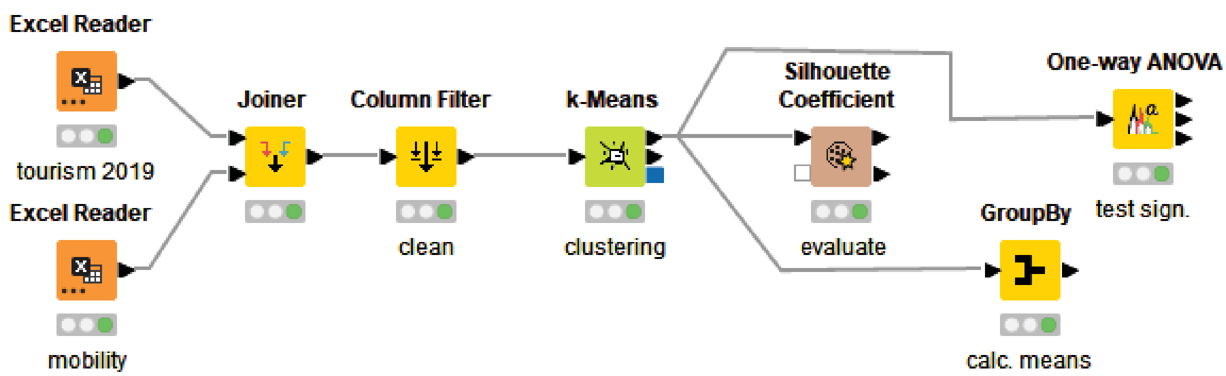

FIGURE 5. Knime workflow for clustering

Evaluation of the appropriate number of k was performed using the Silhouette coefficient. This coefficient has a range -1 to +1. Table 2 presents the Silhouette coefficient for each cluster component and mean for k=2, 3, 4. The highest value is k=2; thus, it is selected.

TABLE 2. Variables and data type

Cluster	k=2	k=3	k=4
cluster_0	0.166	0.116	0.143
cluster_1	0.452	0.146	0.168
cluster_2	---	0.189	0.085
cluster_3	---	---	0.218
Mean Silhouette coef.	0.402	0.145	0.157

K-means clustering was performed to produce two clusters. One small cluster contains six provinces, and a big cluster has 28 provinces, as shown in Table 3. The small cluster consists of Bali, Yogyakarta, and Jakarta, well-known as domestic and international tourist destinations. In addition, North Sulawesi with Bunaken National Marine Park, West Papua with Raja Ampat, and Riau Islands are also popular tourist spots.

TABLE 3. Variables and data type

Cluster_0	Cluster_1		
Bali	Aceh	Gorontalo	South Kalimantan
Jakarta	Bangka Belitung Isl.	Jambi	South Sulawesi
Yogyakarta	Banten	Lampung	South Sumatra
North Sulawesi	Bengkulu	Maluku	West Java
Riau Islands	Central Java	North Kalimantan	West Kalimantan
West Papua	Central Kalimantan	North Maluku	West Nusa Tenggara
	Central Sulawesi	North Sumatra	West Sulawesi
	East Java	Papua	West Sumatra
	East Kalimantan	Riau	
	East Nusa Tenggara	South-East Sulawesi	

ANOVA test was performed to investigate whether there is a significant difference between clusters for each variable. Table 4 shows the mean value of each variable for each cluster and the ANOVA test. It shows high significance results with a p-value less than 0.001 for four variables, less than 0.01 for two variables, and less than 0.05 for one variable. Cluster_0 has higher mean values of all variables. Overall, this result proves the difference between both clusters.

TABLE 4. Variable means and ANOVA test

Cluster	Mean						
	ts	**rr**	**pa**	**s_ls**	**n_ls**	**s_or**	**n_or**
cluster_0 [6 provinces]	0.794	0.724	0.850	0.461	0.388	0.772	0.443
cluster_1 [28 provinces]	0.328	0.298	0.418	0.273	0.210	0.494	0.226

ANOVA test	**ts**	**rr**	**pa**	**s_ls**	**n_ls**	**s_or**	**n_or**
F	27.751	24.680	24.073	7.381	9.363	7.891	17.137
p-value	0.000	0.000	0.000	0.011	0.004	0.008	0.000

The small cluster with six provinces has both high mobility fluctuation and high tourism performance. It is reasonable; for example, Bali and Yogyakarta have high tourism performance indicated by visitor's length-of-stay and hotel occupancy rate. The result is likely to show that provinces with high mobility fluctuation are those with high tourism-related performance. It is apparent that tourist destination provinces experience tremendous mobility change.

