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APRIORI ALGORITHM AND TIME SERIES FOR PURCHASING PATTERNS AND SALES FORECASTING: MATAHARI CIPUTRA JAKARTA

Taufiq Muhaziz[-1*)], Hendri Ardiansyah[-2]

Informatics Engineering
Faculty of Computer Science
Universitas Pamulang
[1]tfq213@gmail.com[-1*)], dosen00832@unpam.ac.id[-2]

(*) Corresponding Author

Abstract

Retailers face a difficult planning problem before Eid al-Fitr: they need to understand which products are purchased together while also estimating future demand. This study integrates the Apriori algorithm with ARIMA, SARIMA, and Prophet using transaction data from Matahari Department Store Ciputra Jakarta. The dataset contained 389,588 product-line records representing 194,854 transactions from January-April 2025 and January-April 2026. Transaction records were converted into a binary market-basket matrix and processed with a minimum support of 1% and a minimum confidence of 10%. Daily sales series were created for 50 high-volume products; January-April 2025 was used for model training and the corresponding 2026 period for testing. Forecast accuracy was compared using MAE, RMSE, and MAPE. Apriori generated 59 frequent itemsets and 24 association rules. Hoodie to Celana Jeans produced the highest reported confidence (43.63%), while Kaos Kaki to Sneakers produced the highest lift (11.39). ARIMA delivered the lowest average errors (MAE 42.46, RMSE 76.86, and MAPE 102.14%) and was therefore selected comparatively for a 90-day forecast. The integrated results were implemented in a Flask-based web application to support product bundling, display planning, and inventory prioritization. The high MAPE indicates that the forecasts should be treated as decision support rather than automatic replenishment quantities, particularly for volatile products.

Keywords: Apriori; Association Rules; Eid Al-Fitr; Inventory Planning; Time Series

Abstrak

Menjelang Idulfitri, peritel menghadapi persoalan perencanaan yang cukup rumit karena perlu memahami produk yang sering dibeli bersamaan sekaligus memperkirakan permintaan pada periode berikutnya. Penelitian ini mengintegrasikan algoritma Apriori dengan ARIMA, SARIMA, dan Prophet menggunakan data transaksi Matahari Department Store Ciputra Jakarta. Dataset terdiri atas 389.588 baris produk yang mewakili 194.854 transaksi pada periode Januari-April 2025 dan Januari-April 2026. Data transaksi diubah menjadi matriks market basket biner dan diproses menggunakan minimum support 1% serta minimum confidence 10%. Deret penjualan harian dibentuk untuk 50 produk dengan volume penjualan tinggi; Januari-April 2025 digunakan sebagai data pelatihan dan periode yang sama pada 2026 sebagai data pengujian. Kinerja model dibandingkan menggunakan MAE, RMSE, dan MAPE. Apriori menghasilkan 59 frequent itemset dan 24 aturan asosiasi. Aturan Hoodie ke Celana Jeans memiliki confidence tertinggi sebesar 43,63%, sedangkan Kaos Kaki ke Sneakers menghasilkan lift tertinggi sebesar 11,39. ARIMA memperoleh kesalahan rata-rata terendah, yaitu MAE 42,46, RMSE 76,86, dan MAPE 102,14%, sehingga dipilih secara komparatif untuk prediksi 90 hari. Hasil kedua pendekatan diintegrasikan ke dalam aplikasi web berbasis Flask untuk mendukung bundling produk, penataan produk, dan prioritas persediaan. Nilai MAPE yang masih tinggi menunjukkan bahwa hasil prediksi sebaiknya digunakan sebagai pendukung keputusan, bukan sebagai jumlah pemesanan otomatis, terutama untuk produk dengan permintaan yang sangat fluktuatif.

Kata kunci: Apriori; Aturan Asosiasi; Idulfitri; Perencanaan Persediaan; Time Series

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INTRODUCTION

Retail transaction records contain more than sales totals. They provide evidence about products that appear together in the same basket and about changes in demand over time. This information is particularly relevant in fashion retail around Ramadan and Eid al-Fitr, when demand can change within a short period (Lienata, Fenriana, and Safitri 2021); .The practical problem is therefore not only to identify what customers buy together, but also to estimate how much of each product may be required in the following period. Treating these two questions separately can leave inventory decisions without a direct link between product relationships and expected demand.

