

Implementing ECLAT to Analyze Retail Purchase Pattern Using Web-Based Transaction Data

Arthio Dipa Wiraguna^{1*}, Taufiq²

^{1,2}Department of Informatics, Faculty of Engineering, Universitas Malikussaleh, Aceh, Indonesia

¹ arthio.240170183@mhs.unimal.ac.id, ² taufiq.te@unimal.ac.id



*Corresponding Author

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ABSTRACT

Retail transaction data provide useful insights into the products customers tend to purchase together. However, identifying these purchasing patterns can be challenging when a dataset contains thousands of different products. This study investigates the effect of minimum support on the results and execution time of the Equivalence Class Transformation (ECLAT) algorithm for market basket analysis. The study also implements the analysis in a web-based application.

The experiment uses the Online Retail dataset from the UCI Machine Learning Repository. After preprocessing, 530,104 records were retained, forming 19,960 transactions involving 3,812 unique products. Five minimum support thresholds were evaluated, ranging from 1% to 3%, while minimum confidence was set to 50% and the maximum itemset length was limited to six items. The results show that increasing minimum support from 1% to 3% reduced the number of frequent itemsets from 2,026 to 142 and the number of association rules from 994 to 12. Execution time also decreased from 303.2885 to 95.9162 seconds under the tested conditions. At the 3% minimum support threshold, all 12 generated rules had lift values greater than one. The strongest representative rule connected pink regency teacup and saucer with green regency teacup and saucer, achieving a confidence of 82.613% and a lift of 16.278. The web-based application brings together data preprocessing, frequent pattern mining, parameter testing, result visualization, and data export. Overall, the findings demonstrate how minimum support influences the number of patterns identified and the execution time observed in this experiment.

INTRODUCTION

The growing use of information technology has led to an increase in the amount of data generated by retail transactions. Beyond serving as records of completed sales, these data can reveal valuable information about customer behavior and purchasing habits. Customers often buy several products in a single transaction, creating relationships between items that may help retailers make informed business decisions. However, identifying such relationships manually becomes increasingly difficult as transaction data grow in size. A systematic analytical approach is therefore needed to discover meaningful associations among products.

Market Basket Analysis (MBA) is one technique commonly used to examine purchasing patterns in transaction data. It relies on association rule mining to identify relationships between items using measures such as support, confidence, and lift. Support indicates how frequently a combination of items occurs across transactions, while confidence measures how often the consequent appears in transactions that contain the antecedent. Lift evaluates the strength of this relationship relative to the consequent's overall frequency. These measures help reveal products that tend to be purchased together (Agrawal, Mannila, Srikant, Toivonen, & Verkamo, 1996).

The Equivalence Class Transformation (ECLAT) algorithm is one method used to discover frequent itemsets and generate association rules. Unlike the horizontal transaction representation used by Apriori, ECLAT organizes data vertically through Transaction ID (TID) lists. It identifies frequent itemsets by intersecting the transaction lists associated with different items (Zaki, 2000; Zaki, Parthasarathy, Ogihara, & Li, 1997). Previous studies have applied ECLAT to retail market basket analysis, including convenience store transaction analysis and web-based product recommendation systems (Haristyarini & Yustanti, 2021; Patandean, Palelleng, & Pasinggi, 2023; Resmi, Hermanto, & Al Ghazali, 2022).

Previous research has shown that ECLAT can be used to identify purchasing patterns and generate association rules from retail transaction data. Thariq et al. (2023) applied the algorithm to supermarket transactions, using support and confidence to evaluate the resulting rules. Handika and Satwika (2024) compared ECLAT with Apriori in minimarket transactions, while Nugroho et al. (2024) examined ECLAT and FP-Growth in sales data analysis. These findings suggest that algorithm selection and parameter settings can influence the patterns discovered and the computational performance

of the analysis. ECLAT has also been applied to e-commerce product placement to support retail decision-making (Naden, Sudianto, & Athiyah, 2024).

Although ECLAT has been widely applied to retail transaction analysis, the effects of different minimum support thresholds on mining results and execution performance still warrant further examination. Some previous studies have concentrated on comparing algorithms, whereas others have focused on generating association rules in particular retail environments. This study addresses this issue by examining how changes in minimum support affect the number of frequent itemsets, the number of association rules, and ECLAT execution time. A publicly available retail dataset is used to make the experimental process more transparent and support reproducibility.

