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Apriori Algorithm Analysis of Mattress Material Usage Data for Enhanced Production Optimization

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Abstract: Production is a value-adding process that transforms raw materials into finished products to meet manufacturing requirements. Association rule analysis serves as a methodological approach to identify relationships between items, particularly in transactional datasets. This analytical method has proven effective in processing exchange data patterns. Analysis of production material usage patterns revealed that when items A and B are utilized, there exists a 50% probability of concurrent item C usage - a significant pattern emerging from transactional data analysis. The study generated association rules for each operational process. Empirical testing through RapidMiner Studio yielded consistent results, demonstrating linear relationships proportional to the modeled scenarios, thereby validating the model's applicability as a decision-making reference. The evaluation of generated association rules through RapidMiner Studio revealed a Lift Ratio value of 1. These results indicate that combinations meeting or exceeding a Lift Ratio threshold of 1 demonstrate statistical validity and practical utility.

Keywords: Material; Mattress; Optimization; Data Mining; Apriori Algorithm.

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1. Introduction

Mattress production represents a complex manufacturing process that incorporates a diverse array of materials serving distinct functions as core components, comfort layers, and outer covers. Each material category possesses unique characteristics that fundamentally influence the mattress's comfort level, long-term durability, and market pricing structure. Based on comprehensive company documentation, daily production monitoring reveals persistent challenges, particularly pronounced during month-end inventory assessment periods. These difficulties are further compounded by non-systematic product placement protocols, significantly impacting material retrieval efficiency and overall operational workflow.

The current operational framework necessitates that the cushion department conduct advance fabric preparation procedures, coordinating with the fabric control section prior to scheduled production activities. This procedural requirement not only introduces potential inefficiencies but also frequently results in excess production quantities, creating inventory management challenges and resource allocation issues. These operational constraints highlight the critical need for systematic process optimization and strategic inventory management solutions.

Data Mining, as a sophisticated analytical approach, represents the systematic extraction and identification of valuable information patterns and knowledge frameworks from extensive databases. This methodological framework facilitates comprehensive knowledge discovery within complex database structures, enabling evidence-based decision-making processes [1]. To effectively address the identified production inefficiencies and develop robust strategic management decisions, this study employed advanced association rule methodology. This analytical approach systematically identifies frequently concurrent activities or transactions through the implementation of the apriori algorithm, enabling detailed analysis of data patterns within specified temporal frameworks using established interestingness measures [2].

Product placement patterns emerge as crucial determinants of sales performance metrics within retail environments. Effective merchandise arrangement strategies not only enhance customer experience but also significantly influence purchasing behaviors and overall sales potential. Suboptimal product layout management can substantially impede natural purchasing decisions and reduce cross-selling opportunities. The analytical framework generates sophisticated product combinations based on confidence thresholds - where higher minimum confidence values consistently yield more substantial combination sets, while elevated minimum support values produce increasingly specific and refined itemset selections [3].

In line with the dynamics of physical products, financial product sales patterns exhibit similar behavioral characteristics. In the banking sector, client preferences for financial products exhibit considerable flexibility, often changing in response to diverse product offerings across competing institutions. Organizations can optimize profitability metrics through the strategic implementation of data mining applications in product sales analysis. A priori algorithms enable the systematic identification of meaningful association rules, establishing reliable patterns in financial product sales to clients, and facilitating targeted marketing strategies [4]. This analytical approach provides a comprehensive framework for understanding and optimizing physical product placement and financial product marketing strategies. This research aims to leverage these methodological tools to increase operational efficiency, improve inventory management, and develop data-driven decision-making protocols for sustainable business growth.