The first analytical need is relational: which products tend to appear in the same transaction? Apriori addresses this need through frequent itemsets and association rules evaluated using support, confidence, and lift (Butsianto, Naya, and Muhammad 2025);(Purnomo, Pratiwi, and Ibnu 2023). Previous retail studies have shown that such rules can support cross-selling, bundling, product placement, and inventory decisions. The second need is temporal: how much may each product sell in a future period? ARIMA models dependence after differencing, SARIMA extends this structure with seasonal terms, and Prophet represents trend and seasonality through an additive forecasting framework (Hyndman, R.J., & Athanasopoulos 2021); (Khaw et al. 2025). These methods answer different aspects of the same retail planning problem and therefore provide complementary evidence rather than interchangeable outputs.

The state of the art also shows that model performance is data-dependent. Recent work has applied Apriori or related association-rule approaches to retail and fashion transactions (Fathurrahman, Sunge, and Butsianto 2024); (Hasugian, Hasibuan, and Sofyan 2023); (Lestari and Damaiyanti 2023). Other studies have compared or applied forecasting approaches such as Prophet, SARIMAX, and time-series models for demand prediction (Albanna and Diana 2025); (Tajrin, Kuswoyo, and Ginting 2024). These studies demonstrate the usefulness of each analytical family, but the evidence is commonly reported as either purchasing-pattern analysis or sales forecasting. A practical decision-support workflow needs both: association rules to explain which products can be considered together and forecasts to indicate the expected demand magnitude. This distinction motivates the integration proposed in the present study.

The research gap is consequently more specific than the simple absence of a combined application. The unresolved issue is how transaction-level product relationships and product-level demand forecasts can be brought together without treating one output as a substitute for the other. The present study addresses this gap in a fashion-retail case by generating interpretable Apriori rules, comparing three forecasting approaches on the same product set, and translating the two outputs into inventory and promotion recommendations. The contribution is therefore an application-level analytical framework rather than a new Apriori or forecasting algorithm. Its scientific value lies in clarifying how two different forms of evidence co-purchase relationships and temporal demand can be combined in a reproducible decision support workflow.

Three contributions are emphasized. First, the study provides a transaction-based view of complementary products using a large set of 194,854 baskets, rather than relying only on product sales totals. Second, it compares ARIMA, SARIMA, and Prophet under the same training and testing periods and reports the error measures used to select the comparatively best model for the case. Third, it integrates forecast magnitude and association strength into one recommendation layer, while explicitly distinguishing system verification from evidence of business impact. This framing also makes the limitations of the current evaluation visible, particularly the short historical window and the absence of price, promotion, holiday, and stock-availability variables.

Table 1. State-of-the-Art Comparison

Study / year	Main approach	Main evidence	Limitation relevant to this study
(Lienata, Fenriana, and Safitri 2021)	Apriori; fashion retail	Product purchase relationships	Association analysis only; no demand forecasting
(Hermawan, Stephani, and Hapsa	Retail sales forecasting	Forecasting product sales	Forecasting focus; no basket relationships

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ri 2021)			
(Purnomo, Pratiwi, and Ibnu 2023)	Market basket analysis	Consumer purchase patterns	Does not integrate product-level forecasting
(Prastika and Pali 2024)	Apriori; minimarket	Frequent product combinations	Association rules only
(Khaw et al. 2025)	Prophet / SARIMAX	Retail forecasting comparison	No association-rule integration
(Rahmawati et al. 2025)	Apriori; fashion retail	Association patterns	No time-series demand comparison
This study	Apriori + ARIMA/SARIMA/Prophet	Rules + comparative forecasts + recommendations	Short history; no external or inventory KPI data

Accordingly, this study aims to (1) identify meaningful purchasing relationships before Eid al-Fitr using Apriori, (2) compare ARIMA, SARIMA, and Prophet for product-level sales forecasting, and (3) integrate association strength and forecast demand into inventory and promotional recommendations. The complete workflow was implemented in a Flask-based web application (Ma'arif and Kurniasih 2024); (Wijayanto and Susetyo 2022). The analysis is evaluated against the available transaction data and actual observations in the testing period; claims about operational inventory improvement are not made because stockout, overstock, service-level, and turnover outcomes were not available in the study data.

