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Analysis of Best-Selling Product Sales at Hatfina Hijab Using Association Rule Mining for Business Intelligence

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Abstract - This study analyzes customer purchasing patterns at Hatfina Hijab and translates the resulting association rules into actionable Business Intelligence (BI) recommendations. The dataset consists of 174 sales transactions recorded from February to April 2024. After data cleaning, product items were transformed into a binary transaction matrix and processed using association rule mining in RapidMiner. The baseline rule set was obtained using a minimum support of 0.30 and a minimum confidence of 0.50. The revised analysis complements the original confidence values with support and lift to distinguish rules that are frequent from those that represent genuinely positive product associations. Nineteen baseline rules were reported, of which sixteen have lift values greater than 1.00 and therefore indicate positive associations. The strongest confidence was found in the rule Hampers Paket Hemat 2 Hijab and Hampers Paket Hemat 1 Hijab -> Souvenir Sajadah (confidence = 1.000; lift = 1.475). Parameter sensitivity analysis shows that stricter support-confidence thresholds reduce the retained rule set from 19 rules at 0.30/0.50 to 14 rules at 0.35/0.60, 13 rules at 0.40/0.70, 3 rules at 0.45/0.80, and 1 rule at 0.50/0.90. The findings are interpreted into recommendations for product bundling, cross-selling, promotional design, and coordinated inventory planning. The study demonstrates how association rule mining can function as an analytical component of BI and Decision Support Systems (DSS), while emphasizing that association patterns indicate co-occurrence rather than causality.

Keywords:
Association Rule Mining; Apriori; Business Intelligence; Market Basket Analysis; Decision Support System; Hatfina Hijab;

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INTRODUCTION

The rapid growth of e-commerce has changed the way retailers interact with customers and has simultaneously increased the volume of transactional data available for analysis. For small and medium-sized online retailers, transaction records can contain information about recurring purchasing combinations that cannot be seen clearly from conventional sales summaries. Understanding these combinations is important because customers frequently evaluate products as part of a basket rather than as isolated items. Market Basket Analysis (MBA) addresses this problem by identifying products that tend to occur together in customer transactions and converting those co-occurrences into association rules [4], [6].

Hatfina Hijab operates in the online retail market and offers hamper products such as premium hijab packages, economical hijab packages, mukena hampers, and prayer-mat souvenirs. In a competitive e-commerce environment, historical sales data should not be treated only as an administrative record. It can also be used to understand consumer purchasing behavior, identify complementary products, and support data-driven decisions regarding promotion, bundling, and stock planning. Previous studies have shown that association-rule approaches can reveal product relationships, support product recommendations, and help retailers design cross-selling or bundling strategies [7]-[10].

Association rule mining commonly evaluates purchasing relationships using support and confidence. Support measures how often a product combination appears in the complete transaction set, while confidence measures how frequently the consequent appears when the antecedent is present. However, relying only on confidence may lead to misleading business interpretations when the consequent product is already very common. Recent studies therefore emphasize the use of lift to distinguish meaningful positive associations from relationships that occur mainly because of high product popularity [9], [11].

The initial Hatfina Hijab analysis reported 19 association rules using 174 transactions, a minimum support of 0.30, and a minimum confidence of 0.50. Nevertheless, the discussion focused primarily on RapidMiner output and confidence values. It did not explain in sufficient depth how the discovered rules should be translated into managerial actions, how threshold selection influences the number of rules, or how the results contribute to Business Intelligence (BI) and Decision Support Systems (DSS). These gaps are important because data mining provides business value only when analytical patterns are converted into information that can support decisions [4], [5].

This revised study therefore expands the original analysis in four directions. First, it develops a conceptual framework connecting transaction data, association-rule analytics, business interpretation, and decision support. Second, it evaluates the reported rules using support, confidence, and lift. Third, it performs a sensitivity analysis using stricter combinations of support and confidence thresholds. Fourth, it translates the strongest positive rules into specific BI recommendations for bundling, cross-selling, promotion, and inventory planning. The study does not claim that these recommendations are effective before implementation; rather, it provides evidence-based options that Hatfina Hijab can test in subsequent business operations.

Research Questions

RQ1. How can association rule mining identify recurring customer purchasing patterns from Hatfina Hijab transaction data?

RQ2. How do changes in minimum support and minimum confidence affect the number and strength of the association rules retained from the baseline results?

RQ3. How can the association-rule results be translated into Business Intelligence recommendations to support Hatfina Hijab marketing, product bundling, cross-selling, and inventory decisions?