2. Related Work

Data mining techniques in business analytics have attracted attention from researchers and practitioners across various fields. Sutrisno (2020) applied the Apriori algorithm to analyze banking product sales patterns at Bank Rakyat Indonesia, revealing specific transaction patterns that helped shape the bank's product development strategies [1]. His findings proved valuable for financial institutions seeking to understand customer behavior through data-driven approaches. Tana *et al*. (2018) advanced the application of Market Basket Analysis using the Apriori algorithm in retail environments. Their work at Toko Oase uncovered customer purchasing patterns and product relationships, leading to improvements in store layout and marketing decisions [3]. The results demonstrated practical benefits for retail managers looking to enhance their operational efficiency. The theoretical groundwork laid by Vulandari (2017) and Suyanto (2017) established clear methodological approaches for business data analysis [3][4]. Their publications serve as essential references for researchers and practitioners implementing data mining solutions. Adding to the knowledge base, Nofriansyah and Widi (2015) detailed testing procedures for data mining algorithms, strengthening the validation processes used in the field [6].

Within the retail sector, Sharif (2019) utilized data mining to predict effective sales promotion combinations through Market Basket Analysis. The research yielded practical guidelines for creating targeted promotional strategies [7]. In a similar vein, Najib and Suryani (2020) employed the Apriori algorithm to

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examine sales data from a traditional food business, showing how small enterprises could benefit from data mining techniques [10]. Recent trends show a move toward combining analytical methods. Silalahi *et al.* (2017) examined feature selection techniques for Support Vector Machine applications in credit risk assessment, opening new possibilities for multi-method approaches in data analysis [11]. Their work sparked interest in developing hybrid analytical solutions for complex business problems. This research takes a novel approach by applying data mining techniques to the mattress manufacturing process. While previous research has demonstrated the effectiveness of the Apriori algorithm in various business scenarios, this research addresses specific challenges in manufacturing operations and inventory management and provides practical solutions for production planning and resource allocation in the mattress industry, adding a new perspective to the existing knowledge of industrial data mining applications.

3. Research Method

The research methodology follows a structured approach to analyze and identify sales patterns. The process begins with data collection, where sales transaction records are systematically gathered and organized. Through careful preprocessing, the data undergoes cleaning, standardization, and validation to ensure accuracy and reliability for subsequent analysis. The analytical framework employs association rule mining techniques, specifically utilizing the Apriori algorithm to process sales data. This approach enables the discovery of meaningful patterns and relationships within transaction records. The methodology incorporates several key phases, starting with raw data preparation and moving through pattern identification to final analysis and interpretation. Data processing involves transforming raw sales information into a format suitable for mining operations. The Apriori algorithm then examines this processed data to uncover frequent itemsets and generate association rules [9]. These rules reveal patterns in customer purchasing behavior and product relationships. Sample calculations using selected data subsets help validate the analytical process and demonstrate the practical application of the methodology. The research stages ensure a systematic progression from initial data collection through final pattern analysis. Each stage builds upon previous steps, creating a cohesive analytical framework that supports the study's objectives. This methodical approach allows for thorough examination of sales patterns while maintaining scientific rigor throughout the research process.

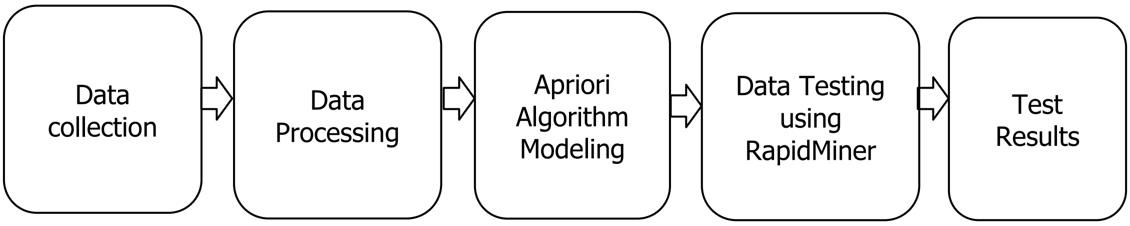

Figure 1. Research Stages

This study uses association rule techniques and stages in data mining sales data apriori algorithm, data processing and which will be used as sample data calculations in this study.