The dataset used in this research is Online Retail, which was obtained from the UCI Machine Learning Repository. It contains transaction records from a UK-based online retailer covering the period from December 1, 2010, to December 9, 2011. The original dataset consists of 541,909 records (Chen, 2015). Using publicly accessible data enables other researchers to obtain the same dataset and repeat the analysis. Before applying ECLAT, the data are filtered according to the study's preprocessing criteria and grouped by invoice number to form transactions.

The experiment evaluates five minimum support thresholds: 1%, 1.5%, 2%, 2.5%, and 3%. Minimum confidence is maintained at 50% during association rule generation. The results are assessed by comparing the number of frequent itemsets, the number of generated rules, execution time, and rule quality based on support, confidence, and lift. In addition to evaluating the algorithm, this study implements the analysis through a web-based application that integrates data preprocessing, frequent itemset mining, association rule generation, parameter testing, result visualization, and data export.

Accordingly, this study aims to evaluate the influence of minimum support on ECLAT's mining results and execution performance when applied to retail transaction data. Specifically, it examines changes in the number of frequent itemsets, the number of association rules, and execution time across the five support thresholds. It also analyzes the resulting purchasing patterns using support, confidence, and lift. The findings are intended to provide empirical evidence of how minimum support affects ECLAT and demonstrate the practical use of a web-based application for analyzing retail purchasing patterns.

LITERATURE REVIEW

ECLAT for Retail Market Basket Analysis

Market Basket Analysis is commonly used to discover products that frequently appear together in transaction data. Association rule mining identifies relationships among items using measures such as support, confidence, and lift (Agrawal et al., 1996). Zaki et al. (1997) introduced algorithms for efficiently discovering association rules, while Zaki (2000) further examined scalable approaches to association mining. These studies provide a foundation for understanding computational methods used to discover relationships in transaction data.

ECLAT uses a vertical data structure in which each product is linked to a list of transaction identifiers. By intersecting these lists and counting the transactions shared by item combinations, the algorithm can identify frequent itemsets that satisfy a specified support threshold. This method has been applied in retail transaction analysis and product recommendation systems. Haristyarini and Yustanti (2021) examined market basket analysis using ECLAT in combination with an artificial neural network for sales prediction. Resmi et al. (2022) developed a web-based product recommendation system using ECLAT. Market basket analysis has also been examined in e-commerce settings, where Apriori and ECLAT are used to identify purchasing relationships in online transaction data (Çatkın, Yüksel, Konyalıoğlu, Apaydın, & Özcan, 2025). Other studies have applied ECLAT to minimarket and supermarket transactions to identify product combinations and generate association rules (Patandean et al., 2023; Thariq et al., 2023). Collectively, these studies demonstrate the applicability of ECLAT to retail purchasing pattern analysis.

Algorithm Comparison and the Role of Minimum Support

Several studies have investigated ECLAT in comparison with other frequent itemset mining algorithms, particularly Apriori and FP-Growth. Handika and Satwika (2024) compared Apriori and ECLAT in identifying purchasing patterns from minimarket transactions. Nugroho et al. (2024) examined the performance of ECLAT and FP-Growth in sales data analysis. Other research has compared Apriori, FP-Growth, and ECLAT to investigate consumer purchasing patterns (Husain, Oktaviyani, & Christina, 2023; Nindyya, Testiana, & Jaya, 2023). More recent comparisons have also evaluated these algorithms using execution time, memory usage, and scalability, highlighting that performance can vary with dataset characteristics (Rana, Mondal, & Islam, 2025).

These comparisons provide a basis for understanding how different algorithms may produce different mining results and computational performance.

