e-ISSN 2549-7472
Edumatic: Jurnal Pendidikan Informatika
Volume 10, Issue 2, **480-489.**
https://e-journal.hamzanwadi.ac.id/index.php/edumatic
DOI: 10.29408/edumatic.v10i2.35983

FP Growth Based Consumer Purchase Patterns for Inventory Optimization in Perishable MSME Supply Chains

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Received: 04 July 2026 | Revised: 14 July 2026 | Accepted: 26 August 2026 | Published: 29 August 2026

Abstract
Perishable inventory management remains a major challenge for fresh produce MSMEs because of demand uncertainty, product deterioration, and limited data-driven replenishment strategies. Although FP-Growth has been widely applied in market basket analysis, its role in transforming consumer purchasing patterns into operational inventory decisions is limited. This study develops an FP-Growth-based decision-support framework to identify purchasing associations that can support replenishment planning in perishable retail environments. This study adopts the Knowledge Discovery in Databases (KDD) framework and analyzes 100 real-world transaction records from a traditional fresh produce retailer. Transaction data were preprocessed and analyzed using association rule mining with a minimum support of 18% and a minimum confidence of 90%. The results generated 12 relevant association rules, with the strongest rule involving shallots and oranges leading to chili purchases, with 100% confidence and a lift value of 1.493. These findings indicate that FP-Growth can extract interpretable purchasing relationships to support coordinated procurements and inventory planning. This study contributes to the literature by extending association rule mining from descriptive market analysis to an explainable inventory decision-support approach for perishable MSMEs. Further validation using larger and multi-location datasets is recommended for future studies.

Keywords: association rule mining; fp-growth; inventory decision support; knowledge discovery in databases; perishable products

To cite this article: Rahman, A. A., & Hasan, F. N. (2025). FP Growth Based Consumer Purchase Patterns for Inventory Optimization in Perishable MSME Supply Chains. *Edumatic: Jurnal Pendidikan Informatika*, *10*(2), 480–489. https://doi.org/10.29408/edumatic.v10i2.35983

INTRODUCTION

Food loss and waste present significant challenges in fresh product supply chains owing to the inherent characteristics of perishable commodities, such as limited shelf life, deterioration, and unpredictable demand. In contrast to durable goods, inventory decisions for fresh commodities must carefully balance product availability with the risk of spoilage, expiration, and unmet demand. Consequently, perishable inventory systems necessitate adaptive replenishment policies, as excessive stock can exacerbate deterioration and waste, whereas insufficient inventory may result in stockouts and lost sales. Prior research has highlighted that shelf life limitations and stochastic demand significantly complicate the management of perishable inventories (Boxma et al., 2024; Gulecyuz et al., 2025). These challenges are particularly pertinent for Micro, Small, and Medium Enterprises (MSMEs), which frequently operate with constrained technological resources and depend largely on experience-based purchasing decisions rather than systematic data analysis (Hasan et al., 2023; Musdalifah & Jananto, 2022; Wulandari et al., 2025).

Traditional retailers of fresh produce encounter additional challenges due to the influence of local eating habits, seasonal demand fluctuations, product complementarity, and the rapidly changing quality of products on purchasing behavior. Consequently, decisions regarding restocking should consider not only past sales figures but also the connections between items that are frequently bought together. Recent approaches that utilize data in fresh food retail have integrated demand forecasting, pricing data, loss rates, and analysis of purchasing patterns to enhance restocking strategies (Ding & Peng, 2024; Ping et al., 2024). However, numerous small-scale retailers continue to rely on manual estimates to determine procurement quantities, which restricts their capacity to uncover hidden product relationships and convert transactional data into practical insights.

