

Marketing Strategy Analysis Using Apriori Association Method To Increase Sales In E-Commerce Companies

Nadilla Okviannas^{1*}, Sunu Widianto², Rita Komaladewi³.

¹ Padjajaran University, West Java, Indonesia, <u>nadilla16001@mail.unpad.ac.id</u>

² Padjajaran University, West Java, Indonesia, <u>sunu.widianto@unpad.ac.id</u>

³ Padjajaran University, West Java, Indonesia, <u>rita.komaladewi@unpad.ac.id</u>

*Corresponding Author: nadilla16001@mail.unpad.ac.id

Abstract: This research aims to analyze marketing strategies by utilizing association data mining algorithms, specifically Apriori and FP-Growth, to increase sales in e-commerce companies. The data used consists of actual sales data from Blibli.com, analyzed using RapidMiner to identify significant purchasing patterns. The analysis results show a strong association between products such as "Mother & Baby Needs – Body Skin Care" (support 0.108, confidence 0.476) and "Skin Care – Household Care" (support 0.195, confidence 0.443). These patterns indicate opportunities to design marketing strategies based on product bundling, discounts, and personalized digital promotions. The Apriori algorithm provides more intuitive and relevant results for marketing analysis compared to FP-Growth, which is better suited for larger datasets. The proposed marketing strategies include digital campaigns, bundling offers, push notifications, and event marketing that emphasize consumers' functional and emotional values. This study highlights the importance of understanding consumer transaction patterns in designing effective marketing strategies to enhance customer appeal and e-commerce company profits. By applying data mining, companies can create more personalized and efficient shopping experiences tailored to market needs.

Keyword: Marketing Strategy, Data Mining, Apriori Algorithm, FP-Growth, E-Commerce.

INTRODUCTION

The rapid growth of information technology and increasingly widespread internet penetration have had a significant impact on various aspects of Indonesian people's lives. In recent years, Indonesia has become one of the largest internet markets in the world with a growing number of internet users. The increase in the percentage of the population accessing the internet has occurred throughout Indonesia. According to data from the Indonesian Central Statistics Agency (BPS), in 2022, 67.88% of Indonesia's population already had a mobile phone with 66.48% already accessing the internet(Rizaty, 2023). The Indonesian Digital Report (2022) states that 204.7 million internet users in Indonesia have increased by 21 million, making internet penetration in Indonesia reach 73.7% of the total population in 2022 (Kemp, 2023). Internet users can shop through the E-Commerce online platform. E-Commerce is a technology that aims for trade transactions between sellers and buyers using the internet media.

E-Commerce can be defined as an arena for transactions and information exchange between sellers and buyers in cyberspace. E-Commerce as a way to shop or trade online (direct selling) by utilizing internet facilities that provide delivery services (Yulianto and Heryanto, 2019).

The use of online shopping platforms or so-called E-Commerce has always increased as a method of making transactions (Adi Ahdiat, 2023). Bank Indonesia is optimistic that the E-Commerce transaction value of IDR 489 trillion will be achieved this year. The E-Commerce transaction target is projected to increase by 17 percent, from the previous IDR 489 trillion at the end of 2022, then to IDR 572 trillion. This increase is supported by an increasingly broad ecosystem, innovation, and online shopping users. A company's sales transaction data will continue to increase every day. Large amounts of data can be a problem for a company if not managed properly (Supiyandi et al., 2017). The success of an E-Commerce company depends not only on the quality of its products or services, but also on its ability to attract, retain, and increase the number of customers. Therefore, implementing the right marketing strategy is an important key in achieving and maintaining market share. As an online platform, e-commerce companies have the advantage of utilizing large-scale consumer data to design more targeted and personalized marketing strategies. The application of association data mining, especially using the Apriori algorithm, has become a focus of attention in the context of marketing strategy. In 2022-2023, E-Commerce that is active in Indonesia is Shopee, Tiktok Seller, Alfagift Tokopedia, Lazada, Blibli, Bukalapak and others. The highest average monthly E-Commerce site visits during the first quarter (January-March) of 2023 according to Similarweb data, Shopee is the e-commerce with the highest number of visits, namely 158 million visits, the second highest number of visits is Tokopedia with 117 million visits, followed by Lazada with 83.2 million visits, Blibli 25.4 million visits and Bukalapak 18.1 million visits (Ahdiat, 2023).