Minimum support is another important factor in frequent itemset mining because it determines the minimum frequency an item combination must reach to be considered frequent. A lower threshold generally allows more itemsets to be retained, including combinations that occur less often. By contrast, a higher threshold filters out combinations that do not appear frequently enough. As a result, the selected minimum support can influence the number of frequent itemsets

and association rules generated. It can also affect execution time, depending on the dataset and the implementation. Evaluating minimum support is therefore useful for understanding the balance between the number of patterns discovered and the computational effort required. The reliability of association rules is also an important consideration, as the presence of a pattern alone does not necessarily establish that the resulting rule is sufficiently trustworthy for interpretation (Datta, Mali, Datta, & Mondal, 2026). The large number of generated association rules may also complicate interpretation, motivating research into methods for reducing redundant rules and simplifying the representation of product relationships (Đurišić, Vujošević, Kaščelan, & Vuković, 2026).

Previous research has applied ECLAT to a range of retail settings, including e-commerce product placement, grocery transactions, seasonal sales, and supermarket purchasing patterns (Ahmad, Witanti, & Ramadhan, 2025; Lavanza & Kudus, 2025; Naden et al., 2024; Pradana & Khoironi, 2025). These studies illustrate the continued use of association mining to examine retail purchasing behavior. Research across multiple retail branches has also used association rules to examine purchasing patterns and identify opportunities for targeted marketing and inventory management (Wahidi & Ismailova, 2025). Related research has also explored the use of frequent purchasing patterns to support product recommendations and store-layout decisions (Kumar, Manisha, & Nivetha, 2024). Association rule mining can also be combined with customer-value analysis and machine learning to provide a broader understanding of e-commerce purchasing behavior (Pai, Lin, & Lu, 2025). However, the present study does not aim to establish that ECLAT is universally superior to other algorithms. Instead, it focuses on how five minimum support thresholds affect the number of frequent itemsets, the number of association rules, and execution time when ECLAT is applied to the Online Retail dataset.

Research Position

Previous studies have demonstrated the use of ECLAT in retail market basket analysis, product recommendation, and comparisons with other frequent itemset mining algorithms. Building on this research, the present study evaluates five minimum support thresholds: 1%, 1.5%, 2%, 2.5%, and 3%. Throughout the experiments, minimum confidence is kept at 50%, and the maximum itemset length is limited to six items. The evaluation focuses on changes in the number of frequent itemsets, the number of association rules, execution time, and rule characteristics measured through support, confidence, and lift. Beyond these commonly used measures, statistical approaches can provide additional perspectives for evaluating the quality of association rules (Pamnani, Raja, & Ives, 2026).

Beyond evaluating the algorithm, this study incorporates ECLAT into a web-based application. The application brings together transaction data processing, ECLAT execution, association rule generation, parameter testing, result visualization, and data export. This integration provides a practical environment for examining the effects of minimum support and reviewing the resulting purchasing patterns. The study therefore combines an empirical evaluation of parameter settings using a public retail dataset with a web-based implementation that supports a structured analysis process.

METHOD

Research Design and Dataset

This study adopts an experimental approach to investigate how minimum support affects the results and execution time of the Equivalence Class Transformation (ECLAT) algorithm. Several minimum support thresholds are tested using the same minimum confidence setting and maximum itemset length to maintain consistent experimental conditions. ECLAT is used because it represents transaction data vertically and identifies frequent itemsets by intersecting transaction identifier lists (Zaki, 2000; Zaki et al., 1997).

The dataset used in this study is Online Retail, obtained from the UCI Machine Learning Repository (Chen, 2015). It contains transaction records from a UK-based online retailer covering December 1, 2010, to December 9, 2011. The original dataset consists of 541,909 records and eight attributes: InvoiceNo, StockCode, Description, Quantity, InvoiceDate, UnitPrice, CustomerID, and Country. The dataset was provided in CSV format and imported into the web-based application for preprocessing and analysis.

Data Preprocessing

The preprocessing stage was designed to retain records relevant to valid product purchases. Four filtering criteria were applied: Quantity had to be greater than zero, UnitPrice had to be greater than zero, Description could not be empty or null, and invoices beginning with the letter C were excluded because they represent cancellation transactions.

After applying these criteria, 530,104 records remained from the original 541,909 records. The filtered data were then prepared for transaction formation before the ECLAT algorithm was executed. These preprocessing rules define the records included in the subsequent analysis.

Transaction Formation

The filtered records were grouped by invoice number (InvoiceNo), with each invoice treated as a transaction containing one or more products. Within the application, transaction records and transaction items were stored separately. Transaction records retained information such as invoice number, transaction date, customer, and country, while transaction items stored product codes, descriptions, quantities, and unit prices.

