Application of the Apriori Algorithm in Identifying Association Patterns in Car Parts Sales Based on Transaction Data

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Abstract.
This study is motivated by the increasing use of transaction data as a strategic information source in business decision-making, particularly in the sale of vehicle parts. However, large and complex transaction datasets are often not fully utilized to identify consumer purchasing patterns. Therefore, this study aims to identify association patterns between products using the Apriori algorithm, thereby providing recommendations to support marketing strategies, inventory management, and sales growth. The research method employed is a quantitative approach based on data mining using the Association Rule Mining (ARM) technique. The research stages include transaction data collection, preprocessing (cleaning, transformation, and conversion to transaction format), itemset formation, and the application of the Apriori algorithm using a minimum support parameter of 0.5% and a confidence level of 60%. The analyzed data consists of 10,922 transactions divided into training and testing datasets. The results of the study indicate that the Apriori algorithm is capable of generating association rules with high confidence values of up to 83%, indicating strong relationships between items. Specific items such as 9-09060-EXCHEM emerge as the central item in various rules, demonstrating a dominant role in purchasing patterns. These findings prove that the Apriori approach is effective in uncovering purchasing patterns and can be used as a basis for data-driven decision-making.

Keywords: *Association rules, Data mining, Spare parts and APRIORI algorithm.*

I. INTRODUCTION

Advances in information technology and digital transformation have driven significant changes in how business organizations utilize data, particularly in the retail and automotive sectors. Data mining has become one of the primary approaches for extracting insights from large and complex transaction datasets. This process enables organizations to identify previously unknown hidden patterns and transform them into valuable information for decision-making (1,2). In the context of modern retail, the analysis of historical transaction data can yield deep insights into consumer behavior and purchasing preferences, thereby serving as the foundation for data-driven business strategies (3).

Additionally, the COVID-19 pandemic has significantly accelerated the adoption of data mining technologies, especially within the retail sector as businesses transition from conventional models toward digital B2C frameworks. This shift has increased reliance on transaction data to develop accurate sales prediction models and personalized recommendation systems, which are crucial for maintaining competitiveness and ensuring long-term business sustainability. Furthermore, the growing volume and complexity of consumer data require more advanced analytical approaches to extract meaningful insights. In this context, integrating multiple analytical techniques, particularly association rule mining, plays a vital role in uncovering hidden patterns, identifying product relationships, and understanding consumer purchasing behavior more comprehensively (4,5). Such insights not only support strategic decision-making but also enhance customer experience through targeted marketing and efficient inventory management.

Nevertheless, the management of sales transaction data, particularly for automotive spare parts, still faces various challenges. The large and continuously growing volume of data poses a major challenge in the analysis process, especially when the data encompasses thousands of component types with diverse attributes (6). Additionally, inconsistent and poorly integrated data quality can reduce the accuracy of analysis results, leading to suboptimal decisions (7). Another issue arises regarding the efficiency of the algorithms used, where algorithms such as Apriori require repeated database scans, which can increase computational complexity (8).

To address these issues, an analytical approach is needed that can effectively extract purchasing patterns from transaction data. One widely used approach is association rule mining, which enables the identification of relationships between items in transactions (9). By utilizing this method, companies can understand consumer purchasing patterns and use them to support business strategies such as inventory management, product layout, and sales enhancement through cross-selling (10).

Specifically, the Apriori algorithm has been widely used in previous research to discover frequent itemsets and association rules in transaction data. This algorithm operates on the principle that if an itemset frequently appears, then all subsets of that itemset must also frequently appear (11). Various studies indicate that the application of Apriori can yield significant insights in purchase pattern analysis and recommendation systems (12). In the context of e-commerce, the development of methods such as Fuzzy Association Rule Mining has also demonstrated improvements in the quality of the generated information by accounting for sales volume (13).

A number of studies have also shown that association rule analysis plays a crucial role in understanding consumer behavior and improving operational efficiency. This analysis enables the identification of products frequently purchased together, which can then be used to optimize store layouts and marketing strategies (14). Furthermore, the application of association rule mining across various sectors, including commodity distribution and e-commerce, has proven effective in improving distribution efficiency and profitability (15). However, most studies remain focused on the general retail sector and have not specifically examined the application of the Apriori algorithm to automotive spare part sales, which involve highly complex data.