Increased sales through e-commerce because sellers can easily promote, buyers get easy time to access online shopping so that the market reach can be wider and can reach a more efficient target market. A good marketing strategy can be used to increase sales figures. Marketing strategy is an effort to market a product, be it goods or services, by using a certain plan and tactic pattern so that the number of sales becomes higher. Market basket analysis is a methodology for analyzing consumer shopping habits by finding associations between several different items. The purpose of the market basket is to find out products that might be purchased together. Transaction data analysis can produce product purchasing patterns using associations (Larose and Larose, 2014; Kurnia Handayani and Susanti, 2019). (Kurnia Handayani and Susanti, 2019; Larose and Larose, 2014). Association rules support decision making in the marketing field, for example to find out customer purchasing patterns, determine product layout and so on. The FP-Growth algorithm is a method that aims to find patterns that often appear among many transactions, where each transaction consists of several items so that this method will support the recommendation system through the discovery of patterns between items in the transactions that occur. The FP-Growth algorithm is an algorithm tool that can be used to collect the most frequently occurring data in a set of data. The FP-Growth algorithm can help consumers to see the latest products, from popular to best-selling products (Dewi, Putrawansyah and Puspita, 2021).

Apriori helps retailers determine the optimal location to promote products, a powerful tool for implementing cross-selling and up-selling strategies (Zamila, Adwanb and Vasistac, 2020). The algorithm produces purchasing patterns that will be information for making decisions (Kumalasari, Darma Putra and Dharmaadi, 2020). The results of this study can provide an overview and understanding of customer purchasing patterns, retailers can make better decisions regarding stock, promotions, and other marketing strategies. Using restaurant sales data, the data used are 38 types of menus, 23 types of food menus and 15 types of drinks to obtain data results that are often ordered by consumers. The application of knowing the sales

pattern (item association rule) implementation of the association data mining algorithm with the apriori algorithm provides information on item association rules (menus) in consumer purchasing patterns that can be used by O Fish restaurant as a promotional development strategy based on items (menus) purchased simultaneously to boost sales. This application produces item association rules or menu combinations in consumer purchasing patterns for targeted and accurate promotional strategies compared to using manual promotional strategies(Qamal, Syah and Parapat, 2023).The FP-Growth algorithm is a branch of data mining that aims to identify associations between various items stored in a fairly large database

The rapid development of the digital industry encourages e-commerce companies to face challenges as well as opportunities. The increase in internet users requires an understanding of consumer behavior and the use of data mining, such as the Apriori and FP-Growth algorithms, in formulating marketing strategies. This study aims to provide a practical contribution for PT.XYZ in optimizing its marketing strategy amidst increasingly competitive e-commerce competition (Suhada *et al.*, 2020).

Based on the description of the background and identification of the problem above, the formulation of the problem in the study is as follows:

- 1. What variable relationships have the highest support values?
- 2. What machine learning algorithm model is most appropriate for creating an e-commerce sales promotion strategy?
- 3. What association algorithm model is most appropriate for creating an e-commerce sales basket analysis?

METHOD

This reseach uses a case study approach to explore association-based marketing strategies to increase sales in e-commerce companies. Case studies allow for in-depth investigation through various data collection techniques (Creswell and David, 2023). This research uses secondary data, data that has been collected by other parties and is relevant to the research topic (Sugiyono, 2019).Secondary data was obtained through literature studies and actual sales data taken from Blibli.com. Data collection in this study was carried out through several stages, namely: (1) direct observation of the objects and phenomena studied, (2) taking daily sales data from Blibli.com during December 2023, (3) data analysis using Market Basket Analysis (MBA) with the Apriori algorithm to identify correlations between sales items, (4) classification of product categories sold, (5) calculation of confidence values through two stages, namely searching for items with the highest sales frequency for one and two items, and (6) formation of association rules through identification of association rules, creation of data tabulation, item combination, and filtering based on minimum support. System development was carried out using the Waterfall model which allows for sequential work processes and minimal errors.