The resulting dataset contained 19,960 transactions, 519,600 transaction items, and 3,812 unique products. Of these transactions, 1,641 contained only one product, whereas 18,319 contained more than one product. These transactions were used as the input for frequent itemset mining.

ECLAT Algorithm

ECLAT was applied to identify frequent itemsets using a vertical representation of the transaction data. In this representation, each product is associated with a Transaction ID (TID) list containing the identifiers of transactions in which the product appears. Frequent itemsets are discovered by intersecting the TID lists of individual items and retaining combinations whose transaction counts satisfy the minimum support requirement (Zaki, 2000; Zaki et al., 1997).

For two items, A and B, the intersection of their transaction identifier lists is expressed as:

$$TID(A, B) = TID(A) \cap TID(B) \quad (1)$$

Where (TID(A)) and (TID(B)) represent the transaction identifier lists for items A and B, respectively. The intersection identifies transactions containing both items.

The minimum support count was calculated from the total number of transactions and the selected minimum support value:

$$MinCount = N \times MinSupport \quad (2)$$

Where (N) is the total number of transactions, (MinSupport) is the minimum support threshold expressed as a proportion, and the ceiling function rounds the result up to the nearest integer. With 19,960 transactions, the minimum support count changes according to the selected threshold.

The implementation performs the search recursively by intersecting TID lists and retaining itemsets that satisfy the minimum support count. The maximum itemset length was set to six items for all experiments.

Association Rule Mining

The frequent itemsets generated by ECLAT were used to construct association rules. A rule is represented as:

$$A \rightarrow B \quad (3)$$

where (A) is the antecedent and (B) is the consequent. The rules were evaluated using support, confidence, and lift, following the association rule mining framework described by (Agrawal et al., 1996).

Support measures the proportion of transactions containing both the antecedent and the consequent:

$$Support(A \rightarrow B) = \frac{Count(A \cup B)}{N} \quad (4)$$

Confidence measures the proportion of transactions containing (A) that also contain (B):

$$Confidence(A \rightarrow B) = \frac{Support(A \cup B)}{Support(A)} \quad (5)$$

Lift measures the confidence of a rule relative to the support of its consequent:

$$Lift(A \rightarrow B) = \frac{Confidence(A \rightarrow B)}{Support(B)} \quad (6)$$

A lift value greater than one indicates a positive association between the antecedent and consequent relative to their independent occurrence. However, association does not establish a causal relationship between products.

Candidate rules were generated from the frequent itemsets and retained when their confidence reached the fixed minimum threshold of 50%. The resulting rules were then examined using their support, confidence, and lift values.

Experimental Scenarios and Evaluation

Five experiments were conducted to evaluate the effect of minimum support on ECLAT mining results and execution time. The minimum support thresholds were set to 1%, 1.5%, 2%, 2.5%, and 3%. Minimum confidence remained fixed at 50%, and the maximum itemset length was limited to six items throughout all experiments.

The minimum support count for each experimental scenario was calculated from the total number of transactions and the corresponding support threshold, as summarized in Table 1.

Table 1. Minimum Support Experimental Scenarios

Experiment	Minimum Support (%)	Minimum Count
1	1.0	200
2	1.5	300
3	2.0	400
4	2.5	499
5	3.0	599

Each experiment was evaluated based on the number of frequent itemsets, the number of association rules, and the time required to execute ECLAT. The generated rules were also examined using average and maximum support, confidence, and lift. These measurements were used to compare the number of patterns discovered, the characteristics of the resulting rules, and the execution time across the five experimental scenarios.

Web-Based System Implementation

The analysis was implemented as a web-based application using Laravel as the application framework and MySQL for database management. The user interface was developed with Blade, HTML, CSS, and JavaScript, while Chart.js was used to display experimental results visually.

The application supports the main stages of the analysis, beginning with CSV data import and preprocessing, followed by transaction formation and ECLAT execution. The frequent itemsets obtained from the mining process are then used to generate association rules. Users can conduct experiments with different minimum support values, review the results through tables and charts, and export the analysis results in CSV format.

