Frontiers in Business and Economics 1 (1) April 2022, pp.24-34.

Content lists available at SRN Intellectual Resources

Frontiers in Business and Economics

Journal homepage: https://journal.srnintellectual.com/index.php/finbe

Article

Investigating the Online Shopping Pattern for Beauty Brands Most Liked by Indonesian Women

Thamrin Thamrin [a,*], Stefvy Stefvy [a], Tina Linda [a] and Lismardiana Sembiring [b]

[a] Department of Information System, Institut Informasi Teknologi dan Bisnis, Medan, Indonesia; stefvy90@gmail.com (S.S), tina@itnb.ac.id (T.L).
[b] Department of Information System, Sekolah Tinggi Ilmu Komputer Medan, Medan, Indonesia; lismardianasembiring@gmail.com (L.S).
* Correspondence: thamrin@itnb.ac.id (T.T)

Citations: Thamrin, T., Stefvy, S., Linda, T. & Sembiring, L. (2022). Investigating the Online Shopping Pattern for Beauty Brands Most Liked by Indonesian Women. *Frontiers in Business and Economics, 1*(1), 24-34.

Academic Editor: Mariyudi.

Received: 25 January 2022 | Accepted: 8 April 2022 | Published: 30 April 2022

Abstract: Many Indonesian women want to look beautiful and healthy when appearing anywhere. so that many Indonesian women love to shop online choosing which beauty products are more appropriate for their needs. The development of e-commerce in the sale of beauty products has increased in recent years due to the Covid-19 pandemic where everyone is required to stay at home to avoid the spread of covid-19. With so many consumers shopping online at e-commerce, IG and Google, more and more business actors are turning their businesses online in the form of e-commerce, both large and retail companies are all switching or developing their businesses towards digital. Many branded beauty products are circulating in Indonesia, such as: Wardah, Innisfree, Purausari, Viva, Trulum, Makeover, Garnier, Laneige, Emina and Nature Republic. All types of beauty product brands are favored by Indonesian women in general. With so many beauty product brands circulating in Indonesia, companies take advantage of this opportunity, especially e-commerce, such as: Lazada, Tokopedia, Bukalapak, blibli.com, shopee, and JD.Id. This has become a fierce competition in promoting and providing big discounts on these beauty brand products where in making sales of beauty products grow rapidly in terms of marketing each of these beauty product brands; beauty products always experience an increase in sales every year.

Keywords: beauty products; google; e-commerce; Instagram.

1. Introduction

In general, beauty products are very popular among teenagers, adults and even people who are 50 years old and above also still like beauty and body care products. this shows that with the beauty that is obtained by a woman, it will increase her confidence to appear in all things coupled with inner beauty. Looking beautiful and healthy is every woman's dream. Mulyawan & Sutrisno (2020) looked at the beautiful and healthy, of course, it costs quite a lot so that women compete to try various types of beauty products that are suitable and suitable for them (Ananda & Wandebori 2016) and of course also light in terms of finances. With this, many beauty brand products have sprung up in the midst

e-ISSN: 2976-2952/ @ 2022 SRN Intellectual Resources
https://doi.org/10.56225/finbe.v1i1.82

of society, ranging from brands (Pramushinta & Junaedi 2021) to foreign products and domestic product brands ranging from the lowest prices to the most expensive ones. All beauty products are marketed through social media, e-commerce and many other applications that can attract consumers to buy these products. It is easy for people to shop online using Instagram (IG), Facebook (FB), Whatshaap, search Engine (Google) (Kidane & Sharma 2016) or using e-commerce services. With this, more and more business actors develop strategies in preparing steps to promote beauty brand products.

