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Design and Implementation of a Culinary Tourism Promotion System for Ternate Using the FP-Growth Algorithm with the Waterfall Development Model

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Abstract

Based on this research, he application of the FP-Growth algorithm to identify culinary patterns. tourism promotion strategy in Ternate by knowing customer purchasing patterns in making promotional decisions so that it is targeted. The evaluation analysis indicates that applying FP-Growth is beneficial in devising effective promotional strategies by detecting frequently bought products. The detected patterns facilitate more efficient cross-selling and up-selling approaches, enabling businesses to react faster to marketplace shifts, enhance stock management efficiencies, and result in higher consumer satisfaction. The novelty of this study is the application of an extended FP-Growth framework attraction analysis not only used to determine interaction patterns but also directly incorporate association rules results in culinary tourism promotional strategy design according to Ternate regional characteristics.

Keywords: ***FP-Growth, Promotion, Culinary Tourism, Data Analysis, Ternate Island***

INTRODUCTION

Technological advances have adversely affected economic growth. With the advent of technology, many e-commerce platforms have sprung up, supporting baking businesses, while brick-and-mortar stores continue to offer customers a more direct experience. Specialty bake shops are facing fierce competition in the culinary industry. Therefore, a promotional strategy tailored adapting to customer preferences plays an important role in enhancing competitiveness while preserving product quality. Consequently, a strategic approach that is both effective and efficient is required to support the development and implementation of culinary tourism strategies in Ternate.

To address these challenges, this study proposes the application of the FP-Growth algorithm to analyze association

In the culinary business, attracting customers requires a strong and effective promotional strategy. The strategy includes working with hotels or business partners for reservations, offering customer discounts and incentives through memberships, promotions through social media, and working directly with various organizations within Ternate.

When conducting sales promotions, weaknesses in sales tactics are inevitably discovered. Inappropriate qualifications and promotional activities may obstruct optimal decision-making processes if not properly managed. Therefore, sales data analysis is conducted to uncover associations among products, enabling promotional strategies to be aligned with customer preferences and priorities.

patterns. Through the implementation of FP-Growth, Pakesang can detect complex customer purchasing behaviors from transaction data and identify relationships among culinary products. These findings can be utilized to create more focused promotional strategies. Furthermore, the algorithm supports the generation of promotional recommendations that align with customer preferences based on the identified association patterns.

The FP-Growth (Frequent Pattern Growth) algorithm is considered an efficient method for identifying frequent itemsets in large datasets while avoiding the generation of numerous candidate itemsets. Compared with conventional association rule mining approaches such as Apriori, FP-Growth makes use of a compact structure called the Frequent Pattern Tree (FP-tree) and applies a recursive mining technique to obtain frequent itemsets directly once the tree has been formed. Consequently, this approach provides better computational performance and more efficient memory utilization [1].

In association rule mining, the process typically involves identifying sets of items that frequently occur together based based on a specified minimum support value, followed by the generation of strong association rules that meet predetermined minimum confidence levels, which reflect the conditional probability of items occurring together. The FP-Growth algorithm has been widely adopted in recent research for efficient association rule discovery due to its performance advantages over candidate generation approaches, making it suitable for applications such as market basket analysis and transaction pattern discovery [2].

One of the main limitations of the Apriori algorithm in frequent pattern mining is its reliance on generating a large number of candidate itemsets through multiple database scans, which leads to increased computational complexity and execution time when handling large transactional datasets. In contrast, the FP-Growth algorithm avoids this costly candidate generation step by constructing a compact Frequent Pattern Tree (FP-Tree) that encodes the frequency information of itemsets directly, enabling the extraction of frequent patterns more efficiently. A recent comparative study reported that FP-Growth demonstrated superior computational efficiency in frequent pattern extraction over Apriori by avoiding explicit candidate generation and reducing redundant database scans, while maintaining comparable accuracy in terms of identified association rules [3].

In association rule mining tasks, FP-Growth has been It is widely utilized because of its capability to compress datasets into a tree-based structure and conduct recursive mining of frequent itemsets using a divide-and-conquer approach. By storing transaction data in a compact FP-Tree representation and extracting patterns directly from the structure, FP-Growth significantly reduces the search space and execution overhead associated with traditional candidate-based approaches. As a result, FP-Growth is considered a practical and efficient alternative for discovering frequent patterns and association rules in large and complex datasets used in applications such as market basket analysis, customer behavior modeling, and sales optimization [1].