4. Result and Discussion

4.1 Results

4.1.1 Testing on RapidMiner Studio Application

In this process, association methods and Apriori algorithms are applied to find the relationship of itemsets with the right accuracy. In this study, testing is performed using the RapidMiner Studio application, with the following steps:

1) In the RapidMiner Studio application, import the required data by clicking Import Data, then select the tabular dataset to be used.
2) Click the Design menu, and in the process view, add the tabular dataset from the folder to the process view window.
3) Add the Numerical to Binomial function operator (to convert binary to binomial numbers) and drag it to the process view.
4) To apply the frequency item, select the FP-Growth function operator in the Associations submenu, then drag it to the process display window.
5) In the FP-Growth function operator parameters, set the minimum Support value to 0.95 (95%). You can also determine the minimum and maximum number of itemsets for creating k-itemset combinations.

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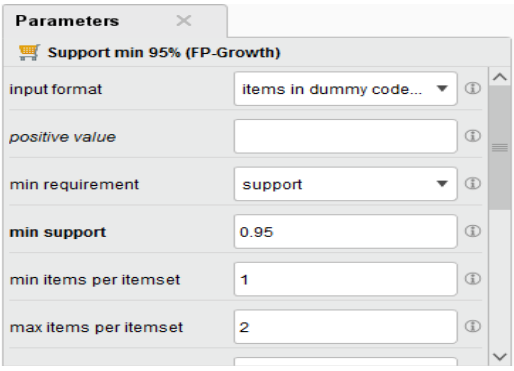

Figure 2. FP-Growth function operator parameters

6) To create an association rule, select the Create Association Rule function operator and drag it to the process view.
7) Set parameters in the Create Association Rule function operator, specifically the Min. Confidence value. In this test, the Confidence value is set to 0.95 (95%). For other parameters, use the RapidMiner Studio application defaults.

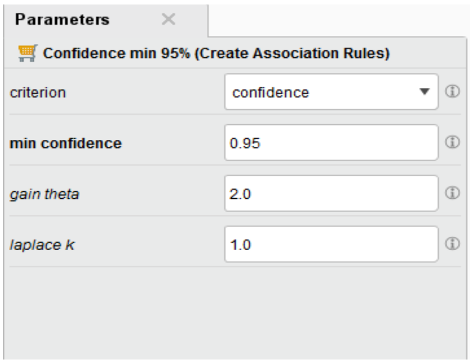

Figure 3. Parameters of the Create Association Rule function operator

8) Connect all function operators so that the display in the process window is as follows:

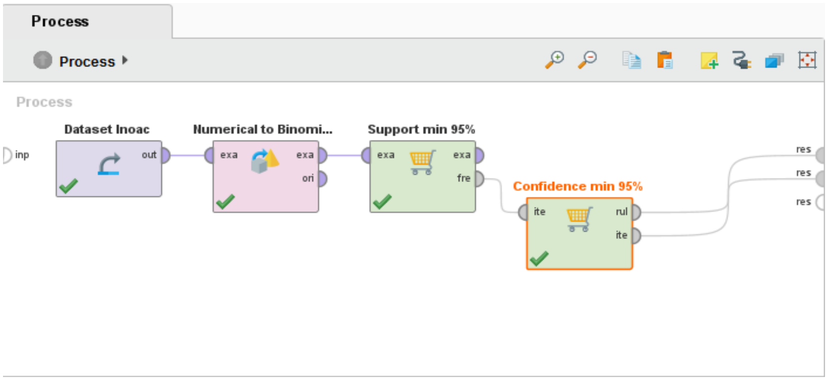

Figure 4. RapidMiner Process

9) The results of the Association rules formation from testing on the RapidMiner Studio application can be seen in the following image:

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AssociationRules

```
Association Rules
[ARCOL 3553] --> [VORANOL 4701] (confidence: 0.983)
[GLYCERIN] --> [VORANOL 4701] (confidence: 0.983)
[LV33] --> [VORANOL 4701] (confidence: 0.983)
[1-5309] --> [VORANOL 4701] (confidence: 0.983)
[ARCOL 3553] --> [GLYCERIN] (confidence: 1.000)
[GLYCERIN] --> [ARCOL 3553] (confidence: 1.000)
[ARCOL 3553] --> [LV33] (confidence: 1.000)
[LV33] --> [ARCOL 3553] (confidence: 1.000)
[ARCOL 3553] --> [1-5309] (confidence: 1.000)
[1-5309] --> [ARCOL 3553] (confidence: 1.000)
[VORANOL 4701] --> [ARCOL 3553] (confidence: 1.000)
[GLYCERIN] --> [LV33] (confidence: 1.000)
[LV33] --> [GLYCERIN] (confidence: 1.000)
[GLYCERIN] --> [1-5309] (confidence: 1.000)
[1-5309] --> [GLYCERIN] (confidence: 1.000)
[VORANOL 4701] --> [GLYCERIN] (confidence: 1.000)
[LV33] --> [1-5309] (confidence: 1.000)
[1-5309] --> [LV33] (confidence: 1.000)
[VORANOL 4701] --> [LV33] (confidence: 1.000)
[VORANOL 4701] --> [1-5309] (confidence: 1.000)
```

Figure 5. Formation of association rules in the RapidMiner Studio application

4.1.2 Analysis of Results

After conducting an experiment on the application of the association method and the Apriori algorithm in finding patterns of association rules for the relationship between material items in historical data on the use of production materials, association rules can be produced from each process carried out. The dataset used contains 2,500 data records and consists of 13 items that will be tested in the process of forming association rules with the Apriori algorithm. Through testing using the RapidMiner Studio application, a minimum support value of 0.95 (95%) and a minimum confidence of 0.95 (95%) are applied. In the first stage, the process of calculating the support value for each item results in only 5 items out of 13 items in the dataset that meet the requirements for the specified minimum support value:

1) ARCOL 3553 with a support value of 1.00 (100%)
2) GLYCERIN with a support value of 1.00 (100%)
3) LV33 with a support value of 1.00 (100%)
4) I-5309 with a support value of 1.00 (100%)
5) VORANOL 4701 with a support value of 0.983 (98.3%)

These five items form a set of k-1 itemsets and will be candidates for the combination search in the next process, namely k-2 itemsets.

Table 1. Number of k-1 itemsets that meet the min. support value requirement in the RapidMiner Studio application

Item 1	Support
ARCOL 3553	1.000
GLYCERIN	1.000
LV33	1.000
I-5309	1.000
VORANOL 4701	0.983

In the calculation of support for the combination of k-2 itemsets, this test produces 10 combinations of itemsets, and all combinations meet the requirements in achieving the specified minimum support value. The following is an image of the test results on the RapidMiner Studio application.

Table 2. K-2 itemset that meets the min. support value requirement in the RapidMiner Studio application

Support	Item 1	Item 2
1.000	ARCOL 3553	GLYCERIN
1.000	ARCOL 3553	LV33
1.000	ARCOL 3553	I-5309
0.983	ARCOL 3553	VORANOL 4701
1.000	GLYCERIN	LV33

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1.000	GLYCERIN	I-5309
0.983	GLYCERIN	VORANOL 4701
1.000	LV33	I-5309
0.983	LV33	VORANOL 4701
0.983	I-5309	VORANOL 4701

From the 10 combinations of k-2 itemsets, it is possible to form 20 association rules from each item. Furthermore, to determine the strength of the relationship between each item, in this testing stage the minimum confidence value is set to 0.95 (95%) in the RapidMiner Studio application. The first combination group, which is related to item ARCOL 3553, has an average support value of 99.6% and a confidence value of 100.0% with details as shown in the following figure.

Table 3. Association rules for ARCOL 3553 item

Premises	Conclusion	Support	Confidence	Lift
GLYCERIN	ARCOL 3553	1	1	1
LV33	ARCOL 3553	1	1	1
I-5309	ARCOL 3553	1	1	1
VORANOL 4701	ARCOL 3553	0.983	1	1

The graph below also shows how each item relates to the ARCOL 3553 item.

