The Impact of COVID-19 Pandemic on E-commerce Firms: Data Mining for the Provinces in Indonesia

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Abstract

The COVID-19 pandemic has brought an impact on the global retail industry. Some studies have investigated e-commerce during the pandemic. However, most of them focused on consumer behavior in online shopping. This paper focuses on e-commerce firms, as an aggregate, among regions. This study departs from a question: what we can learn from the e-commerce firms in regions during the pandemic. The objectives of this study are: (1) to classify the intensity of e-commerce firms in a region and to specify the regional and e-commerce profiles, (2) to classify the intensity of pandemic impact on e-commerce firms and to specify the regional and e-commerce profiles, and (3) to specify the observed association between the characteristics of e-commerce, pandemic impact, and region profiles of e-commerce firms with high intensity and high pandemic impact. This quantitative and secondary research collected data from the Indonesian official statistics and Google mobility report. Data mining was implemented with the Knime Analytics Platform. The analysis classifies provinces with high and low e-commerce intensity and high and low pandemic impact and specifies the regional and e-commerce profiles regarding those classifications. This article contributes to the literature by presenting data mining using the official statistics among regions at a country level on e-commerce during the COVID-19 pandemic. More facilitation for regions with low e-commerce intensity is suggested. For example, local governments and marketplace companies could support firms entering online sales channels.

Keywords
e-commerce, online retail, data mining, COVID-19, Indonesia

1. Introduction
The impact of the COVID-19 pandemic on the retail industry was apparent globally. The governments' lockdown, social distancing, and movement control policies have been implemented in most countries. As a result, reduced people's mobility was detected, for example, in Japan, Hongkong, Singapore, and Australia (Hakim et al., 2021), Malaysia (Aziz et al., 2020), and Indonesia (Djalante et al., 2020). Those studies indicated the effectiveness of the government's movement control policy (Mendolia et al., 2021). As people's mobility was restricted, conventional or brick-and-mortar retailers experienced declined sales transactions. Many retail outlets closed their business because of high fixed costs incurred, and sales dropped.

For online retailers or e-commerce firms, the COVID-19 pandemic impact might come to two conditions. First, fewer people's (consumers) mobility could reduce the goods to buy and shrink the online sales transaction. Second, the pandemic might shift the way consumers shop from visiting retail outlets to online shopping. Therefore, some e-commerce firms could suffer a sales decline, and others enjoy increased sales. For example, the Indonesian National Statistics (BPS) reported that e-commerce firms, at the country level, experienced three conditions: a transaction volume decline (72%), an increased (10%), and the same (18%) (BPS, 2021). The numbers denote that most firms experience the negative impact of the pandemic.

Several studies have investigated e-commerce during the COVID-19 pandemic. However, most of them focused on consumer behavior in online shopping, such as in Indonesia (Iriani & Andjarwati, 2020), Saudi Arabia (Albliwi & Alsolami, 2021), Poland (Wiscicka-Fernando, 2021), and Finland (Eriksson & Stenius, 2021). Other studies proposed retail-related technologies for facing the COVID-19 pandemic and beyond (Har et al., 2022; Shankar et al., 2021). The analysis in this paper focuses on e-commerce firms in Indonesian provinces. Electronic commerce (e-commerce) refers to a business model that allows companies and individuals to buy and sell goods and services over the Internet.

The term e-commerce firm refers to firms selling goods and services over the Internet. E-commerce firms as an aggregate within a province mainly cover many micro, small, and medium enterprises (MSMEs). Those firms sell online mainly through social media and the marketplace, as a common practice in developing countries.

This study departs from a question: what we can learn from the e-commerce firms in regions during the pandemic. Therefore, the objectives of this study are: (1) to classify the intensity of e-commerce firms in a region and to specify the regional and e-commerce profiles, (2) to classify the intensity of pandemic impact on e-commerce firms and to specify the regional and e-commerce profiles, and (3) to specify the empirical pattern of association between the characteristics of e-commerce, pandemic impact, and region profiles of e-commerce firms with high e-commerce intensity and high pandemic impact. The finding will add information to managerial decisions to cope with the pandemic. It is relevant because the immediate spread of the global pandemic teaches us that upcoming pandemics are unavoidable (Keane & Neal, 2021).

This article is structured as follows. Section 2 presents the work related to e-commerce during the pandemic. Section 3 presents a research method covering framework, data collection, and data analysis. Section 4 describes the result of the analysis. Finally, the main conclusions from the study performed are presented in section 5.

2. Literature Review

In the past, the study of e-commerce focused on major online retailers such as Amazon.com, Walmart.com, and Tesco.com. E-commerce transactions and the number of e-commerce firms have grown significantly. Now, most e-commerce firms are micro, small, and medium enterprises (MSMEs). Those e-commerce firms emerged as pure online retailers or brick-and-mortar retailers adopting an online sales channel. A survey among Indonesian SMEs indicated that the determinant factors influencing SMEs adopting e-commerce are: perceived benefits, technology readiness, owners' innovativeness, owners' IT ability, and owners' IT experience (Rahayu & Day, 2015). Prior studies indicated that offline (brick-and-mortar) retailers add online channels, or online retailers add offline channels to increase overall sales (Timoumi et al., 2022). However, pure e-commerce firms face a greater risk of bankruptcy than brick-and-click ones (Cuellar-Fernández et al., 2021).

