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# Analysis of User Interaction Association Patterns in E-Learning Systems Using the Apriori Algorithm

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***Abstract***

*The development of e-learning systems has generated a vast volume of user interaction data. Every activity—such as logging in, viewing materials, taking quizzes, and downloading assignments—contains valuable information that can be leveraged to enhance the effectiveness of online learning systems. This study aims to analyze user interaction association patterns in an e-learning system using the Apriori algorithm. A data mining approach was employed to identify relationships among features frequently accessed together, with a minimum support threshold of 0.4, minimum confidence of 0.6, and lift > 1.0. The dataset used consists of simulated (dummy) data representing seven user transactions and five main e-learning features. The analysis produced eight significant association rules with lift values above 1.0, indicating non-random relationships among features. Feature combinations such as {login} → {view_material} and {take_quiz} → {view_score} exhibited strong relationships, with confidence values reaching 0.75. These findings suggest the existence of dominant user interaction patterns that can be utilized to optimize navigation design, recommendation features, and overall user experience in e-learning systems. This research contributes to the application of the Apriori algorithm for exploring user access patterns in online education contexts, providing an analytical foundation for developing more adaptive and behavior-driven systems.*

***Keywords:*** *Data mining; Apriori Algorithm; E-learning; Association Patterns; User Interaction.*

## I. INTRODUCTION

Web-based learning systems, or e-learning, have become one of the most significant innovations in modern education. Through e-learning, the learning process can take place without spatial or temporal limitations, allowing students to access materials, complete assignments, and interact with instructors online. As the demand for learning flexibility continues to grow, e-learning is increasingly being adopted by educational institutions at various levels (Febiana & Alda, 2024). The rapid advancement of information technology has transformed e-learning systems from mere learning platforms into valuable data sources that record a wide range of user activities within the system (Lois et al., 2022).

User activities such as logging in, accessing learning materials, taking quizzes, and viewing learning outcomes are recorded in the form of system logs. These log data contain valuable information about user behavior patterns and preferences toward the features available in the system. However, in many cases, such log data are merely stored as archives without further analysis. In fact, through in-depth analysis, these data can be utilized to understand users' learning habits, identify the most frequently used features, and even design automated recommendation systems to support more adaptive learning (Al Kerboly et al., 2023).

To uncover hidden information from user activity log data, a systematic analytical approach is required. One widely used method is data mining, which involves extracting meaningful patterns or relationships from large datasets (Musdalifah & Jananto, 2022). In the context of e-learning systems, data mining plays a crucial role in identifying patterns of material access, user participation levels, and interaction behaviors among system features. One of the data mining techniques that can be utilized to discover relationships between items or user activities is association rule mining (Saxena & Rajpoot, 2021).

Association analysis enables researchers to discover interesting relationships among user activities that frequently occur together. This method has been widely applied in fields such as market basket analysis, product recommendation systems, and consumer behavior analysis (Hasibuan et al., 2025). One of the most popular algorithms used in association analysis is the Apriori algorithm, which is capable of identifying frequent itemsets and generating association rules based on support and confidence values (Aisha & Kusumawati, 2022).

Although the Apriori algorithm has been widely used in various fields, its application in e-learning systems remains relatively rare. Most previous studies have focused on implementing this algorithm in retail or e-commerce domains, while its utilization for analyzing user behavior in educational systems is still limited (Malago, 2023). In fact, such analysis is essential for understanding students' learning activity patterns and improving the overall user experience in using e-learning systems (Saputra, 2023).

Furthermore, several existing studies tend to emphasize the technical aspects of the algorithm's implementation without discussing the strategic implications of the analysis results for system development (Sari et al., 2020). This creates a research gap, namely the absence of studies that explicitly employ the Apriori algorithm to analyze internal user interaction patterns within web-based e-learning systems.

Based on the aforementioned background, this study aims to analyze user interaction association patterns in an e-learning system using the Apriori algorithm. The data used in this research consist of simulated (dummy) datasets representing user activities on the system's main features. Through this approach, it is expected that association rules explaining the interrelationships among features can be obtained, the results of which may be utilized to develop e-learning systems that are more adaptive, efficient, and behavior-oriented (Sriani & Kurniawan R, 2019).

