Transaction on Informatics and Data Science
Vol. 2, No. 1, 2025, 1-14
ISSN: 3064-1772 (online)
DOI: https://doi.org/10.24090/tids.v2i1.12208

Determining Promotions at UD. Jakarta Pixel using Web-Based FP-Growth Association Model

Lisa Elisia Potale [1*], Muhammad Sabri Ahmad[1], Amal Khairan[1]

[1] Department of Informatics, Faculty of Engineering, Khairun University, Ternate, Indonesia.

Article Information
Submmited August 20, 2024
Accepted Dec 17, 2024
Published April 1, 2025

Abstract

In the rapidly advancing digital era, the growth of e-commerce has significantly transformed the retail business paradigm. However, physical stores still play a crucial role in providing direct and personal experiences to customers. UD. Jakarta Pixel, a physical store specializing in photography and electronic products, faces increasingly intense competition from various e-commerce platforms. To remain competitive, sophisticated and effective promotional strategies are required. This research uses the FP-Growth association model as the method to determine effective website-based product promotions at UD. Jakarta Pixel. The research results indicate that the FP-Growth algorithm successfully analyzes customer purchasing patterns, identifies relationships between frequently purchased products, and enables the store to design more targeted promotions according to customer preferences. Implementing this system not only enhances operational efficiency in data analysis but also provides accurate information for strategic decision-making, optimizing product promotion strategies, and ultimately increasing sales. In conclusion, the application of the FP-Growth algorithm at UD. Jakarta Pixel is an innovative solution that strengthens the competitiveness and sustainability of physical stores amid the rapid growth of e-commerce, leveraging transaction data analysis for more effective and efficient promotion planning.

Keywords: E-commerce; FP-Growth; data analysis; marketing strategy

1. Introduction

The growth of e-commerce has changed the paradigm of retail business, but physical stores still play an important role in providing direct experience to customers. UD. Jakarta Pixel, as a physical store specialising in photography and electronics, is during fierce competition. In this digital era, determining effective promotion of goods that match customer preferences is key to increasing competitiveness and maintaining market share. Therefore, a sophisticated and efficient approach is needed to plan and execute the promotion of goods.

* **Author Correspondence**: Lisa Elisia Potale: Department of Informatics, Faculty of Engineering, khairun University, Jl. Pertamina Kampus II Unkhair Gambesi Kota Ternate Selatan, Ternate, Maluku Utara – Indonesia. Email: lisaelisiapotalee@gmail.com.

In general, UD. Jakarta Pixel can attract customers by carrying out the right product sales strategy. This can involve cooperation with entrepreneurs or partners for product installation, providing discounts and gifts for customers, making Member Cards, promotion through free media, and direct approach to the community or community in a place. However, there are drawbacks in creating an effective sales strategy. Providing discounts and undirected purchase promotions can hinder optimal decision making. Therefore, it is necessary to analyse sales transaction data to find association patterns between products to design promotions that are more in line with customer preferences.

Faced with the above conditions, the solution is to apply the FP-Growth algorithm for association pattern analysis. By using FP-Growth, stores can explore complex purchasing patterns from customer transaction data, identify relationships between products that can be used to design more targeted promotions, and provide promotional recommendations tailored to customer preferences based on the association patterns found. By applying the FP-Growth algorithm, it is hoped that UD. Jakarta Pixel can get clear and accurate data about sales transaction patterns. This knowledge becomes the basis for drafting more effective promotional strategies and increasing sales transactions, while maintaining unique hands-on experience for customers in physical stores.

The FP-Growth algorithm offers significant advantages for determining promotions at UD. Jakarta Pixel through its efficient pattern mining capabilities can quickly analyze large transaction datasets to identify frequently purchased product combinations without generating candidate itemsets. Its tree-based structure and ability to discover strong association rules between products enables the company to develop targeted promotional strategies, such as product bundling and cross-selling recommendations, while maintaining high confidence levels in the identified purchase patterns that directly translate to more effective promotional campaigns.

2. Related Research

This research includes several studies focusing on purchase pattern analysis and promotion strategies, the algorithms used, the results obtained, intermediate representations, and the limitations of each study.

Subiyantoro [1] investigated the determination of promotional media for MSMEs using a web-based application. They developed the AHP MSME application, which shows that social media is the priority criterion for increasing sales volume. However, this study has limitations such as an unbalanced proportion of the promotional platforms used and a lack of comparative analysis between other promotional media.