Research Objectives and Contribution

The objectives of this research are to identify frequent product associations in Hatfina Hijab transactions, evaluate the stability and quality of the reported rules under stricter parameter settings, and convert analytically meaningful rules into managerial recommendations. The contribution of the study lies in bridging data-mining output with BI and DSS logic. Rather than treating association rules as the final result, the research positions them as an analytical layer that supplies structured evidence for managerial decisions.

RESEARCH METHODOLOGY

Literature Review and Research Positioning

Recent research confirms that Market Basket Analysis remains relevant for retail analytics because it provides interpretable relationships among products. Sjarif et al. [4] position MBA as an important data-mining technique in Business Intelligence. Phillips-Wren et al. [5] further explain that BI and analytics should be understood within the broader tradition of Decision Support Systems, where data are converted into insight for decision making. Hsieh [6] demonstrates that co-purchased product networks can support inventory and marketing analysis, while Pradhan et al. [7] show how basket patterns can be translated into product-bundling decisions. In e-commerce, Dogan [8] extends association-rule logic by incorporating profitability into product recommendations, illustrating the importance of connecting analytical patterns with business objectives.

More recent empirical studies compare different frequent-itemset algorithms and emphasize the quality of the generated rules. Hashad et al. [9] compare Apriori and FP-Growth in retail data and report that FP-Growth can be computationally more efficient for large datasets. Hery and Widjaja [10] similarly compare Apriori and FP-Growth in bakery transactions. Hendra et al. [11] use lift ratio to validate association rules for e-commerce product recommendations, while Heikal and Gandhi [12] translate market-basket patterns into product-bundling and promotional strategies. Pardeshi et al. [13] explicitly compare several support and confidence combinations, showing that parameter choice directly determines the number and usefulness of generated rules. These studies provide the theoretical basis for adding lift, parameter sensitivity, and business interpretation to the Hatfina Hijab analysis.

Table 1. State-of-the-Art and Research Positioning

Study	Year	Focus	Main Contribution	Relevance
Sjarif et al. [4]	2021	MBA and BI	Positions MBA as a BI technique	Provides BI foundation for the present study
Phillips-Wren et al. [5]	2021	BI, analytics and DSS	Connects BI analytics with DSS architecture	Supports data-to-decision framework
Hsieh [6]	2022	Grocery product networks	Analyzes co-purchased product structures	Supports purchasing-pattern interpretation
Pradhan et al. [7]	2022	Product bundling	Links basket analysis with bundling decisions	Supports managerial translation
Dogan [8]	2023	E-commerce recommendation	Introduces profit-aware association rules	Shows need for business-oriented rule evaluation
Hashad et al. [9]	2024	Apriori vs. FP-Growth	Compares retail association-rule algorithms	Supports methodological clarification
Hendra et al. [11]	2024	E-commerce recommendation	Uses lift for rule validation	Supports lift-based filtering
Pardeshi et al. [13]	2025	Parameter sensitivity	Compares support and confidence settings	Supports threshold comparison
Current study	2026 revision	Hatfina Hijab	Connects rules, sensitivity, BI and DSS	Adds actionable business interpretation

Theoretical Basis

Data Mining and Market Basket Analysis

Data mining is the process of extracting useful patterns and relationships from large datasets through computational, statistical, and machine-learning methods. In retail settings, Market Basket Analysis focuses on discovering combinations of items that repeatedly occur within transactions. The objective is not merely to identify best-selling individual products, but to understand the relationships between products and the structure of customer baskets [4], [6].

Apriori and Frequent-Itemset Logic

Apriori is a classical association-rule algorithm based on the downward-closure property: if an itemset is frequent, all of its subsets must also be frequent. The algorithm first identifies frequent itemsets that satisfy a minimum-support threshold and then generates directional rules that satisfy a minimum-confidence threshold. This study retains Apriori as the principal theoretical reference for association-rule reasoning. However, the RapidMiner workflow used in this study employs the FP-Growth operator to generate frequent itemsets before the Create Association Rules operator. Therefore, the computational stage is described accurately as association rule mining using RapidMiner, while Apriori and FP-Growth are discussed as alternative frequent-itemset procedures [9], [10]. This methodological clarification prevents the software workflow from being interpreted as a pure Apriori implementation.

Association-Rule Evaluation

An association rule is written as A -> B, where A is the antecedent and B is the consequent. Three measures are used in the revised analysis: support, confidence, and lift.

Support(A -> B) = Transactions containing A and B / Total transactions

Support represents the proportion of all transactions containing both the antecedent and consequent.

Confidence(A -> B) = Support(A union B) / Support(A)

Confidence represents the conditional probability that B appears in a transaction containing A.