Many Indonesian women want to look beautiful and healthy when appearing anywhere. so that many Indonesian women love to shop online choosing which beauty products that more appropriate for their needs (Agustin & Hellianto, 2020). Many branded beauty products are circulating in Indonesia, such as: Wardah, Innisfree, Purausari, Viva, Trulum, Makeover, Garnier, Laneige, Emina and Nature Republic. All types of brands of these beauty products are favored by Indonesian women in general (Sharma et al 2013). With so many beauty product brands circulating in Indonesia, companies take advantage of this opportunity, especially e-commerce (Fahrurrozi et al 2020) such as: Lazada, Tokopedia, Bukalapak, blibli.com, shopee, and JD.Id. This has become a fierce competition in promoting and providing big discounts on these beauty brand products where in making sales of beauty products grow rapidly in terms of marketing each of these beauty product brands; beauty products always experience an increase in sales every year. This can also be seen in e-commerce, especially during a campaign with various attractive promos (Upasna & Rebello 2014) offered by several e-commerce services such as: shopee, Bukalapak, Tokopedia, blibli.com and Jd.id. so that the total revenue from the beauty and body care market in Indonesia increased fantastically at the start of the Covid-19 pandemic.

The development of e-commerce in selling beauty products has increased in recent years due to the Covid-19 pandemic where everyone (Kurdi 2020) is required to stay at home to avoid the spread of covid-19. With so many consumers shopping online, more and more business actors are turning their businesses online in the form of e-commerce, both large and retail companies are all turning or developing their businesses towards digital. The number of e-commerce players will continue to grow, this is reinforced by several surveys from domestic and foreign information and communication technology research institutions. The e-Commerce industry in Indonesia. With the above advantages, having an official store in the marketplace for retail businesses not only supports business digital transformation but also helps a brand reach consumer and gain their trust (Rahayu & Day 2017). So, in order to expand the reach of the retail business, a brand can create an official store at once in several marketplaces. Increasing the e-commerce business in Indonesia, there are several e-commerce businesses that are developing (Rahmi et al 2017). One of them is Shopee, which is an e-commerce company that applies the form of customer to customer (C2C), (Kumar & Raheja 2012), namely the activity of buying and selling goods or services that provide a Marketplace for consumers to make sales and purchases online. Users can display their merchandise on the C2C site so that other users can see and be interested in buying. each marketplace has its own official store designation. Like in Shopee and Bukalapak, for example, official stores are called Shopee Mall and Buka Mall.

Meanwhile, in Tokopedia and Blibli, the name is Official Store. The Official Store itself offers various advantages over regular stores. Marketplaces usually offer special promos for official store merchants (Lip-Sam & Hock-Eam 2011). This will provide an advantage for marketplace business actors who always have special promo programs for official stores on certain days. When regular stores that sell products similar to other stores offer regular prices, business actors attract potential buyers through these promos. Several marketplaces also offer a number of special promo features for official stores such as Tokopedia where sellers are given the freedom to plan and arrange discounts according to their budget. At Shopee, the official store can get information in advance about the latest promos compared to regular sellers so that buyers adjust their strategy with promos held by the marketplace (Rizal et al 2020). The average marketplace offers access to sales data related to official store merchants. This means that we understand consumer spending habits. From this data, business actors can plan the right marketing and sales strategies for the future so that they can get maximum profit. The purpose of this research was conducted as a reference for e-commerce business actors in supporting the sale of beauty brand products in Indonesia and meeting the needs as a lecturer to carry out the Tri Dharma of Higher Education, namely Research, Teaching and Community Service at the Indonesian Institute of Technology & Business at the College of Science Medan Computer.

2. Materials and Methods

2.1. Frequent Pattern (FP) Growth

FP-Growth is an alternative algorithm that can be used to determine the most frequently occurring data set (frequent item set) in a data set. The FP-Growth algorithm is a development of a priory algorithm. FP-growth is a method that often itemset mining without candidate Generation. Mining without candidate generation is an FP-Growth technique using data structures. By using this method, the database scan is only done twice, there is no need to repeat it. The data will be represented in the form of FP-Tree. After the FP-Tree is formed, a very good data structure for Frequent itemset will be obtained. FP-Tree is a very good data structure for frequent pattern mining, this structure provides complete information to form Frequent Patterns. Items that are not frequent (infrequent) no longer exist in the use of FP-tree (Vora et al 2021). Construction of FP-Tree from a set of transaction data, the FP-Growth algorithm will be applied to find a significant Frequent itemset. The FP-tree algorithm is divided into three main steps, namely:

Generation Phase Conditional Pattern Base Conditional Pattern Base is a sub database that contains path prefixes (lines e:1 prefix) and patterns (suffix patterns). Generating conditional pattern base is obtained through the previously built FP-tree. Conditional FP-tree Generation Stage At this stage, the support count of each item in each conditional pattern base is added up, then each item that has a support count greater than the minimum support count will be generated using a conditional FP-tree. Frequent itemset search stage if the conditional FP-tree is a single path, then the frequent itemset is obtained by combining items for each conditional FP-tree. If it is not a single path, then the FP-growth generation is done recursively. These three stages are the steps that will be taken to get the frequent itemset. By using FP-Growth, we can do pattern frequent itemset without taking a long time.

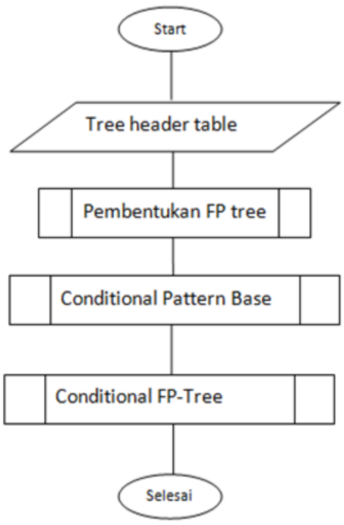

Figure 1. Flowchart FP_Growth.

2.2. Analysis Association Rule Mining

Association rules are in data mining that find frequent item sets in the database. Association of data mining rules is a mechanism in data mining in association rules, the implication expression of the form X → Y where X is Y. The antecedent and consequent are specified items in the domain I. (diana Sembiring 2018) the introduction and the consequent are a set of items from domain I. Thus, X Y =. The support of the item set is defined as the ratio of the number of transactions containing the item set to the total number of transactions. The trust of association rule X → Y is the probability that Y transaction contains association rule mining algorithm X. The formula to find the support and confidence values is:

$$\text{Support (A)} = \frac{\text{Number of Transaction in A}}{\text{Total Number of Transaction}} \tag{1}$$

$$\text{Confidence } (A \rightarrow B) = \frac{\text{Support } (A \cup B)}{\text{Support (A)}} \tag{2}$$

Association analysis is a process to find all association rules that meet the minimum requirements for support (minimum support) and minimum requirements for confidence (minimum confidence). Association rules mining is an important technology in data mining. FP-Growth (frequent-pattern growth) algorithm is a classical algorithm in association rules mining. But the FP-Growth algorithm in mining needs two times to scan database, which reduces the efficiency of algorithm.

3. Results and Discussion

Techniques in data processing using FP_Growth (Liu 2014). The data source comes from: https://digimind.id/data-produk-kecantikan-terlaris-di-e-commerce/ which shows that the data comes from the results of research by the

Indonesian digital marketing association. Data processing is carried out starting from the stage of analysing the graph of total sales data from the 3 Largest E-Commerce in Indonesia such as Shopee, Tokopedia and Bukalapak as shown in the graph below:

Data Total Penjualan Dari 3 E-Commerce Terbesar Di Indonesia

Figure 2. The Largest E-Commerce Sales Data in Indonesia.

Figure 2 shows the largest e-commerce sales in Indonesia in 2020 is converted into a table form and explains the items from the graph such as: part of (Iqbal et al., 2014) beauty brands: Wardah, Nature Republic, Innisfree, Emina, Prubasari, Viva, Laneige, Trulum, Garnier and make over where Wardah excels in sales through e-commerce. The percentage figures from the sales of the three e-commerce: Shopee, Tokopedia and Bukalapak are as shown in Table 1 below:

Table 1. The Largest E-Commerce Sales Data Conversion in Indonesia.