E-commerce should not only be seen as another sales channel as it has changed consumers' shopping behavior and shaped the future of retail business (Ratchford et al., 2022). The COVID-19 pandemic opened opportunities for consumers to shop online with less person-to-person contact. A study in Saudi Arabia revealed a shift in consumer behavior from offline to online shopping during the pandemic (Albliwi & Alsolami, 2021). Additionally, a survey study in Finland showed an increase in online grocery shopping during the pandemic, which was dominated by consumers aged less than 45 years (Eriksson & Stenius, 2021). After the COVID-19 pandemic ends, some new habits practiced during the pandemic might continue to replace some old habits; for example, the convenience of enjoying streaming services such as Netflix makes fewer consumers go to the movie theatre (Sheth, 2020). Furthermore, the pandemic provides opportunities to deploy more retail technologies. In response to the COVID-19 pandemic and beyond, retailers might need to invest in 'smart distancing' technologies, such as smart dome, drone delivery, and robot delivery, to keep shoppers and store employees safe (Shankar et al., 2021). Adopting Industry 4.0 technologies to the retail industry - named Retail 4.0 - is another solution for the new practices in the pandemic to limit physical contact between buyers and retail staff (Har et al., 2022).

Prominent emerging marketplaces contribute to the growth of e-commerce firms. Statista.com reported that the Indonesian marketplaces Tokopedia, Shopee, and Bukalapak were the most clicked sites in the first quarter of 2021. In the past, a 2013 article reported a problem in Indonesian MSMEs adopting e-commerce through a marketplace regarding the lack of customer trust and payment methods (Syuhada & Gambett, 2013). However, those problems have now been eliminated by those major marketplaces. High trust between sellers and buyers is apparent as millions of sellers join marketplaces and buyers shop online. In addition, various trusted methods of payment are available for customers. The increase in online transactions also contributes to the expanding use of electronic money (e.g., Gopay, OVO) as an alternative payment method in the marketplace. A prior study in Indonesia found that online buyers will continue using electronic money because of its usefulness, their satisfaction, and their trust in it (Sasongko et al., 2022).

Using social media as a sales channel is more straightforward and less sophisticated than a marketplace or a seller's e-commerce site. Instagram and Twitter have become popular social media platforms for online selling, primarily by micro and small enterprises. Though social media is not intended for online shopping, it provides distinct features. An online survey in Malaysia revealed that social media's user-friendly and visually appealing features motivate young generations to purchase goods and services through social media (Hassan et al., 2021). Moreover, a study on customer perspective in Indonesia confirmed the positive association between social media use and purchase intentions (Permatasari & Kuswadi, 2017).

On a macroeconomic level, e-commerce significantly relates to gross domestic product (GDP) growth, as shown in Ukraine, Poland, and Austria (Zatonatska, 2018). Positive economic impacts are generated as e-commerce creates jobs and revenue for retailers, production firms, and delivery companies. Similarly, e-commerce growth is associated with an increase in per-capita income, as proven by studies in India (Anuj et al., 2018) and Indonesia (Nashar et al., 2020). However, this association could be interpreted as an indication that regions with higher per-capita income provide their inhabitants with a higher ability to spend, including through online shopping.

In summary, the COVID-19 pandemic impacted e-commerce firms as the lockdown, social distancing, and community mobility control policies were implemented. As a result, most e-commerce firms suffered declining sales transactions; meanwhile, some enjoyed increased transactions. E-commerce firms depend on marketplaces and social media platforms as sales channels. Furthermore, the growth of e-commerce in a region is associated with the growth of per-capita income. This short review provides an idea to explore the e-commerce firms of a specific region, the pandemic's impacts, and regional profiles.

3. Methods

This study is categorized as secondary and quantitative research. The secondary data comes from the BPS-Statistics Indonesia (the national statistics agency) and the Google Mobility Reports. This study is exploratory by adopting a data mining approach to reveal hidden information from a dataset. Data mining was implemented through a process framework named the Cross-Industry Standard Process for Data Mining (CRISP-DM) (Martinez-Plumed et al., 2019). The framework contains six phases of the data mining life cycle: Business understanding, Data understanding, Data preparation, Modelling, Evaluation, and Deployment. The first phase, business understanding, was adapted into research, referring to the data mining objective. The objective was to find a pattern of e-commerce firms in regions during the COVID-19 pandemic. Furthermore, the computational analysis was performed using the Knime Analytics Platform as open-source software for data mining.

3.1 Framework

Data mining is a data-driven approach in which the analysis is to find a pattern or relationship from a dataset. It is not aimed to test a hypothesis as in a theory-driven approach. Instead, a framework is developed to outline the variables for analysis. Figure 1 presents the diagram covering e-commerce intensity, pandemic impact on e-commerce firms, e-commerce profile, and regional profile. E-commerce intensity refers to the portion of MSMEs adopting e-commerce, the percentage of residents using the Internet, and the economic indicator representing buying capacity of buyers in a region. Pandemic impact on e-commerce firms refers to the business impact of the pandemic on e-commerce firms, and community mobility decreased during the pandemic. E-commerce profile refers to product and operation. Region profile refers to resident-related indicators such as population density and the resident's skill/education.