RESEARCH METHODS

Research design and setting

A quantitative case-study design was used. The research was conducted using internal transaction data from Matahari Department Store Ciputra Jakarta. The observation periods covered January-April 2025 and January-April 2026, which included the months leading to and surrounding Eid al-Fitr. The raw dataset contained transaction date, transaction identifier, product name, brand, color, size, quantity, and net sales value. Customer identities were not required for the analysis.

The workflow followed the sequence shown in Figure 1: data cleaning and selection, transaction transformation, Apriori analysis, daily time-series construction, forecasting, model evaluation, result integration, and web implementation. Missing identifiers and invalid dates were checked, duplicate rows were reviewed, and numeric fields were standardized. Product labels were retained in Indonesian because they are the category names used by the store dataset. The same sequence is used in the following methodological description to keep the written procedure consistent with the research workflow figure.

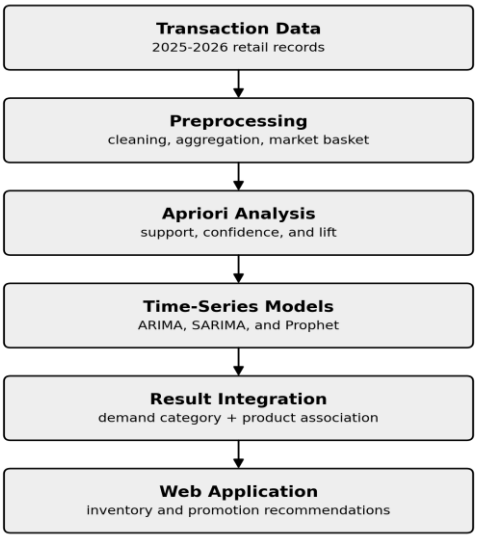


Figure 1. Research workflow

Transaction transformation and Apriori analysis

For association analysis, product-line records were grouped by Transaction_ID and Product_Name. The grouped data were pivoted into a binary market-basket matrix: a value of one indicated that a product appeared in a transaction, and zero indicated absence. Multiple units of the same product in a single transaction were treated as one occurrence because association rules evaluate co-presence rather than quantity.

The Apriori algorithm was applied to 194,854 unique transactions with minimum support set to 0.01 and minimum confidence set to

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0.10. The 1% support threshold corresponds to approximately 1,949 transactions, which is high enough to exclude isolated co-occurrences while remaining feasible for a large transaction base. The 10% confidence threshold was used as an exploratory lower bound so that directional relationships with meaningful conditional occurrence were not discarded prematurely. These values were therefore selected as practical thresholds for pattern discovery, not as globally optimal parameters. Rules were interpreted using support, confidence, and lift, with lift greater than one used as evidence that the co-occurrence was stronger than the baseline frequency of the consequent (Saad, Azizah, and Yani 2025). The threshold choice should be interpreted in relation to the size and sparsity of the present transaction data.

$$Support(A \rightarrow B) = \frac{n(A \cup B)}{N}$$

$$Confidence(A \rightarrow B) = \frac{n(A \cup B)}{n(A)}$$

$$Lift(A \Rightarrow B) = \frac{Confidence(A \Rightarrow B)}{Support(B)}$$

Control of product selection

The implemented analysis selected the 50 products with the highest total quantity over the study window. This criterion was used to focus forecasting on products with the largest observed sales contribution. However, because the ranking uses observations from both 2025 and 2026, and 2026 is the evaluation period, the implemented selection is not strictly leakage-free. Therefore, the forecasting results should be interpreted as a retrospective comparison for the selected product set rather than as an unbiased prospective model-selection exercise. A leakage-free replication should rank products using training-period data only before evaluating the fixed set on 2026 observations. This limitation is reported explicitly rather than being treated as resolved without re-running the analysis.

Time-series modeling and evaluation

Daily sales were constructed by summing Qty for each Date and Product_Name. The implemented analysis then modeled the selected 50 products separately. ARIMA was specified as (2,1,2), where d=1 represents first differencing and p=2 and q=2 represent autoregressive and moving-average terms. SARIMA was specified as (2,1,2)(1,1,1,7), adding a weekly seasonal structure with period 7 to the non-seasonal component. Prophet was configured as a comparison model with weekly seasonality (Hyndman & Athanasopoulos, 2021; Petropoulos et al., 2022; Khaw et al., 2025). The available research record documents these configurations, but it does not provide a systematic grid-search table or AIC/BIC comparison for all candidate specifications. Accordingly, the models are described as predefined comparative specifications, not as globally optimal parameter selections.