Name Product	Shopee (in Billions)	Tokopedia (in Thousands)	Bukalapak (in Thousands)
Wardah	6,6	616	63
Nature Republic	5,3	470	36
Innisfree	3,5	160	4
Emina	3,2	79	4
Purbasari	1,9	201	15
Viva	1,5	154	11
Laneige	1,4	156	10
Trulum	1,4	64	4
Garnier	1,2	50	15
Make Over	0,9	90	7

Table 1 captures the classification is formulated based on the range of the number of e-commerce sales data as follows: A1> 7 million, A2 => 5 million, A3 => 3 million, A4 => 2 million and A5 <= 2 million so that the results of changing the graphic data into the form The table shows the percentage of sales from e-commerce such as: shopee, tokopedia and Bukalapak. It can be seen from the Shopee column, Tokopedia column, and Bukalapak column. It can be seen the number of people accessing beauty products through Shopee, Tokopedia and Bukalapak. beauty products with a total of 6.6 million, namely Shopee, Wardah products, both Tokopedias with a total of 616 thousand, and Bukalapak with a total of 63 thousand. This shows that Wardah products are the most popular beauty brands, followed by Nature Republic for 5.3 million shopee, 470 thousand Tokopedia, and 63 thousand Bukalapak.

Figure 3. Total Product Disbursement Data from Google.

Figure 3 displays the total product search data on Google in 2020 is converted into a table and explains the items from the graph such as: parts of beauty brands: Wardah, Nature Republic, Innisfree, Emina, Purbasari, Viva, Laneige, Trulum, Garnier and make over. The percentage figures for the total search for beauty brand products from Google can be seen in Table 2 below:

Table 2. Convert Product Search Total Data on Google.

Name Product	Google (in thousand)
Wardah	831
Nature Republic	69
Innisfree	42
Emina	88
Purbasari	62
Viva	33
Laneige	38
Trulum	2,9
Garnier	47
Make Over	57

Table 2 describes the classification is formulated based on the range of total product search data from Google as follows: B1 > 616 thousand, B2 > 470 thousand, B3 > 160 thousand and < 150 thousand is B4. So that after being converted into tabular form, the total data figures for beauty brand product searches using Google are: Wardah with a total search of 831 thousand, then followed by nature republic with a total search of 69 thousand in number. Not only that, there is also the lowest beauty brand: Trulum with a total access on Google of 2.9 thousand. This shows that the Wardah beauty brand is superior to Nature Republic.

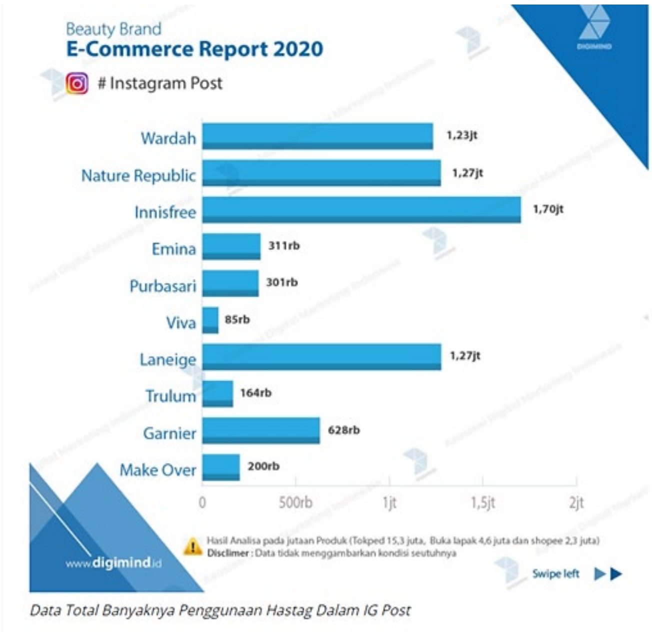

Figure 4. Total Data of Hashtag Usage in IG Post.

Figure 4 indicates the use of hashtags on Instagram (IG) in 2020 is converted into a table and explains the items from the graph such as: parts of beauty brands: Wardah, Nature Republic, Innisfree, Emina, Purbasari, Viva, Laneige, trulum, garnier and make over. The total amount of data on the total number of hashtags used in Instagram (IG) can be seen in Table 3 below:

Table 3. Data Conversion Total Number of Usage Hashtags in IG Post.