Each analysis run is stored separately, allowing users to review and compare the outcomes of different parameter configurations. By bringing these functions together, the application provides an integrated environment for conducting the experiments and examining the purchasing patterns identified in the transaction data.

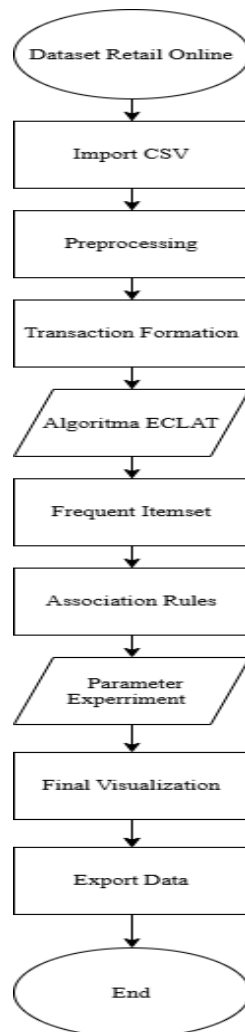


Figure 1. Workflow of the Web-based ECLAT Analysis System

RESULTS

Dataset Preprocessing Results

The original Online Retail dataset contained 541,909 records. Following preprocessing, 530,104 records were retained for further analysis. These records were grouped by invoice number, resulting in 19,960 transactions involving 3,812 unique products. Among these transactions, 18,319 contained more than one item, while 1,641 contained only one item. This means that approximately 91.78% of all transactions involved multiple products, providing a basis for examining purchasing relationships among items.

Table 2. Summary of the Preprocessed Dataset

Stages	Count
Initial Data	541,909
Data after filtering	530,104
Total Transactions	19,960
Total Transaction Items	519,600
Unique Products	3,812
Transactions with 1 Item	1,641
Transactions with More Than 1 Item	18,319

ECLAT Experimental Results

Five experiments were performed using minimum support thresholds of 1%, 1.5%, 2%, 2.5%, and 3%. Throughout these experiments, minimum confidence was maintained at 50%, and the maximum itemset length was set to six items. The number of frequent itemsets, the number of generated association rules, and the execution time were recorded for each configuration.

Table 3. ECLAT Experimental Results at Different Minimum Support Values

No.	Minimum Support (%)	Minimum Count	Frequent Itemsets	Association Rules	Execution Time (s)
1	1.0	200	2,026	994	303.2885
2	1.5	300	745	213	173.8397
3	2.0	400	385	62	124.1732
4	2.5	499	231	39	107.5215
5	3.0	599	142	12	95.9162

The results show a consistent decline in the number of frequent itemsets as the minimum support threshold increased. At a support level of 1%, ECLAT identified 2,026 frequent itemsets and generated 994 association rules. When the threshold reached 3%, the number of frequent itemsets fell to 142, while the number of association rules decreased to 12. Execution time also declined, from 303.2885 seconds at 1% support to 95.9162 seconds at 3% support.