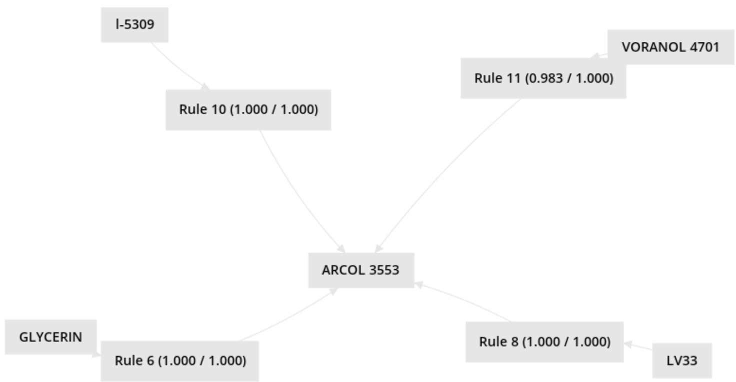

Figure 6. Association rule graph for ARCOL 3553 item

In the second group, the combination related to the GLYCERIN item has an average support value of 99.6% and a confidence value of 100.0% with details as shown in the following image.

Table 4. Association rules for the GLYCERIN item

Premises	Conclusion	Support	Confidence	Lift
ARCOL 3553	GLYCERIN	1	1	1
LV33	GLYCERIN	1	1	1
I-5309	GLYCERIN	1	1	1
VORANOL 4701	GLYCERIN	0.983	1	1

The graph below also shows how each item is related to the GLYCERIN item.

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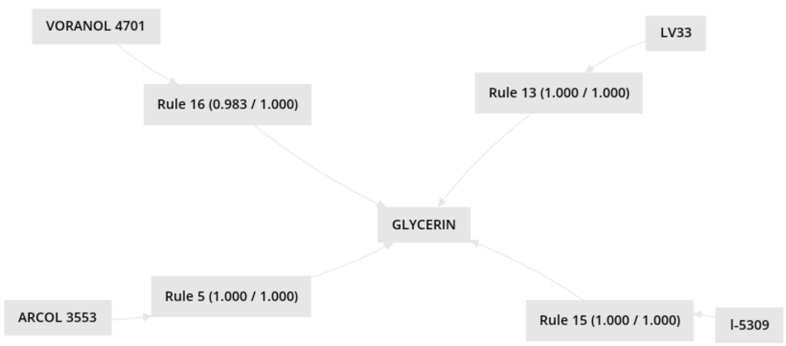

Figure 7. Association rule graph for GLYCERIN item

Next, in the third combination group related to the LV33 item, it has an average support value of 99.6% and a confidence value of 100.0% with details as shown in the following image.

Table 5. Association rules for LV33 item

Premises	Conclusion	Support	Confidence	Lift
ARCOL 3553	LV33	1	1	1
GLYCERIN	LV33	1	1	1
I-5309	LV33	1	1	1
VORANOL 4701	LV33	0.983	1	1

The graph below also shows how each item relates to the LV33 item.

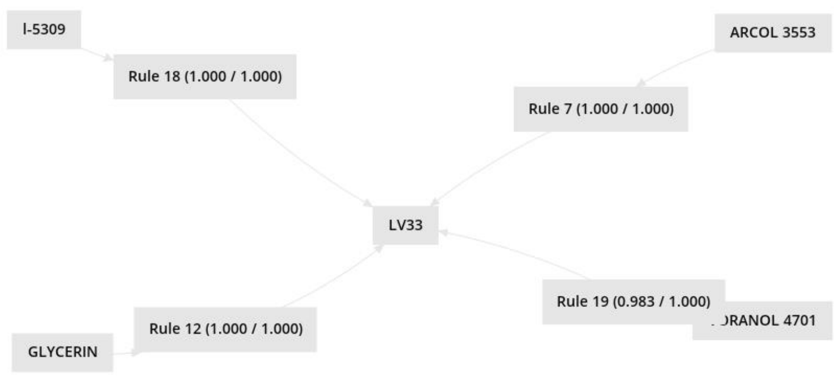

Figure 8. Association rule graph for LV33 item

Furthermore, the fourth combination group related to item I-5309 has an average support value of 99.6% and a confidence value of 100.0% with details as shown in the following image.