Name Product	IG (in billion)
Wardah	1,23
Nature Republic	1,27
Innisfree	1,70
Emina	311
Purbasari	301
Viva	85
Laneige	1,27
Trulum	164
Garnier	628
Make Over	200

Table 3 displays the classification is formulated based on the range of data. The total number of uses of beauty brands on Instagram (IG) Posts is as follows: C1 > 63 thousand, C2 > 36 thousand, C3 > 15 thousand, C4 10 thousand, C5 < 7 thousand can be seen the number of data from beauty brands using hashtags on Instagram (IG) are: wardah with a total use of 1.23 million IG hashtags, then followed by nature republic with a total use of 1.27 million hashtags on IG. Not only that, there is also the lowest beauty brand: viva with a total use of hashtags on Instagram (IG) of 85 thousand. This shows that the Wardah beauty brand is still superior to other beauty brands.

3.1. Formation of FP_Tree Assosiasi Rule Mining

From classifying data from each table that has been prepared starting from Tables and Figures the next step is to make it into the FP_Tree concept for processing the data so as to produce FP_Tree images (Singh & Jain 2016) as below:

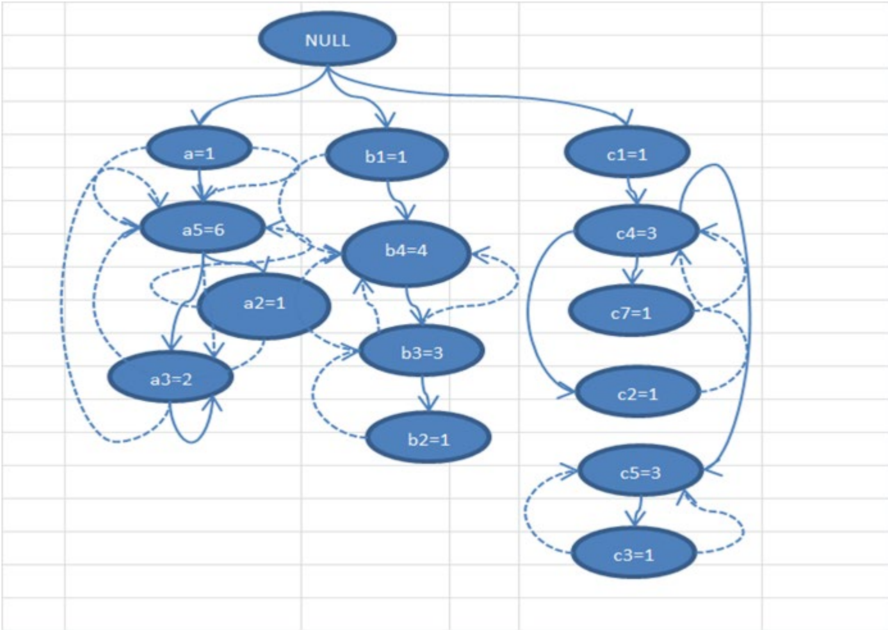

Figure 5. FP_Tree Data the Largest E-Commerce Sales in Indonesia.

Figure 5 captures the results of the FP_Tree process with the data collection in Table 1, Table 2 and Table 3. From Figure 5 above, there are several frequent items (Kamepalli & Bandaru 2019) that appear several times in the formation of FP_Tree, namely: A5=6x, A3=2x, B4=4x, B3=3x, e-commerce sales data, product search data from Google, total data The use of hashtags in Instagram (IG) can be seen in table 4 below:

Table 4. K1 Frequent Items.

K1- Item	Frequent Item
A1	1
A5	6
A2	1
A3	2
B1	1
B4	4
B3	3
B2	1
C1	1
C4	3
C7	1
C2	1
C5	3
C3	1

Table 4 describes the classification is formulated based on the range of total product search data from Google as follows: B1 > 616 thousand, B2 > 470 thousand, B3 > 160 thousand and < 150 thousand is B4. So that after being converted into tabular form, the total data figures for beauty brand product searches using Google are: Wardah with a total search of 831 thousand, then followed by nature republic with a total search of 69 thousand in number. Not only that, there is also the lowest beauty brand: Trulum with a total access on Google of 2.9 thousand. This shows that the Wardah beauty brand is superior to Nature Republic.