Association Rule Mining (ARM) provides a suitable analytical approach for discovering recurring relationships among products from historical transaction data. Within ARM, Market Basket Analysis identifies combinations of products that frequently occur within the same transactions and evaluates these patterns using support, confidence, and lift. This approach has been widely applied to understand purchasing behavior and support recommendations, product arrangement, and sales strategies (Satria et al., 2023; Wulandari et al., 2025). Among frequent pattern mining methods, Frequent Pattern Growth (FP-Growth) is particularly relevant because it constructs an FP-Tree and avoids the iterative candidate-generation process required by Apriori. Its flexibility has also been demonstrated in recommendation systems and other pattern-discovery environments (Kannout et al., 2023; Pan & Liu, 2023; Srivastava & Sinha, 2025).

Although FP-Growth has wide-ranging uses, earlier research has largely concentrated on descriptive analyses, such as market-basket analysis, recommendation systems, identifying customer preferences, and strategies for product placement. In retail research, association rules derived from FP-Growth are often seen as signs of products frequently bought together; however, their practical application in making inventory restocking decisions is less advanced. For instance, Ping et al. (2024) illustrated that purchasing patterns identified using FP-Growth can be combined with forecasting models to aid in decisions about restocking and pricing vegetables. However, these integrated methods typically require extensive datasets and analytical resources, which may not be easily accessible to MSMEs with limited resources.

Another methodological challenge is determining and understanding the thresholds for association rules. The minimum support and confidence levels directly impact the quantity and nature of the rules produced. If these thresholds are set too low, they may result in an abundance of patterns that are difficult to interpret, whereas overly high thresholds may discard relationships that could be significant. Moreover, high confidence by itself does not always signify a meaningful dependency, as it can be artificially increased by frequently occurring consequent items. Consequently, support, confidence, and lift should be considered together, especially when dealing with smaller datasets, where strong associations might indicate context-specific purchasing habits rather than consistent or widely applicable demand trends.

These constraints highlight the disconnect between discovering purchasing patterns at the transaction level and providing operational inventory decision support for perishable MSMEs. Current research illustrates the FP-Growth algorithm's capability to uncover recurring product associations, whereas studies on perishable inventory typically emphasize optimization models that consider demand, shelf life, cost, and replenishment strategies (Boxma et al., 2024; Gulecyuz et al., 2025). In response, this study introduces a decision-support framework based on FP-Growth to identify frequent purchasing trends, assess association rules through support, confidence, and lift, analyze threshold sensitivity, and interpret significant product relationships for integrated stock monitoring and procurement planning. The innovation lies in advancing association rule mining from a descriptive market-basket analysis to a transparent inventory decision-support system for resource-limited perishable retailers.

METHOD

This study utilizes the Knowledge Discovery in Databases (KDD) framework as a structured and repetitive method to convert raw transaction data into practical insights for retail inventory management. This framework is particularly effective in uncovering purchasing trends and aiding data-driven decisions for stock replenishment. In the data mining stage, the Frequent Pattern Growth (FP-Growth) algorithm was chosen instead of Apriori and ECLAT because of its computational efficiency and appropriateness for MSMEs with limited computing resources. These features are particularly significant for the retail of perishable goods, where regular analysis is crucial for making timely inventory decisions (Hashad et al. 2024). Figure 1 provides an overview of the research process.

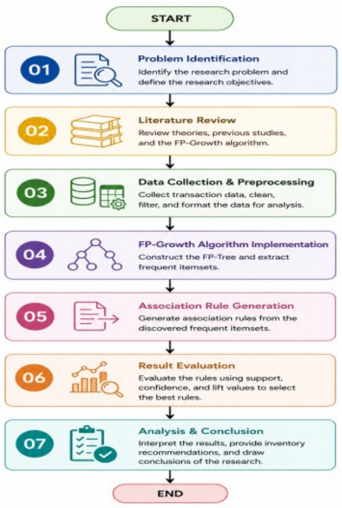

Figure 1. Flowchart

The dataset was obtained during the period of peak sales turnover and comprised 100 valid transactions involving 42 unique types of fresh products. Prior to pattern mining, the transaction data underwent systematic preprocessing, including data cleaning, removal of incomplete and duplicate records, product name standardization, and transformation into a binary market-basket matrix. These procedures were performed to ensure data consistency, structural integrity, and compatibility with the FP-Growth algorithm.