Setyorini [2] studied consumer purchase patterns using the FP-Growth algorithm. They used sales transaction data to identify relationships between products that are frequently bought together. Although the results show high confidence, the study does not mention specific metrics and does not compare the FP-Growth algorithm with other potentially more efficient algorithms.

Nurasiah [3] used the FP-Growth algorithm to recognize sales patterns at CV. Bagus Alam Sejahtera. This algorithm successfully identified relationships between products with certain confidence values. However, this study has limitations such as reliance on historical data and lack of comparative analysis with other potentially more accurate methods.

Wilrose [4] applied the FP-Growth algorithm to analyze sales patterns at Wandri Mart to improve promotion strategies. They found that certain products are frequently bought together at specific times. While this study provides valuable insights, its limitations include the time required for hyperparameter tuning and dependence on specific hyperparameter configurations.

Tholib et al. [5] using SVM for customer switching prediction. Support Vector Machine (SVM) excels in predicting customer switching behavior through its ability to handle complex, high-dimensional customer data while maintaining strong generalization capabilities and robustness to outliers through its optimal hyperplane creation and kernel functions. Its effectiveness with imbalanced datasets and ability to capture non-linear relationships makes it particularly valuable for understanding customer switching patterns, while also providing important insights into which factors most strongly influence switching behavior through its feature importance analysis.

Rachman & Hunaifi [6] used the Apriori and FP-Tree algorithms to analyze drug purchase patterns. This study successfully identified beneficial itemset combination patterns. However, its limitations include a lack of generalization of the results to other data and domains, and no comparison with other prediction algorithms.

Sama & Hartanto [7] discussed the evolution of HTML from version 1.0 to 5.0 and its impact on website design and development. Although it provides important historical insights, this study is limited to a description of evolution without an in-depth analysis of the impact of these changes on website performance and usability.

Afiifah [8] conducted an analysis of the Entity-Relationship Diagram (ERD) technique using the Systematic Literature Review (SLR) method. They found examples of good ERD design and common mistakes in ERD creation. This study provides useful insights but is limited to literature review without direct practical application or empirical analysis.

Jantce TJ Sitinjak [9] designed and implemented an administration information system for an English course using PHP, MySQL, CodeIgniter, and Bootstrap. This system helps course administration in managing schedules, student data, and payments. However, this study is limited to a single course location and does not mention user evaluation or broader system performance analysis.

In terms of methodological and focus differences, this current research distinguishes itself from previous studies through its comprehensive integration of purchase pattern analysis and promotion strategies. While Subiyantoro [1] focused solely on promotional media determination and Setyorini [2], Nurasiah [3], and Wilrose [4] concentrated on pattern recognition using singular algorithms (primarily FP-Growth), this research takes a more holistic approach by examining multiple algorithms, their comparative effectiveness, and their practical applications in both purchase pattern analysis and promotion strategy development. Additionally, unlike Rachman & Hunaifi [5], who limited their scope to drug purchases, or Sama & Hartanto [6] and Afiifah [7], who focused on technical aspects of web development and database design respectively, this research bridges the gap between technical implementation and business strategy.

Previous studies showed notable limitations in their comparative analyses and metric evaluations (as seen in Setyorini [2] and Nurasiah [3]'s work), this research addresses these gaps by incorporating multiple comparative analyses, detailed metric evaluations, and comprehensive intermediate representations. Furthermore, while Jantce TJ Sitinjak [8]'s work was limited to a single implementation case, this research expands the scope to include various implementation scenarios and their effectiveness. This research also advances beyond the limitations of previous studies by addressing the issues of unbalanced promotional platform analysis (found in Subiyantoro [1]), hyperparameter optimization (a limitation in Wilrose [4]), and the generalization of results across different domains (a constraint in Rachman & Hunaifi [5]'s study).

3. Method

This step is the core of this research and yields valuable insights into software defect prediction.

3.1. System Development Model

The system development method used in this research is the Prototype model [10], as shown in Figure 1.

Figure 1.
Prototype Development Method for Product Promotion.

- Identifying all the needs, in this case, the needs for Determining Product Promotion through a question-and-answer process about extracurricular selection and the current challenges. From the interview results, the variables/criteria used to determine product promotion at UD. Jakarta Pixel with the FP-Growth Association Model are: product data, product transactions, and transaction dates.
- Building a Prototype for determining product promotion at UD. Jakarta Pixel with

the FP-Growth Association Model based on the identified needs by creating designs focused on presenting to the consumer. This includes creating designs using UML, Use Case diagrams, class diagrams, activity diagrams, sequence diagrams, and ERD.