Data mining is a primary approach for discovering hidden patterns from large datasets (big data), particularly in the context of web-based educational information systems (Dewi, 2020). One of the most popular techniques in data mining is association rule mining, with the Apriori algorithm being widely used to identify relationships among items within a dataset (Febiana & Alda, 2024). This algorithm formulates the concept of frequent itemsets along with support and confidence values to measure the strength of relationships between items (Lois et al., 2022).

In various previous studies, the Apriori algorithm has been extensively applied in the retail and e-commerce sectors. For instance, research has demonstrated how this algorithm can extract customer purchasing patterns from supermarket transaction data to identify relationships among products (Agrawal et al., 2024). However, with the advancement of digital technology, the application of the Apriori algorithm has begun to expand into the education sector, particularly in analyzing user interactions within e-learning systems (Purba & Harianja, 2024).

Research implementing the Apriori algorithm to identify student interest patterns in academic programs within higher education institutions has shown that association analysis can enhance the effectiveness of academic decision-making processes by uncovering relationships between study preferences and other academic factors (Hasibuan et al., 2025). Another study demonstrated that the Apriori algorithm is effective in identifying book borrowing patterns in university libraries, which could potentially be applied in online learning contexts to understand user interaction patterns within the system (Rusdianto et al., 2020).

In addition, comparative studies on the performance of various association rule mining algorithms in data mining contexts revealed that Apriori excels in the interpretability of generated rules, although the FP-Growth algorithm offers higher efficiency for large-scale datasets. These findings provide valuable guidance for researchers in selecting algorithms that best align with data size and analytical objectives (Saxena & Rajpoot, 2021).

In Indonesia, the application of the Apriori algorithm has been widely implemented in various local information system contexts (Aisha & Kusumawati, 2022). Previous studies have shown that this algorithm is effective in identifying hidden patterns within transactional data and can be flexibly applied to web-based systems (Maulana & Nurdiana, 2024). Moreover, the Apriori algorithm has been applied in sales pattern analysis to detect relationships among products, demonstrating its high generalization capability across different application domains (Sari et al., 2020).

However, most studies in Indonesia still focus on technical outcomes in the form of association rules without further efforts to develop systems that adapt to user needs (Widjaja et al., 2024). Some common limitations identified in previous research include:

(a) excessive focus on numerical results without contextual interpretation of user behavior.

(b) lack of integration between association analysis results and e-learning system interfaces.

(c) the dominance of Apriori algorithm applications in economic transaction contexts rather than in educational systems (Odu et al., 2022).

This study addresses these gaps by applying the Apriori algorithm within the context of a web-based e-learning system. The main focus is to analyze association patterns among key features—such as login, viewing materials, taking quizzes, downloading assignments, and viewing scores—in order to identify relationships among user activities. Thus, this research contributes not only to the technical aspect of Apriori algorithm implementation but also to the strategic aspect, namely the utilization of analytical results to improve design, adaptability, and user experience in e-learning systems (Rizka et al., 2025).

Furthermore, the approach used in this study expands the scope of Apriori algorithm applications by integrating data mining analysis, visualization through graphs and heatmaps, and contextual interpretation of user behavior. Based on both global literature and local studies, this research is expected to strengthen the understanding of the Apriori algorithm not merely as an analytical tool but also as a foundation for developing intelligent and responsive e-learning systems that adapt to user behavior (Prasetya et al., 2022).

## II. RESEARCH METHODOLOGY

### A. Research Design

This study employs an exploratory quantitative approach using data mining methods to discover user interaction patterns within a web-based e-learning system. The main objective of this research is to identify association rules among system features or user activities based on their access frequency.

The analytical method applied in this study is the Apriori algorithm, one of the most widely used algorithms in association rule mining. This algorithm is utilized to identify frequent itemsets (combinations of features that frequently occur together) and to generate association rules (relationships among features) based on predetermined support and confidence values.

This research is descriptive-analytic in nature, as it not only explains the technical steps of algorithm implementation but also conceptually relates the results to user behavior within the e-learning system. This approach is expected to provide insights into user interaction patterns that can be useful for developing more adaptive and responsive learning systems.