Based on previous studies, it can be concluded that most FP-Growth research has focused on general retail sectors, inventory management, and sales prediction. There is still limited research that specifically integrates the FP-Growth algorithm with promotional strategy determination in the context of culinary tourism based on local wisdom, particularly in the Ternate region.

This study introduces novelty by applying the FP-Growth algorithm to determine promotional strategies for Ternate's traditional culinary tourism. The study not only identifies purchasing patterns of culinary products but also directly links these patterns to the design of contextual promotional strategies, including cross-selling and up-selling, in accordance with local culinary tourism characteristics. Thus, this research extends the application of FP-Growth from mere transaction analysis into a strategic tool for regional culinary tourism promotion development.

MATERIALS AND METHODS

The system development method used in this study is the Waterfall model. The Waterfall approach is applied because it provides a structured and sequential development process, where each phase is completed before moving to the next stage. This model is considered suitable for this study because the system requirements can be identified clearly at the beginning of development, allowing systematic planning, detailed documentation, and controlled implementation. In addition, the Waterfall model helps minimize development risks by ensuring that each stage is verified before proceeding to subsequent phases. Recent studies also emphasize that the Waterfall model remains relevant for projects with stable requirements and structured system development processes [4].

The Waterfall method used in this system development consists of the following stages:

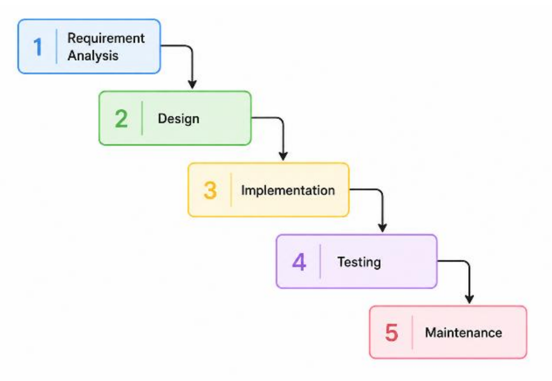

Figure 1. Promotional Waterfall Development Method

The first stage is requirement analysis, where the needs and objectives of culinary tourism promotion are identified. This process includes collecting information regarding the target audience, promotional content, system functionality, and supporting features such as social media integration, promotion scheduling, and interactive tourism information.

The second stage is system design, where the system architecture is prepared based on the identified requirements. This includes interface design, database structure, process flow, and navigation planning. The purpose of this stage is to provide a clear blueprint for system implementation.

The third stage is implementation, where the designed system is developed into a functional application. In this phase, all planned features such as culinary tourism information pages, promotion management, and scheduling mechanisms are programmed according to the design specifications.

The fourth stage is testing, where the developed system is evaluated to identify errors and ensure that each feature works according to system requirements. This testing process includes validating navigation, interface consistency, functionality, and overall usability of the promotional system.

The final stage is maintenance, where the system is monitored and improved after deployment. Updates, bug fixes, and adjustments can be carried out to improve system performance and support future promotional needs.

The system analysis approach, which combines business process mapping (as-is) and proposed system design (to-be), follows best practices in system analysis and process modeling as recommended in the CRISP-DM literature and related methodological studies, ensuring that the data processing steps and integration of the FP-Growth module are aligned with operational requirements [5].

The current system analysis can be seen in Figure 2.

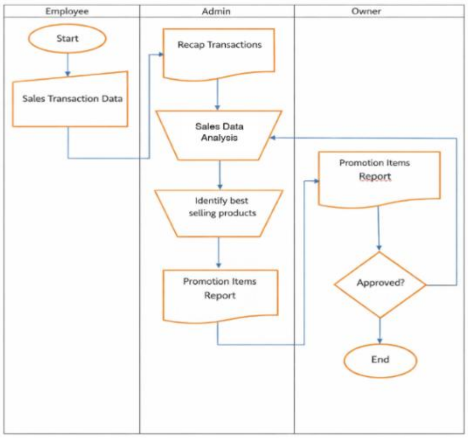

Figure 2. Current System Analysis

The sales team records all sales transactions in detail, including information about the products sold and their quantities. The data is then submitted to the administrator, who examines it to identify products with high and low sales levels. The administrator analyzes sales trends in the online store, advertising methods, and online promotions to determine products that can be paired with popular items or those frequently purchased together. The administrator applies a market basket analysis strategy to identify combinations of products that are often bought simultaneously. After the identification process, the administrator prepares a report of products targeted for promotion and submits it to the manager or owner for approval. If the products are approved, they will be promoted; otherwise, the administrator needs to conduct further analysis to identify products with high and low sales levels, and the analysis cycle will begin again.