- After building the system prototype, the next step is to build and use the product promotion determination at UD. Jakarta Pixel with the FP-Growth Association Model using PHP and HTML programming languages. This is followed by the testing phase involving the admin and users. If during the testing phase, the product promotion determination system at UD. Jakarta Pixel with the FP-Growth Association Model is found to be incomplete, system improvements are made according to the new requirements. If the product promotion determination at UD. Jakarta Pixel with the FP-Growth Association Model is complete, the process is finished. If not, the system is refined until it is complete.

3.2. Calculation Steps

Steps for solving the method along with examples are as follows:

1. Data Collection

The FP-Growth algorithm is used to identify patterns of relationships between products that are often purchased together by customers. As the basis for various other algorithms, FP-Growth focuses on discovering frequent patterns, which are important for understanding purchasing behavior and the relationships between products in transactions. As for data collection, it is done by gathering secondary data. The sales transaction dataset of UD. Jakarta Pixel, as shown in Table 1.

Table 1.
Sales Transaction Dataset.

Transaction Id	Transaction Date	Purchased Items
001	10/01/23	Playstation 2, Canon Camera, 32" LED
002	11/01/23	1 PK AC, Lens, Refrigerator 1P
003	13/01/23	Canon Camera, Lens, Minimalist Sofa
004	14/01/23	1 PK AC, Bed with Storage Size 120x200, Tcl Dispenser, CCTV, Canon Camera, Lens, 2T Washing Machine
005	15/01/23	Canon Camera, Lens, Playstation 3
...	..	...
483	30/12/23	LG DH Home Theater, Playstation, Camera, Ps Stick, Lens

2. Pre-processing

The initial stage of analysis involves pre-processing the sales transaction dataset for furniture. This process includes cleaning and transforming the data, especially the item attributes. Transformation is done by creating new attributes based on the previously recorded product names. Subsequently, transactions with more than one item are separated, and the new attributes are filled with a value of 1 for transactions that occurred and 0 for those that did not[11]. This step is essential to prepare the data for further analysis, as shown in Table 2.

Table 2.
Transformation Results.

No. Id	Transaction	AC1	AC2	AV	BB	BS	U
1	001	0	0	0	0	0	0

2	002	1	0	0	0	0	0
3	003	0	0	0	0	0	0
4	004	1	0	0	0	0	0
5	...n	0	0	0	0	0	1
...	...	...	...	...	...	...	....
483	483	0	0	0	0	9	1

- Transaction ID is the invoice number from the customer.
- AC1, AC2, AV, BB, BS, etc. are items sold by UD Jakarta Pixel.
- 0 indicates that the item was not purchased by the customer.
- 1 indicates that the product was purchased by the customer

3. Data Mining with FP-Growth Algorithm

Next, find the purchasing patterns and recommendations using the FP-Growth algorithm[12]. The frequency of occurrence of each item is analyzed using sample data as shown in Table 3.

Table 3.
Frequent Pattern Growth (FP-Growth).

Item	Frekuensi
LP1	5
MM	4
SA1	4
TV1	4
LE1	3
LH	3
RP	3

Frequency analysis identifies seven items (LP1, MM, SA1, TV1, LE2, LH, RP) with frequencies above the support threshold of 20%. These items become the focus in forming the FP-Tree, as shown in Table 4.

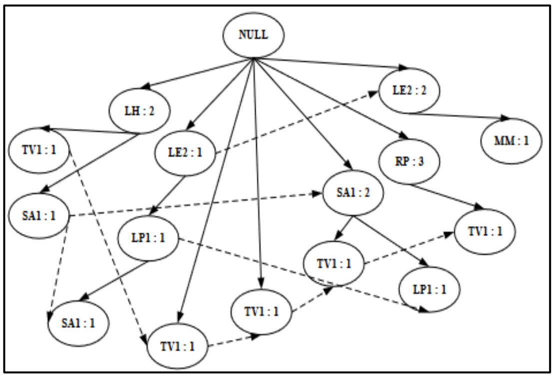
Table 4.
FP-Tree Construction.