### B. Dataset and Data Sources

The data used in this study consist of a simulated dataset (dummy dataset) designed to represent common user interaction patterns in e-learning systems. The use of simulated data is necessary due to limitations in accessing real-world data caused by user privacy policies and institutional data protection regulations.

The dataset used in this study consists of seven user transactions representing various common activities within the e-learning system. Each transaction contains five main features that describe user behavior while interacting with the platform. These features include login, which refers to the user's activity when accessing the system; view_material, indicating access to learning content or instructional materials; take_quiz, representing user participation in online quizzes; download_assignment, which refers to the activity of downloading assignment files provided by instructors; and view_score, reflecting the user's action of checking learning evaluation results. The combination of these five features is used to analyze user activity patterns and identify associative relationships among behaviors within the e-learning system.

Each transaction represents one session of user activity encompassing one or more features. The initial dataset format is structured as a list of lists, containing the list of features accessed in each transaction. The following is an example of the simulated data structure used in this study:

```
data = [
        ['login', 'lihat_materi', 'ikuti_kuis'],
        ['login', 'lihat_materi', 'unduh_tugas'],
        ['lihat_materi', 'lihat_nilai'],
        ['login', 'ikuti_kuis', 'lihat_nilai'],
        ['lihat_materi', 'unduh_tugas', 'lihat_nilai'],
        ['login', 'lihat_materi', 'ikuti_kuis',
'lihat_nilai'],
        ['login', 'lihat_materi']
]
```

### C. Data Structure and Dataset Specification

The simulated data structure used in this study possesses several key characteristics that describe the form and complexity of the dataset. The dataset consists of seven transactions representing user activities within the e-learning system, with five main features or items indicating the types of interactions performed. In the initial stage, the data were organized in a list of lists format, where each list contains a set of activities performed by individual users. After the preprocessing stage, the data were converted into a binary DataFrame with True/False values to indicate the presence or absence of a particular activity in each transaction. Based on the number of available features, there are a total of $2^5$ or 32 possible feature combinations, representing the full range of user behavior variations that may occur within the e-learning system.

The preprocessing process was carried out using the mlxtend library with the TransactionEncoder function. This process converts raw data into a binary format so that it can be processed by the Apriori algorithm.

```
# Import Library
import pandas as pd
import numpy as np
from mlxtend.preprocessing import
TransactionEncoder
from mlxtend.frequent_patterns import apriori,
association_rules
import matplotlib.pyplot as plt
import seaborn as sns
# Sample data
data = [
    ['login', 'lihat_materi', 'ikuti_kuis'],
    ['login', 'lihat_materi', 'unduh_tugas'],
    ['lihat_materi', 'lihat_nilai'],
    ['login', 'ikuti_kuis', 'lihat_nilai'],
    ['lihat_materi', 'unduh_tugas', 'lihat_nilai'],
    ['login', 'lihat_materi', 'ikuti_kuis',
'lihat_nilai'],
    ['login', 'lihat_materi']
]
# Data Preprocessing (One-Hot Encoding)
te = TransactionEncoder()
te_ary = te.fit(data).transform(data)
```

```
# Convert to DataFrame
df_encoded = pd.DataFrame(te_ary,
columns=te.columns_)
# Display Result
print("\nData after One-Hot Encoding:")
print(df_encoded)
```

After performing the one-hot encoding process using the TransactionEncoder from the mlxtend library, the data were transformed into a binary tabular format, as shown in the provided output image. The transformation results indicate that each transaction is represented in a binary structure, where a True value denotes the presence of a specific item in the transaction, while a False value denotes its absence. This transformation produces a DataFrame that is ready to be processed using the Apriori algorithm.