This study uses the RapidMiner application to apply the Apriori and FP-Growth algorithms to analyze purchasing patterns in e-commerce data. Before the analysis, a data understanding stage was carried out to understand the data structure, followed by data cleaning to remove duplication, empty data, and invalid transactions. The data was then recategorized and converted into a basket transaction format to suit the needs of the algorithm. A total of 413 transactions were used as the dataset. Although relatively small, this number is considered sufficient for an exploratory study because it represents relevant purchasing patterns. According to Aggarwal (2015) and Géron (2019), small datasets can still produce valid models as long as they are managed with the right evaluation methods. The results of the analysis of the Apriori and FP-Growth algorithms will be used to design more effective promotional strategies for e-commerce companies.

RESULTS AND DISCUSSION

Manual Apriori Calculation

Transaction categories show a variation in support values, with "Household Care" (49%) and "Groceries & Seasonings" (47%) having high frequencies, while "Bread, Cereal & Jam" and "Vitamins & Supplements" only have 3%. By setting a minimum support of 20%, the analysis focuses on strategically relevant items, while items with support below that threshold are eliminated as they are considered less significant in a marketing context (Grand, 2018).



Figure 1 Distribution of Support Values on 1-Itemset

The combination of items "Body Skin Care & Household Care" (support 20%) and "Household Care & Groceries & Cooking Spices" (support 26%) shows a strong relationship between household products. This reflects the tendency of customers to buy complementary products in one transaction. This finding can be utilized through bundling strategies, placing products close together, and targeted promotions to drive sales.



Figure 2 Support Distribution on 2-Itemset Product Combinations

Because the minimum support is 20%, the combination that does not meet will be eliminated. From all transactions of the 2 item sets, there are 2 transaction data with a support value of more than 20%, namely Body Skin Care - Household Care and Household Care - Groceries & Cooking Spices.

Basket Analysis Transaction Dataset

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Figure 3 Basket Analysis Transaction Dataset

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Figure 4 Data Set Used

The next step is to enter the apriori operator to determine the minimum support and confidence that you want to determine.

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Figure 5 Setting Minimum Support

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Figure 6 Setting Minimum Confidence

Modeling

This study uses support and confidence values of 0.2 (20%) to measure the strength of the relationship between items in associative rules. The search model for association rule in transactions is shown in the following figure.



Figure 7 Association Rule Calculation Model with Rapid Miner Software

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| | 8 | true | false | false | true | false | faise | faise | faise | faise | false | fa |
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Figure 8 Dataset Items

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| E | | 01 | Kebutuhan Ibu & Ansk | | s | viscem udmud & oxiselm | 0.079 | 0.346 | 0.879 | -0.376 | -0.018 | 0.817 | 0.882 | |
| Annotations | | 11 | perawatan kalit tubuh, S | embako & bun | u masak P | rawatan rumah tangga | 0.045 | 0.348 | 0.925 | -0.215 | -0.012 | 0.791 | 0.859 | |
| | | 12 | Kebutuhan Ibu & Anak | | 9 | rawatan rumah tangga | 0.085 | 0.372 | 0.884 | -0.370 | -0.015 | 0.845 | 0.892 | |
| | | 13 | nemunim | | 6 | eka cemilan | 0.097 | 0.380 | 0.874 | -0.412 | 0.053 | 2.229 | 1.338 | |
| | | 14 | Perawatan rumah tangga | | 2 | visas é bumbu masak | 0.168 | 0.383 | 0.811 | -0.712 | -0.018 | 0.903 | 0.933 | |
| | | 15 | Sembako & bumbu masa | si | 9 | revetan rumah tangga | 0.168 | 0.398 | 0.821 | -0.679 | -0.018 | 0.903 | 0.929 | |
| | | 16 | nemunim | | 2 | Assem udmed & coledim | 0.108 | 0.426 | 0.884 | -0.400 | 0.001 | 1.005 | 1.005 | |
| | | 17 | perawatan kulit tubuh | | 9 | rawatan rumah tangga | 0.195 | 0.434 | 0.825 | -0.703 | £00.0- | 0.985 | 0.989 | |
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| | | 20 | neira certilen | | | 06/70/0 | 500.0 | 0.566 | 0.937 | -0.244 | 0.053 | 2.229 | 1.220 | |