The mining parameters were established through a preliminary sensitivity analysis and consideration of operational requirements rather than arbitrary selection. The resulting frequent itemsets and association rules were evaluated using three principal measures: Support, Confidence, and Lift. Support, as formulated in Equation (1), measures the frequency of occurrence of a particular item or itemset in the entire transaction dataset. A higher support value indicates that the product combination appears more frequently, and therefore, represents a more common purchasing pattern among customers.

$$\text{Support}(A \rightarrow B) = \frac{\text{Number of transactions containing both A and B}}{\text{Total number of transactions}} \quad (1)$$

$$\text{Confidence}(A \to B) = \frac{\text{Support}(A \cup B)}{\text{Support}(A)} \quad (2)$$

Confidence, presented in Equation (2), represents the probability that the consequent occurs when the antecedent occurs. A higher confidence value indicates a more consistent relationship between the associated products and suggests that the consequent frequently appears with the antecedent. Lift, calculated using Equation (3), evaluates the strength of the relationship between the antecedent and consequent relative to their expected occurrence under statistical independence. A lift value greater than 1 indicates a positive association, a value equal to 1 indicates independence, and a value below 1 indicates a negative association. A lift value greater than 1 indicates a positive association between the antecedent and consequent, suggesting that their co-occurrence is stronger than expected by chance.

$$\text{Lift}(A \to B) = \frac{\text{Confidence}(A \to B)}{\text{Support}(B)} \quad (3)$$

Following the initial evaluation and operational needs, the minimum support threshold was determined to be 18%, and the minimum confidence threshold was 90%. These thresholds were designed to maintain sufficiently frequent purchasing patterns while ensuring that the derived rules exhibit a high level of reliability for managing perishable inventories. Ultimately, the results of FP-Growth were compared with those of Apriori. Both algorithms produced the same high-confidence association rules; however, FP-Growth showed better computational efficiency in terms of processing time and memory usage, making it more suitable for retail applications aimed at MSMEs.

RESULTS AND DISCUSSION

Result

In this section, the results of applying the FP-Growth algorithm to the Parent Fruit & Vegetable (IBS) dataset are detailed step-by-step. The process began with an analysis of 100 sales transactions, where the dataset was scanned to determine the precise frequency of each item sold. Items that did not reach the initial frequency threshold were removed to save computational memory, ensuring that only the most frequently occurring items were retained.

Table 1. The result based on the most frequently occurring data

No	Item	Quantity	Support
1	Shallots	25	25%
2	Garlic	27	27%
3	Tomatoes	23	23%
4	Lime	23	23%
5	Chili	20	20%
6	Orange	18	18%
7	Mushrooms	18	18%
8	Potatoes	18	18%
9	Cabbage	18	18%

Table 1 illustrates that the FP-Growth algorithm efficiently compresses the transaction database into a Frequent Pattern Tree (FP-Tree) format. This method allows the algorithm to capture recurring item relationships without repeatedly scanning the entire database. Unlike methods that rely on candidate generation, FP-Growth extracts frequent itemsets directly from the FP-Tree it constructs. In this study, a minimum support threshold of 18% was used, which was deemed optimal for detecting frequently occurring purchasing patterns. The generated frequent itemsets offer a structured depiction of recurring product combinations, forming the basis for generating association rules and making inventory decisions.

Table 2. Minimum support threshold sensitivity analysis

Scenario	Minimum Support	Minimum Confidence	Number of Generated Rules	Implication for MSME Inventory
1	10%	90%	145	Too broad, risk of over-stocking irrelevant items.
2	15%	90%	42	Moderate, but still contains weak associations.
3	18%	90%	12	Optimal and highly actionable for traditional retail.
4	20%	90%	2	Too restrictive, misses critical local spice patterns.