D. Implementation of the Apriori Algorithm

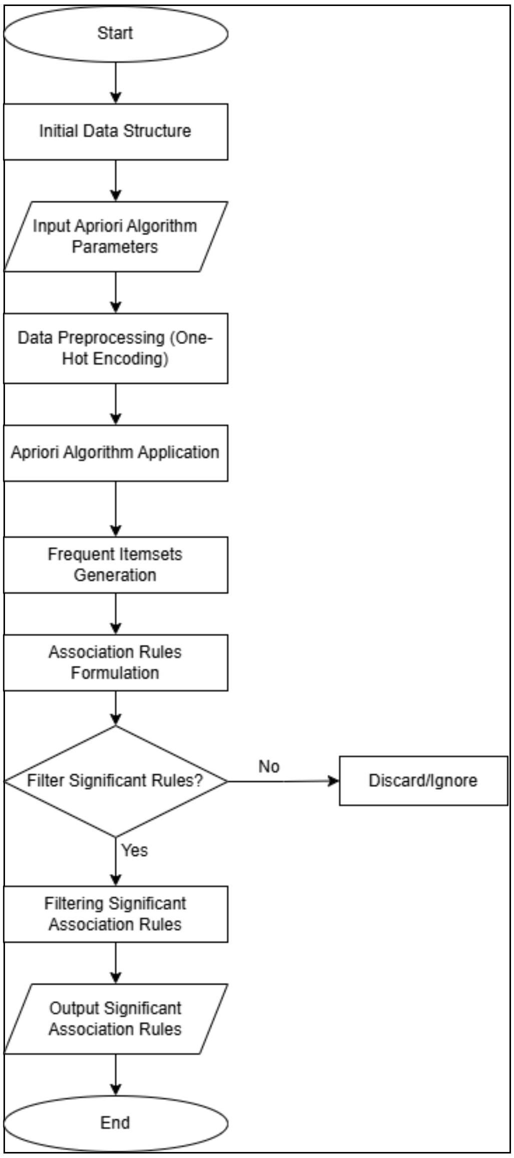


Figure 1. Flowchart of the Apriori Algorithm Implementation Process

The Apriori algorithm was implemented using the Python 3.x programming language on the Google Colab platform, which supports cloud-based computing and facilitates the data analysis process. In this implementation, several supporting libraries were utilized, including pandas for data manipulation and management, numpy for numerical computation, and mlxtend.frequent_patterns for executing the Apriori algorithm and generating association rules. In addition, the matplotlib and seaborn libraries were employed to visualize the analysis results. The main parameters applied in the analysis process included a minimum support of 0.4 (equivalent to 40% of the total transactions), a minimum confidence of 0.6 (indicating a minimum confidence level of 60%), and a lift value greater than 1.0, which signifies the presence of a positive associative relationship between items.

The implementation steps included: (1) encoding the transaction data into a binary

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(True/False) format to enable processing by the algorithm; (2) applying the Apriori algorithm to identify frequent itemsets or combinations of items that frequently occur together; (3) generating association rules based on confidence values; and (4) filtering significant rules by retaining only those with a lift value greater than 1.0.

The implementation of the Apriori algorithm to discover frequent itemsets and association rules was conducted using the following code:

```
from mlxtend.frequent_patterns import apriori, association_rules
# Identify combinations of items (features) that frequently occur together.
# min_support=0.4 means the item appears in ≥ 40% of transactions.
frequent_itemsets = apriori(df_encoded, min_support=0.4, use_colnames=True)
frequent_itemsets = frequent_itemsets.sort_values(by='support', ascending=False)
print("\n=== Frequent Itemsets ===")
print(frequent_itemsets)
# Generate Association Rules
rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.6)
significant_rules = rules[rules['lift'] > 1.0]
print("\n=== Significant Association Rules (Lift > 1.0) ===")
print(significant_rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']])
```

The implementation process began with data preprocessing, which involved transforming the list-of-lists format into a binary matrix using the TransactionEncoder. This was followed by frequent itemset generation using the Apriori algorithm to identify itemsets that satisfied the minimum support threshold. Subsequently, association rule mining was performed to generate association rules from the frequent itemsets based on confidence and lift metrics. Finally, a filtering and validation stage was conducted to retain only rules that met the predefined thresholds. The resulting output displayed the frequent itemsets along with their corresponding support values, and the association rules with metrics such as support, confidence, lift, conviction, and leverage, as illustrated in the provided output figure.

