## Social Commerce from Seller and Region Perspective: A Data Mining for Indonesian E-commerce

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Abstract— As a subset of e-commerce, social commerce grows fast in many countries. Studies on social commerce primarily focused on consumer behavior, especially purchase intention. This study takes a different perspective by focusing on the e-commerce sellers as an aggregate in regions within a country. The study object is provinces in Indonesia, a country with the most prominent e-commerce and social commerce among Southeast Asian countries. The general objective of this study is to characterize social commerce firms across regions in Indonesia. The specific objectives are (1) to group provinces based on the e-commerce and social commerce-related variables and (2) to specify a group of provinces based on business and ecommerce profiles. This secondary and quantitative research adopts a data mining approach to analyze the official data from the BPS-Statistics Indonesia. The Cross-Industry Standard Process for Data Mining framework was adopted as a methodology and the Knime Analytics Platform as a computational software. The result classifies provinces into two: high and low social commerce. Provinces with high social commerce firms are characterized by younger entrepreneurs, more entrepreneurs with university backgrounds, newer ecommerce establishments, more fashion and beauty products, more resellers, and more revenue from the social media channel. Local governments might consider the finding to understand their province's position in the cluster and make policies to increase social commerce entrepreneurs.

*Keywords*—social commerce, e-commerce, data mining, cluster, Indonesia

#### I. INTRODUCTION

Social commerce is a subset of e-commerce and is generally defined as selling and buying products and services online through social media platforms. Social commerce is also specified as a blend of e-commerce activities and social interactions. Consumers interact with other consumers and sellers via social media platforms to make purchasing decisions [1]. The social media platforms such as Facebook, Instagram, WhatsApp, Line, and WeChat started as communication or media sharing platforms. However, because of the vast number of their users, those social media have developed e-commerce capabilities where users can sell, buy, and transact within one app, for example, Instagram Shopping, Tik Tok Shop, Line Shopping, and WhatsApp business accounts.

Several reports stated that the growth of social commerce in Asia is faster than in other continents. Social commerce in Indonesia is also growing because its residents are very active in using social media. Statista reported that the social commerce portion of the total e-commerce sales has grown, with around a quarter in Indonesia, a third in Malaysia, twothirds in Vietnam, and a half in Thailand [2]. This fraction is predicted to grow significantly in the coming years.

A systematic review of social commerce literature identified behavioral intention as an essential topic [3]. It parallels the business perspective to understand factors that stimulate consumers to buy. Trust is a vital factor, which is more important in social commerce than classical e-commerce stores. It is reasonable as social commerce mainly comprises individual or micro businesses without a well-known company name or brand. A positive association of trust on purchase intention in social commerce was identified whether a trust was treated as an antecedent, e.g. [4] or a mediating variable [4]. Social commerce trust has been investigated from the four aspects: consumers, social commerce features, e-commerce sites, and social media [5]. Another study contended that behavioral purchase intention correlates more strongly with interpersonal than organizational trust [6].

In addition to trust, social interaction through information sharing and personal support is a critical part of social commerce. An individual who has received support from others will intend to offer support to others [7]. Intention to buy is related to the social commerce attributes (e.g., forum, rating, reviews) and the platform attributes (e.g., perceived interactivity and perceived personalization) [4]. Moreover, national cultural values such as collectivism and masculinity also relate to social commerce adoption [8]. Many studies have focused on social commerce consumers to find factors contributing to buying intention.

Social commerce has evolved from a person-to-person transaction via social media to a start-up firm facilitating the transaction process. The actual transaction e-commerce requires product sourcing and delivery. Start-ups have emerged to facilitate sellers of social commerce by integrating producer, distribution, and seller, for example, Reselle from the Philippines, WeBuy from Singapore, and Dagangan from Indonesia. Some start-ups focus on fresh produces or rural consumers. For example, they provide product sourcing from farmers and facilitate delivery. These kinds of start-ups will play a vital role in boosting social commerce in a country.