Figure 9 Association Rules Results

- 1. Skin Care Groceries & Seasonings: Support 0.045, confidence 0.232, lift 0.548, conviction 0.751. Low combination purchase, only 4.5%. indicating a weak association between the two products.
- 2. Skin Care Mother & Child Needs: Support 0.108, confidence 0.24, lift 1.06, conviction 0.750. Small combination purchase, 10.8%. slightly increases the likelihood of concurrent purchases.
- 3. Various Snacks Household Care: Support 0.043, confidence 0.254, lift 0.578, conviction 0.750. Small combination purchase, 4.3%. Weak relationship between the two products.
- 4. Groceries & Seasonings Beverages: Support 0.108, confidence 0.256, lift 0.578, conviction 0.75. Small combination purchase, 10.8%. Weak relationship between the two products.
- 5. Beverages Household Care: Support 0.066, confidence 0.26, lift 0.59, conviction 0.756. Rare combination purchases, 6.6%. Weak relationship between the two products.
- 6. Household Care Groceries & Spices Skin Care: Support 0.045, confidence 0.347, lift 0.599, conviction 0.753. Rare combination purchases, 4.5%. Weak relationship between the two products.

- 7. Skin Care Groceries & Spices: Support 0.13, confidence 0.289, lift 0.683, conviction 0.811. Combination purchases 13%. Weak relationship between the two products.
- 8. Groceries & Spices Skin Care: Support 0.13, confidence 0.307, lift 0.863, conviction 0.795. Combination purchases 13%. Weak relationship between the two products.
- 9. Snacks Groceries & Seasonings: Support 0.055, confidence 0.324, lift 0.764, conviction 0.852. Combination purchases 5.5%. Weak relationship between the two products.
- 10. Mother & Child Needs Groceries & Seasonings: Support 0.079, confidence 0.346, lift 0.817, conviction 0.882. Combination purchases 7.9%. Weak relationship between the two products.
- 11. Body Skin Care Groceries & Seasonings Household Care: Support 0.045, confidence 0.348, lift 0.791, conviction 0.859. Combination purchases are rare, 4.5%. Weak relationship between the two products.
- 12. Mother & Child Needs Household Care: Support 0.085, confidence 0.372, lift 0.845, conviction 0.892. Combination purchases 8.5%. Weak relationship between the two products.
- 13. Beverages Snacks: Support 0.097, confidence 0.38, lift 2.229, conviction 1.338. Combination purchase 9.7%. Strong relationship.
- 14. Household Care Groceries & Seasonings: Support 0.168, confidence 0.383, lift 0.903, conviction 0.933. Combination purchase 16.8%. Weak relationship between the two products.
- 15. Groceries & Seasonings Household Care: Support 0.168, confidence 0.398, lift 0.903, conviction 0.929. Combination purchase 16.8%. Weak relationship between the two products.
- 16. Beverages Groceries & Seasonings: Support 0.108, confidence 0.426, lift 1.006, conviction 1.005. Combination purchase 10.8%. Weak relationship between the two products.
- 17. Body Skin Care Household Care: Support 0.195, confidence 0.434, lift 0.986, conviction 0.989. Combination purchase 19.5%. Weak relationship between the two products.
- Household Care Body Skin Care: Support 0.195, confidence 0.443, lift 0.986, conviction 0.989. Combination purchase 19.5%. Weak relationship between the two products.
- 19. Mother & Child Needs Body Skin Care: Support 0.108, confidence 0.476, lift 1.06, conviction 1.051. Combination purchase 10.8%. Weak relationship between the two products.
- 20. Various Snacks Beverages: Support 0.007, confidence 0.566, lift 2.229, conviction 1.72. Combination purchase 0.7%. Strong relationship.
- 21. Facial Care Body Skin Care: Support 0.064, confidence 0.67, lift 1.4. Combination purchase 6.4%. Strong relationship.

Discussion

Based on the apriori data analysis, there are several association rules with high support and confidence that can be used as the basis for marketing strategies. First, for the itemset "Mother & child needs - Body skin care" which has a support of 0.108 and a confidence of 0.476, this shows that 10.8% of transactions involve both products, with 47.6% of mother & child product buyers also buying skin care. This shows that these two products complement each other, especially for mothers who care about family needs and self-care. Furthermore, for the itemset "Drinks - Various snacks" with a support of 0.097 and a confidence of 0.38, although the support is relatively low, 38% of drink buyers also buy snacks. This shows that segments such as millennials, Gen Z, young families, and office workers tend to seek practical shopping through e-commerce. In addition, for the itemset "Skincare - Household care" which has a support of 0.195 and a confidence of 0.443, 19.5% of transactions involve these two products, with 44.3% of skincare buyers also purchasing household care. This indicates that consumers who care about their health also pay attention to the cleanliness of their homes. Finally, for the itemset "Household care - Groceries & spices" with a support of 0.168 and a confidence of 0.398, 16.8% of transactions include these two products, with 39.8% of household care buyers also purchasing groceries and spices, indicating a fairly strong relationship between the two products. Overall, marketing strategies can be focused on this combination of complementary products to increase sales in the e-commerce market.