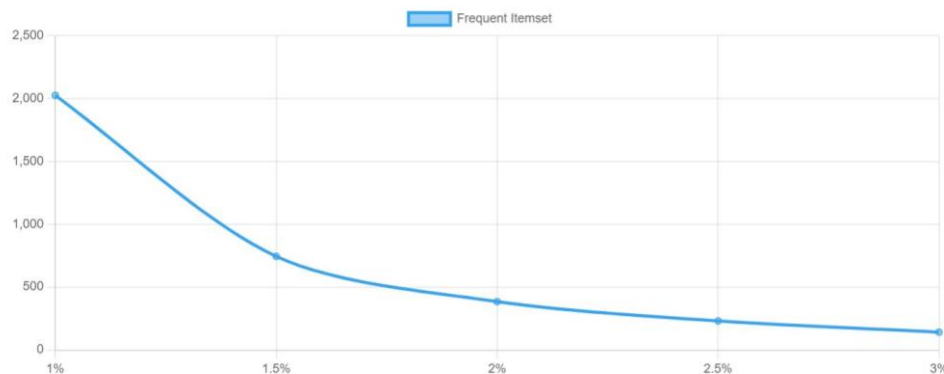


Figure 2. Effect of Minimum Support on the Number of Frequent Itemsets

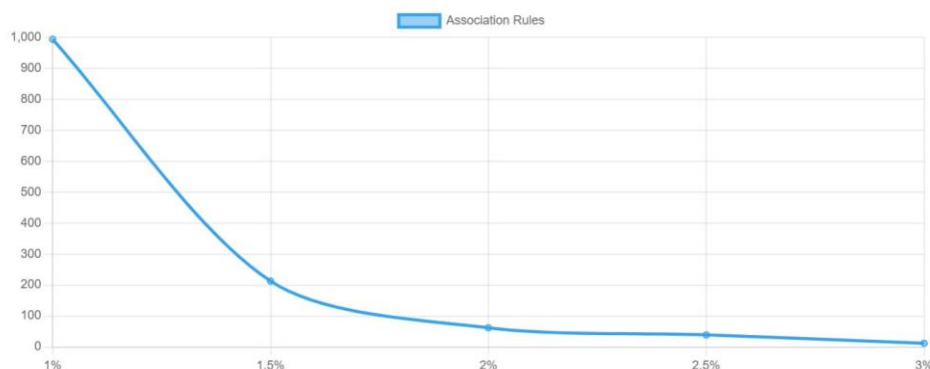


Figure 3. Effect of Minimum Support on the Number of Association Rules

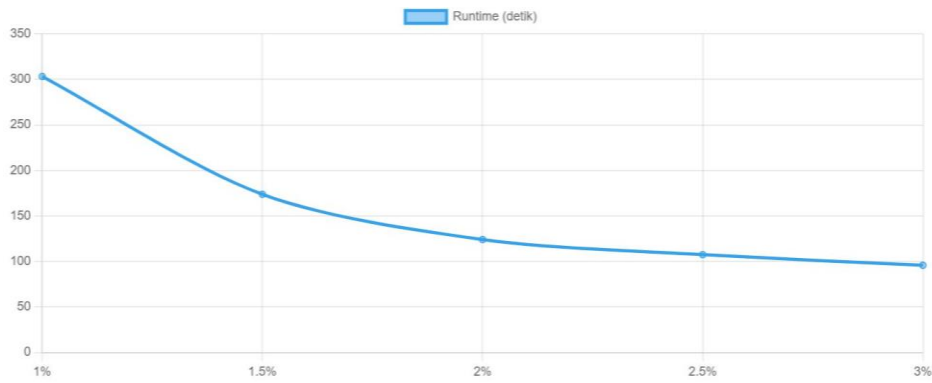


Figure 4. Effect of Minimum Support on ECLAT Execution Time

These findings indicate that the selected minimum support threshold influenced both the number of patterns retained and the execution time observed during the experiments.

Association Rule Evaluation

The association rules produced by each experiment were assessed using average support, average confidence, maximum confidence, average lift, and maximum lift. These metrics provide information about how frequently the identified patterns occur and how strongly the antecedents are associated with their consequents.

Table 4. Summary of Association Rule Metrics

Minimum Support (%)	Association Rules	Avg. Support (%)	Avg. Confidence (%)	Max. Confidence (%)	Avg. Lift	Max. Lift
1.0	994	1.333	65.156	97.568	17.054	79.511
1.5	213	1.953	62.918	90.937	12.524	37.555
2.0	62	2.647	62.317	90.467	10.888	18.403
2.5	39	2.922	63.320	90.467	11.425	18.403
3.0	12	3.427	63.554	82.613	10.300	16.278

At the 3% minimum support threshold, the algorithm generated 12 association rules. All of these rules had lift values greater than one. The maximum lift was 16.27774, while the maximum confidence reached 82.6128%. These results indicate that the retained rules showed positive associations between the antecedents and consequents in the transaction data.

Representative Association Rules

The 3% minimum support experiment was selected for a closer examination because it produced the smallest set of association rules and the shortest execution time among the five tested configurations. Table 5 presents representative rules obtained from this experiment.