Model application

Modeling and evaluation phases of CRISP-DM have produced the K-means clustering model. In the deployment phase, this model is applied to a new dataset. In this study, the model was applied to the past years' dataset to see whether provinces were grouped in the same clusters as 2019 or not. The shifting of cluster membership could indicate the significant performance change in the tourism indicators.

Figure 6 exhibits a Knime workflow for model deployment. First, the excel reader node reads the tourism performance of 2018/2017, then applies the model (with PMML Reader) to predict (with PMML Predictor) the cluster membership of the data.

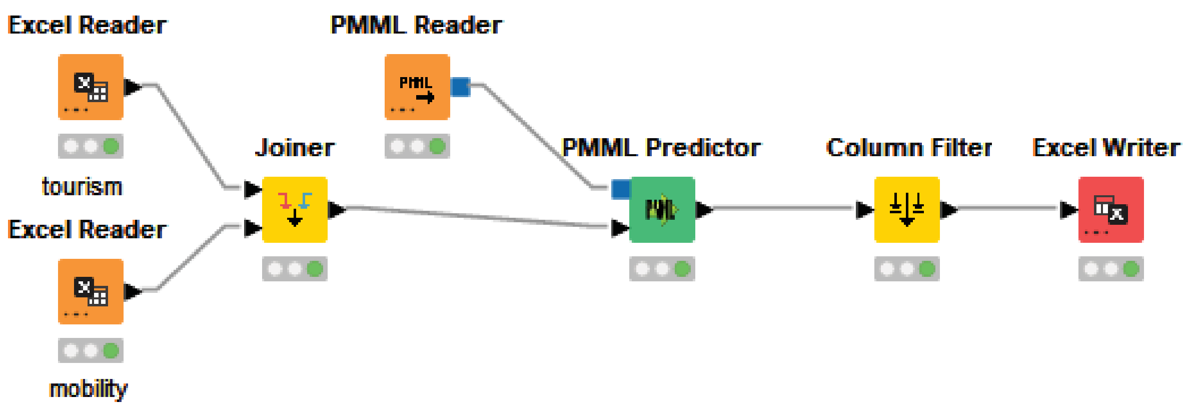

FIGURE 6. Model deployment

The application of the clustering model to the 2018 and 2017 datasets shows precisely the same result of cluster membership with the 2019 dataset. It shows the validity of the PMML model. In addition, the same clustering result might indicate the non-substantial performance change within tourism-related indicators.

CONCLUSION

This study has completed the three objectives. For the first objective, this study found the characteristics of mobility fluctuation among provinces: (1) relationship exist between mobility change in retail-and-recreation, park, and transit-and-station, (2) retail-and-recreation experienced the highest fluctuation, (3) province with the highest mean fluctuation is Bali, DKI Jakarta, and Yogyakarta. For the second objective, all 34 provinces were clustered, based on the mobility fluctuation and tourism indicators, into two groups. One group consists of provinces with higher mobility fluctuation and tourism performance. Another group is those with lower mobility fluctuation and tourism performance. The result indicates that those with higher tourism performance before the pandemic experience a higher decrease in mobility during the pandemic. For the third objective, provinces in a cluster with high mobility fluctuation and high tourism indicators are well-known as tourist destinations, such as Bali, Yogyakarta, North Sulawesi (with Bunaken National Marine Park), and West Papua (with Raja Ampat). In summary, the finding shows that the intensity of mobility change during the pandemic could be explained by the tourism-related indicators of prior years.

This study has added the literature on the application of data mining to macro socio-economics studies. While the application is considered simple, this study shows the contribution of the data mining to relate data from different sources (Google mobility and Indonesian statistics), from different types (time series and static), to achieve a better understanding of the actual Indonesian condition in the Covid-19 pandemic.

This study must acknowledge several limitations. First, the finding is limited to the Indonesian context. Further study might extend the scope to other neighboring countries to find a better generalization of this finding. Local governments, especially provinces with popular tourist destinations, might have to use the result to plan a recovery strategy. The strategic concept from tourism experts and experiences from other countries published by the World Tourism Organization (UNWTO) might be adopted and adapted to restore the tourism industry. Finally, this study suggests that tourism academia adopt a data mining or data science approach to reveal the meaning of the increasing volume of tourism-related data.

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We thank all keynote speakers, presenters, and reviewers/scientific committees for the generous supports. We thank the University of Surabaya, the Faculty of Engineering UBAYA, and all InCITE 2021 committees that enable InCITE 2021.

We wish you a very pleasant and rich conference experience in InCITE 2021 and look forward to seeing you again on InCITE 2023! Thank you.

Yours sincerely,
Asst. Prof. Dr. Jimmy
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