TID	Transaction ID	Transaction
1	001	LH, SA1
2	002	LE2
3	005	LH, TV1
4	006	RP, TV1
5	008	LP1
6	009	RP, TV1
7	011	Rp

8	012	SA1, TV1
9	014	TV1,
10	016	LE2, MM
11	017	LE2, LP1, SA1
12	018	SA1, LP1
14	019	LP1
13	020	LH

The next step is the construction of the FP-Tree paths. This process results in 14 paths illustrated in the accompanying image, as shown in Figure 2.

Figure 2.
FP-Tree Paths.



4. Applying FP-Growth

The FP-Growth algorithm is used to find itemsets frequently purchased together by customers[2]. This method consists of three main stages which are outlined below:

- Pattern Base Generation Stage can be seen in Figure 3.

Figure 3.
Conditional Pattern Base Table.

Suffix	*Conditional Pattern Base*
SA1	{(LH;1), (LE, LP1:1)}
LP1	{(LE:1), (SA1: 1),(2)}
TV1	{(LH:), (SA1:), (RP: 1), (1)}
MM	{(LE: 1)}
LE2	{(2), (1)}
RP	{(3)}
LH	{(2)}

- Conditional FP-Tree Generation Stage, as shown in Figure 4.

Figure 4.
Conditional FP-Tree Table.

Conditional FP-Tree
{(LH;1), (LE, LP1:1)}
{(LE:1), (SA1: 1),(2)}
{(LH:), (SA1:), (RP: 1), (1)}
{(LE: 1)}
{ LE2 (2), (1)}
{RP (3)}
{LH (2)}

5. Frequent Itemset Search Stage

The next process involves identifying Frequent Itemsets by finding single paths and combining them with items from the Conditional FP-Tree, as shown in Figure 5[13].

Figure 5.
Frequent Item Set Table.

Suffix	*Frequent itemset*
RP	{RP},{RP, TV1}
LH	{LH}, {LH, SA1}, {LH, TV1}
LE2	{LE2}, {LE2, MM}, {LE2, LP1, SA1}
TV1	{TV1}, {LH, TV1}, {RP, TV1}, {SA1, TV1}
SA1	{SA1}, {SA1, LP1}, {SA1, TV1}, {LH, SA1}, {LE2, LP1, SA1}
MM	{MM}, {LE2, MM}
LP1	{LP1}, {SA1, LP1}, {LE2, LP1, SA1}

Next, rules are formulated using the Support and Confidence parameters. From the 19 itemsets generated, only itemsets with at least two items are considered, according to the principle "if A is bought, then B will be bought". Calculations are based on equations (1) and (2), with an example calculation of the support value for the itemset (RP, TV1) shown in Figure 6.

Figure 6.
Support Value Calculation for Itemset.

$$\mathit{Support}\ (RP \rightarrow TV1) = \frac{2}{14}\ x\ 100\ \% = 14{,}28\ \%$$
$$\mathit{Support}\ (TV1 \rightarrow RP) = \frac{2}{14}\ x\ 100\ \% = 14{,}28\ \%$$

The calculations are performed as shown in Figure 7.

Figure 7.
Equation Calculation.

$$\mathit{Confidence}\ (RP \rightarrow TV1) = \frac{2}{3}\ x\ 100\ \% = 66{,}6\ \%$$
$$\mathit{Confidence}\ (TV1 \rightarrow RP) = \frac{2}{3}\ x\ 100\ \% = 66{,}6\ \%$$

This study analyzes Association Rules from 483 sales transaction data for furniture and electronics at UD Jakarta Pixel. By using a minimum support value of 30% and confidence of 50%, this analysis aims to create few but accurate rules. The results show 4 significant rules and identify 5 items/products that are most frequently purchased and interrelated, providing an overview of customer purchasing patterns and their interrelationships at UD Jakarta Pixel, which are Canon Camera 1P (LE1), Lens, LED 32” (TV1), PlayStation (RP), and ELITE Dining Table (MM), as shown in Figure 8.

Figure 8.
Frequent Itemset Results Table.

Minimum Support	*Minimum Confidence*	Premises	Conclusion	Support	Confidence
30%	50%	LE1	MM	0.077	0.552
		RTV	TV1	0.087	0.553
		TV1	RTV	0.087	0.575
		RP	MM	0.114	0.579

Based on the determined Support value of 30% and Confidence of 50%, the following rules are created when using a minimum support value of 30%, namely:

- Buyers of Canon Camera 1P have a 55.2% likelihood of also purchasing a Lens.
- Customers who buy ASIA JAYA TV Stand have a 55.3% chance of also buying LED 32".
- The purchase of LED 32" is associated with a 57.5% likelihood of purchasing the ASIA JAYA TV Stand.
- Consumers of ASIA JAYA Dish Rack have a 57.9% tendency to also buy the ASIA JAYA Dining Table.