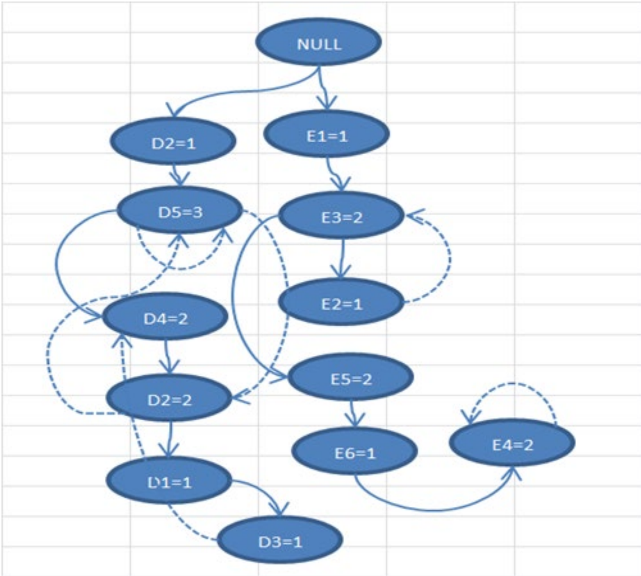

Figure 6. FP_Tree Total Product Disbursement Data from Google and IG

Figure 6 shows the results of the FP_Tree process with the data collection in Tables 2 and 3. From Figure 6 above, there are several frequent items that appear several times in the formation of FP_Tree, namely: D5=3x(<300 thousand); D4=2x,(>300 thousand); D2=2x (>1.23 million); E5=2x (<33 thousand); E3=2x (>69 thousand), E4=2x (>42 thousand);, product search data from Google, data on the total number of hashtags used on Instagram (IG) can be seen in Table 5 below:

Table 5. K1 Frequent Item

K1-Item	Frequent Item
D1	1
D5	3
D4	2
D2	2
D1	1
D3	1
E1	1
E3	2
E2	1
E5	2
E6	1
E4	2

Table 5 describes the results of frequent items (Venkateswari & Suresh 2011) generated by FP_tree are: D5=3x, D4=2x, D2=2x, E3=2x, E5=2x, E4=2x where the item is part of :D5:instagram<300k,

Table 6. Association Rule Mining

K1 Item	Frequent Item	50% Support	60% Confidence
A5	6	25%	60%
B4	4	17%	60%
B3	3	13%	45%
C4	3	13%	45%
C5	3	13%	45%
D5	3	13%	45%
A3	2	8%	20%
D2	2	8%	20%
D4	2	8%	20%

E3	2	8%	20%
E4	2	8%	20%
E5	2	8%	20%

Table 6 above, the results from the list of association rules mining minimum support 50% & minimum confidence 60% there are several parts as follows: 1. Frequent itemset results with support value 25%: A5, support value 17% is B4, 13% support value : B3,C4,C5,D5, and 8% support value : A3: D2,D4,E3,E4,E5, 60% confidence value : A5,B4, 45% confidence value : B3,C4 ,C5,D5 and a confidence value of 20% : A3,D2,D4,E3,E4,E5 with Thus, it was concluded that those with the highest support and confidence values were those with a value of 6, followed by a value of 4.3, which had a support value of 7% and 5%. And the confidence value has a value of 48% and 36%.

Table 7. Association of Rule Mining Beauty Products to Google, IG, e-commerce

K1 Item	50% Support	60% Confidence	Information
A5	25%	60%	<2 billions Shopee:Viva;Trulum;Purbasari;Laneige;Garnier;Make Over
B4	17%	60%	<150 thousands: Tokopedia:Viva;Trulum;Garnier;Emina;Make Over
B3	13%	45%	>160 thousands: Tokopedia:Purbasari;Innisfree;Laneige
C4	13%	45%	>10 thousands: Bukalapak:Viva;Purbasari;Laneige
C5	13%	45%	<7 thousands: Bukalapak: Emina;Makeover
D5	13%	45%	<300 thousands:IG: Viva,Trulum,Makeover
A3	8%	20%	>3jt: Shopee: Innisfree;Emina
D2	8%	20%	>1,23 billion: IG: Wardah;Nature Republic
D4	8%	20%	>300 thousands: IG:Prubasari;Emina
E3	8%	20%	>69 thousands: Google:Nature Republic;Purbasari
E4	8%	20%	>42 thousands: Google:Innisfree;Garnier;Make Over
E5	8%	20%	<33 thousands: Google:Viva;Laneige