Predictions were compared with observed sales using mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). MAE summarizes average absolute deviation, RMSE gives greater weight to larger errors, and MAPE expresses error relative to the actual value. MAPE was retained because it was part of the original evaluation, but its interpretation requires caution when actual sales are small or highly variable. The study therefore does not interpret the 102.14% MAPE of ARIMA as evidence of high absolute forecasting accuracy. Measures such as sMAPE and MASE would provide useful complementary evidence in a future re-evaluation, but they were not available in the original computational output and are not reported as newly calculated results here.

Recommendation logic and system testing

Forecast totals were divided into high, medium, and low categories using the first and third quartiles. Association strength was treated as strong when a rule met the Apriori thresholds and had lift greater than one. A high forecast combined with a strong association produced a priority-restock recommendation; a medium forecast with a strong association indicated a supporting product; and a low forecast without a strong rule was assigned minimum or normal stock. These labels were intended to guide review rather than replace existing inventory policies. No claim is made that the recommendation logic itself has been empirically proven to reduce stockout or overstock rates because actual inventory-position, lead-time, and service-level outcomes were not available in the study data.

The application was developed in Python using pandas for data processing, mlxtend for Apriori, statsmodels for ARIMA and SARIMA, Prophet for additive forecasting, and Flask with Bootstrap for the web interface. Black-box testing covered file upload, parameter validation, analysis output, navigation, and responsive presentation.

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White-box testing examined the principal logic paths for Apriori, time-series processing, and recommendation generation.

RESULTS AND DISCUSSION

Data preparation

The source data contained 389,588 product-line records. After grouping by transaction identifier, 194,854 unique baskets were available for Apriori. The daily aggregation produced 11,848 product-date observations. The forecasting analysis was restricted to 50 high-volume products to reduce sparse-series effects and focus the analysis on products contributing substantially to observed sales. Celana Jeans, Kaos, and Celana Formal were the three highest-volume products in the reported selection.

The market-basket transformation also removed quantity effects from the association stage. This distinction is important: a basket containing two units of Sneakers and one unit of Kaos Kaki contributes one co-occurrence to the rule, while the time-series stage retains the quantities for demand forecasting. Using separate representations allowed each method to answer its intended question.

Apriori results and interpretation

At one percent minimum support, Apriori produced 59 frequent itemsets, including 12 two-product combinations. Applying the confidence threshold generated 24 directional rules. Table 2 presents representative rules with the strongest or most useful values. Hoodie → Celana Jeans had the highest confidence among the reported rules, whereas Kaos Kaki → Sneakers had the largest lift.

Table 2. Selected Association Rules

Antecedent	Consequent	Support	Confidence	Lift
Hoodie	Celana Jeans	1.46 %	43.63%	3.63
Kemeja	Celana Formal	3.31 %	40.88%	4.59
Kaos Kaki	Sneakers	1.17 %	36.68%	11.39
Crop Shirt	High-Waist Pants	1.60 %	36.62%	7.78
Kaos	Celana Jeans	3.18 %	33.66%	2.80
Skirt	Blouse	1.72 %	31.39%	5.54

A confidence of 43.63% for Hoodie → Celana Jeans means that approximately 43.63% of baskets containing Hoodie also contained Celana Jeans. The lift of 3.63 indicates that Celana Jeans appeared with Hoodie more often than expected from its general transaction frequency. The Kaos Kaki → Sneakers rule had lower support but a lift of 11.39, revealing a highly specific complementary relationship. Kemeja → Celana Formal combined a relatively high support of 3.31% with confidence of 40.88% and lift of 4.59, making it relevant for both reach and association strength.