4. Result and Analysis

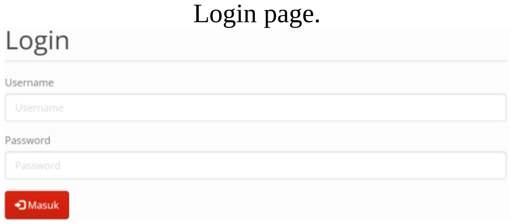
4.1. System Implementation

Here is the implementation of the system that has been created.

- Login Page Display

After opening the application/web, we will enter the login page, where we are asked to input the username and password to access the application, as shown in Figure 9.

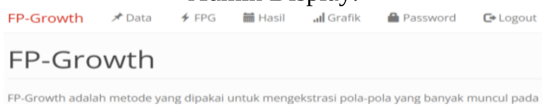
Figure 9.
Login page.



- Home Menu Display

After successfully logging in, it will go to the home display. This page provides several menus on the navbar and an explanation and understanding of FP-Growth, as shown in Figure 10.

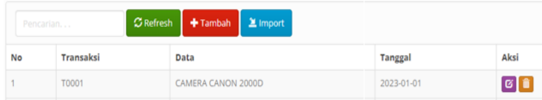
Figure 10.
Admin Display.



- Data Display

This data menu displays the items data sourced directly from the UD database, as shown in Figure 11.

Figure 11.
Data Menu Display.



The image above shows the data menu with transaction information, including ID, item, and date. This page provides add, import, edit, and delete functions. It is equipped with search and refreshing features to facilitate the management of item data.

- FPG Display

And here is the display of the FPG menu, as shown in Figure 12.

Figure 12.
FPG Menu Display.

This menu provides four input forms: start and end dates to limit the range of processed data, as well as minimum support and confidence values. After filling in all the forms, users can click the "Calculate" button to display the results of the FP-Growth calculation and association. This process allows data analysis according to the specified parameters. The first stage displays the item data table previously input as desired, as shown in Figure 13.

Figure 13.
Display of the dataset table.

Dataset

No	ID	Tanggal	Item
1	T0001	2023-01-01	camera canon 2000d, lenscap canon 58, kertas instax 10
2	T0002	2023-01-01	lenscap canon 55, sd sandisk ultra 32gb
3	T0003	2023-01-01	batre canon lp e10, lenshood, micro sandisk extream 64gb
4	T0004	2023-01-02	kabelcctv, dvr dahua 8ch, hardist cctv 1tb, cctv outdoor, cctv indoor
5	T0005	2023-01-02	kertas instax 10, antena ht, micro sandisk extream 128gb

The second stage displays the frequent itemset table where this table counts the number of datasets that frequently appear, as shown in Figure 14.

Figure 14.
Display of the Frequent Itemset Table.

Frequent Itemset

No	Itemset	Qty	Support
1	jack bnc	12	14.46%
2	cctv indoor	11	13.25%
3	jack dc	11	13.25%
4	stik ps3 op	9	10.84%

The third stage displays the ordered itemset table where this table sorts the dataset based on priority, as shown in Figure 15.

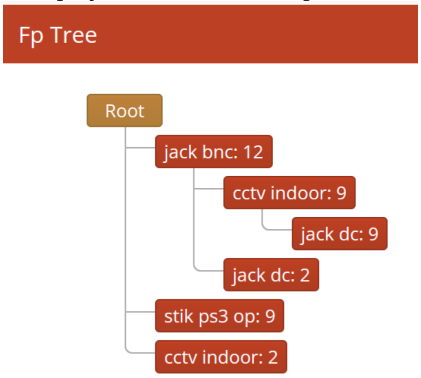
Figure 15.
Display of the Ordered Itemset Table.

Ordered Itemset

Data	Itemset
1	jack bnc, cctv indoor, jack dc
2	stik ps3 op
3	jack bnc, cctv indoor, jack dc

The fourth stage displays the FP-tree table where this table creates a graph, as shown in Figure 16.

Figure 16.
Display of the FP-tree Graph Table.