According to the findings presented in Table 2, setting the minimum support parameter at 18% provided the best stability. When the threshold is reduced to between 10% and 15%, it results in statistical noise, producing as many as 145 random rules that do not pertain to the inventory management. Conversely, increasing the threshold to 20% eliminated essential patterns. By maintaining an 18% support threshold alongside a 90% confidence level, the rules remain stable and are straightforward to implement in retail settings.

Table 3. The strongest association rules for the procurement of fresh business esults

No	Association Rules	Support	Confidence	Lift Ratio
1	{Shallots, Oranges}→{Chili}	0.18	1	1.493
2	{Tomato, Garlic}→{Chili}	0.19	0.95	1.418
3	{Shallot} →{Garlic}	0.25	0.926	1.362
4	{Lime, Cabbage}→{Tomato}	0.18	0.9	1.343
5	{Mushrooms, Potatoes}→{Chili}	0.18	0.9	1.343

The quantitative metrics of the FP-Growth algorithm offer crucial insights into purchasing trends and their effects on managing perishable inventory. Support, confidence, and lift go beyond mere descriptive statistics; they evaluate how often products are bought together, the reliability of these associations, and their strengths. In the realm of fresh product retail, these metrics can aid in pinpointing product combinations that might require synchronized procurement and restocking. Thus, when interpreting association rules, it is essential to consider both their statistical properties and potential impact on inventory management decisions. This method allows the conversion of transaction-level purchasing patterns into more strategic inventory management approaches.

Support measures the percentage of transactions that include specific products. When the support value is relatively high, it suggests that these products often appear together in the transaction data being analyzed. For instance, the rule {Shallots, Oranges} → {Chili} with a support of 18% means that this combination is found in 18% of all transactions recorded. From the perspective of inventory management, combinations that occur frequently may require more focus when setting procurement priorities and planning restocking. Nonetheless, support should be considered alongside other metrics, as a high frequency does not automatically imply a strong relationship between the products.

Confidence evaluates the likelihood that the consequent item is purchased when the antecedent items appear together in a transaction. In the case of the rule {Shallots, Oranges} → {Chili}, a confidence score of 1.00 (or 100%) signifies that every transaction observed with shallots and oranges also included the chili. This finding indicates a consistent buying pattern within the examined dataset. From an operational standpoint, this pattern might justify the synchronized restocking of related items. However, a 100% confidence score should not be considered conclusive proof of future buying trends, as it relies on the specific traits and size of the transaction dataset available.

Lift measures the strength of an association by contrasting the actual co-occurrence of items with what would be expected if the items were purchased independently. A lift value exceeding 1 suggests a positive link between the antecedent and consequent products. In this study, the rule {Shallots, Oranges} → {Chili} has a lift value of 1.493, signifying that chili purchases occur more frequently when shallots and oranges are bought together than when they are purchased independently. For perishable goods, such positive associations can offer additional insights into managing procurement and restocking activities. Nonetheless, lift should be evaluated alongside support and confidence to confirm that the identified relationship is statistically significant and frequent enough to be useful for inventory decision-making.

The findings reveal linked buying behaviors among perishable goods using an association rule network graph. Items positioned centrally exhibit more robust and frequent connections, suggesting their significance in coordinating stock replenishment. Consequently, the network graph functions as both a visualization tool and an analytical foundation for identifying product relationships that can aid in synchronized procurement and inventory control.

Figure 2 illustrates that chili acts as the main hub, closely linked to Shallots, Garlic, and Tomatoes. This highlights their significant influence on observed buying trends and offers a foundation for synchronized inventory choices. To clarify these connections, items were organized into clusters based on co-occurrence. These clusters signify products that are often bought together and can aid in making more unified procurement and restocking decisions in conventional retail settings.