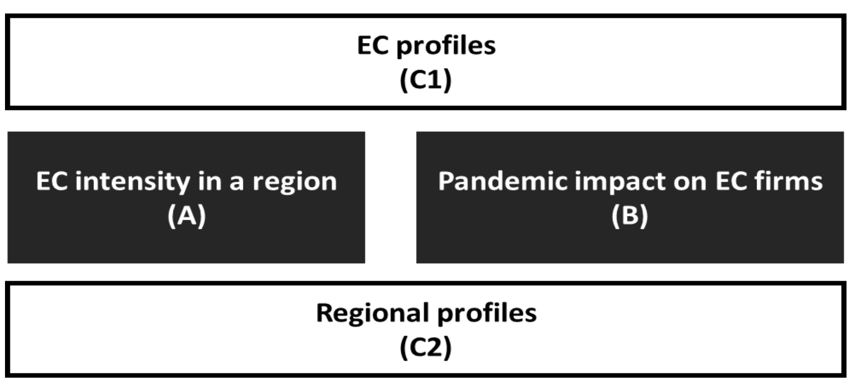

Figure 1. Framework for analysis

Following the CRISP-DM framework, Business Understanding was implemented by defining the objective of data mining as follows:

1. Clustering provinces based on the EC intensity (block A) and specifying their e-commerce and regional profiles (block C1, C2)
2. Clustering provinces based on the pandemic impact on e-commerce firms (block B) and specify their e-commerce and regional profiles (C1, C2)
3. Specifying provinces based on the intensity of e-commerce firms (A), pandemic impact (B) and their e-commerce and regional profiles (C1, C2).

3.2 Data Collection

Data understanding was implemented by identifying and selecting variables for analysis. The first data source is the official site of BPS-Statistics Indonesia www.bps.go.id. Data about e-commerce was extracted from the E-commerce Report 2021, which reports e-commerce data for 2020. Data about region profiles were collected from the interactive table on that site. The second data source is the Google Mobility Reports released by Google (www.google.com/covid19/mobility/). Google described that the reports were created with accumulated and anonymized data sets from mobile device users who activated the location history setting. The reports differentiate six places: residential, workplaces, retail-and-recreation, grocery-and-pharmacy, parks, and transit stations. This study selected the retail-and-recreation area as related to the shopping activities. The raw data collected is a daily time series from 16 Feb 2020 to 31 Dec 2020, covering all 34 Indonesian provinces. The mobility fluctuation during that period was negative, which means the people's mobility was reduced compared to before the pandemic.

Data preparation was implemented by cleaning data, formatting, and transforming data about e-commerce and regions into an Excel table. Furthermore, each province's root means square of retail area mobility was calculated from daily mobility's root means square (RMS). The RMS scores represent the strength of mobility decline in the retail area during the pandemic period year 2020.

3.2 Data Analysis

A Knime workflow was created for analysis, as shown in Figure 2. The primary analysis was presented in the workflow through a series of nodes such as k-means clustering, ANOVA test, GroupBy, and Scatterplot. In addition, multiple boxplots were created using the multiple boxplot component based on the R-package. The data outlier was identified. Jakarta, as a capital city region, indicates some outliers; therefore, Jakarta was removed from further analysis. Some provinces have one or two missing values; these provinces were retained with missing values replaced by the closest value. Data were normalized to a scale of 0 to 1 to reduce bias.

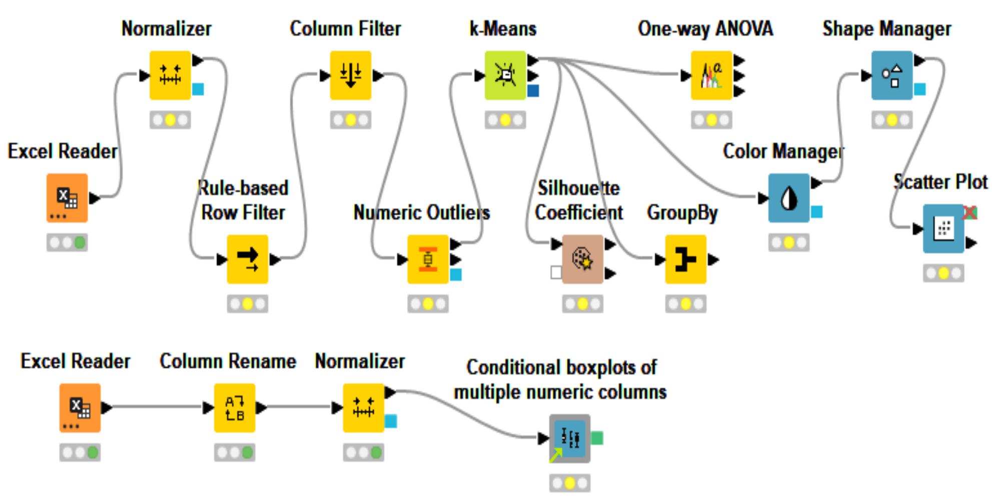

Figure 2. Knime's workflow

4. Results and Discussion

The results are presented based on the three research objectives.