Table 7 indicates the results from the list of association rule mining minimum support 50% & minimum confidence 60% there are several parts as follows: 1. Frequent itemset results with support value 25%: A5, support value 17 % is B4, 13% support value : B3,C4,C5,D5, and 8% support value : A3: D2,D4,E3,E4,E5, 60% confidence value : A5,B4, 45% confidence value : B3 ,C4,C5,D5 and a confidence value of 20% : A3,D2,D4,E3,E4,E5 with Thus, it was concluded that those with the highest support and confidence values were those with a value of 6, followed by a value of 4.3, which had a support value of 7% and 5%. And the confidence value has a value of 48% and 36%.

4. Conclusions

In conclusion, this study indicates that women prefer to shop online to buy beauty products through e-commerce services. In the results of data processing, online purchases using e-commerce services are: Shopee excels in first place in the number of transactions with the most beauty products: Viva, Trulum, Purbasari, Laneige, Garnier and make over. Then, the second order is online shopping for beauty products through Tokopedia's e-commerce service with beauty products: viva, trulum, garnier, emina, make over and the third place is still Tokopedia's e-commerce service with beauty products: Purausari, Innisfree and Laniege. The most preferred by the online shopping community using e-commerce are viva, trulum, purbasari, laneige, garnier, make over emina and innisfree. For sales of online shopping beauty products through Instagram (IG) are: Wardah and Natur Republic, while sales of online shopping beauty products through Google are: Nature Republic and Pursusari. From the overall statement of each beauty product in online shopping: ecommerce; instagram (IG); Google which produces frequent itemset are {viva, trulum, purbasari, laneige, garnier, make over emina and innisfree}. With the statement above, it shows that there are variations in consumer online shopping for beauty product brands sold on the market. This needs to be considered by e-commerce business actors to always maintain authenticity and service to consumers in purchasing beauty products to satisfy consumers in online shopping.

Author Contributions: Conceptualization, T.T. and S.S.; methodology, T.L.; software, L.S.; validation, T.T., S.S., T.L. and L.S.; formal analysis, S.S.; investigation, T.T.; resources, S.S.; data curation, T.L.; writing—original draft preparation, T.T., S.S., T.L. and L.S.; writing—review and editing, T.T., S.S., T.L. and L.S.; visualization, L.S.; supervision, S.S.; project administration, T.T.; funding acquisition, T.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

Acknowledgments: We would like to thank Institut Informasi Teknologi dan Bisnis and Sekolah Tinggi Ilmu Komputer Medan, Indonesia for supporting this research and publication. We would also like to thank the reviewers for their constructive comments and suggestions.

Conflicts of Interest: The authors declare no conflict of interest.

References

Agustin, C. A., & Hellianto, G. R. (2020). Pengaruh Reputasi Terhadap Minat Beli Produk Skincare di Shopee. *Business Economic, Communication, and Social Sciences Journal*, *2*(1), 39–52. https://doi.org/10.21512/becossjournal.v2i1.6050

Ananda, A. F., & Wandebori, H. (2016). The impact of drugstore makeup product reviews by beauty vlogger on YouTube towards purchase intention by undergraduate students in Indonesia. *International Conference on Ethics of Business, Economics, and Social Science*, *3*(1), 264–272.

diana Sembiring, L. (2018). Sistem Pendukung Keputusan Penerapan Algortima Apriori & FP-Growth untuk Pengambilan Keputusan di Pemko Medan. *Jurnal Pembangunan Perkotaan*, *6*(1), 46–54.

Fahrurrozi, M., Soekiman, J. F. X., Philipus Kurniawan Gheta, A., Sudaryana, Y., & Husain, T. (2020). Business to Business ecommerce and role of Knowledge Management. *Business to Business Ecommerce and Role of Knowledge Management*, *82*(January-February 2020), 16347–16357.