Lift(A -> B) = Confidence(A -> B) / Support(B)

Lift compares the observed confidence with the confidence expected if A and B were independent. Lift > 1 indicates a positive association, lift = 1 indicates independence, and lift < 1 indicates a negative or weaker-than-expected relationship.

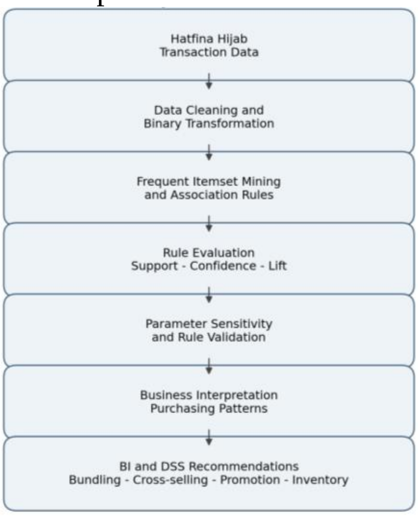
Business Intelligence and Decision Support Systems

Business Intelligence refers to the technologies and analytical processes used to transform organizational data into information that supports decision making. From a DSS perspective, analytics do not replace managerial judgment; they provide structured evidence that can be combined with operational considerations such as margins, inventory, seasonality, and promotional costs [5]. In this research, association rules form the analytical layer. Validated rules are subsequently translated into recommendations for bundling, cross-selling, promotional placement, and inventory coordination.

Conceptual Framework

The conceptual framework connects four layers: (1) the data layer, consisting of Hatfina Hijab transaction records; (2) the processing and analytical layer, covering cleaning, binary transformation, frequent-itemset mining, and association-rule evaluation; (3) the knowledge layer, where rules are validated using support, confidence, lift, and parameter sensitivity; and (4) the decision layer, where the patterns are translated into BI and DSS recommendations.

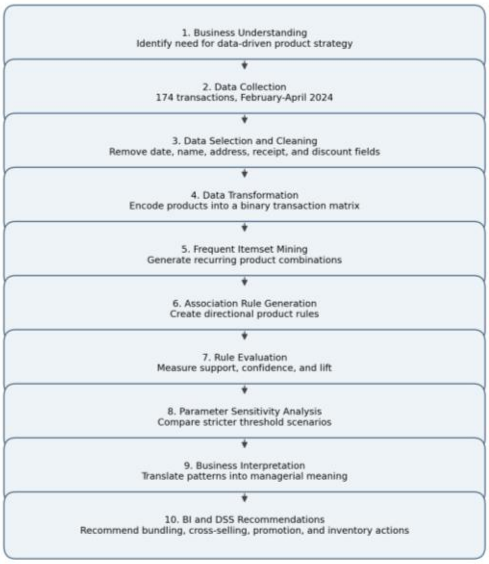
Figure 1. Conceptual Framework of the Research



Detailed Research Workflow

The research workflow expands the original process into ten explicit stages so that the transition from raw transaction data to managerial recommendations can be followed and replicated.

Figure 2. Detailed Research Workflow



Data Source and Data Collection

The study uses Hatfina Hijab sales transaction data from February 2024 to April 2024, totaling 174 transaction records. Each record contains a date, one or more product items, and other administrative attributes such as customer identity, receipt information, and discounts. The transaction period and the number of records are retained from the submitted manuscript. The analysis focuses on product co-occurrence within each transaction.

Table 2. Sample of Collected Transaction Data

Date	Items	Discount
01-02-2024	premium paket A, premium paket C, hemat 1 hijab, hemat 2 hijab, souvenir sajadah	MAR35VCHR
02-02-2024	premium paket A, premium paket C, hemat 1 hijab	-
03-02-2024	premium paket A, premium paket C, hemat 1 hijab, hampers mukena	-
04-02-2024	premium paket A, hemat 1 hijab, souvenir sajadah	MAR30DISC
...	...	...
03-04-2024	hemat 1 hijab, hemat 2 hijab, souvenir sajadah	-
04-04-2024	premium paket A, premium paket C, hampers mukena	FREEONG3X
05-04-2024	premium paket A, premium paket C, hemat 1 hijab, hemat 2 hijab, souvenir sajadah, hampers mukena	MAR30DISC

Data Preprocessing and Transformation

Data preprocessing removes attributes that are not required for association-rule analysis, namely customer name, address, receipt number, transaction date, and discount. Product items are retained because the objective is to identify co-occurrence patterns. The cleaned transaction data are then transformed into a binary matrix in which 1 indicates that a product appears in a transaction and 0 indicates that it does not.