The proposed system is a new model for determining product promotion using the FP-Growth algorithm with an association-based approach. The flowchart of the proposed system illustrates the process flow for determining product promotions implemented at Pakesang. For further details, the proposed system flowchart can be seen in Figure 3.

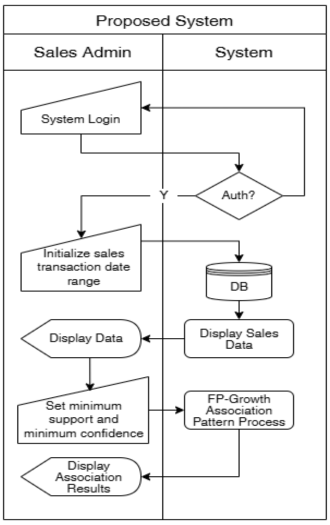

Figure 3. Proposed System Analysis

1) The admin logs into the system; if the username and password are correct, the login is successful.
2) The admin initializes the product data by defining the sales transactions.

3) The system displays the sales transactions, after which the admin specifies the minimum support and confidence values.
4) The system processes the data using the FP-Growth algorithm.
5) The system then displays the association results.

The use of secondary transaction data (sales documentation) as the primary data source follows common practices in transaction and retail research, which emphasize the need to describe the period, scope, and transaction attributes to ensure the reproducibility and validity of purchasing pattern analysis. Modern transaction analysis studies recommend reporting detailed POS/transactional datasets within the context of consumer behavior analysis [6].

The data collection stage in determining product promotion involves analyzing transaction data using the FP-Growth algorithm to identify relationship patterns among products frequently purchased by customers. This algorithm discovers patterns that form the basis for identifying regular pattern growth in the dataset. Data collection was carried out by gathering secondary data. Table 1 presents the dataset of Pakesang sales transactions.

Table 1. Sales Transaction Dataset

Transaction_Id	Transaction_Date	Purchase Item
A001	10/01/2024	Bagea, Pupeda,
A002	11/01/2024	Bagea, Kopi Rempah
A003	12/01/2024	Bagea, Ikan Fufu
A004	14/01/2024	Popeda, Roti Kenari
A005	15/01/2024	Bagea,Roti Kenari
….	….	….
A480	30/06/2024	Bagea, Popeda, Roti Kenari

Preprocessing is the initial stage in the data cleaning process. The preprocessing and data transformation stages (cleaning, tokenization/transformation into binary format for association mining, etc.) are important because they affect the quality of pattern mining and algorithm performance; recent reviews of preprocessing and feature engineering techniques indicate that these procedures improve the accuracy and reproducibility of data mining analysis. Therefore, the preprocessing steps are implemented in accordance with best practices recommended in the literature [7].

At this stage, the product sales transaction data, consisting of 39 records, are cleaned. The transformation process is performed on the attributes of the objects by converting item attributes into unique attributes based on the item or product names, which are then transformed into records. In the previous attributes, data containing more than one element and missing data are separated. The new attribute values are filled with 1 if a transaction occurs and 0 if no transaction occurs.

The next step is to identify FP-Growth algorithm can be utilized to recognize purchasing patterns and generate recommendation results. The frequency level of each product is obtained from sample data that has already been processed during the preprocessing stage. The selection of FP-Growth is based on the efficiency of this method in extracting frequent itemsets without explicit candidate generation; comparative literature and recent implementation studies indicate that FP-Growth reduces the number of database scans and accelerates the pattern extraction process in large transactional datasets, making it suitable for market basket analysis and promotional recommendation tasks [8].

System performance evaluation using a confusion matrix and derived metrics (accuracy, precision, recall, F1-score) follows modern classification model evaluation practices, where methodological reviews indicate that these metrics provide a comprehensive view of classification performance on imbalanced datasets and facilitate result interpretation for decision-making purposes [9].

Accuracy testing is conducted to determine the level of system precision in recommending promotional products based on the analysis results of the FP-Growth algorithm. Although FP-Growth is an association algorithm, the evaluation is performed using a confusion matrix approach to measure the consistency between promotional recommendations generated by the system and actual transaction data. In this testing process, the promotional recommendations are compared with the actual purchasing patterns observed in the transaction dataset.