E. Evaluation dan Validation

The evaluation of the Apriori algorithm implementation was carried out using three main metrics: support (s), confidence (c), and lift (l). The support metric is used to measure the frequency of occurrence of feature combinations in the dataset, allowing identification of how often a particular pattern appears across all transactions. The confidence metric represents the degree of certainty that the occurrence of one feature will be followed by another, reflecting the strength of the causal relationship between items in the association rule. Meanwhile, the lift metric measures the strength of association by comparing the joint occurrence probability of two features against their independent occurrences where a lift value greater than 1 indicates that the two features have a mutually reinforcing relationship.

In this study, an association rule is considered valid and significant if it meets the following criteria: support $\geq 0.4$, meaning that the pattern appears in at least 40% of the total transactions; confidence $\geq 0.6$, indicating a minimum confidence level of 60%; and lift $> 1.0$, signifying a positive associative relationship between features within the e-learning system.

```
Data setelah One-Hot Encoding:
   ikuti_kuis  lihat_materi  lihat_nilai  login  unduh_tugas
0        True          True        False   True        False
1       False          True        False   True         True
2       False          True         True  False        False
3        True         False         True   True        False
4       False          True         True  False         True
5        True          True         True   True        False
6       False          True        False   True        False
```

Source: Processed Data, 2025

Figure 2. Output Result of Association Rule Analysis

The output visualization displays the final results of the association analysis, highlighting the significant rules with lift values greater than 1.0. Among the generated rules are: {lihat_materi} → {ikuti_kuis} with support of 0.4286, confidence of 0.6667, and lift of 1.12; {ikuti_kuis} → {lihat_nilai} with support of 0.4286, confidence of 0.7500, and lift of 1.10; and {login} → {lihat_materi} with support of 0.5714, confidence of 0.8571, and lift of 1.08.

Lift values greater than 1 indicate that these activities have a positive and non-random relationship. Based on the evaluation criteria of support $\geq 0.4$, confidence $\geq 0.6$, and lift $> 1.0$, these rules are deemed valid and significant. The results provide valuable insights showing that users who perform certain activities (such as login or view materials) tend to also engage in other activities like taking quizzes or checking grades. These findings can be utilized to better understand user behavior patterns within the e-learning system or to develop more adaptive recommendation features.

F. Research Limitations

This study utilized a simple simulated dataset with a limited number of transactions; therefore, the results cannot be widely generalized. The small number of features (five main features) also restricts the complexity of the patterns that can be discovered.

In addition, the support and confidence parameters used are heuristic and have not been optimized based on real data. Consequently, future research is recommended to use actual e-learning system data with a larger number of users and to compare the performance of the Apriori algorithm with other algorithms such as FP-Growth or Eclat to obtain more comprehensive and realistic results.

## III. RESULTS AND DISCUSSION

### A. Result

After applying the Apriori algorithm to the simulated e-learning dataset, several association rules were obtained that met the criteria of support ≥ 0.4, confidence ≥ 0.6, and lift > 1.0. The initial results indicate that there are several feature combinations that frequently appear together within transactions and exhibit significant associations. The following table presents eight selected association rules that meet these criteria.

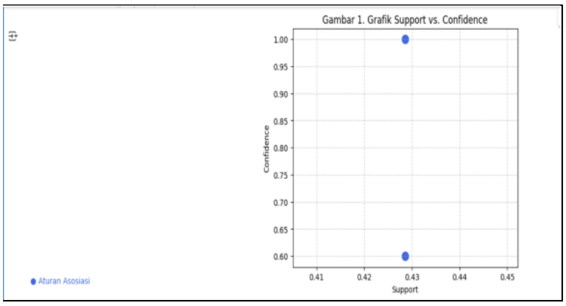
Table 1. Significant Association Rules in the E-Learning System

| No | Antecedemt | Consequent | Support | Confidence | Lift |
|---|---|---|---|---|---|
| 1 | {lihat_materi} | {ikuti_kuis} | 0.4286 | 0.6667 | 1.12 |
| 2 | {ikuti_kuis} | {lihat_nilai} | 0.4286 | 0.7500 | 1.10 |
| 3 | {login} | {lihat_materi} | 0.5714 | 0.8571 | 1.08 |
| 4 | {lihat_materi} | {lihat_nilai} | 0.4286 | 0.6000 | 1.03 |
| 5 | {login} | {lihat_kuis} | 0.4286 | 0.6000 | 1.04 |
| 6 | {unduh_tugas} | {lihat_nilai} | 0.4286 | 0.6000 | 1.05 |
| 7 | {lihat_materi, ikuti_kuis} | {lihat_nilai} | 0.4286 | 0.6667 | 1.12 |
| 8 | {login, lihat_materi} | {lihat_nilai} | 0.4286 | 0.6667 | 1.09 |