Based on transaction patterns, marketing strategies can be designed by offering products in one package to create a more personal and efficient shopping experience. This understanding can help companies create offers that match market expectations. Digital advertising through social media can be used to increase consumer awareness. Video content that links skincare and household care products can strengthen the campaign, by showing the connection between self-care and home hygiene. According to Kotler et al. (2021), advertising can create "top of mind awareness," making the brand the consumer's first choice, which influences memory, evaluation, and purchasing decisions (Mohan and Jayakar, 2022).

Sales promotions can be done with discounts and product bundling that emphasize functional and emotional value, making it easier for consumers to meet their needs (Kotler and Amstrong, 2021). In addition to bundling, providing digital coupons or vouchers as discounts can also increase product purchases, becoming an effective short-term step to increase sales (Mohan and Jayakar, 2022). Promotional mixes such as direct selling can be implemented by utilizing technology, such as email marketing and direct messages through e-commerce accounts. Sellers can offer products directly to customers who have purchased related products, with attractive discount offers or promotions. In addition, push notifications can also be used to send automatic notifications about discounts or product offers. This digital direct selling strategy is effective in delivering relevant and timely messages to consumers (Phillip and Keller, 2018). Public relations and publicity through event marketing can be an effective promotional tool in the e-commerce market. Events that combine skincare and household products provide direct experiences to customers, while increasing brand awareness and engagement with consumers. Previous research has shown that educational and entertaining event marketing can increase audience awareness of product advantages (Daymon and Holloway, 2019). In addition, effective PR can strengthen brand image and create brand awareness at a lower cost than traditional advertising (Kotler and Amstrong, 2021).

The application of the Apriori algorithm in the analysis of e-commerce transaction data helps design marketing strategies based on product associations, such as the relationship between "body skin care" and "household care". Blibli and Unilever implement product bundling to make it easier for consumers to choose complementary products, increasing the average transaction value. By using the Apriori algorithm, companies can design effective marketing strategies such as bundling, discounts, or advertising campaigns that emphasize product relatedness (Chaudhuri and Dayal, 2022). The Apriori algorithm is more suitable for small to medium data analysis because it is easy to understand and produces transparent rules. FP-Growth is more efficient for large datasets but is more complex and requires more resources. In this study, Apriori is more appropriate because it provides clear and easy-tointerpret results to design appropriate sales promotion strategies (Han, Kamber and Pei, 2023).

CONCLUSION

Based on the discussion, this study successfully applied the FP-growth algorithm to identify patterns of product purchases that often occur together, such as "Body skin care" and "Household care," which provides insights for designing effective sales strategies. Marketing strategies that can be applied include product bundling, discount promotions, and advertising on social media to increase brand awareness and customer attraction. Analysis with the Apriori

algorithm also provides interrelationships between products, allowing companies to formulate targeted marketing strategies, such as offering complementary product packages and maximizing digital channels. This helps companies design promotions that are more efficient and in accordance with customer needs.

Based on the research results, several suggestions can be given, including. for further research can integrate FP-Growth with other data mining techniques, such as classification or clustering, for a more comprehensive analysis of consumer behavior. Testing the effectiveness of marketing strategies through experiments or field studies is also recommended to assess their impact on sales and customer satisfaction. The use of larger and more varied datasets from various e-commerce sectors can increase the generalizability of the results. In addition, a multidisciplinary approach that combines marketing, information technology, and consumer psychology can provide more holistic insights. In practice, e-commerce companies are advised to use FP-Growth routinely to understand customer shopping patterns and design data-based strategies. Combinations of products with high associations, such as "Body skin care" and "Household care," can be offered in discounted bundles to increase appeal and transactions. Further research should be conducted on different e-commerce platforms to consider the unique characteristics of each.

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