The evaluation classification results are defined as follows:

1) True Positive (TP), Products are recommended for promotion and are indeed frequently purchased together based on transaction data.
2) False Positive (FP), Products are recommended for promotion but are not frequently purchased together.
3) False Negative (FN), Products are not recommended for promotion but are actually frequently purchased together.
4) True Negative (TN), Products are not recommended for promotion and are indeed not frequently purchased together.

System testing is conducted to ensure that all functions of the culinary tourism promotion determination system based on the FP-Growth algorithm operate in accordance with the specified functional requirements. The testing method used is Black Box Testing, which focuses on verifying the conformity between system inputs and outputs. Functional testing using the Black Box approach (e.g., equivalence partitioning, boundary value analysis) is selected to ensure that the input–output functions of each module operate according to the specifications without examining the internal code, where recent software engineering literature supports the use of Black Box testing for verifying the functionality of interface modules and business processes in information systems [10]. Testing is performed on the main system functions, including user authentication, transaction data management, determination of minimum support and confidence parameters, the FP-Growth calculation process, and the display of association rule results and promotional recommendations.

RESULTS AND DISCUSSION

This section presents the results of the implementation of the FP-Growth algorithm in determining culinary tourism promotion strategies in Ternate, along with the corresponding discussion. The results presented are obtained from the processing of transaction data that has undergone preprocessing and association analysis stages. The discussion focuses on the interpretation of the generated purchasing patterns, the evaluation of system performance, and the implications of the analysis results in supporting promotional decision-making.

After completing the data collection and preprocessing stages as described in the methods section, the transaction data are analyzed to identify customer purchasing patterns. This stage aims to examine the relationships among culinary products that frequently appear within a single transaction as the basis for applying the FP-Growth algorithm. The results of the data transformation process can be seen in Table 2.

Table 2. Data Transformation Results

No_id	Transaction	BG	PD	KR	IF	RK
1	A001	1	1	0	0	0
2	A002	1	0	1	0	0
3	A003	1	0	0	1	0
4	A004	0	1	0	0	1
5	A005	1	0	0	0	1
..	..	…	…	…	…	…
480	A480	3	5	0	0	6

Using selected sales data, the FP-Growth model is used to identify the most purchased products that meet the selected support level. This shows the food groups that consumers tend to buy at the same time. The results of the categorical analysis are shown in Table 3.

Table 3. Frequency Analysis Results

ITEM	FREQUENCY
BG	6
PD	8
KR	9
RK	25
IF	40

Based on the frequency of occurrence, the items that have frequencies above the support count of 20% are (BG, SG, BS, GP, GR, RK). Therefore, these items have a significant influence and are included in the FP-Tree. The FP-Tree construction can be seen in Table 4.

Table 4. FP-Tree Construction

No	Transaction_Id	Transaction1
1	A001	BG, PD
2	A002	BG
3	A003	PD, KR
4	A004	IF,RK
5	A007	RK,PD
6	A014	RK,BG
7	A019	KR,RK
8	A021	BG, GP
9	A029	IF,RK
10	A035	BG,RK
11	A041	RK,PD
12	A083	BG,PD
13	A101	PD, RK

After accessing the main dashboard of the culinary tourism promotion determination system for Ternate City, which was developed by implementing the FP-Growth algorithm, the dashboard functions as an information and analysis center for administrators to monitor transaction data, customer purchasing patterns, and data-driven promotional recommendations. For more details, see Figure 4.

Figure 4. Dashboard Page

Figure 4 illustrates the core process of the FP-Growth algorithm in analyzing culinary sales transaction data. Using an iterative approach and clearly defined minimum support parameters, the system is able to identify frequently occurring items as the basis for determining more targeted and data-driven promotional strategies.

The stages of the FP-Growth algorithm calculation are presented manually and step-by-step using the culinary sales transaction data. This display is designed to help users understand the analysis process, starting from data input until the results in the form of frequent itemsets are obtained. For further details, see Figure 5.

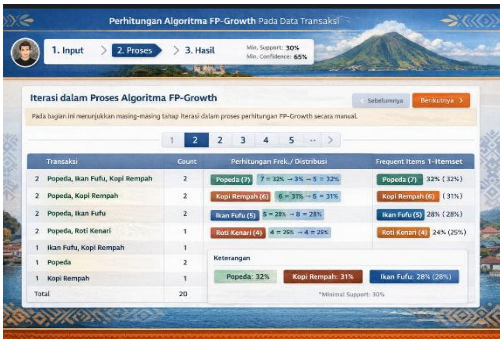

Figure 5. Fp-Growth Menu Display

Figure 5 illustrates the core process of the FP-Growth algorithm in analyzing culinary sales transaction data. Using an iterative approach and clearly defined minimum support parameters, the system is able to identify frequently occurring items as the basis for determining more targeted and data-driven promotional strategies.