Most studies focus on consumer behavior especially purchase intention, as described above. Only a few investigate the seller side, for example, a survey among the owners of micro, small, and medium enterprises (MSMEs) about social commerce [9]. Limited studies on the part of sellers hinder the understanding of e-commerce firms and recommendations for them. In addition, the benefits of the survey method are limited as it covers only a tiny part of a large number of ecommerce firms. Therefore, the generalization of the finding is limited.

This research contributes, firstly, to filling the limited study gap on the side of e-commerce firms. Second, this study focuses on the overall number of e-commerce firms in the aggregate in regions within a country. This method allows a conclusion for a broader range of e-commerce firms than the survey method.

The study object is provinces in Indonesia, a country with growing e-commerce, including social commerce. Statista reported that Indonesia has US\$ 47 billion in e-commerce sales, the biggest among Southeast Asian countries, and around a quarter is from social commerce [2]. In addition, some social commerce start-ups have emerged and grown fast in Indonesia, such as Super, Evermos, RateS, Dagangan, and Tokobox [10].

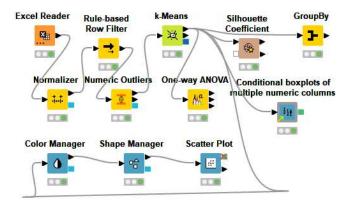
The position of this study is the application of data mining for government official data about e-commerce as a part of the integrated social commerce research framework [11]. The general objective of this study is to characterize social commerce firms across regions in Indonesia. These firms are micro, small, and medium enterprises (MSMEs). The specific objectives are as follows: (1) grouping provinces based on the e-commerce and social commerce-related variables and (2) specifying the group of provinces based on region and ecommerce profiles. Through the macro-level view of the country, this study could draw a conclusion about regions facilitating e-commerce.

The remainder of the study continues as follows. Section II presents the variables, data source, and planned research activity; Section III presents the findings. Finally, the last section concludes and proposes corresponding implications.

#### II. METHOD

This secondary and quantitative research adopts a data mining approach to analyze the BPS-Statistics Indonesia's official data. First, the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework was adopted as a methodology [12]. Then, the Knime Analytical Platform, a code-free, open-source software, was selected as a computational tool. As shown in Fig. 1, a Knime's workflow was developed with major analysis represented by some Knime's nodes: k-means clustering to group provinces, ANOVA test to identify variables differentiating clusters, and GroupBy to calculate the variables' mean score. In addition, graphs are created with Scatter plots and Conditional boxplot nodes, as presented in Fig. 1.

The data mining analysis is aimed to reveal the information (data-driven) rather than to test the hypothesis (theory-driven). Data were gathered from the E-commerce report 2021, published by the BPS-Statistics Indonesia [13]. The report was based on the Indonesian e-commerce activity during the year 2020. A guiding framework for data analysis was developed by composing four elements: e-commerce adoption, e-commerce maturity, social commerce, and entrepreneur, as shown in Fig. 2. In addition, two other aspects: the business aspect and firm profile, are used to find the characteristics of social commerce within regions. Furthermore, the measures of each element were explored from the available secondary data. Table I presents the selected variables.



#### Fig. 1. Knime's Workflow.



Fig. 2. Research Framework.

TABLE I. RESEARCH VARIABLES

| Factor               | Measures  |
|----------------------|---|
| E-commerce adoption  | <ul> <li>MSMEs adopting e-commerce in a region</li> </ul>   |
| E-commerce maturity  | Year of e-commerce establishment  |
| Social media channel | <ul> <li>Using social media as a sales channel</li> </ul>   |
| Entrepreneur         | <ul> <li>Entrepreneur's age</li> </ul>  |
| Business aspect      | <ul> <li>Revenue from social commerce</li> <li>Revenue increase compared to the previous year</li> <li>Selling fashion product</li> <li>Selling beauty product</li> </ul> |
| Firm profiles        | <ul><li>Reseller</li><li>Owner with university education</li></ul>  |

Collected data were examined to detect outliers. Jakarta, a special region of the capital city, indicates some outliers. Therefore, this region is removed, and the total of objects is 33 provinces.