Iqbal, A., Danish, M. H., & Tahir, M. R. (2014). Exploitation of women in beauty products of Fair and Lovely: A critical discourse analysis study. *International Journal on Studies in English Language and Literature*, *2*(9), 122–131.

Kamepalli, S., & Bandaru, S. (2019). Weighted Based Frequent and Infrequent Pattern Mining Model for Real-Time E-Commerce Databases. *Advances in Modelling and Analysis B*, *62*(2–4), 53–60.

Kidane, T. T., & Sharma, R. R. K. (2016). Factors Affecting Consumers' purchasing Decision through ECommerce. *Proceedings of the 2016 International Conference on Industrial Engineering and Operations Management Kuala Lumpur, Malaysia*, *8*(10), 159–165.

Kumar, V., & Raheja, G. (2012). Business to business (b2b) and business to consumer (b2c) management. *International Journal of Computers & Technology*, *3*(3), 447–451.

Kurdi, M. (2020). Menggagas pelayanan prima di masa pandemic COVID 19. *Jurnal Lingkar Widyaiswara*, *7*(4), 4–9.

Lip-Sam, T., & Hock-Eam, L. (2011). Estimating the determinants of B2B e-commerce adoption among small & medium enterprises. *International Journal of Business & Society*, *12*(1), 15–30.

Liu, T. (2014). The New Algorithms of Weighted Association Rules based on Apriori and FP-Growth Methods. *TELKOMNIKA Indonesian Journal of Electrical Engineering*, *12*(5), 4071–4078.

Mulyawan, B., & Sutrisno, T. (2020). Product recommendation system on building materials shopping using FP-Growth algorithm. *IOP Conference Series: Materials Science and Engineering*, *1007*(1), 12144.

Pramushinta, A. D. A., & Junaedi, S. (2021). Pengaruh Brand Experience Dan Keterlibatan Merek Terhadap Loyalitas Merek Melalui Kepercayaan Dan Komitmen Merek Pada E-Commerce Sociolla. *Prosiding Seminar Nasional Ekonomi Dan Bisnis*, 140–151.

Rahayu, R., & Day, J. (2017). E-commerce adoption by SMEs in developing countries: evidence from Indonesia. *Eurasian Business Review*, *7*(1), 25–41.

Rahmi, Y., Sekarasih, L., & Sjabadhyni, B. (2017). The influence of beauty vlog on perceived source credibility and purchase intention. *Makara Human Behavior Studies in Asia*, *21*(1), 13–23.

Rizal, R., Fikry, M., & Helmina, A. (2020). Opinion Mining about Parfum On E-Commerce Bukalapak. Com using the Naïve Bayes Algorithm. *Jurnal Ilmu Pengetahuan Dan Teknologi Komputer*, *6*(1), 107–114. https://doi.org/10.33480/jitk.v6i1.1448

Sharma, A., Bhola, S., Malyan, S., & Patni, N. (2013). Impact of brand loyalty on buying behavior of women consumers for beauty care products-Delhi region. *Global Journal of Management and Business Studies*, *3*(7), 817–824.

Singh, A., & Jain, N. (2016). Internet Surfing Prediction System using Association Rule Mining based on FP-Growth. *International Journal of Scientific Research in Computer Science and Engineering*, *4*(4), 1–6.

Upasna, R., & Rebello, S. (2014). E-Commerce Growth and Opportunities in Indian Scenario-A Survey on Ecommerce Eco System. *International Journal of Innovative Research in Computer and Communication Engineering*, *2*(5), 419–426.

Venkateswari, S., & Suresh, R. M. (2011). Frequent Itemset Discovery in E-commerce Domain: A novel Approach. *International Journal on Computer Science and Engineering*, *3*(1), 83–88.

Vora, B., Patel, N. J., & Jani, N. N. (2021). based product automated recommendation system in E-commerce using improved Frequent Pattern Mining and Artificial Intelligence. *International Journal Of Research In Electronics And Computer Engineering*, *6*(2), 1331–1336.