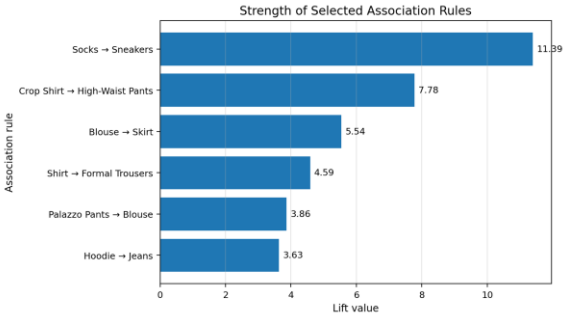


Figure 2. Lift values of selected association rules

Manual recalculation was performed on Hoodie to Celana Jeans, Kemeja to Celana Formal, and Kaos Kaki to Sneakers. The calculations matched the system outputs when unrounded support values were used. This qualification matters because percentages displayed to two decimal places can produce small differences if they are reused as the basis for division. The verification therefore supports the three sampled rules rather than claiming that every possible rule was independently recalculated.

Forecasting performance

Table 3 compares the mean evaluation values across the 50 products. ARIMA recorded the smallest reported MAE, RMSE, and MAPE, followed by SARIMA and Prophet, so it was selected comparatively for the subsequent 90-day forecast.

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Table 3. Average Forecasting Errors for 50 Products

Model	MAE	RMSE	MAPE
ARIMA	42.46	76.86	102.14 %
SARIMA	53.98	84.78	173.76 %
Prophet	110.42	129.56	497.01 %

The ordering of the models can be related to the structure of the available data. The observed series contain a mixture of baseline demand and short-lived increases around the Eid period. A more complex seasonal specification does not automatically improve accuracy when the available historical window is short, because the model has limited repeated seasonal cycles from which to learn. Prophet also provides a flexible trend-seasonality representation, but flexibility alone does not guarantee lower error for sparse product-level series. These observations are consistent with the general forecasting principle that model performance depends on the characteristics and amount of information in the series . A longer history and rolling-origin evaluation would be needed to determine whether the ranking remains stable across forecast origins.

The selected ARIMA model was retrained for each of the 50 products to produce a 90-day forecast. Celana Jeans had the largest forecast total at 9,793 units, followed by Celana Formal at 8,520.60 units and Jogger Pants at 7,900.83 units. These figures are planning estimates, not direct purchase orders, and should be adjusted using current stock, lead time, warehouse capacity, promotion schedules, and safety-stock policy. Because the forecasting history is short and no external variables were modeled, the forecast should be used as one input to inventory review rather than as a standalone replenishment rule.

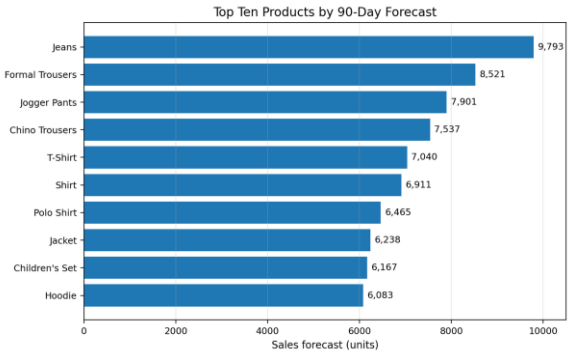


Figure 3. Top ten products by 90-day forecast

Integrated inventory recommendations

The integrated logic combines demand magnitude with basket relationships. Table 4 shows selected outputs. Products such as Celana Jeans, Celana Formal, Jogger Pants, Kaos, Kemeja, and Hoodie received priority-restock recommendations because their forecasts were high and they were linked to another product by a strong association rule.

Table 4. Selected Integrated Stock Recommendations

Product	90-day forecast	Association	Recommendation
Celana Jeans	9,793.00	Hoodie	Priority restock
Celana Formal	8,520.60	Kemeja	Priority restock
Jogger Pants	7,900.83	Kaos	Priority restock
Kaos	7,040.40	Celana Jeans	Priority restock
Kemeja	6,910.78	Celana Formal	Priority restock
Hoodie	6,083.29	Celana Jeans	Priority restock
Blouse	4,507.77	Skirt	Supporting product
A-Line Dress	2,987.37	None	Maintain stock

The integration prevents one metric from dominating the decision. A high forecast total indicates a potentially important replenishment priority, while an association rule provides

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evidence about products that may be considered together for bundling or placement. The two signals are therefore interpreted as complementary rather than causal: an association rule does not imply that purchasing one product causes demand for another. Likewise, the recommendation layer does not prove that inventory performance will improve because actual stockout, overstock, service-level, and turnover measures were not included in the dataset. The practical value of the output is consequently best described as decision support that can be evaluated further when operational inventory data become available.