Table 3. Sample Data After Cleaning

Items
premium paket A, premium paket C, hemat 1 hijab, hemat 2 hijab, souvenir sajadah
premium paket A, premium paket C, hemat 1 hijab
premium paket A, premium paket C, hemat 1 hijab, hampers mukena
premium paket A, hemat 1 hijab, souvenir sajadah
hemat 1 hijab, hemat 2 hijab, souvenir sajadah
premium paket A, premium paket C, hampers mukena
...
premium paket A, premium paket C, hemat 1 hijab, hemat 2 hijab, souvenir sajadah, hampers mukena

Table 4. Illustration of Binary Transaction Transformation

Premium A	**Premium C**	**Hemat 1**	**Hemat 2**	**Sajadah**	**Mukena**
1	1	1	1	1	0
1	1	1	0	0	0
1	1	1	0	0	1
1	0	1	0	1	0
0	0	1	1	1	0
1	1	0	0	0	1
...	...	...	...	...	...
1	1	1	1	1	1

Mining Process and Parameter Selection

The baseline configuration uses minimum support = 0.30 and minimum confidence = 0.50, consistent with the initial analysis. With 174 transactions, minimum support of 0.30 requires a combination to occur in at least approximately 53 transactions. Minimum confidence of 0.50 means that the consequent must appear in at least half of the transactions containing the antecedent. These values provide an exploratory baseline that retains a sufficiently broad set of rules for interpretation while excluding infrequent relationships.

Higher support and confidence thresholds do not necessarily decrease analytical accuracy; instead, they primarily determine how selective the rule-generation process becomes. Higher thresholds normally produce fewer rules; whether those rules are more useful depends on lift, stability, and business relevance. The revised analysis therefore evaluates stricter threshold scenarios instead of treating the baseline values as universally optimal.

Figure 3. Submitted RapidMiner Workflow for Frequent-Itemset Mining and Association Rule Generation

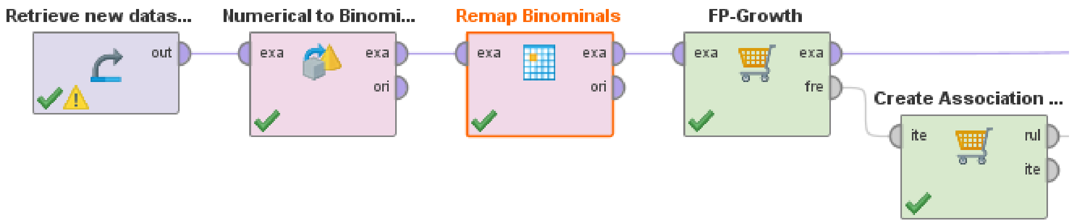


Figure 4. Binary Remapping Configuration in RapidMiner

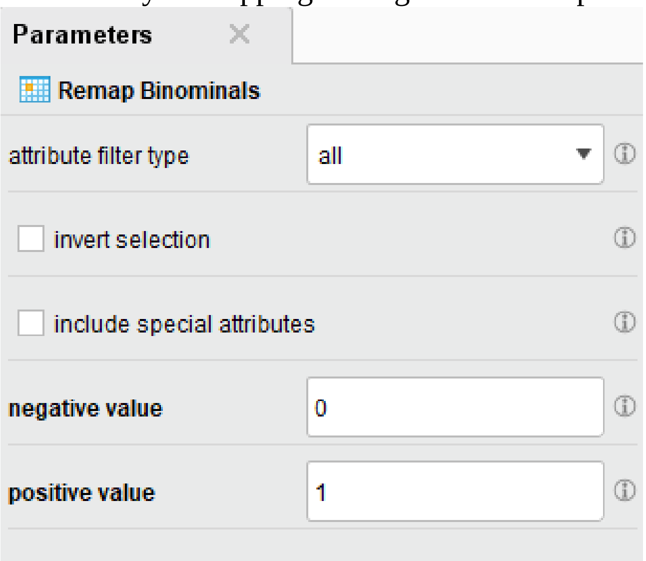
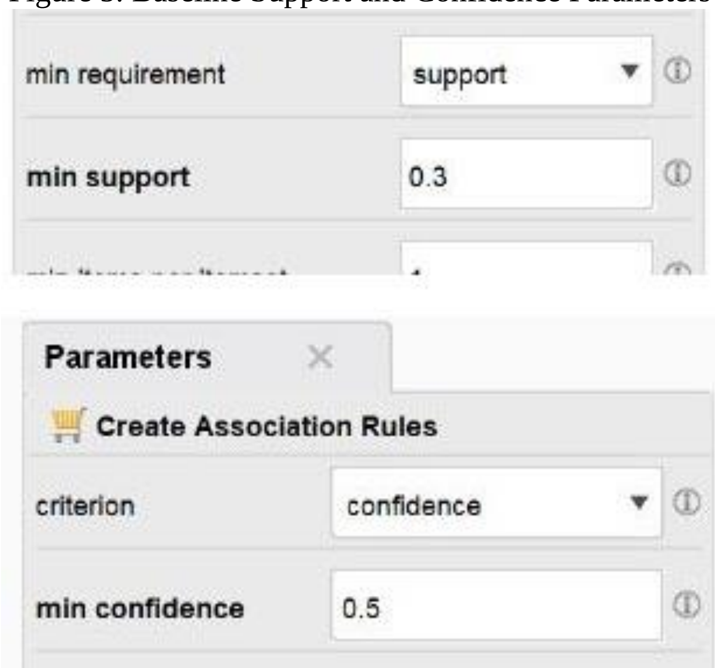