Based on the discussion above, a clear research gap emerges in the application of the Apriori algorithm within automotive spare part sales, which involve complex, heterogeneous, and dynamic transaction data patterns. Unlike general retail products, automotive spare parts often exhibit irregular demand, interdependent usage, and brand-specific compatibility, making pattern identification more challenging. Therefore, this study aims to implement the Apriori algorithm to systematically identify meaningful association patterns derived from transaction data in this domain. By doing so, the research seeks to generate reliable association rules based on defined support and confidence thresholds. The expected contribution is the development of an analytical framework that supports data-driven decision-making, particularly in inventory planning, product bundling, and marketing strategies. Additionally, this study aims to provide deeper insights into consumer purchasing behavior in the automotive sector, ultimately helping businesses improve operational efficiency and strategic responsiveness.

II. METHODS

This study employs a quantitative approach based on data mining to extract association patterns from car parts sales transaction data. This approach was chosen because it is capable of identifying hidden patterns in large datasets that cannot be directly observed through conventional analysis. Data mining is defined as the process of deriving knowledge from a database using statistical techniques, machine learning, and database management, thereby generating valuable information for decision-making (16). This study focuses on exploring relationships between items in transactions through the Association Rule Mining (ARM) approach using the Apriori algorithm. Methodologically, the study adopts the data science life-cycle framework, which includes the stages of data understanding, preprocessing, modeling, evaluation, and interpretation of result. Additionally, the concept of Market Basket Analysis (MBA) is used to identify product associations frequently purchased together, thereby providing insights into consumer behavior (17).

The preprocessing stage is conducted systematically through data collection, cleaning, transformation, and conversion into transaction format to ensure the quality of the analysis. Incomplete or inconsistent data is cleaned to avoid result bias , then transformed into a form suitable for Apriori analysis, including binary transaction representations and matrices to improve computational efficiency (18). The modeling process involves identifying frequent itemsets based on the minimum support threshold and formulating association rules using the confidence parameter (19). Threshold determination is performed experimentally by referring to previous studies, such as the use of a minimum support of 20% and a confidence level of 50%, and evaluated using an additional parameter lift to measure the strength of relationships between items (20).

III. RESULT AND DISCUSSION

The subject of this study is spare parts sales data from "X Car Dealer" for the year 2025, which is used to analyze purchase association patterns based on transaction data. The dataset is divided into two sets training data and test data to ensure the validity and reliability of the resulting model. The training data covers the period from January to November, which is used to build association patterns using the Apriori algorithm, while the test data is collected in December to evaluate the consistency and relevance of the identified patterns against new data.

Data collection was conducted by retrieving spare parts sales transaction data from the relevant car dealer's information system. The dataset consists of approximately 10,922 transaction records reflecting actual customer purchasing activity. This data contains important information such as spare part type, purchase quantity, and transaction time. Before analysis, the data was organized into a transaction format to support both manual calculations and algorithm implementation, as shown in the sample data in Table 2.

Table 2. Sales Sample Data

No	TID	DATE	PARTS CODE	PARTS NAME	TOTAL	UNIT	INIT
1	TID-01	02/01/2025	4-94109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
2	TID-01	02/01/2025	8-08200-P9909ZE1	HONDA ENGINE Cleaner	1	PCS	B
3	TID-01	02/01/2025	8-08233-P99-F6NN1	HAO BLUE 5W-30 SN GF-5	1	LTR	C
4	TID-02	01/02/2025	4-94109-14000	Washer, Drain Plug (14mm)	1	PCS	A
5	TID-02	01/02/2025	5-15400-RK9-F01	CARTRIDGE, OIL Filter	1	PCS	D
6	TID-03	01/02/2025	4-941109-14000	WASHER, DRAIN PLUG (14MM)	1	PCS	A
7	TID-04	14/03/2025	4-941109-14000	Washer, Drain Plug (14mm)	1	PCS	A
8	TID-04	14/03/2025	8-08233-P99-F6NN1	hao BLUE 5W-30 SN GF-5	1	LTR	C
9	TID-04	14/03/2025	M-AM24B-ROCK	brake & PAD CLEANER (250ML)	1	PCS	E
10	TID-05	17/03/2025	E-EXC-CARB	exchem CARB CLEANER (220ML)	1	PCS	F
11	TID-05	17/03/2025	I-FIC-08956-3M	fuel INJECTOR CLEANER 3M	1	PCS	J
12	TID-06	17/03/2025	4-94109-14000	washer, DRAIN PLUG (14MM)	1	PCS	A
13	TID-06	17/03/2025	5-15400-RK9-F01	cartridge, OIL FILTER	1	PCS	D
14	TID-06	17/03/2025	9-09060-EXCHEM	engine FLUSH EXCHE (250ML)	1	PCS	G
15	TID-06	17/03/2025	X- EXC-CARB	exchem CARB CLEANER (220ML)	1	PCS	F
16	TID-07	18/03/2025	4-941109-14000	washer, DRAIN PLUG (14MM)	1	PCS	A
17	TID-08	22/03/2025	4-941109-14000	washer, DRAIN PLUG (14MM)	1	PCS	A
18	TID-	22/03/2	5-15400-	cartridge, OIL	1	PCS	D