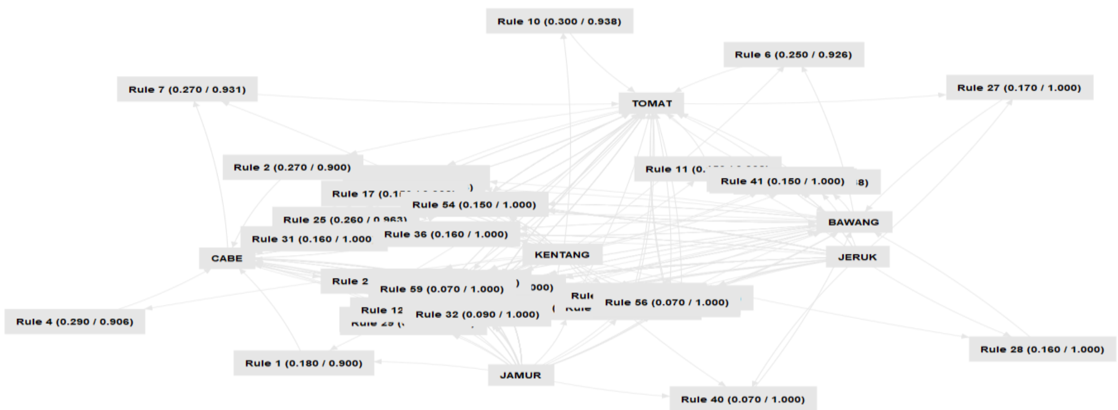

Figure 2. Association rules network graph

The findings revealed that chili, tomatoes, and garlic play significant roles as key commodities within the identified association groups. Chili is linked to various products, such as shallots, oranges, tomatoes, garlic, mushrooms, and potatoes, indicating a fairly extensive purchasing network. Tomatoes were connected with lime and cabbage, whereas garlic was strongly associated with shallots. These connections offer a factual foundation for categorizing related commodities in inventory-tracking and procurement-planning. Nonetheless, this suggested inventory approach should be considered a decision-support tool based on transaction patterns rather than definitive proof of causal links between products.

Table 2. Product co-emergence clusters and inventory layout strategies

ID	Central Centers (Consequences)	Related Items (Antecedents)	Number of Support	Culinary/Cultural Categorization	Actionable Inventory Strategy
C1	Chili (Chile)	Shallots, Oranges	18	Primer Spicy Seasoning Base (Sambal Seasoning)	Proportional Filling: Cross-ordering chili whenever the onion or garlic inventory is replenished.
		Tomatoes, Garlic	19		
		Mushrooms, Potatoes	18		
C2	Tomatoes (Tomatoes)	Lime, Cabbage	18	Fresh Vegetables & Acid Enhancers	Strategic Proximity Placement: Place lime racks directly adjacent to tomatoes to induce impulse bundles.
		Lime	23		
C3	Garlic	Shallots	25	Aromatics of Allium Essential Tree	Joint Bulk Procurement: Synchronize the purchasing cycle from farmers to minimize shipping logistics costs.

Table 3 illustrates the key connections between the primary ingredients and their associated items. Garlic has the highest support value at 25, with the tomato–lime combination following at 23. Chili is regularly linked to multiple ingredients, especially shallots and oranges. These trends can aid in developing effective inventory strategies, such as synchronized procurement, cross-ordering, and positioning frequently bought products closer together, which can enhance inventory management and promote complementary purchasing.

Discussion

The results indicate that FP-Growth can uncover understandable purchasing patterns among perishable goods and offers valuable transaction-level insights for inventory management decisions. The sensitivity analysis revealed that setting a minimum support of 18% and a minimum confidence of 90% resulted in 12 association rules. In contrast, lower support levels led to significantly larger sets of rules, whereas a 20% threshold preserved only two rules. This trend illustrates the balance between the comprehensiveness and clarity of the rules. Consequently, the 18% threshold should be considered an appropriate choice within the tested scenarios rather than a universally best threshold. Selecting the appropriate threshold is crucial in association rule mining, as overly lenient thresholds can produce too many patterns, whereas overly strict ones might discard potentially valuable relationships.