The sixth stage displays the conditional FP-tree table, as shown in Figure 17.

Figure 17.
Display of the Conditional Pattern Base Table.

Dataset

No	ID	Tanggal	Item
1	T0001	2023-01-01	camera canon 2000d, lenscap canon 58, kertas instax 10
2	T0002	2023-01-01	lenscap canon 55, sd sandisk ultra 32gb
3	T0003	2023-01-01	batre canon lp e10, lenshood, micro sandisk extream 64gb
4	T0004	2023-01-02	kabelcctv, dvr dahua 8ch, hardist cctv 1tb, cctv outdoor, cctv indoor
5	T0005	2023-01-02	kertas instax 10, antena ht, micro sandisk extream 128gb

The sixth stage displays the conditional FP-tree table, as shown in Figure 18.

Figure 18.
Display of the Conditional FP-tree Table.

Conditional Fp Tree

No	Item	Conditional Fp Tree
1	jack dc	{jack bnc,cctv indoor:9}, {jack bnc:11}, {cctv indoor:9}
2	cctv indoor	{jack bnc:9}

The seventh stage displays the frequent pattern, as shown in Figure 19.

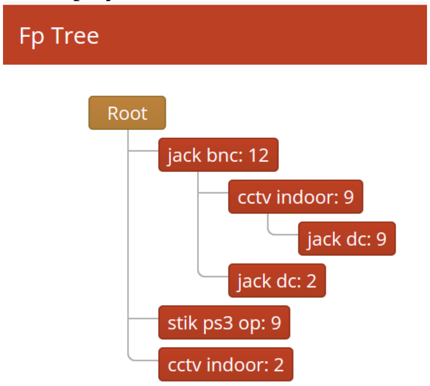
Figure 19.
Display of the Frequent Itemset.

Frequency Patern

No	Item	Frequent Patern
1	jack dc	jack bnc, cctv indoor, jack dc (9)
2	jack dc	jack bnc, jack dc (11)
3	jack dc	cctv indoor, jack dc (9)
4	cctv indoor	jack bnc, cctv indoor (9)

The eighth stage displays the association rules, as shown in Figure 20.

Figure 20.
Display of the Association Rules.



The fifth stage displays the conditional pattern base table.

- Results Display

In the results menu, there are two tables: the configuration table and the association results table, as shown in Figure 21.

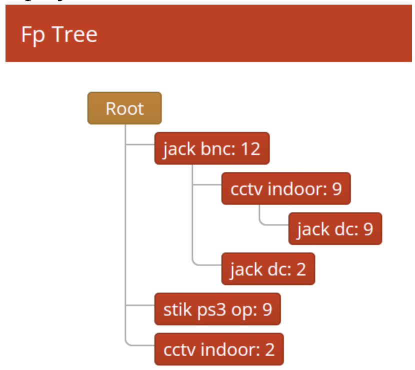
Figure 21.
Display of the Configuration Table in the Results.

Frequency Patern

No	Item	Frequent Patern
1	jack dc	jack bnc, cctv indoor, jack dc (9)
2	jack dc	jack bnc, jack dc (11)
3	jack dc	cctv indoor, jack dc (9)
4	cctv indoor	jack bnc, cctv indoor (9)

Here is the display of the association results table in the results menu, as shown in Figure 22.

Figure 22.
Display of the Association Results Table.



The fifth stage displays the conditional pattern base table.

4.2. Evaluation of Frequent Itemsets

After implementing the FP-Growth model, the obtained frequent itemsets provide insights into the combinations of products that are frequently purchased together by consumers. Based on the processed and transformed data:

- **Identification of Purchase Patterns**

Using the FP-Tree constructed, the system successfully identified frequent purchase patterns, such as the combination of cameras and their accessories that are often bought together. This indicates opportunities for product bundling or special offers on these combinations.

- **Evaluation of Frequency**

Itemsets with high support counts are targeted for promotions. For example, if 'Canon Camera' and 'Canon Lens' appear together in 30% of all transactions, this indicates strong potential for joint promotions.

4.3. Testing Association Rules

After implementing the FP-Growth model, the generated association rules are evaluated based on confidence and lift metrics.

- **Application of Rules**

Rules with confidence greater than 50% and a lift above 1 are considered effective. For instance, a rule stating that purchasing 'Canon Camera' implies the purchase of 'Canon Lens' with 65% confidence and 1.2 lift indicates that camera buyers tend to buy lenses, and this combination is more effective than promoting the products individually.