4.1 Clustering of e-commerce intensity

First, the clustering was made to classify and identify the characteristics of provinces based on the e-commerce intensity. Then, as data mining aims to find a pattern from a dataset, clustering was conducted with secondary data related to MSMEs adopting EC, inhabitants using the Internet, and economic aspects. Finally, three variables show significant contribution in the differentiating group of provinces, as follows:

1. Percentage of MSEs adopting EC (variable name: portionEC)
2. Percentage of inhabitants using the Internet (variable name: useInternet)
3. Gross Regional Domestic Products (variable name: GRDPpcapita)

K-means clustering was performed for those three variables. The k-means algorithm requires the predetermined number of clusters (k) as an analysis input. The optimum number of k was determined by evaluating Silhouette coefficients (-1 to +1). The Silhouette coefficient is a metric to calculate the goodness of a clustering technique. Table 1 presents the Silhouette coefficients for alternative k as 2, 3, and 4. The highest mean score of the Silhouette coefficient is 0.42 (overall score) for k=2. Therefore, the k-means clustering was accomplished to create two groups of provinces.

Table 1. Silhouette coefficients

Cluster	k=2		k=3		k=4	
	Mean SC	no. prov	Mean SC	no. prov	Mean SC	no. prov
cluster_0	0.48	20	0.28	12	0.38	10
cluster_1	0.33	13	0.37	7	0.11	6
cluster_2			0.35	14	0.35	6
cluster_3					0.22	11
Overall	0.42	33	0.33	33	0.27	33

Furthermore, an ANOVA test was performed to investigate each variable's strength in differentiating two clusters. The result indicates highly significant p-values ($p<0.001$), as shown in Table 2. Next, the normalized mean scores of each variable for each cluster are presented in Table 3. The table shows that cluster_0 has higher mean scores than cluster_1. Both clusters are named High EC with 13 provinces and Low EC with 20 provinces.

Table 2. ANOVA test

variable name	F	p-value
portionEC	48.99	7E-08
useInternet	37.07	1E-06
GRDPpcapita	16.28	3E-04

Table 3. The normalized mean score of clustering variables

Cluster	Mean portionEC	Mean useInternet	Mean GRDPpcapita	Cluster name	No. of provinces
cluster_0	**0.55**	**0.63**	**0.41**	High EC	13
cluster_1	0.23	0.36	0.22	Low EC	20

Figure 3 displays the distribution of provinces based on the percentage of inhabitants using the Internet and the percentage of MSMEs adopting EC. It shows that the High EC cluster has a higher score for both variables than the Low EC cluster. Similarly, Figure 4 also indicates that provinces in the High EC cluster tend to have higher GRDP and a higher portion of MSMEs adopting EC than those in the Low EC cluster.

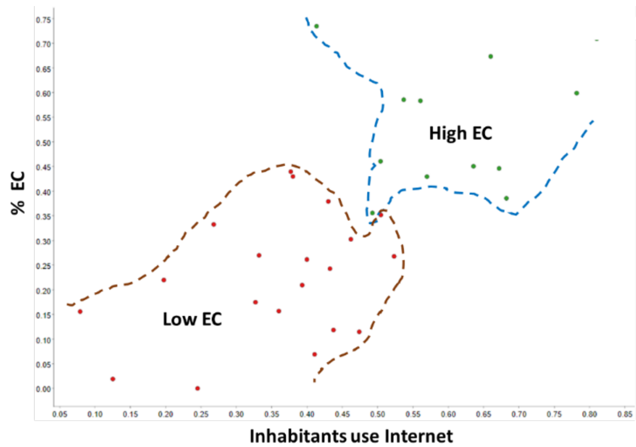

Figure 3. Scatter plot internet use vs. number of EC firms

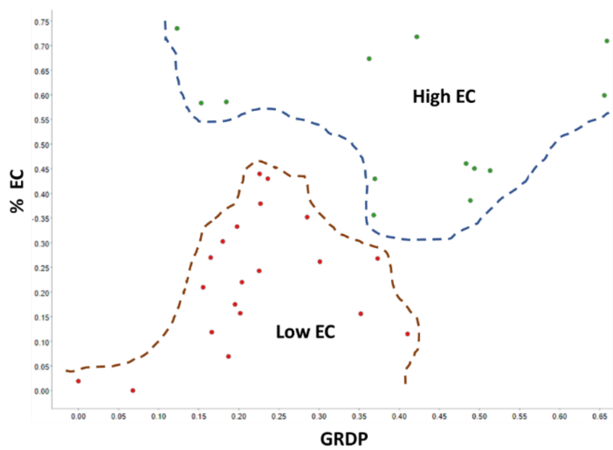

Figure 4. Scatter plot GRDP vs. number of EC firms

Furthermore, analysis was performed to identify the two clusters' EC and regional profile differences. The GroupBy node in Knime's workflow (Figure 2) was applied to identify variables that significantly differentiate both clusters. A p-value ≤ 0.01, instead of 0.05, was applied to have a more substantial relationship. The result produced two regional profiles: population density and the percentage of inhabitants having IT skills. In addition, four EC profiles were identified: use of social media as a sales channel, the use of the Internet for marketing, the percentage EC selling fashion products, and the percentage EC selling beauty products. Table 4 presents the normalized mean scores of those variables for High EC and Low EC clusters.