	08	025	RK9-F01	FILTER			
19	TID-08	22/03/2025	7-17220-RB6-ZOO	element AIR FILTER (GE/B/M/DD)	1	PCS	H
20	TID-08	22/03/2025	8-08234-P99-A6NN1	hao GOLD 0W-20 SN GF-5	4	LTR	I
21	TID-08	22/03/2025	9-09060-EXCHEM	engine FLUSH EXCHEM (250ML)	1	PCS	G
22	TID-08	22/03/2025	I-FIC-08956-3M	fuel INJECTOR CLEANER 3M	1	PCS	J
23	TID-09	23/03/2025	X- EXC-CARB	exchem CARB CLEANER (220ML)	1	PCS	F
24	TID-10	26/03/2025	4-941109-14000	Washer, Drain Plug (14mm)	1	PCS	A
25	TID-10	26/03/2025	5-15400-RK9-F01	Cartridge, Oil Filter	1	PCS	D
26	TID-10	26/03/2025	9-09060-EXCHEM	engine FLUSH EXCHE (250ML)	1	PCS	G
27	TID-10	26/03/2025	X- EXC-CARB	exchem CARB CLEANER (220ML)	1	PCS	F
28	TID-11	26/03/2025	4-941109-14000	washer, DRAIN PLUG (14MM)	1	PCS	A
29	TID-12	26/03/2025	4-941109-14000	washer, DRAIN PLUG (14MM)	1	PCS	A
30	TID-12	26/03/2025	5-15400-RK9-F01	cartridge, OIL FILTER	1	PCS	D

This dataset contains sales transaction data for vehicle parts from January through March 2025. Each transaction includes attributes such as transaction ID (TID), date, part code and name, purchase quantity, unit of measure, and product initialization code. The data reveals purchasing patterns for various components, such as washers, oil filters, and cleaning fluids, which can be used for association analysis to understand consumer behavior and support sales strategies.

Data Transformation

After undergoing the cleaning stage, the data then enters the transformation process, which involves converting the data into a format suitable for data mining analysis. In this study, the data, which was originally stored in an SQL Server 2005 Management Studio database, was converted to .xlsx format using Microsoft Excel (21). This transformation aims to facilitate the processing, analysis, and implementation of the Apriori algorithm. Additionally, the data structure was adjusted to meet the requirements for transaction representation. The results of this transformation process are presented in a structured table, as shown in Figure 2.