Table 6. Association rules for I-5309 item

Premises	Conclusion	Support	Confidence	Lift
ARCOL 3553	I-5309	1	1	1
GLYCERIN	I-5309	1	1	1
LV33	I-5309	1	1	1
VORANOL 4701	I-5309	0.983	1	1

The graph below also shows how each item relates to the I-5309 item.

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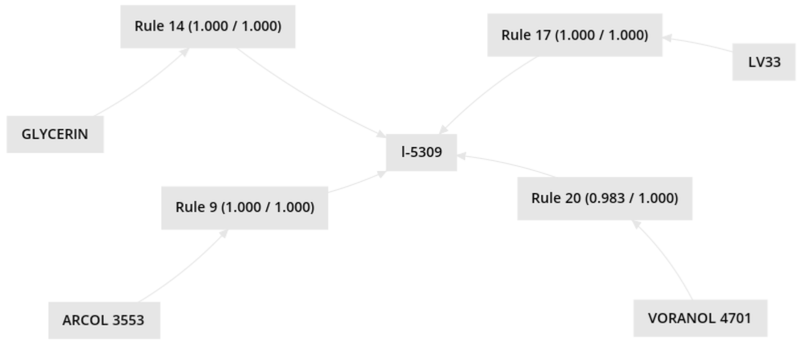

Figure 9. Association rule graph for I-5309 item

In the last or fifth combination group related to the VORANOL 4701 item, it has an average support value of 99.6% and a confidence value of 99.6% with details as shown in the following image.

Table 7. Association rules for VORANOL 4701 item

Premises	Conclusion	Support	Confidence	Lift
ARCOL 3553	VORANOL 4701	0.983	0.983	1
GLYCERIN	VORANOL 4701	0.983	0.983	1
LV33	VORANOL 4701	0.983	0.983	1
I-5309	VORANOL 4701	0.983	0.983	1

The graph below also shows how each item relates to the VORANOL 4701 item.

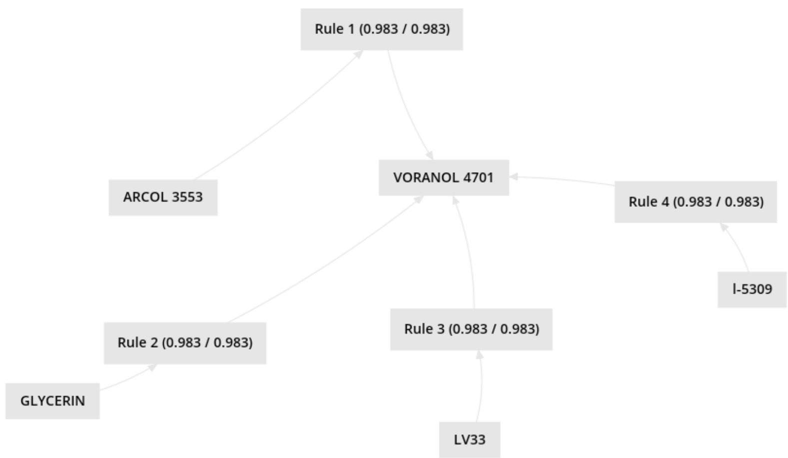

Figure 10. Association rule graph for VORANOL 4701 item

Thus, from the existing dataset of 2,500 records after going through the data mining process with the association method and the application of the Apriori algorithm, a new insight can be produced: 5 items are often used together in production, namely VORANOL 4701, ARCOL 3553, GLYCERIN, I-5309, and LV33. These items have a fairly close relationship with each other, considering that each combination between these items has a fairly good confidence value.