Table 4. The normalized mean score of regional and EC profiles

Cluster	density	ITskill	socmed	intmark	fashion	beauty
High EC (13)	**0.40**	**0.74**	0.30	0.67	0.26	0.20
Low EC (20)	0.07	0.45	**0.66**	**0.87**	**0.51**	**0.40**
p-value	0.001	0.000	0.000	0.001	0.006	0.007

Boxplots are created to observe the difference between High EC and Low EC. Figure 5 denotes that provinces in the High EC cluster tend to have a higher population density and a higher portion of residents with IT skills. Figure 6 displays that provinces in Lower EC are more likely to sell fashion and beauty products than those in the Higher EC cluster. Next, Figure 7 shows that Low EC provinces seem to use social media for marketing and use the Internet for marketing than High EC provinces.

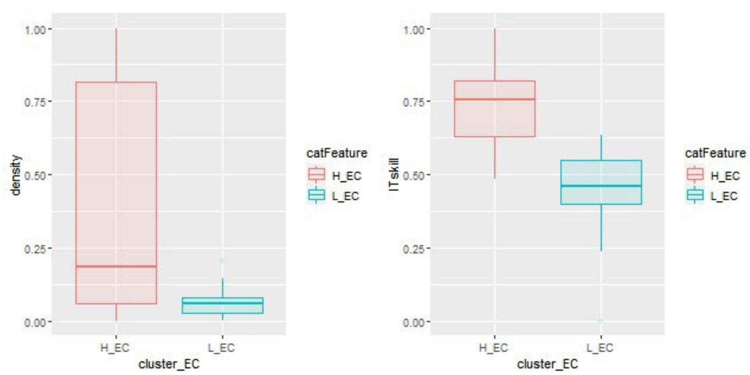

Figure 5. Boxplot cluster vs. population density and IT skills

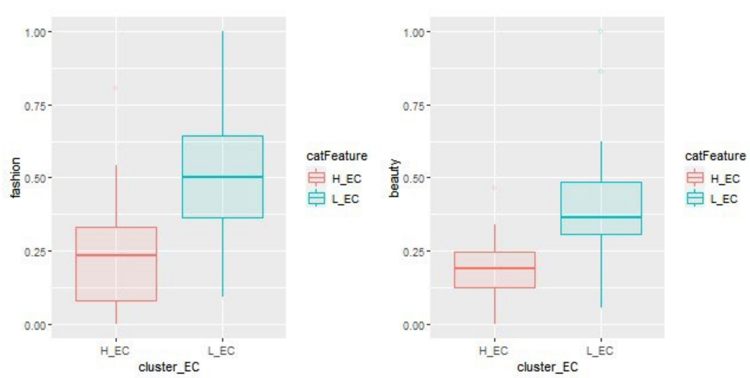

Figure 6. Boxplot cluster vs. fashion and beauty products

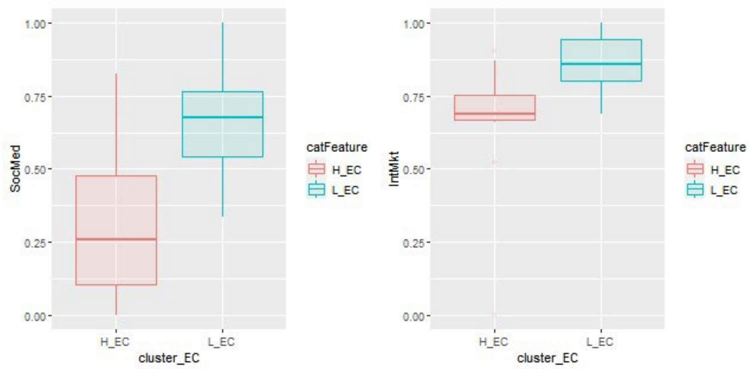

Figure 7. Boxplot cluster vs. social media and Internet marketing

4.2 Clustering of pandemic impact

The second clustering was performed to classify and identify characteristics of provinces based on the impact of the COVID-19 pandemic on e-commerce firms. The exploratory clustering was performed for retail and recreation mobility and the variables of the pandemic impacts (volume or revenue decrease). As the effects of volume and revenue decrease are highly correlated (r = 0.988), the volume decrease was chosen. Furthermore, the k-means clustering was performed for two variables: (1) retail and recreation mobility fluctuation and (2) percentage of e-commerce confirmed sales volume decrease. The optimum number of clusters (k) was evaluated through Silhouette coefficients. Table 5 presents the mean of Silhouette coefficients for k=2, 3, 4, and the number of provinces in each group. Cluster with k=3 and k=4 contain a cluster with only one province. It means that the clustering with k=2 or 3 was not appropriate. The highest mean score is 0.43 (overall score) for k=2. Therefore, further clustering use k=2.