#### **III. RESULTS AND DISCUSSION**

#### A. Clustering

Clustering with k-means requires the number of clusters (k) as an input for analysis. Since the number of objects is only 33, it is not a large data set; alternatives k were defined as 2, 3, and 4. The best option of k was evaluated using the Silhouette coefficient, as shown in Table II. The highest mean score of overall (0.36) and individual (0.45) clusters is for k=2. Therefore, k-means clustering was performed to create two clusters. Two clusters obtained have 9 and 24 provinces. The variable mean scores of each two clusters are presented in Table III. That table also shows the significance value (p-value) as the result of the ANOVA test. The four variables significantly differentiated both clusters (p<0.001).

As one cluster has higher mean scores than another cluster for three variables (Table III), both clusters are named Low social commerce (Low SC) with nine provinces and High social commerce (High SC) with 24 provinces. Table IV presents provinces for each cluster. It is interesting to observe that all provinces in Java belong to the Low SC cluster. E- commerce firms (sellers) in Java are more likely to use the marketplace as their major sales platform than social media. The possible reason is that the marketplace has a wellestablished mechanistic process based on technology for ecommerce transactions. For some provinces, e-commerce firms rely on social media with less complicated processes and more personalized marketing and sales channels.

Furthermore, scatter plots were created to provide the visualized distribution of provinces in both clusters. Fig. 3 shows that provinces with a higher percentage of firms using social media as a sales channel (social commerce) are likely to be provinces with fewer firms adopting e-commerce. It means that the use of social media as a sales channel is more prevalent in provinces with low e-commerce adoption. Next, Fig. 4 shows that provinces with higher social commerce firms are likely having more entrepreneurs with university backgrounds. This figure indicates that non-university graduates contribute more to the provinces with high e-commerce adoption (Low SC cluster).

| TABLE II.  | SILHOUETTE | COEFFICIENTS |
|------------|------------|--------------|
| I ABLE II. | SILHOUETTE | COEFFICIENTS |

| Cluster   | k = 2 |    | k = 3 |    | <b>k</b> = 4 |    |
|-----------|-------|----|-------|----|--------------|----|
| Cluster   | SC    | n  | SC    | Ν  | SC           | n  |
| cluster_0 | 0.45  | 9  | 0.40  | 3  | 0.19         | 9  |
| cluster_1 | 0.32  | 24 | 0.37  | 8  | 0.36         | 3  |
| cluster_2 |       |    | 0.07  | 22 | 0.44         | 7  |
| cluster_3 |       |    |       |    | 0.01         | 14 |
| Overall   | 0.36  | 33 | 0.18  | 33 | 0.18         | 33 |

TABLE III. MEAN SCORE OF CLUSTER PROFILES

| Cluster | %EC     | Est.<br>2017-2020 | Social<br>media | Entr.<br>15-34y |
|---------|---------|-------------------|-----------------|-----------------|
| Low SC  | 0.60    | 0.26              | 0.29            | 0.10            |
| High SC | 0.26    | 0.59              | 0.67            | 0.40            |
| p-value | 2.3E-07 | 2.2E-05           | 1.6E-05         | 5.7E-05         |

| TABLE IV. | CLUSTER MEMBERS |
|-----------|-----------------|
| ГАBLE IV. | CLUSTER MEMBERS |

| Provinces in low soc   | ial commerce cluster |
|------------------------|----------------------|
| Lampung                | East Java            |
| Riau Islands           | Banten               |
| West Java              | Bali                 |
| Central Java           | East Kalimantan      |
| Yogyakarta             |                      |
| Provinces in high soc  | ial commerce cluster |
| Aceh                   | South Kalimantan     |
| North Sumatra          | North Kalimantan     |
| West Sumatra           | North Sulawesi       |
| Riau                   | Central Sulawesi     |
| Jambi                  | South Sulawesi       |
| South Sumatra          | South-East Sulawesi  |
| Bengkulu               | Gorontalo            |
| Bangka Belitung Island | West Sulawesi        |
| West Nusa Tenggara     | Maluku               |
| East Nusa Tenggara     | North Maluku         |
| West Kalimantan        | West Papua           |
| Central Kalimantan     | Papua                |