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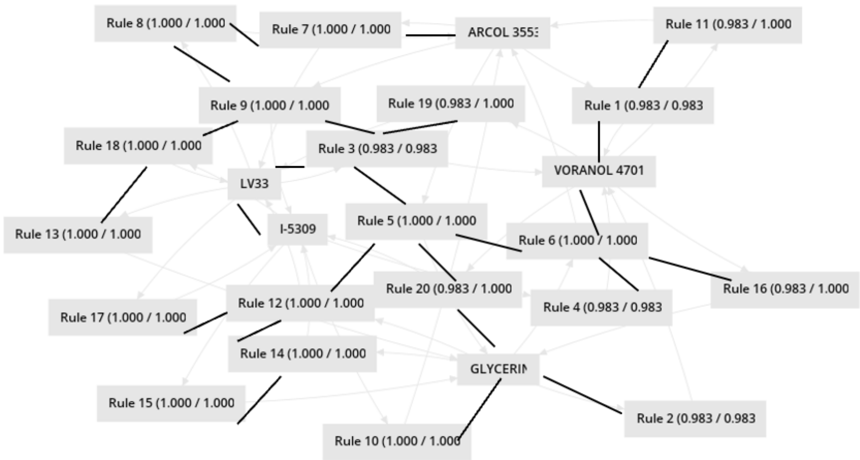

Figure 11. Association rule graph in RapidMiner Studio application

4.1.3 Model Evaluation

Evaluation and validation of the model is carried out by measuring the analysis results to determine the Lift Ratio value. From all the association rules formed, in the evaluation test of the model using the RapidMiner Studio application, the Lift Ratio value is 1. Thus, according to the applied model, if the Lift Ratio value is ≥ 1, then the resulting combination is valid and has benefits. Details of the lift ratio results can be seen in the following table.

Table 8. Lift Ratio Results on RapidMiner Studio Application

Premises	Conclusion	Support	Confidence	Lift Ratio
ARCOL 3553	VORANOL 4701	0.9828	0.9828	1.0
GLYCERIN	VORANOL 4701	0.9828	0.9828	1.0
LV33	VORANOL 4701	0.9828	0.9828	1.0
I-5309	VORANOL 4701	0.9828	0.9828	1.0
ARCOL 3553	GLYCERIN	1.0	1.0	1.0
GLYCERIN	ARCOL 3553	1.0	1.0	1.0
ARCOL 3553	LV33	1.0	1.0	1.0
LV33	ARCOL 3553	1.0	1.0	1.0
ARCOL 3553	I-5309	1.0	1.0	1.0
I-5309	ARCOL 3553	1.0	1.0	1.0
VORANOL 4701	ARCOL 3553	0.9828	1.0	1.0
GLYCERIN	LV33	1.0	1.0	1.0
LV33	GLYCERIN	1.0	1.0	1.0
GLYCERIN	I-5309	1.0	1.0	1.0
I-5309	GLYCERIN	1.0	1.0	1.0
VORANOL 4701	GLYCERIN	0.9828	1.0	1.0
LV33	I-5309	1.0	1.0	1.0
I-5309	LV33	1.0	1.0	1.0
VORANOL 4701	LV33	0.9828	1.0	1.0
VORANOL 4701	I-5309	0.9828	1.0	1.0