Application testing and limitations

The web application provided five principal pages: dashboard, Apriori analysis, time-series analysis, stock recommendations, and system information. Black-box scenarios for CSV upload, parameter validation, table generation, chart display, navigation, and responsive layout produced the expected outputs. White-box testing covered the independent logic paths of the Apriori, forecasting, and recommendation modules. These tests verify software execution and interface behavior; they do not establish statistical forecast accuracy or business impact. Table 5 summarizes the main test outcomes.

Table 5. Main System Test Results

Module	Test scenario	Result
Apriori	CSV upload, parameters, rule output	Passed
Time series	Model process, metrics, chart output	Passed
Recommendation	Rule and forecast integration	Passed
Navigation	Page transitions and menu links	Passed
Responsive view	Desktop and mobile layouts	Passed

Several limitations should be considered when interpreting the results. First, the historical window covers only January-April 2025 and January-April 2026, so the models observe only a limited number of repeated seasonal cycles. Second, the dataset does not contain external predictors such as price, discount, promotion, holiday indicators, stock availability, or competitor activity; these factors may explain demand changes that a univariate time-series model cannot capture. Third, the implemented Top-50 selection uses the full study window, which introduces a potential selection-leakage issue because 2026 is also used for testing. Fourth, the forecasting evaluation uses MAE, RMSE, and MAPE, while additional scale-free metrics and rolling-origin validation were not part of the original computation. Finally, inventory recommendations were not validated against operational KPI such as stockout rate, overstock, service level, or inventory turnover. These limitations restrict the strength of claims about prospective operational performance, although they do not invalidate the descriptive association results or the retrospective comparison of the three tested forecasting specifications.

CONCLUSIONS AND SUGGESTIONS

Conclusion

The Apriori analysis processed 194,854 transaction baskets and produced 59 frequent itemsets and 24 association rules using minimum support of 1% and minimum confidence of 10%. The strongest reported relationship by lift was Kaos Kaki → Sneakers (11.39), while Hoodie → Celana Jeans reached 43.63% confidence. These results provide interpretable evidence for considering complementary products in promotion and placement decisions.

Among the three tested forecasting specifications, ARIMA achieved the lowest reported average MAE (42.46), RMSE (76.86), and MAPE (102.14%) and was therefore selected comparatively for the 90-day forecast. The main contribution is the integration of interpretable basket relationships and product-level demand estimates into one decision-support workflow rather than the introduction of a new forecasting or association algorithm. However, the high MAPE, short historical window, absence of external variables, and potential Top-50 selection leakage mean that the forecasts should not be interpreted as exact operational demand estimates. The system results support analytical decision making but do not constitute evidence of improved inventory KPIs.

Suggestion

Future research should repeat product selection using training-period data only, apply automated parameter search and rolling-origin evaluation, and report complementary metrics such as sMAPE and MASE. Longer historical records

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should also incorporate promotion, price, holiday, and stock-availability variables, while inventory recommendations should be evaluated against stockout, overstock, service-level, and turnover indicators. Alternative association approaches such as FP-Growth and hybrid or ensemble forecasting can also be investigated. For implementation, integration with a Point-of-Sale database would allow the workflow to be updated continuously rather than through manual file uploads.

REFERENCES

Albanna, Haikal Tirta, and Diana Diana. 2025. "Forecasting Penjualan Sembako Berbasis Model Prophet: Strategi Efisiensi Stok Pada Pada Ritel Tradisional." *Edumatic: Jurnal Pendidikan Informatika* 9(3): 698–707. doi:10.29408/edumatic.v9i3.32251.

Butsianto, Sufajar, Candra Naya, and Anggi Muhammad. 2025. "BULLETIN OF COMPUTER SCIENCE RESEARCH Implementasi Algoritma Apriori Dalam Menemukan Pola Asosiasi Pada Data Penjualan Produk Retail." 5(5): 938–47. doi:10.47065/bulletincsr.v5i5.731.

Fathurrahman, Humam, Aswan S Sunge, and Sufajar Butsianto. 2024. "Journal of Computer Networks , Architecture and High Performance Computing Association Relationship Analysis in Finding Sales of Goods With Apriori Algorithm Journal of Computer Networks , Architecture and High Performance Computing." 6(3): 1224–31.