Figure 5. Baseline Support and Confidence Parameters



Parameter Sensitivity Design

Parameter sensitivity is examined using equal or stricter support and confidence combinations applied to the baseline rule set. Increasing the threshold can only remove rules already generated at the baseline setting, which makes the comparison internally consistent. Thresholds below support 0.30 are not estimated because lowering the baseline could generate additional rules and would require rerunning the complete transaction matrix. The tested scenarios are shown below.

Table 5. Combined Support-Confidence Sensitivity Scenarios

Scenario	Min. Support	Min. Confidence	Rules Retained	Interpretation
A - Baseline	0.30	0.50	19	Exploratory rule set
B	0.35	0.60	14	Removes low-support and low-confidence rules
C	0.40	0.70	13	Retains stronger recurring patterns
D	0.45	0.80	3	Highly selective rules
E	0.50	0.90	1	Very strict operational rule

Translating Association Rules into BI Recommendations

To address the gap between algorithmic output and managerial use, the study applies a rule-to-action mapping. A rule is considered a candidate for business action when it meets the analytical thresholds, has lift greater than 1, and has a clear operational interpretation. The antecedent becomes a potential business trigger and the consequent becomes a candidate recommendation. For example, when the rule Hemat 2 -> Souvenir Sajadah has high confidence and positive lift, the BI layer can recommend displaying the souvenir as a complementary item when Hemat 2 is selected. The final managerial action remains subject to stock availability, product margin, and promotional objectives.

RESULTS AND DISCUSSION

Baseline Association-Rule Results

The analysis produces 19 association rules. The revised evaluation uses support, confidence, and lift. Support values are derived from the transaction frequencies represented in the RapidMiner output and are internally consistent with the reported confidence values for N = 174. During data verification, a transcription inconsistency was identified in the initial association-rule table. The reciprocal frequency structure indicates that Rule 3 corresponds to Premium Package C -> Souvenir Sajadah with confidence 0.573, and the revised table uses this internally consistent rule.

Table 6. Revised Association-Rule Evaluation

No.	Association Rule	Support	Confidence	Lift
1	Premium A -> Souvenir Sajadah	0.305	0.530	0.782
2	Souvenir Sajadah -> Premium C	0.385	0.568	0.844
3	Premium C -> Souvenir Sajadah	0.385	0.573	0.844
4	Premium A -> Hemat 1 Hijab	0.333	0.580	1.030
5	Hemat 1 Hijab -> Premium A	0.333	0.592	1.030
6	Premium C -> Premium A	0.483	0.718	1.249
7	Souvenir Sajadah -> Hemat 1 Hijab	0.506	0.746	1.324
8	Hemat 2 Hijab -> Hemat 1 Hijab	0.448	0.765	1.358
9	Souvenir Sajadah -> Hemat 2 Hijab	0.534	0.788	1.344
10	Hemat 1 Hijab -> Hemat 2 Hijab	0.448	0.796	1.358
11	Premium A -> Premium C	0.483	0.840	1.249
12	Hemat 1 Hijab -> Souvenir Sajadah	0.506	0.898	1.324
13	Hemat 2 Hijab -> Souvenir Sajadah	0.534	0.912	1.344
14	Souvenir Sajadah -> Hemat 2 Hijab + Hemat 1 Hijab	0.448	0.661	1.475
15	Hemat 2 Hijab -> Souvenir Sajadah + Hemat 1 Hijab	0.448	0.765	1.512
16	Hemat 1 Hijab -> Souvenir Sajadah + Hemat 2 Hijab	0.448	0.796	1.489
17	Souvenir Sajadah + Hemat 2 Hijab -> Hemat 1 Hijab	0.448	0.839	1.489
18	Souvenir Sajadah + Hemat 1 Hijab -> Hemat 2 Hijab	0.448	0.886	1.512
19	Hemat 2 Hijab + Hemat 1 Hijab -> Souvenir Sajadah	0.448	1.000	1.475

The addition of lift changes the interpretation of the baseline results. Rules 1-3 have confidence values above 0.50 but lift values below 1.00. These relationships should not be prioritized for cross-selling because the co-occurrence is weaker than would be expected from the popularity of the consequent product. In contrast, Rules 4-19 have lift values greater than 1.00 and therefore represent positive associations. This distinction is important because confidence alone would have classified all 19 rules as potentially strong, whereas lift shows that only 16 rules provide evidence of positive product complementarity.