Table 5. Representative Association Rules at 3% Minimum Support

No.	Antecedent	Consequent	Support	Confidence	Lift
1	pink regency teacup and saucer	green regency teacup and saucer	3.166%	82.613%	16.278
2	green regency teacup and saucer	pink regency teacup and saucer	3.166%	62.388%	16.278
3	green regency teacup and saucer	roses regency teacup and saucer	3.843%	75.715%	14.190

4	roses regency teacup and saucer	green regency teacup and saucer	3.843%	72.019%	14.190
5	alarm clock bakelike green	alarm clock bakelike red	3.206%	65.306%	12.403
6	alarm clock bakelike red	alarm clock bakelike green	3.206%	60.895%	12.403
7	lunch bag pink polkadot	lunch bag red retrospot	3.036%	55.597%	7.091
8	lunch bag suki design	lunch bag red retrospot	3.282%	51.013%	6.506
9	jumbo bag pink polkadot	jumbo bag red retrospot	4.133%	67.735%	6.472
10	lunch bag black skull	lunch bag red retrospot	3.211%	50.353%	6.422
11	jumbo storage bag suki	jumbo bag red retrospot	3.627%	61.149%	5.843
12	jumbo shopper vintage red paisley	jumbo bag red retrospot	3.407%	57.872%	5.530

The results show associations among several product groups, including Regency teacup and saucer items, Bakelike alarm clocks, and shopping bags with related designs. The rule from pink regency teacup and saucer to green regency teacup and saucer achieved a confidence of 82.613% and a lift of 16.278. The other representative rules also had lift values greater than one, indicating that the associated products occurred together more frequently than would be expected from the consequent's overall frequency alone.

Web-Based Application Results

The ECLAT algorithm was implemented in a web-based application that brings together the main stages of the analysis. Through the application, users can access retail transaction data, review preprocessing results, execute ECLAT, inspect frequent itemsets and association rules, conduct parameter experiments, and export the resulting data.

The experimental interface allows users to compare outcomes obtained with different minimum support thresholds. The results are presented in tables and charts, making it easier to examine the patterns identified and review the differences between experimental configurations.

DISCUSSION

Effect of Minimum Support on ECLAT Results

The experimental results show that minimum support has a substantial influence on the number of frequent itemsets and association rules generated by ECLAT. When the minimum support threshold increased from 1% to 3%, the number of frequent itemsets dropped from 2,026 to 142, while the number of association rules declined from 994 to 12. This occurred because a higher threshold excluded item combinations that appeared in fewer transactions. As fewer itemsets met the required support count, the number of association rules that could be generated also decreased.

This pattern reflects the basic principle of frequent itemset mining: an itemset must appear in a sufficient number of transactions to be retained. A lower minimum support threshold allows the algorithm to identify a wider range of purchasing patterns, including less frequent combinations. However, it also produces more results that may require additional effort to review. A higher threshold, on the other hand, produces a smaller and more manageable set of patterns, although some less frequent combinations may no longer be identified.

The findings also illustrate how ECLAT can be applied to retail transaction data through a vertical representation of transaction identifiers and set-intersection operations. By examining the transactions in which products appear together, the algorithm identified frequent itemsets and generated association rules across all five support configurations. In this study, the analysis covered 19,960 transactions involving 3,812 unique products.

Effect of Minimum Support on Execution Time

Execution time decreased from 303.2885 seconds at a minimum support of 1% to 95.9162 seconds at 3%, representing a reduction of approximately 68.4% under the tested conditions. This decline occurred alongside a substantial decrease in the number of frequent itemsets retained for further processing. As the support threshold increased, fewer item combinations satisfied the frequency requirement, and the overall mining process required less time in these experiments.

Nevertheless, execution time should be interpreted in the context of the dataset and implementation used in this study. The observed results do not establish that increasing minimum support will always reduce execution time in every situation. Dataset characteristics, implementation details, available hardware resources, and other algorithm parameters may also influence performance.

Selecting a minimum support threshold therefore involves balancing the breadth of the patterns identified against the time required to obtain them. At 1% support, the experiment produced a larger collection of frequent itemsets and association rules, which may be useful when examining less frequent purchasing combinations. At 3% support, the output was more compact and the execution time was shorter. The 3% configuration was selected for closer examination because it generated 12 rules and had the shortest execution time among the five tested configurations. This choice reflects the objectives and results of the present experiment rather than a universally optimal threshold.