Fig. 5 shows that firms in provinces with a High SC cluster are likely to be managed by younger entrepreneurs from 15-34 years old, and e-commerce was established from 2017 to 2020. The result is reasonable as young people are familiar with social media and can see the business opportunity from social media. Furthermore, Fig 6. displays those provinces in the High SC cluster tend to be less mature in e-commerce (established 2017-2020) and emerge in provinces with low ecommerce adoption. This result reveals that social commerce firms contribute to e-commerce adoption among MSMEs.

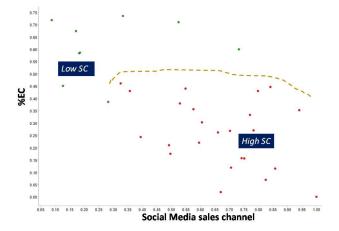


Fig. 3. Scatter Plot Social Media as Sales Channel Vs. Percent EC.

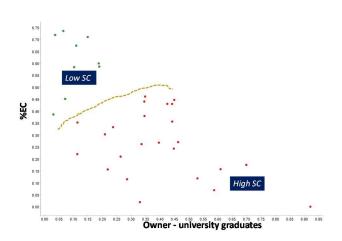


Fig. 4. Scatter Plot Owner University Graduates Vs. Percent EC.

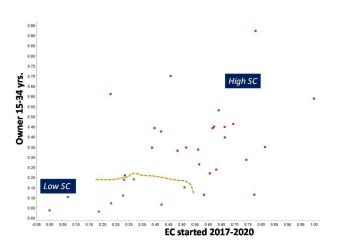


Fig. 5. Scatter Plot EC Established Vs. Owner's Age.

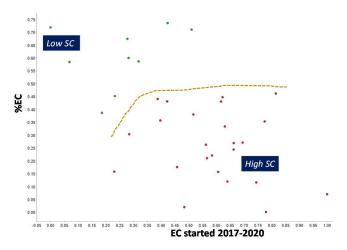


Fig. 6. Scatter Plot EC Established Vs. Percent EC.

#### B. Cluster characteristics

Further analysis was performed to specify the characteristics of each cluster based on selected four businessrelated indicators and two e-commerce firm profiles, as presented in Table I above. Table V presents the mean scores of six variables for two clusters. It shows that the high social commerce cluster (High SC) has higher mean scores for all variables than the low social commerce (Low SC).

Boxplot graphs were created to visualize the difference between two clusters on six business and e-commerce profile indicators. Fig.7-9 presents boxplots of those six indicators across high social commerce (High SC) and low social commerce (Low SC) clusters. Boxplot demonstrates the location, spread, skewness as well as tails of the data through their quartiles [14]. The three horizontal lines in each box indicate the 1<sup>st</sup> quartile, median, and 3<sup>rd</sup> quartile. The ends of vertical lines indicate the minimum and maximum data points. The first graph of Fig 7. shows that provinces with higher social commerce have a higher portion of firms receiving revenue from social media (Revenue SM). The second graph shows that the high social commerce cluster experiences a revenue increase compared to the previous year (Revenue\_Up). This result indicates the positive impact of ecommerce firms adopting social commerce.