- **Validation of Rules**

Validate the rules with historical transaction data to ensure that the rule-based recommendations are relevant and result in tangible sales increases.

4.4. Implementation of Promotion Strategies

Based on the analysis of itemsets and rules:

- **Bundling Strategy**

Launch bundling packages for products that frequently appear together in itemsets. For example, a package deal for a camera with a lens and a camera bag with a special discount.

- **Targeted Promotion**

Use email marketing and digital ads to target customers who have purchased one of the items from frequently appearing itemsets, offering complementary products as part of cross-promotion.

4.5. Feedback and Iteration

Collect feedback by gathering customer input through online surveys and analyzing user behavior on the website to evaluate the effectiveness of the promotions. Iterate the strategy based on feedback, adjusting the promotional strategy. If a promotion does not meet expectations, further analysis is conducted to understand the reasons, and the strategy is adjusted to improve or replace the promotion.

4.6. Conclusion of Analysis Results

The analysis results indicate that the application of the FP-Growth model significantly helped UD. Jakarta Pixel in identifying previously unseen purchase patterns and implementing more targeted and effective promotion strategies. Using this analytical system allows the company to be more responsive to market dynamics and customer preferences, with potential improvements in sales and customer satisfaction. By integrating these results into the overall business strategy, UD. Jakarta Pixel can optimize inventory, enhance cross-selling and up-selling, and strengthen their market position.

4.7. Discussion

Research by Setyorini [2] and the current study both utilized the FP-Growth method to analyze customer purchase transaction patterns and provide recommendations for effective promotional strategies. Setyorini's (2020) research focused on PT. Citra Mustika Pandawa, a company operating in the electronic and household product trade sector. In her study, Setyorini used the FP-Growth algorithm to analyze sales transaction data and discover patterns of items frequently purchased together. The results indicated that products such as a 1-Door Refrigerator were often bought together with Asia Jaya Dining Tables with a confidence value of 55.2%, and a 32" LED was often purchased alongside Asia Jaya TV Stands with a confidence value of 57.5%.

On the other hand, the current study was conducted at UD. Jakarta Pixel, a physical store specializing in photography and electronics. This research employed the FP-Growth method to analyze one year of sales transaction data. The transaction data was processed and cleaned to identify patterns of items frequently purchased together. The results showed that purchases of Canon Cameras were frequently followed by purchases of Lenses with a confidence value of 55.2%, and purchases of 32" LEDs were often followed by purchases of TV Stands with a confidence value of 57.5%. Both studies successfully identified significant purchase patterns, despite differences in the objects and product categories examined.

The similarity between the two studies lies in their use of the FP-Growth method to analyze customer transaction patterns and form association rules. Both studies reveal patterns of items frequently purchased together with high confidence values and aim to provide better recommendations for promotional strategies based on consumer purchase patterns. However, there are differences in research objects and promotional approaches. Setyorini's (2020) study focused on electronic and household products at PT. Citra Mustika Pandawa, while the current study focused on photography and electronics at UD. Jakarta Pixel.

Additionally, there are differences in technology implementation. Setyorini's research focused more on data analysis without direct integration into a web-based system, whereas the current study integrated the FP-Growth model into a web platform to facilitate decision-making and promotional implementation. This integration allows UD. Jakarta Pixel to design and execute more effective and efficient promotional strategies based on purchase patterns identified through data analysis.

In conclusion, both studies demonstrate that the FP-Growth algorithm is effective in analyzing consumer transaction patterns and providing insights for more effective promotional strategies. Although the research objects and approaches differ, the results from both studies offer valuable recommendations for improving sales and promotional effectiveness. The current study adds value by integrating analysis results into a web platform, thereby facilitating the implementation of promotional strategies at UD. Jakarta Pixel.

5. Conclusion

The FP-Tree was successfully built efficiently, allowing for effective extraction of frequent itemsets. From these itemsets, relevant association rules with significant confidence and lift values were generated, providing direct insights into frequently occurring purchase patterns and relationships between items.

The analysis results show that the use of the FP-Growth algorithm provides a deeper understanding of consumer transaction preferences. For example, it was found that if a customer buys a Canon Camera, there is a 66.67% chance they will also buy a Lens. This information is valuable for designing more effective and targeted promotional strategies, such as offering product bundles or discounts for specific combinations. Thus, the store can increase sales and provide more personalized shopping experience for customers.