In the set of identified rules, the association {Shallots, Oranges} → {Chili} emerged as the most significant, with a support of 0.18, confidence of 1.00, and lift of 1.493. These metrics revealed that this combination appeared in 18% of all transactions, and chili was present in every transaction that included shallots and oranges. A lift value exceeding 1 suggests that this association was stronger than expected if the items were statistically independent. Nonetheless, 100% confidence should be approached with caution, as the analysis was conducted on a sample of only 100 transactions. Strong rules derived from such a limited dataset may reflect specific purchasing patterns rather than causal or universally stable relationships. Consequently, support, confidence, and lift should be evaluated together to assess the practical significance of identified patterns.

The product relationships identified align with earlier research that highlights the capability of FP-Growth to derive significant association structures from both transactional and diverse datasets. Satria et al. (2023) illustrated the effectiveness of FP-Growth in uncovering valuable food-package purchasing trends, while Kannout et al. (2023) confirmed its utility in recommendation systems. This adaptability has also been observed in various analytical scenarios, such as discovering correlation patterns (Pan & Liu, 2023), analyzing real-time data streams (Srivastava & Sinha, 2025) and identifying multidimensional patterns (Wang et al., 2025). Pertinent to this study, Ping et al. (2024) demonstrated that purchasing relationships derived from FP-Growth can be integrated with forecasting models to aid vegetable restocking and pricing strategies. These results endorse the application of association rules not only for descriptive market-basket analysis but also as supplementary data for operational decision-making in the food industry.

The repeated presence of chili and various other items within the association network suggests that the demand for some perishable goods may be interconnected rather than entirely separate. Consequently, products that hold key positions in the network may require synchronized stock tracking and procurement evaluation. However, association rules should not be considered explicit instructions for restocking, as they do not specify order amounts, safety stock levels, shelf life, supplier lead times, or risk of deterioration. Instead, they offer an additional layer of insight that can enhance traditional inventory metrics. This distinction is crucial in systems dealing with perishable inventories, where restocking decisions must consider demand unpredictability, the limited lifespan of products, and the risk of spoilage (Boxma et al., 2024; Ding & Peng, 2024; Gulecyuz et al., 2025). Therefore, the contribution of this study is in converting purchasing associations into understandable decision-support cues rather than asserting direct inventory optimization.

This research broadens the use of FP-Growth from merely uncovering descriptive patterns to providing an explainable decision-support framework for inventory management in resource-limited perishable MSMEs. However, this study has certain limitations. The dataset was limited to 100 transactions from a single retailer, which affects both the statistical reliability and the ability to generalize the findings. Moreover, factors such as product pricing, purchase quantities, shelf life, inventory levels, deterioration rates, supplier lead times, and seasonal demand were omitted. Consequently, the current results do not confirm that the suggested strategies will effectively decrease stockouts, spoilage, procurement expenses, or food waste. Future research should aim to confirm the consistency of the identified rules by employing larger datasets that span multiple locations and time periods. Additionally, integrating association rule mining with demand forecasting, shelf-life data, and dynamic replenishment models is recommended to assess tangible operational impacts.

CONCLUSION

This study illustrates that the FP-Growth algorithm can uncover significant purchasing patterns among perishable goods, aiding inventory-related decisions in small retail settings. By analyzing 100 transaction records, the study uncovered 12 pertinent association rules with a minimum support of 18% and a minimum confidence of 90%. The most robust rule, {Shallots, Oranges} → {Chili}, achieved a confidence level of 100% and lift value of 1.493. These results suggest that association rules can provide understandable insights into synchronized stock monitoring, procurement planning, and restocking strategies. Nonetheless, these outcomes should be viewed as decision-support evidence rather than definitive proof of inventory optimization, as the study was confined to a single retailer, utilized a relatively small dataset, and did not account for factors such as shelf life, stock levels, prices, supplier lead times, or seasonal demand. Future studies should test the framework using larger, multi-location datasets and combine association rule mining with forecasting and dynamic inventory models to assess their effects on stockouts, spoilage, procurement costs, and food waste.

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