Table 5: Silhouette coefficients

	k=2		k=3		k=4	
	Mean SC	no. prov	Mean SC	no. prov	Mean SC	no. prov
cluster_0	0.49	20	0.45	20	0.39	12
cluster_1	0.34	13	0.00	1	0.42	8
cluster_2			0.30	12	0.00	1
cluster_3					0.22	12
Overall	0.43	33	0.38	33	0.32	33

Furthermore, an ANOVA test was executed to examine each variable's strength in discriminating between two clusters. The result specifies highly significant p-values ($p<0.001$), as shown in Table 6. Afterward, Table 7 displays the normalized mean scores of each variable for each cluster. The table shows that cluster_1 has higher mean scores than cluster_0. The two clusters are named H-impact with 13 provinces and L-impact with 20 provinces.

Table 6. ANOVA test

variable	F	p-value
ret_mob	36.01	1.2E-06
vol_dec	29.33	6.5E-06

Table 7. The normalized mean score of clustering variables

Cluster	vol_dec	ret_mob	Cluster name	No. of provinces
cluster_0	0.30	0.21	L-impact	20
cluster_1	**0.59**	**0.50**	H-impact	13
p-value	6.5E-06	1.2E-06		

The distribution of provinces within High and Low pandemic impact clusters is exhibited along with mobility and volume decrease in Figure 8. The High impact cluster scores higher for both variables than the Low impact cluster. Furthermore, the exploration was conducted to identify e-commerce and regional profiles that differentiate both clusters. ANOVA test found no significant relationship. It means that there is no difference in regional and e-commerce profiles to provinces in the high or low pandemic impact clusters.

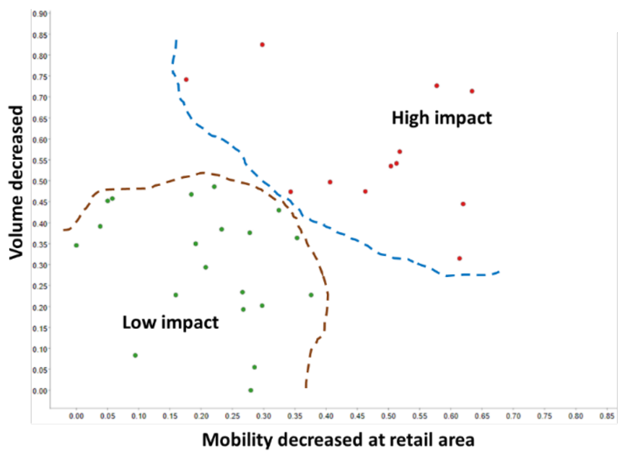

Figure 8. Scatter plot mobility vs. volume decrease

4.3 Ecommerce intensity and pandemic impact

The clustering analysis performed above produces two groups of High EC - Low EC: and two groups of High impact – Low impact. Furthermore, a crosstabulation analysis with two-by-two was conducted. The Chi-square test informs whether the difference between groups is significant. The p-value of the Chi-square test indicates a non-significant ($p>0.05$) outcome, as shown in Table 8. It means no difference between provinces with high or low e-commerce intensity and the level of pandemic impact.

Table 8. Crosstabulation of EC intensity and pandemic impact

Groups	High pandemic impact	Low pandemic impact	Total
High EC intensity	5 (38%)	8 (40%)	13
Low EC intensity	8 (62%)	12 (60%)	20
Total	13	20	33

Chi-Square	*DF*	*p-value*
0.008	*1*	*0.930*

Further investigation was performed for groups of High EC - High impact and Low EC - Low impact across e-commerce and regional profiles. As shown in Table 9, six variables are significant ($p \leq 0.01$). High EC intensity – High pandemic impact cluster has higher mean scores for population density, the portion of inhabitants having IT skills, and the use of the marketplace as a selling channel.

Table 9. Regional and EC profiles Mean scores and p-values

Groups	density	ITskill	socmed	markplc	int_mark	fashion
High EC—High impact (5)	**0.70**	**0.87**	0.17	**0.74**	0.66	0.14
Low EC—Low impact (12)	0.07	0.46	**0.66**	0.37	**0.89**	**0.56**
p-value	0.000	0.000	0.000	0.001	0.000	0.002

Figure 9 presents two clusters' boxplots against the normalized e-commerce and regional profiles. Provinces with high e-commerce intensity and high pandemic impact belong to denser provinces, with more percentage of inhabitants having IT skills. Furthermore, provinces within this group tend to use the marketplace as a sales channel, as shown in Figure 10.