	TID	TANGGAL	KODE SUKU CADANG	NAMA SUKU CADANG	JUMLAH	SATUAN
2	TID-010124	30-Dec-25	1-71101-TE7-K002ZZ	FACE, FRONT BUMPER	1	PCS
3	TID-010586	30-Dec-25	0-90667SVZ003ZE	CLIP, TRIM 7MM (YR32ZL)	5	PCS
4	TID-010586	30-Dec-25	8-68100-TE7-K20ZZ	TAILGATE COMP. DOOR (DD4/S)	1	PCS
5	TID-010586	30-Dec-25	4-34155-TE7-T01	PANEL ASSY, LID	1	PCS
6	TID-010586	30-Dec-25	3-73225-TE7-K00	RUBBER A, WINDSHIELD DAM	1	PCS
7	TID-010586	30-Dec-25	1-91502-S70-003	FASTENER B, WINDSHIELD	2	PCS
8	TID-010586	30-Dec-25	4-74890-TE7-K01ZC	GARNISH ASSY, RR LICENSE	1	PCS
9	TID-010586	30-Dec-25	1-71501-TE7-K002ZZ	FACE, RR BUMPER	1	PCS
10	TID-010586	30-Dec-25	1-91501-S70-003	FASTENER B, WINDSHIELD	4	PCS
11	TID-010586	30-Dec-25	3-73525-SYY-000	RUBB, RR QUARTER WINDS DAM	2	PCS
12	TID-010586	30-Dec-25	9-8901003	SEALENT GLASS BLACK (310ML)	3	PCS
13	TID-010586	30-Dec-25	1-91536-SS0-J01	FASTENER A, WINDSHIELD	2	PCS
14	TID-100518	29-Dec-25	1-91536-SS0-J01	FASTENER A, WINDSHIELD	2	PCS
15	TID-100518	29-Dec-25	3-73525-SYY-000	RUBB, RR QUARTER WINDS DAM	5	PCS
16	TID-100518	29-Dec-25	5-75450-SDE-T00	AIR OUTLET ASSY R	1	PCS
17	TID-100518	29-Dec-25	9-8901003	SEALENT GLASS BLACK (310ML)	3	PCS
18	TID-100518	29-Dec-25	S-MS-930	SEALENT BODY WHITE (310ML)	1	PCS
19	TID-100518	29-Dec-25	1-71501-TE7-K002ZZ	FACE, RR BUMPER	1	PCS

Fig 1. Transformation Results Data

Figure 1 illustrates the transformation of raw transaction data into a structured Microsoft Excel (.xlsx) format, enabling more efficient data handling and analysis. The dataset contains essential attributes, including transaction ID, transaction date, part code, part name, quantity, and unit, which collectively provide a comprehensive representation of each transaction. Organizing the data in this tabular format ensures consistency, reduces redundancy, and simplifies preprocessing steps required for data mining techniques. Moreover, this structured arrangement is particularly suitable for implementing the Apriori algorithm, as it allows transactions to be clearly defined and easily converted into binary item sets. As a result, the prepared dataset supports more accurate identification of association patterns and enhances the overall effectiveness of subsequent analytical processes.

Apriori Algorithm Process

After the data transformation process is complete, the dataset is organized into a structured transaction format as shown in Table 3 before being processed using RapidMiner software. This format allows each transaction to be represented as a set of items purchased together. This step is crucial because it determines the success of the pattern mining process using the Apriori algorithm in identifying frequent itemsets and relevant association rules.

Table 3. Sales itemset sample data

Transactions	0-00001-P	0-50820TG	0-50890TF	0-60100-T	0-60211-T	0-60610TE	0-80050-S	0-80291-T	0-80292-T	0-80410-T	0-90004-P
TID-010124	0	0	0	0	0	0	0	0	0	0	0
TID-010586	0	0	0	0	0	0	0	0	0	0	0
TID-100518	0	0	0	0	0	0	0	0	0	0	1
TID-101555	1	0	0	0	0	0	0	0	0	0	0
TID-110870	0	0	0	0	0	0	0	0	0	0	0
TID-111095	0	0	0	0	0	0	0	0	0	0	0
TID-111134	0	0	0	0	0	0	0	0	0	0	0
TID-111142	0	0	0	0	0	0	0	0	0	0	0
TID-111250	0	0	0	0	0	0	0	0	0	0	0
TID-111267	0	0	0	1	0	0	1	0	0	1	0
TID-111410	0	0	0	0	0	0	0	0	0	0	0
TID-111501	0	0	0	0	1	1	0	0	0	0	0

Table 3 presents the transformation of transaction data into binary item set representation, which serves as input for the Apriori algorithm. In this format, each row corresponds to a unique transaction (TID), while each column represents a specific item, marked with 1 if present and 0 if absent. This binary structure simplifies the computation process by standardizing item occurrences across all transactions. As a result, it enables more efficient identification of frequent itemsets and underlying association patterns. Furthermore, the structured dataset ensures compatibility with data mining tools such as RapidMiner, allowing for systematic analysis and generation of meaningful association rules.