Parameter Sensitivity Analysis

The baseline parameters retain all 19 reported rules. When support and confidence are made more restrictive, the number of retained rules decreases. At 0.35 support and 0.60 confidence, 14 rules remain. At 0.40/0.70, 13 rules remain. At 0.45/0.80, only three rules remain: Premium A -> Premium C, Hemat 1 Hijab -> Souvenir Sajadah, and Hemat 2 Hijab -> Souvenir Sajadah. At the strictest scenario of 0.50 support and 0.90 confidence, only Hemat 2 Hijab -> Souvenir Sajadah remains. This result demonstrates that parameter selection determines the balance between exploratory coverage and operational selectivity.

A separate confidence-only comparison produces the same directional conclusion. A minimum confidence of 0.50 retains 19 rules, 0.60 retains 14, 0.70 retains 13, 0.80 retains 6, and 0.90 retains 2. The support-only comparison gives 19 rules at 0.30, 16 at 0.35, 14 at 0.40, 6 at 0.45, and 4 at 0.50. Therefore, the baseline values are suitable for discovering a broad set of patterns, while higher values are preferable when managers require a smaller shortlist of recurrent and reliable relationships.

Table 7. One-Parameter Sensitivity of the Baseline Rule Set

Parameter	Threshold	Rules Retained
Support only	0.30	19
Support only	0.35	16
Support only	0.40	14
Support only	0.45	6
Support only	0.50	4
Confidence only	0.50	19
Confidence only	0.60	14
Confidence only	0.70	13
Confidence only	0.80	6
Confidence only	0.90	2

Business Interpretation of the Strongest Rules

The strongest rule by confidence is Hemat 2 Hijab + Hemat 1 Hijab -> Souvenir Sajadah, with support 0.448, confidence 1.000, and lift 1.475. This means that within the observed transaction set, every transaction containing both economical hijab packages also contains the prayer-mat souvenir. Because lift is greater than 1, the relationship is not explained only by the high frequency of the souvenir. The pattern supports testing a three-item bundle that combines both economical hijab packages and the souvenir. It also indicates that the company should monitor souvenir availability when demand for the two economical packages increases.

The rule Hemat 2 Hijab -> Souvenir Sajadah has support 0.534, confidence 0.912, and lift 1.344. This is particularly relevant for cross-selling because it occurs in more than half of all transactions and the probability of the souvenir appearing with Hemat 2 is substantially higher than expected under independence. A practical action is to display the prayer-mat souvenir as a recommended add-on when customers select Hemat 2 Hijab. A similar interpretation applies to Hemat 1 Hijab -> Souvenir Sajadah, which has confidence 0.898 and lift 1.324.

Premium A -> Premium C has support 0.483, confidence 0.840, and lift 1.249. This pattern indicates a positive relationship between the two premium packages and may be used to test premium cross-selling or a paired premium hamper. However, the action should be evaluated against product margins and whether both products are substitutes or complements from the customers perspective.

The largest lift values are found in Hemat 2 Hijab -> Souvenir Sajadah + Hemat 1 Hijab and Souvenir Sajadah + Hemat 1 Hijab -> Hemat 2 Hijab, both with lift 1.512. These rules indicate a particularly strong relationship within the three-product economical basket. They are more informative for bundle design than a high-confidence rule with lift below 1. The result illustrates why business interpretation should use several rule metrics simultaneously rather than focusing only on RapidMiner confidence output.