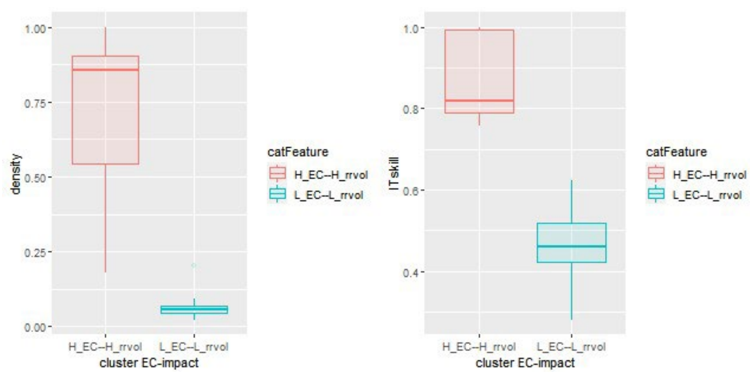

Figure 9. Boxplot cluster vs. population density and IT skill

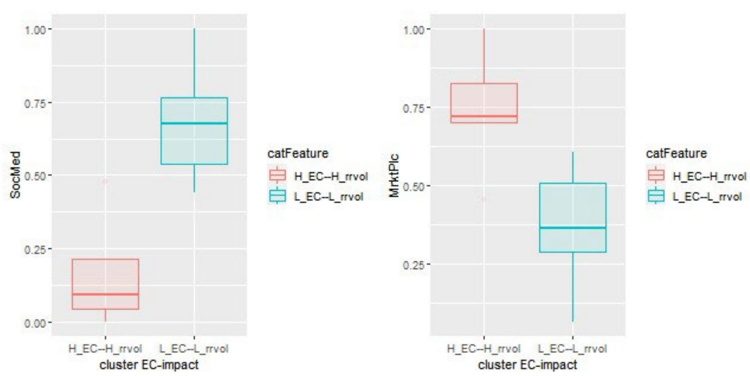

Figure 10. Boxplot cluster vs. social media and Internet marketing

The findings from clustering and crosstabulation are summarized in Table 10. Higher e-commerce intensity in a region is associated with a region having a higher per-capita income, higher portion of people using the Internet, higher population density, and higher people having IT skills. Those indicators indicate that demographic, economic, ICT infrastructure, and education factors contribute to the growth of e-commerce firms. Those e-commerce firms are likely to use the marketplace as a sales channel.

Table 10. Summarized findings

Group of provinces	Composing variables	EC profile	Regional profile
High EC intensity	High MSEs adopting EC High internet use High GRDP per capita	Low soc-med sales channel High marketplace sales channel Low Internet marketing Low fashion product Low beauty product	High population density High people with IT skills
High pandemic impact	High retail area mobility decreases High volume decrease	-	-
High EC intensity and High pandemic impact	High MSMEs adopting EC High internet use High GRDP per capita High retail mobility decreases High volume decrease	Low soc-med sales channel High marketplace sales channel Low Internet marketing Low fashion product	High population density High people with IT skills

The growth of e-commerce in Indonesia was attributed to a few big marketplaces such as Tokopedia, BliBli, Bukalapak, Lazada, and Shopee. Those e-commerce firms use social media less as a sales channel than those with less e-commerce intensity. Social media as a sales channel is a Consumer-to-Consumer (C2C) business model in which transaction such as payment is set up between seller and buyer. The use of social media as a sales channel is less advanced than in a marketplace. Fashion is the second highest product category sold after food-and-beverages in all provinces. Those firms with less e-commerce intensity focus more on fashion products. In contrast, those with high e-commerce intensity sell more product variety to serve the customer demand.

Higher mobility decline in the retail area relates to the decreasing sales volume of e-commerce firms. The restriction on people's activities has reduced the demand for products. When the pandemic ends, and the economy recovers, those e-commerce firms will likely increase transactions. Furthermore, the pandemic impact was experienced by e-commerce firms in any province and was not associated with regional and e-commerce profiles. Furthermore, provinces with high e-commerce intensity and experiencing high pandemic impact have similar characteristics as provinces with high e-commerce intensity, as discussed earlier.

5. Conclusion

This study has implemented a data mining approach for official statistics about e-commerce firms among Indonesia provinces during the COVID-19 pandemic. The analysis reveals that a region with high e-commerce intensity has a high population density and inhabitants with IT skills. Those e-commerce firms use the marketplace more than low e-commerce intensity as a sales channel. Furthermore, the finding shows the pandemic impact of e-commerce firms in all provinces regardless of regional and e-commerce profiles.

This article adds to the literature by presenting data mining using the official statistics among regions at a country level on the topic of e-commerce during the pandemic. Furthermore, the data-driven analysis implemented in this study reveals an empirical association between variables based on the available secondary data. However, the generalization of the finding is limited to e-commerce firms in Indonesian provinces. Further study in other countries could generalize the finding. In addition, as the unit of analysis is e-commerce firms as an aggregate number in a region, the behavior of any single firm responding to the pandemic could not be identified.

Motivated by the economic impact of e-commerce activities, this study suggests more facilitation for regions with low e-commerce intensity. For example, local governments and marketplace companies could support MSMEs entering online sales channels through training about e-commerce, product quality, production process, and management. In addition, the improvement in Internet access and ICT skills among residents, as this study found, could become a priority program for the local governments.

References

Albliwi, S., and Alsolami, L. A., Willingness to Use E-commerce during Coronavirus Pandemic in Saudi Arabia, *Marketing and Management of Innovations*, vol. 4, pp. 68–78, 2021.

Anuj, K., Fayaz, F., and Kapoor, M. N., Impact of E-Commerce in Indian Economy, *IOSR Journal of Business and Management (IOSR-JBM)*, vol. 20, no. 5, pp. 59–71, 2018.

Aziz, N. A., Othman, J., Lugova, H., and Suleiman, A., Malaysia's approach in handling COVID-19 onslaught: Report on the Movement Control Order (MCO) and targeted screening to reduce community infection rate and impact on public health and economy, *Journal of Infection and Public Health*, vol. 13, no. 12, pp.1823–1829, 2020.