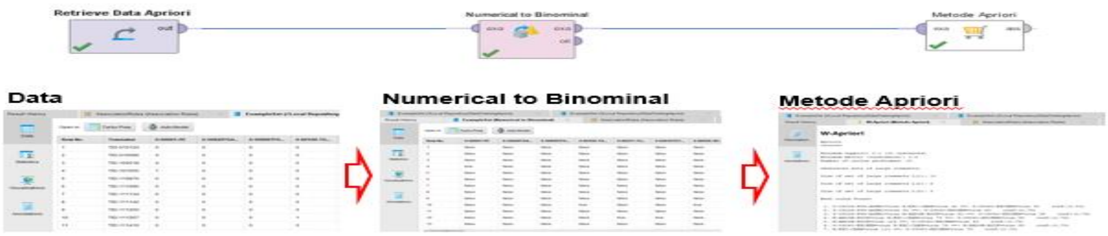

Fig 2. Apriori Algorithm Process

The analysis process begins with the collection of sales transaction data, which statistically reflects the frequency and distribution of item purchases within a defined time period. This initial dataset generally exhibits multivariate characteristics, consisting of numerous transactions and diverse item variations. To ensure data reliability, a preprocessing stage is conducted, including data cleaning to remove inconsistencies and transformation to standardize formats. Subsequently, the data is converted into a binary representation (0 and 1), indicating the presence or absence of items in each transaction. This transformation facilitates efficient computational processing. The next stage involves forming item sets to identify frequent combinations of items that commonly appear together. Finally, the Apriori algorithm is applied to systematically extract meaningful association rules based on predefined support and confidence thresholds, enabling the discovery of significant patterns within the transaction data.

In conducting this study, the primary parameters used to determine the validity of an association rule are the support and confidence values. These two parameters form the basis for selecting the item combination patterns to be analyzed using RapidMiner software. The minimum support value was set at 0.005 or 0.50% to identify item sets that appear frequently enough in transactions. Meanwhile, the minimum confidence threshold was set at 0.6 or 60% to ensure that the resulting rules have an adequate level of confidence, making them relevant and usable in business decision-making.

Training Data

The transaction data used in this study covers the period from January to November 2022, comprising a total of 9,851 transactions. The dataset was then processed and analyzed to identify patterns of relationships between items. Based on the results of the analysis of this data, association rules consisting of combinations of two items (2-itemsets) were identified, which are presented in detail in Table 4.

Table 4. Rapidminer 2 itemset test results

No	Premises	Condusion	Confidence
			Apriori
1	8-08200-P9909ZE1	M-AM24B-ROCK	61.0%
2	X-EXC-CARB	9-09060-EXCHEM	62.0%
3	0-09060-EXCHEM	X-EXC-CARB	62.0%

Based on Table 4, the Apriori algorithm testing produced three association rules involving 2-item set combinations with confidence values ranging from 61% to 62%, indicating moderately strong relationships between items. These results suggest that certain products are frequently purchased together within transactions. Notably, some association patterns are reciprocal, such as the relationship between X-EXC-CARB and 9-09060-EXCHEM, implying mutual co-occurrence. From a statistical perspective, this consistency reflects a stable co-purchasing tendency among customers. Such patterns are valuable for supporting strategic decisions, including product bundling, cross-selling strategies, and inventory planning to better align with observed consumer purchasing behavior.

Table 5. Rapidminer 3 itemset test results

No	Premises	Condusion	Confidence
			Apriori
1	M-EXC-CARB, 9-09060-EXCHEM	M-AM24B-ROCK	64.0%
2	M-AM24B-ROCK, X-EXC-CARB	9-09060-EXCHEM	67.0%
3	M-AM24B-ROCK, 9-09060-EXHEM	X-EXC-CARB	68.0%

Based on Table 5, the results of the 3-item set testing reveal three association rules with higher confidence values compared to the 2-item set, ranging from 64% to 68%. The highest value of 68% indicates a very strong relationship between the combination of *M-AM24B-ROCK* and *9-09060-EXCHEM* with respect to *X-EXC-CARB*. Statistically, this increase in confidence values indicates that a combination of more items is capable of producing association patterns that are more specific and accurate in describing consumer purchasing behavior.

Data Testing

During the testing phase, this study used sales transaction data from December 2016, comprising a total of 1,071 records. This data served as test data to evaluate the consistency and validity of the patterns generated during the training phase. Through the analysis process using the Apriori algorithm, a number of association rules were obtained, formed from combinations of two items (2-itemsets). The test results were then systematically presented in Table 6 as the basis for evaluating the model's performance.