Figure 6. Data Set Display

Figure 6 presents the transaction dataset used as the primary input data in the FP-Growth algorithm calculation within the culinary tourism promotion determination system. This dataset is the result of the data collection and preprocessing stages of sales transaction data, which are analyzed to discover customer purchasing patterns. Figure 6 illustrates the crucial initial stage in the implementation of the FP-Growth algorithm, namely the presentation and management of the transaction dataset. Through binary data representation and comprehensive data management features, the system is able to effectively analyze purchasing patterns as the basis for determining culinary tourism promotional strategies in Ternate City. Itemsets with high support counts are prioritized for promotion. For example, if “Roti Kenari” and “Bagea” appear together in 30% of transactions, this indicates strong potential for joint promotion.

The evaluation results show that the implementation of the FP-growth model provides significant assistance for Pakesang in identifying hidden buying patterns and developing appropriate and effective marketing strategies. This analytical approach allows the company to quickly adapt to changing market conditions and customer preferences, contributing to higher sales output and improved customer satisfaction. In addition, integrating these insights into the business model can support better inventory management, improve cross-selling and up-selling efforts, and strengthen the company’s market competitiveness.

Analyzing the performance using a confusion matrix to determine the effectiveness of the system in creating appropriate marketing strategies. The purpose of this analysis was to examine the level of consistency between the recommendations made by the system and the actual purchasing behavior observed from transaction data.

Table 5. Confusion Matrix of Accuracy Testing Results

Actual / Predicted	Recommended	Not Recommended
Recommended	18 (TP)	4 (FN)
Not Recommended	3 (FP)	15 (TN)

The evaluation results indicate that the developed system is capable of identifying culinary product purchasing patterns with satisfactory performance. The obtained accuracy value suggests that the implementation of the FP-Growth algorithm can support the decision-making process in determining promotional strategies based on transaction data.

Based on the data presented in Table 5, the evaluation metrics are calculated as follows:

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Accuracy = \frac{18 + 15}{18 + 15 + 3 + 4} = 0{,}825$$

Precision

$$Precision = \frac{TP}{TP + FP} = \frac{18}{18 + 3} = 0{,}857$$

Recall

$$Recall = \frac{TP}{TP + FN} = \frac{18}{18 + 4} = 0{,}818$$

The testing results indicate that the system achieves an accuracy level of 82.5%, demonstrating that the promotional recommendations generated by the FP-Growth algorithm are sufficiently accurate and relevant to customer purchasing patterns.

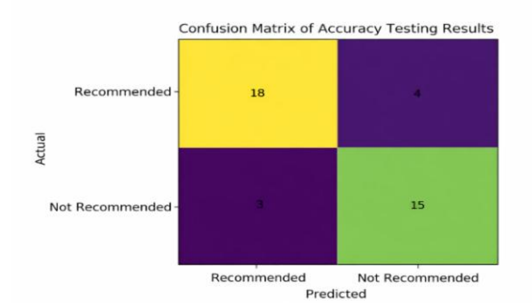

Figure 7. Confusion Matrix

Based on the evaluation results using the confusion matrix, it can be concluded that the culinary tourism promotion determination system based on the FP-Growth algorithm demonstrates good performance in recommending promotional products. The high values of accuracy, precision, and recall indicate that the system is able to accurately and consistently identify products that are suitable for promotion, thereby supporting data-driven promotional decision-making based on transaction data.

CONCLUSION

The implementation of the FP-Growth algorithm in determining culinary tourism promotion strategies in Ternate significantly enhances the ability to identify frequent purchasing patterns among customers. By utilizing existing transaction data, FP-Growth is able to discover combinations of culinary products that are frequently purchased together, providing valuable insights for Pakesang in designing more targeted promotional strategies. The application of FP-Growth enables the optimization of promotional strategies by focusing on products with high potential for cross-selling and up-selling. In addition, it allows stakeholders to respond more quickly to changes in customer preferences and market trends, which ultimately improves competitiveness, increases sales, and strengthens customer loyalty. This implementation also supports more efficient inventory management, reduces waste, and enhances overall operational efficiency.

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