BPS., *E-commerce Statistics 2021*. BPS-Statistics Indonesia, 2021.

Cuellar-Fernández, B., Fuertes-Callén, Y., and Serrano-Cinca, C., Survival of e-commerce entrepreneurs: The importance of brick-and-click and internationalization strategies. *Electronic Commerce Research and Applications*, vol. 46, no. February, 2021.

Djalante, R., Lassa, J., Setiamarga, D., Sudjatma, A., Indrawan, M., Haryanto, B., Mahfud, C., Sinapoy, M. S., Djalante, S., Rafliana, I., Gunawan, L. A., Surtiari, G. A. K., and Warsilah, H., Review and analysis of current responses to COVID-19 in Indonesia: Period of January to March 2020, *Progress in Disaster Science*, vol. 6, no. 100091, 2020.

Eriksson, N., and Stenius, M., Online grocery shoppers due to the Covid-19 pandemic - An analysis of demographic and household characteristics, *Procedia Computer Science*, vol. 196, pp. 93–100, 2021.

Hakim, A. J., Victory, K. R., Chevinsky, J. R., Hast, M. A., Weikum, D., Kazazian, L., Mirza, S., Bhatkoti, R., Schmitz, M. M., Lynch, M., and Marston, B. J., Mitigation policies, community mobility, and COVID-19 case counts in Australia, Japan, Hong Kong, and Singapore, *Public Health*, vol. 194, no. 238–244, 2021.

Har, L. L., Rashid, U. K., Chuan, L. Te, Sen, S. C., and Xia, L. Y., Revolution of Retail Industry: From Perspective of Retail 1.0 to 4.0, *Procedia Computer Science*, vol. 200, pp. 1615–1625, 2022.

Hassan, H., Hsbollah, H. M., and Mohamad, R., Examining the interlink of social media use, purchase behavior, and mental health, *Procedia Computer Science*, vol. 196, pp. 85–92, 2021.

Iriani, S. S., and Andjarwati, A. L., Analysis of perceived usefulness, perceived ease of use, and perceived risk toward online shopping in the era of Covid-19 pandemic, *Systematic Reviews in Pharmacy*, vol. 11, no. 12, pp. 313–320, 2020.

Keane, M., and Neal, T., Consumer panic in the COVID-19 pandemic, *Journal of Econometrics*, vol. 220, no. 1, pp. 86–105, 2021.

Martinez-Plumed, F., Contreras-Ochando, L., Ferri, C., Hernandez Orallo, J., Kull, M., Lachiche, N., Ramirez Quintana, M. J., and Flach, P. A., CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories, *IEEE Transactions on Knowledge and Data Engineering*, vol. 33, no. 8, pp. 3048–3061, 2019.

Mendolia, S., Stavrunova, O., and Yerokhin, O., Determinants of the community mobility during the COVID-19 epidemic: The role of government regulations and information, *Journal of Economic Behavior and Organization*, vol. 184, pp. 199–231, 2021.

Nashar, M., Hariadi D.P., A. and D. Parashakti, R., E-commerce, Economic Growth and Gross Domestic Product to the Demand for Delivery Goods, *International Journal of Organizational Innovation*, vol. 12, no. 3, pp. 106–119, 2020.

Rahayu, R., and Day, J., Determinant Factors of E-commerce Adoption by SMEs in Developing Country: Evidence from Indonesia, *Procedia - Social and Behavioral Sciences*, vol. 195, pp. 142–150, 2015.

Ratchford, B., Soysal, G., Zentner, A., and Gauri, D. K., Online and offline retailing: What we know and directions for future research, *Journal of Retailing*, vol. 98, no. 1, pp. 152–177, 2022

Sasongko, D. T., Handayani, P. W., and Satria, R., Analysis of factors affecting continuance use intention of the electronic money application in Indonesia, *Procedia Computer Science*, vol. 197, pp. 42–50, 2022.

Shankar, V., Kalyanam, K., Setia, P., Golmohammadi, A., Tirunillai, S., Douglass, T., Hennessey, J., Bull, J. S., and Waddoups, R., How Technology is Changing Retail, *Journal of Retailing*, vol. 97, no. 1, pp. 13–27, 2021.

Sheth, J., Impact of Covid-19 on consumer behavior: Will the old habits return or die?, *Journal of Business Research*, vol. 117, pp. 280–283, 2020.

Syuhada, A. A., and Gambett, W., Online Marketplace for Indonesian Micro Small and Medium Enterprises based on Social Media, *Procedia Technology*, vol. 11, pp. 446–454, 2013.

Timoumi, A., Gangwar, M., and Mantrala, M. K., Cross-channel effects of omnichannel retail marketing strategies: A review of extant data-driven research, *Journal of Retailing*, vol. 98, no. 1, pp. 133–151, 2022.

Wiscicka-Fernando, M., The use of mobile technologies in online shopping during the Covid-19 pandemic - An empirical study, *Procedia Computer Science*, vol. 192, pp. 3413–3422, 2021.

Zatonatska, T., Models for analysis of impact of the e-commerce on indicators of economic development of Ukraine, Poland and Austria, *Marketing and Management of Innovations*, vol. 2, pp. 44–53, 2018

Biography

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