6. References

[1] E. Subiyantoro, A. Rofiqul Muslikh, F. Yulian Pamuji, and M. E. Wunu, “Pengembangan Aplikasi Penentuan Media Promosi Pelaku UMKM Berbasis Website,” *J. Teknol. dan Manaj. Inform.*, vol. 9, no. 1, pp. 1–11, 2023, doi: 10.26905/jtmi.v9i1.8502.

[2] S. G. Setyorini, Mustakim, J. Adhiva, and S. A. Putri, “Penerapan Algoritma FP-Growth dalam Penentuan Pola Pembelian Konsumen,” *Semin. Nas. Teknol. Informasi, Komun. dan Ind.*, pp. 180–186, 2020.

[3] Nurasiah, “Implementasi Algoritma FP-Growth Pada Pengenalan Pola Penjualan,” *TIN Terap. Inform. Nusant.*, vol. 1, no. 9, pp. 438–444, 2021.

[4] A. Wilrose, M. Afdal, S. Monalisa, and M. R. Munzir, “Penerapan Algoritma FP-Growth untuk Menentukan Strategi Promosi Berdasarkan Waktu dan Pembelian Produk,” *Build. Informatics, Technol. Sci.*, vol. 5, no. 1, pp. 104–113, 2023, doi: 10.47065/bits.v5i1.3577.

[5] A. Tholib, S. H. Sholeha, and Q. Aini, “Prediction of Customer Switching Using Support Vector Machine Method,” *Trans. Informatics Data Sci*, vol. 1, no. 2, pp. 65–72, 2024.

[6] R. Rachman and N. Hunaifi, “Penerapan Metode Algoritma Apriori dan FP-Tree Pada Penentuan Pola Pembelian Obat,” *Paradig. - J. Komput. dan Inform.*, vol. 22, no. 2, pp. 175–182, 2020, doi: 10.31294/p.v22i2.8258.

[7] H. Sama and E. Hartanto, “Studi Deskriptif Evolusi Website dari Html1 sampai Html5 dan Pengaruhnya terhadap Perancangan dan Pengembangan Website,” *Conf. Manag. Business, Innov. Educ. Soc. Sci.*, vol. 1, no. 1, pp. 589–596, 2021.

[8] K. ’Afiifah, Z. F. Azzahra, and A. D. Anggoro, “Analisis Teknik Entity-Relationship Diagram dalam Perancangan Database Sebuah Literature Review,” *Intech*, vol. 3, no. 2, pp. 18–22, 2022, doi: 10.54895/intech.v3i2.1682.

[9] D. D. Jantce TJ Sitinjak, . Maman, and J. Suwita, “Analisa Dan Perancangan Sistem Informasi Administrasi Kursus Bahasa Inggris Pada Intensive English Course Di Ciledug Tangerang,” *Insa. Pembang. Sist. Inf. dan Komput.*, vol. 8, no. 1, 2020, doi: 10.58217/ipsikom.v8i1.164.

[10] E. W. Fridayanthie, H. Haryanto, and T. Tsabitah, “Penerapan Metode Prototype Pada Perancangan Sistem Informasi Penggajian Karyawan (Persis Gawan) Berbasis Web,” *Paradig. - J. Komput. dan Inform.*, vol. 23, no. 2, pp. 151–157, 2021, doi: 10.31294/p.v23i2.10998.

[11] G. Gunadi and D. I. Sensuse, “Penerapan Metode Data Mining Market Basket Analysis terhadap Data Penjualan Produk Buku dengan Menggunakan Algoritma Apriori dan frequent Pattern Growth (FP-growth): Studi Kasus Percetakan PT. Gramedia,” *Telematika*, vol. 4,

no. 1, 2012.

[12] M. Irfan, H. Siregar, and J. T. Handoko, "Pengembangan Dan Integrasi Aplikasi Prediksi Jumlah Gagal Produksi PC Meggunakan Metode Triple Exponential Smoothing Pada Sistem Aplikasi Produksi Di PT Tera Data Indonusa,Tbk," *Semin. Nas. Has. Penelit. dan Pengabdi. Masyaraka*, no. November 2015, pp. 80–96, 2023.

[13] B. S. Rama Novta, Antonius Rachmat, "Implementasi Algoritma FP-GROWTH Untuk Sistem Rekomendasi Buku di Perpustakaan UKDW," vol. 10, no. l, 2014.