Translation into Business Intelligence Recommendations

Table 8. Translation of Association Rules into BI Recommendations

Rule	Evidence	Business Meaning	BI Recommendation	Potential Managerial Action
Hemat 2 + Hemat 1 -> Sajadah	Conf. 1.000; Lift 1.475	Three-item complementarity	Bundle recommendation	Offer a combined economical hamper and track souvenir stock
Hemat 2 -> Sajadah	Conf. 0.912; Lift 1.344	Strong add-on pattern	Cross-selling trigger	Recommend Sajadah on product and checkout pages
Hemat 1 -> Sajadah	Conf. 0.898; Lift 1.324	Complementary basket	Cross-selling / promotion	Test paired discount or add-on offer
Premium A -> Premium C	Conf. 0.840; Lift 1.249	Premium package relationship	Premium cross-sell	Recommend Premium C to Premium A buyers
Sajadah + Hemat 1 -> Hemat 2	Conf. 0.886; Lift 1.512	Strong three-item basket	Upsell trigger	Offer upgrade to multi-product hamper

In an operational BI environment, the rules can be displayed in a dashboard with fields for antecedent, consequent, support, confidence, lift, transaction frequency, recommendation type, and current stock status. Managers can then rank rules according to analytical strength and operational feasibility. For example, a rule with high lift should not automatically become a promotion if the consequent is out of stock or has an insufficient margin. The role of BI is therefore to combine analytical evidence with operational information.

The proposed decision cycle is Transaction Data -> Association-Rule Engine -> Validated Rules -> BI Dashboard -> Recommended Action -> Managerial Decision -> New Transaction Data. This creates a feedback loop in which future transaction data can be analyzed again after a promotion or bundle has been introduced. Such a process is more consistent with DSS principles than treating the RapidMiner output as a one-time analytical endpoint [5].

Implications for Business Intelligence and Decision Support Systems

The findings have three implications for BI and DSS development. First, association-rule mining can function as an interpretable analytical module because managers can directly observe the antecedent, consequent, and metrics behind a recommendation. Second, threshold sensitivity can be used as a managerial filter: lower thresholds are useful during exploratory analysis, whereas stricter thresholds can generate a shorter list for operational decision making. Third, rule interpretation can be integrated with inventory and sales information so that recommendations are conditioned on stock, product margin, and campaign objectives.

At the operational level, the system can generate cross-selling recommendations when a customer views or selects a product. At the tactical level, managers can use recurring patterns to design weekly or monthly bundles and determine which items should receive joint promotion. At the inventory level, strongly associated products can be monitored together to reduce the risk that a bundle opportunity is lost because one item is unavailable. These applications should be tested empirically before claims of effectiveness are made.

Discussion in Relation to Previous Research

The Hatfina Hijab results are consistent with recent research showing that association-rule mining can identify interpretable purchasing relationships that support retail decisions. The emphasis on bundling and cross-selling is aligned with Pradhan et al. [7] and Heikal and Gandhi [12], while the use of lift to validate rules is consistent with Hendra et al. [11]. The sensitivity results also support Pardeshi et al. [13], who show that support and confidence settings have a direct influence on the number of extracted rules. The revised study contributes by making this connection explicit in a small e-commerce context and by mapping individual rules into BI and DSS actions.

At the same time, the analysis differs from studies that focus primarily on computational performance. Hashad et al. [9] and Hery and Widjaja [10] compare Apriori and FP-Growth, whereas the present study emphasizes the business meaning of the resulting rule set. The RapidMiner workflow used for Hatfina Hijab employs FP-Growth for frequent-itemset generation, and future research should compare the results directly with a native Apriori implementation to determine whether the same high-value rules are produced and to evaluate execution time and memory use.

CONCLUSION

This study analyzes 174 Hatfina Hijab transactions from February to April 2024 and develops a more complete interpretation of the reported association-rule results. The first research question is answered by demonstrating that transaction data can be transformed into recurring product relationships. The baseline analysis reports 19 rules at minimum support 0.30 and minimum confidence 0.50. When lift is added, 16 rules show positive associations with lift greater than 1, while three baseline rules have lift below 1 and should not be prioritized for cross-selling despite meeting the confidence threshold.

The second research question is addressed through parameter sensitivity analysis. Stricter support-confidence combinations progressively reduce the rule set from 19 rules at 0.30/0.50 to 14 rules at 0.35/0.60, 13 rules at 0.40/0.70, 3 rules at 0.45/0.80, and 1 rule at 0.50/0.90. This demonstrates that parameter selection should reflect the purpose of the analysis: broader thresholds are appropriate for exploration, while stricter thresholds produce a smaller shortlist for operational use.

The third research question is answered by translating the strongest rules into Business Intelligence recommendations. The relationship among Hemat 1 Hijab, Hemat 2 Hijab, and Souvenir Sajadah supports testing product bundles and checkout recommendations, while the relationship between Premium A and Premium C provides an additional premium cross-selling opportunity. These findings can also support coordinated inventory monitoring. The study therefore extends the analysis beyond software output by showing how association rules can function as an analytical component of BI and DSS. The results indicate potential decision-support value but do not establish causal effectiveness; business actions based on the rules should be validated through subsequent sales monitoring or controlled promotional experiments.