Interpretation of Association Rules

The generated association rules reveal several product combinations that frequently appeared together in the transaction data. One notable example was the rule linking pink regency teacup and saucer to green regency teacup and saucer, which achieved a confidence of 82.613% and a lift of 16.278. The confidence value means that approximately 82.613% of transactions containing the antecedent also contained the consequent. The lift value indicates that the observed relationship was considerably stronger than would be expected based on the consequent's overall frequency alone.

Other representative rules involved Regency teacup and saucer products, Bakelike alarm clocks, and shopping bags with related designs. These findings may help retailers identify product combinations worth examining for joint promotions, product placement, or bundling. However, association rules describe relationships observed in transaction records; they do not demonstrate that purchasing one product causes a customer to purchase another. Any business decisions based on these patterns should also account for factors such as stock availability, profit margins, product characteristics, and business objectives.

All 12 rules generated at the 3% minimum support threshold had lift values greater than one. This indicates positive associations within the analyzed transaction data. However, the practical usefulness of these rules depends on the retail context and should be considered alongside other business information.

Contribution of the Web-Based Application

The web-based application provides an integrated environment for preprocessing transaction data, executing ECLAT, examining frequent itemsets, generating association rules, comparing minimum support configurations, and exporting analysis results. By bringing these functions together, the application supports a more structured workflow than performing each stage separately through individual scripts. Users can examine how changes in minimum support affect the mining results and access the resulting patterns through the application's interface.

The contribution of the application is primarily practical: it makes the implemented analysis workflow accessible through a web interface and supports the inspection and comparison of experimental results. The application does not, by itself, establish the general superiority of ECLAT over other frequent itemset mining algorithms. Such a conclusion would require a controlled comparison with alternative algorithms using consistent datasets, parameter settings, hardware conditions, and evaluation procedures.

Limitations and Threats to Validity

Several limitations should be considered when interpreting the findings. First, the experiments used a single publicly available Online Retail dataset. The observed results may differ for other retailers, transaction structures, product catalogs, or periods. Second, the evaluation focused on five minimum support values between 1% and 3%, with minimum confidence fixed at 50% and the maximum itemset length limited to six items. Other parameter combinations may produce different results.

Third, the reported execution times reflect the implementation and computing environment used in this study. Because the experiment did not compare ECLAT with alternative algorithms under controlled conditions, the findings cannot establish that ECLAT is faster or more efficient than Apriori or FP-Growth. Fourth, the interpretation of the association rules was based on support, confidence, and lift. The study did not evaluate whether the identified patterns would improve sales, profitability, inventory management, or customer behavior in an operational retail environment.

Future research could address these limitations by testing additional datasets, exploring a wider range of parameter values, and comparing ECLAT with other frequent itemset mining algorithms under consistent experimental conditions. Further work could also evaluate the practical usefulness of the generated rules through retailer feedback or business performance indicators.

CONCLUSION

This study examined the effect of minimum support on the results and execution time of the ECLAT algorithm for market basket analysis using the Online Retail dataset. Five minimum support thresholds were evaluated, ranging from 1% to 3%, while minimum confidence was fixed at 50% and the maximum itemset length was limited to six items.

The results showed that increasing minimum support reduced the number of frequent itemsets from 2,026 to 142 and the number of association rules from 994 to 12. Execution time also decreased from 303.2885 to 95.9162 seconds

across the tested configurations. These findings demonstrate that minimum support influences both the quantity of patterns identified and the execution time observed in this experiment. The rules obtained at the 3% threshold all had lift values greater than one, with the strongest representative rule achieving a confidence of 82.613% and a lift of 16.278.

The study also implemented ECLAT in a web-based application that integrates data preprocessing, frequent itemset mining, association rule generation, parameter experiments, result visualization, and data export. The application provides a practical environment for examining retail purchasing patterns and comparing experimental outcomes under different parameter settings.

This study is limited to one retail dataset, five minimum support thresholds, a fixed minimum confidence of 50%, and a maximum itemset length of six items. The results therefore reflect the experimental conditions used and should not be generalized to all datasets or implementations. Future research could examine additional datasets, compare ECLAT with other frequent itemset mining algorithms under consistent conditions, and investigate how different parameter combinations affect execution time and the usefulness of the resulting association rules.

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