Next, Fig. 8 displays that e-commerce firms in the high social commerce cluster are more likely to sell fashion and beauty products than those in the low social commerce cluster. This finding might indicate that both product categories are highly demanded products, especially among young people who buy from the social media channel. The popularity of fashion products in social commerce was documented in prior studies, e.g. [15], [16]

Furthermore, the first graph of Fig. 9 shows that ecommerce firms in provinces with high social commerce tend to have more reseller types (instead of seller or drop-shipper). Being a reseller is less complex than the seller as the reseller does not need to produce the products or buy from producers. Instead, the reseller could choose which products are on demand. Finally, the second graph of Fig. 9 shows that higher social commerce is associated with higher entrepreneurs with a university educational background (owner\_Univ). The overall data of Indonesia indicate that, on average, only 25% of e-commerce entrepreneurs have a university education background. It means that non-university graduates have the capability and entrepreneurial spirit to manage e-commerce.

TABLE V. MEAN SCORE OF CLUSTER CHARACTERISTICS

| Business and e-commerce<br>profile | Low SC<br>cluster | High SC<br>cluster |
|------------------------------------|-------------------|--------------------|
| Revenue from social media          | 0.53              | 0.65               |
| Revenue increase                   | 0.34              | 0.58               |
| Fashion product                    | 0.19              | 0.50               |
| Beauty product                     | 0.16              | 0.37               |
| Reseller                           | 0.25              | 0.46               |
| Entrepreneur university            | 0.33              | 0.61               |

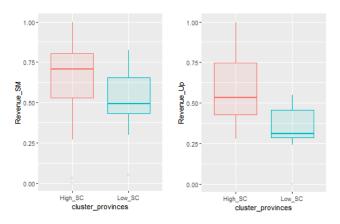


Fig. 7. Boxplots for Revenue Social Commerce and Revenue Increase.

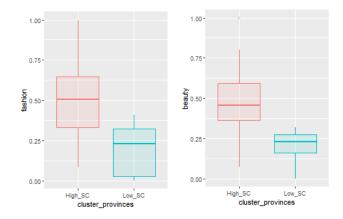


Fig. 8. Boxplots for Fashion and Beauty Products.

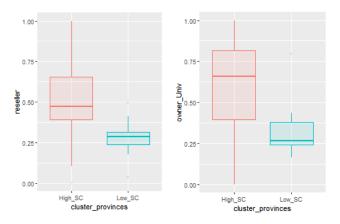


Fig. 9. Boxplots for Reseller and Owner Education.

In sum, the analysis has characterized high and low social commerce clusters. In 2020, businesses faced the Covid-19 pandemic and unexpected mobility restriction policies. Individuals or small businesses affected by both events might turn to social commerce as a solution. Implementing social commerce does not require big investments, high technical skills, and time, because entrepreneurs can use social media functions to transact [17]. Provinces in Java and Bali are included in the high social commerce cluster. The impact of the pandemic may drive the growth of social commerce in these provinces.

#### IV. CONCLUSION

This study has applied a data mining approach to Indonesian e-commerce statistics to reveal information about social commerce from the seller's perspective as an aggregate across Indonesian provinces. Provinces could be grouped into high and low social commerce based on the e-commerce adoption, e-commerce maturity, social media use as a sales channel, and entrepreneur profile. Provinces with high social commerce firms are characterized by younger entrepreneurs, more entrepreneurs with university backgrounds, newer ecommerce establishments, more fashion and beauty products, more resellers, and more revenue from social commerce. In addition, e-commerce and social commerce firms are managed mainly by non-university graduates, which means this sector provides an opportunity for all.

This study enhances our understanding of social commerce research by investigating sellers as an aggregate within regions of a country. The findings enrich the literature about the link between social commerce sellers and their related-contributing factors. Local governments might consider the result to understand their province's position in the cluster and make policies to increase the social commerce adoption. For example, a facilitation program could target young persons with any educational background to enter social commerce.

The generalization of the findings is limited, as this study used only Indonesian data for one year. Further study might focus on different countries to justify the finding more extensively. Furthermore, this study could be extended by comparing the results for e-commerce activities in 2020 with other years.

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