Recommendations and Future Research

Future research should use a longer observation period and a larger transaction dataset to evaluate seasonal purchasing behavior and the stability of the association rules. The complete transaction matrix should be preserved so that support thresholds below 0.30 can also be tested and additional low-frequency but high-lift rules can be evaluated. Researchers should compare native Apriori, FP-Growth, and Eclat implementations using execution time, memory usage, number of frequent itemsets, and rule quality. Additional business measures such as product margin, average order value, and promotion response should also be incorporated so that the BI recommendations reflect not only co-occurrence but also economic value. Finally, the rules can be integrated into a dashboard or e-commerce recommendation module and evaluated using conversion rate, bundle uptake, incremental sales, and stock-out frequency.

REFERENCES

[1] F. S. Amalia, Setiawansyah, and D. Darwis, "Analysis of mobile and electronic sales data using the Apriori algorithm (Case study: CV Rey Gasendra)," TELEFORTECH: Journal of Telematics and Information Technology, vol. 2, no. 1, pp. 1-6, 2021.

[2] Jefi, H. Yovanda, D. N. Kholifah, and D. Oscar, "Penerapan data mining pada penjualan hijab di Elzatta Gallery Pondok Ungu Permai menggunakan algoritma Apriori," Jurnal Sistem Informasi, Informatika dan Komputer, vol. 6, no. 2, pp. 467-475, 2022.

[3] S. A. Miranda, Fahrullah, and D. Kurniawan, "Implementation of association rule in analyzing Sheshop sales data by using Apriori algorithm," METIK Journal, vol. 6, no. 1, 2022.

[4] N. N. A. Sjarif, N. F. M. Azmi, S. S. Yuhaniz, and D. H.-T. Wong, "A review of market basket analysis on business intelligence and data mining," International Journal of Business Intelligence and Data Mining, vol. 18, no. 3, pp. 383-394, 2021, doi: 10.1504/IJBIDM.2021.114475.

[5] G. Phillips-Wren, M. Daly, and F. Burstein, "Reconciling business intelligence, analytics and decision support systems: More data, deeper insight," Decision Support Systems, vol. 146, Art. no. 113560, 2021, doi: 10.1016/j.dss.2021.113560.

[6] P.-H. Hsieh, "Exploratory analysis of grocery product networks," Journal of Management Analytics, vol. 9, no. 2, pp. 169-184, 2022, doi: 10.1080/23270012.2022.2072779.

[7] S. Pradhan, P. Priya, and G. Patel, "Product bundling for efficient vs non-efficient customers: Market Basket Analysis employing Genetic Algorithm," The International Review of Retail, Distribution and Consumer Research, vol. 32, no. 3, pp. 293-310, 2022, doi: 10.1080/09593969.2022.2047756.

[8] O. Dogan, "A recommendation system in e-commerce with profit-support fuzzy association rule mining (P-FARM)," Journal of Theoretical and Applied Electronic Commerce Research, vol. 18, no. 2, pp. 831-847, 2023, doi: 10.3390/jtaer18020043.

[9] A. A. Hashad, K. K. Wah, A. Alnoor, and X. Chew, "Exploratory analysis with association rule mining algorithms in the retail industry," Malaysian Journal of Computing, vol. 9, no. 1, pp. 1746-1758, 2024, doi: 10.24191/mjoc.v9i1.21433.

[10] Hery and A. E. Widjaja, "Analysis of Apriori and FP-Growth algorithms for market basket insights: A case study of The Bread Basket bakery sales," Journal of Digital Market and Digital Currency, vol. 1, no. 1, 2024, doi: 10.47738/jdmdc.v1i1.2.

[11] Hendra, A. Hermawan, and Edy, "Smart product recommendations in web e-commerce: Leveraging Apriori algorithm for market basket analysis," IJCCS (Indonesian Journal of Computing and Cybernetics Systems), vol. 18, no. 3, 2024, doi: 10.22146/ijccs.89075.
[12] J. Heikal and A. Gandhi, "Enhancing retail supermarket financial performance through market basket analytics using Apriori algorithm in Indonesia market case," Applied Quantitative Analysis, vol. 4, no. 1, pp. 42-53, 2024, doi: 10.31098/quant.2153.
[13] A. Pardeshi, Y. Shahare, K. Kumaran, A. M. Mishra, P. K. Shukla, M. M. Hassan, and F. Althobaiti, "An approach to explore consumer behavior patterns in retail markets using market basket analysis," Applied Stochastic Models in Business and Industry, vol. 41, no. 6, Art. no. e70057, 2025, doi: 10.1002/asmb.70057.