4.2 Discussion

This research applies association methods and the Apriori algorithm to analyze patterns of production material usage based on historical data. From testing using the RapidMiner Studio application with a dataset of 2,500 records consisting of 13 items, important findings were obtained that can be utilized for production process optimization. According to Suyanto, data mining with the Apriori algorithm is an effective technique for finding association patterns between items in large datasets [5]. In the initial stage, the process of calculating support values for each item resulted in only 5 items out of 13 items in the dataset meeting the specified minimum support requirement (0.95 or 95%). These five items are ARCOL 3553, GLYCERIN, LV33, I-5309, and VORANOL 4701. This aligns with Sutrisno's research which states that determining the appropriate minimum support value is very important for identifying itemsets that frequently appear in the dataset [1]. From the 5 items that meet the minimum support value, 10 k-2 itemset combinations were formed, all of which meet the minimum support value requirements. Furthermore, from these 10 combinations, 20 association rules can be formed with very high confidence values, namely 100% for most combinations. According to Dicky Nofriansyah and Widi, high confidence values indicate the strength of relationships between items in association rules [6]. The high confidence values in this research indicate that if one item appears in the production process, then other items will also appear with a very high probability. Model evaluation using the Lift Ratio value shows that all formed association rules have a Lift Ratio value = 1. Vulandari explains that a Lift Ratio value = 1 indicates that the occurrence of items in the antecedent and consequent parts is independent, but still has a positive correlation [4].

The findings of this research have important practical implications for inventory management and procurement planning. The five materials (ARCOL 3553, GLYCERIN, LV33, I-5309, and VORANOL 4701) are critical materials that must always be available in sufficient quantities to ensure smooth production processes. This is in line with Tana *et al.*'s research which shows that market basket analysis can help in inventory arrangement and purchase planning [3]. The procurement department can plan the purchase of these five materials simultaneously or in one package, given the high level of association between materials. By knowing that these five materials are almost always used together, companies can optimize warehouse layout and workflow to facilitate access and use of these materials. As stated by Sharif, the results of association analysis can be used to optimize item placement and improve operational efficiency [7]. Although this research successfully identified strong association patterns between items, the Lift Ratio value = 1 indicates that there is no strong dependency relationship between items. Further research could explore datasets with Lift Ratio values > 1 to find more meaningful associations, as suggested by Haris in his research on the Apriori algorithm [9]. Additionally, the very high support and confidence values (almost 100%) indicate that these five items are almost always used in every production process. Further research could lower the minimum support value to identify association patterns for items that are not used as frequently, in accordance with the recommendations of Najib and Suryani in the application of data mining for sales analysis [10].

Kurniadi and Novianto (2020) in their research stated that the linear regression method can be used to predict customer habits, which can also be applied to predict the use of production materials [12]. This can be an alternative or complementary approach to the association analysis conducted in this study. The implementation of the trend moment method for predicting sales of goods, as done by Susatyono *et al.*, (2024) can also provide additional information about the pattern of production material usage from a time series perspective [13]. This approach can help identify seasonal or cyclical trends in material usage that may not be detected by association analysis. Panggabean *et al.* (2020) applied multiple linear regression to predict tree seedling orders, a technique that can be adapted to predict production material needs based on various factors [14]. Similarly, Rizky *et al.* (2019) implemented data mining to predict target stock usage using the multiple linear regression method, which is relevant to the inventory optimization objective in this study [15]. Gaol *et al.* (2019) showed how the implementation of data mining with the multiple linear regression method can be used to predict inventory data, which can be applied to production material inventory management [16]. Wibisono *et al.* (2019) describe the use of multiple linear regression analysis in various research contexts, including operations and supply chain management [17], and Purwadi *et al.* (2019) apply data mining to estimate growth rates using multiple linear regression methods, which can be adapted to estimate the growth in production material requirements over time [18].

5. Conclusion

The results of the application of the Apriori algorithm can produce rules that meet the minimum support value and also the minimum confidence, so in this case the use of the Apriori algorithm is considered appropriate because it is able to optimize the association method process in obtaining various possible rules for the association of items to the use of raw materials for production materials. Testing using the RapidMiner Studio application also produces similar insights, where the results are linear and directly proportional to the model scenario carried out so that the model is quite valid if it is used as an alternative reference for decision making. Of all the association rules formed, in the model evaluation test using the RapidMiner Studio application, the Lift Ratio value = 1. Thus, the applied model if the Lift Ratio value is >= 1 then the resulting combination is valid and has benefits.

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