Table 6. Rapidminer 2 itemset test results

No	Premises	Condusion	Confidence
			Apriori
1	8-08234-P99-A6NN1	9-09060-EXCHEM	79.0%
2	M-AM24B-ROCK	9-09060-EXCHEM	75.0%
3	X-EXC-CARB	9-09060-EXCHEM	72.0%
4	X-EXC-CARB	M-AM24B-ROCK	71.0%
5	M-AM24B-ROCK	X-EXC-CARB	63.0%
6	9-0823-P99-A6NN1	M-AM24B-ROCK	63.0%
7	9-09060-EXCHEM	M-AM24B-ROCK	62.0%

Based on Table 6, the 2-item-set testing results demonstrate seven association rules with confidence values ranging from 62% to 79%, reflecting generally strong relationships between items. The highest confidence value, 79%, highlights a particularly strong association between items 8-08234-P99-A6NN1 and 9-09060-EXCHEM. Statistically, the fact that most rules exceed 70% confidence indicates a high level of reliability and consistency in the identified patterns. Furthermore, the repeated appearance of item 9-09060-EXCHEM across multiple rules suggests its central or dominant role in transaction behavior. This dominance may indicate that the item is frequently co-purchased with others, making it strategically important for cross-selling, product bundling, and inventory optimization decisions.

Table 7. Rapidminer 3 itemset test results

No	Premises	Condusion	Confidence
			Apriori
1	8-08234-P99-A6NN 1, X-EXC-CARB	9-09060-EXCHEM	83.0%
2	8-08234-P99-A6NN 1, M-AM24B-ROCK	9-09060-EXCHEM	76.0%
3	M-AM24B-ROCK, X-EXC-CARB	9-09060-EXCHEM	76.0%
4	9-09060-EXCHEM, X-EXC-CARB	M-AM24B-ROCK	75.0%
5	9-09060-EXCHEM, M-AM24B-ROCK	X-EXC-CARB	63.0%
6	8-08234-P99-A6NN 1, 9-09060-EXCHEM	M-AM24B-ROCK	60.0%

Based on Table 7, the 3-item set test yielded six association rules with confidence values ranging from 60% to 83%. The highest value of 83% indicates a very strong relationship between the combination of items *8-08234-P99-A6NN1* and *X-EXC-CARB* and *9-09060-EXCHEM*. Statistically, most rules have a confidence level above 70%, indicating a high degree of reliability. Additionally, the item *9-09060-EXCHEM* reappears as the dominant consequent, highlighting its role as a central hub in consumer purchasing patterns.

IV. CONCLUSION

Based on the results of this study, it can be concluded that the application of the Apriori algorithm in analyzing vehicle spare parts transaction data is effective in identifying meaningful association patterns among products. Through the Association Rule Mining (ARM) approach, this research successfully generated association rules that reveal relationships between items frequently purchased together. The findings indicate that both training and testing datasets produce rules with relatively high confidence values, reaching up to 83% for 3-itemsets, reflecting strong and reliable patterns in consumer purchasing behavior. The recurring presence of specific items, particularly 9-09060-EXCHEM as a consequent, further highlights its central role in transaction patterns. From a methodological standpoint, systematic preprocessing steps such as data cleaning, transformation, and binary conversion significantly contribute to the quality and accuracy of the analysis. The careful selection of minimum support and confidence thresholds also ensures that only statistically relevant and meaningful rules are generated.

From a practical perspective, the implications of this study are highly valuable for business decision-making in the automotive spare parts sector. The identified association patterns can support strategic initiatives such as cross-selling, product bundling, store layout optimization, and more efficient inventory management. By leveraging insights into frequently co-purchased items, businesses can enhance sales performance and improve customer satisfaction through more targeted offerings. Additionally, these findings can serve as a foundation for developing recommendation systems based on historical transaction data. However, this study has limitations, particularly related to the high computational complexity of the Apriori algorithm and its focus on conventional ARM without incorporating additional dimensions such as time or customer segmentation. Therefore, future research is encouraged to explore more advanced approaches, including FP-Growth, Fuzzy ARM, and integration with machine learning, to produce more adaptive and comprehensive analytical models.

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