Hasugian, Abdul Halim, Muhammad Siddik Hasibuan, and Siti Nurhaliza Sofyan. 2023. "Apriori to Analyze Sales Patterns of Building Tools and Materials." 7(2): 198–208.

Hermawan, Francisca, Set Diana Stephani, and Yudith Dyah Hapsari. 2021. "Analisa Peramalan Penjualan Produk Retailer Pada Pt . Abc Menggunakan Laporan Penjualan 2018 Dan 2019 Forecasting Analysis of Retailer Product Sales at Pt . Abc Using 2018 and 2019 Sales Reports." 13(1): 47–54.

Hyndman, R.J., & Athanasopoulos, G. 2021. *No TitleForecasting: Principles and Practice, 3rd Edition*. otexts: Melbourne, Australia. OTexts.com/fpp3.

Khaw, Brian, Ricky Irwanto, Roni Yunis, Universitas Mikroskil, Fakultas Informatika, Sistem Informasi, and Universitas Mikroskil. 2025. "Analisis Time Series Dan Perancangan Dashboard Untuk Memprediksi Penjualan Dengan Metode Prophet Dan." 25(2). doi:DOI: https://doi.org/10.55601/jsm.v26i2.1797.

Lestari, Sri, and Alfiani Damaiyanti. 2023. "Penerapan Data Mining Menggunakan Metode Algoritma Apriori Untuk Menentukan Penjualan Barang IT Pada PT . Javas Karya Tungga Jakarta Selatan." 5(1): 237–42. doi:https://doi.org/10.55338/saintek.v5i1.1382 Penerapan.

Lienata, Benny, Indah Fenriana, and Ramona Dyah Safitri. 2021. "Penerapan Data Mining Pada Penjualan Pakaian Brand Expand Dengan Algoritma Apriori Menggunakan Metode Association Rules PT . Vidiaelok Lestari Garmindo." 0577(September).

Ma'arif, Oktaviano Miftahqul, and Tatit Kurniasih. 2024. "Perancangan Sistem Inventory Berbasis Web Menggunakan Framework Flask : PT. Gagas Mitra Jaya (Area Salatiga)." *Jurnal Indonesia : Manajemen Informatika dan Komunikasi* 5(2): 1947–59. doi:10.35870/jimik.v5i2.822.

Prastika, Ayu, and Elisabet Pali. 2024. "Analisis Pola Pembelian Konsumen Menggunakan Algoritma Apriori Pada Minimarket Harapan Jaya." 4: 6813–24.

Purnomo, Sarifmata, Heny Pratiwi, and Muhammad Ibnu. 2023. "Penerapan Data Mining Dalam Menganalisis Pola Belanja Konsumen Menggunakan Market Basket Analysis." : 111–20. doi:10.47002/metik.v7i2.678.

Rahmawati, Sinta Devi, Adinda Bintang Oktavia, Fadina Salwa, Aulia Putri, and Diana Laily Fithri. 2025. "Penerapan Algoritma Apriori Untuk Menemukan Pola Asosiasi Pada Data Penjualan Retail Fashion." 10(2): 289–95. doi:10.51717/simkom.v10i2.910.

Saad, Fikri S, Nur Azizah, and Zulfitri Yani. 2025. "Penerapan Algoritma Apriori Untuk Menentukan Pola Permintaan Bahan Makanan Berdasarkan Data Transaksi." : 5–8. doi:DOI : https://doi.org/10.55382/jurnalpustakaai.v5i2.1181 Vol . 5 No. 2 (2025) 388 – 397 Vol.

Tajrin, Tajrin, Yudyi Kuswoyo, and Rido Alfrado Ginting. 2024. "Implementasi Metode Forecasting Dengan Menggunakan Algoritma Time Series Dalam Memprediksi Permintaan Cetak Cv. Grand Grafika." *Djtechno: Jurnal Teknologi Informasi* 5(2): 184–94. doi:10.46576/djtechno.v5i2.4563.

Wijayanto, Candra, and Yeremia Alfa Susetyo. 2022. "IMPLEMENTASI FLASK FRAMEWORK PADA PEMBANGUNAN APLIKASI SISTEM INFORMASI HELPDESK (SIH)." 07(September): 858–68.

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