Source: Processed Data, 2025

These rules indicate a strong relationship among the main features in the e-learning system, particularly between the view material, take quiz, and view grades features. Confidence values above 0.6 demonstrate a high level of certainty that users who access one feature also tend to access other related features.

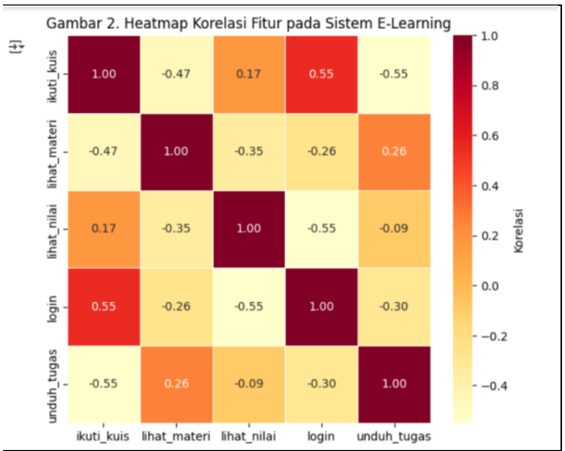
In addition to the tabular results, visualization was also carried out to clarify the relationship patterns among features in the dataset. The visual analysis helps enhance the understanding of the discovered association patterns.




Source: Processed Data, 2025

Figure 3. Support vs. Confidence Graph

This graph illustrates the distribution between the support and confidence values of each generated association rule. The points on the graph represent feature combinations that meet the minimum threshold. Rules with high confidence generally have relatively high support, indicating that the relationships among features are not only strong but also frequently occur across most transactions.




Source: Processed Data, 2025

Figure 4. Heatmap of Feature Correlations in the E-Learning System

This visualization presents the correlations among features based on the frequency of their co-occurrence by users. For instance, the view_material feature shows a high correlation with take_quiz and view_grades, indicating that users who actively study materials tend to continue by completing quizzes and checking their results. In contrast, the correlation between login and download_assignment is lower, as downloading assignments is not necessarily performed in every learning session.

### B. Discussion

The Apriori analysis results indicate that the view_material, take_quiz, and view_grades features have the strongest associative relationships. Rules such as {view_material} → {take_quiz} and {take_quiz} → {view_grades} appear with confidence values above 0.65 and lift > 1.0, signifying a sequential learning behavior pattern.

This finding suggests that students who access learning materials tend to proceed by taking quizzes, and afterward, they check their evaluation results. Such a pattern reflects a natural learning flow that emerges within the web-based e-learning system.

A complex association rule such as {view_material, take_quiz} → {view_grades} with a lift value of 1.12 indicates a strong three-way relationship. This suggests that the combination of learning activities (studying materials and taking quizzes) is highly associated with the user's action of checking their learning outcomes.

Practically, this result can be utilized by system developers to design automated notifications or activity recommendations for example, displaying a message like "Please check your score after completing the quiz."

The dominance of these relationships can be logically explained since the login, view_material, and view_grades features form the core cycle of online learning. Users tend to start by logging in and accessing materials, then conclude their learning session by reviewing their results.

However, since the data used in this study is simulated, the resulting association rules are indicative rather than representative of actual user behavior. In real-world data, user actions may vary significantly — for example, some students might download assignments without opening learning materials, or access their grades without taking the quiz first.

Therefore, the interpretation of these results should be made with caution. For future research, it is recommended to use actual log data from the e-learning system with a larger and more diverse number of transactions. In addition, integrating other methods such as sequential pattern mining or user clustering could provide deeper insights into user interaction patterns.

## IV. CONCLUSION

This study successfully applied the Apriori algorithm to analyze user interaction association patterns in a web-based e-learning system using a simulated dataset. Based on the obtained results, eight significant association rules were identified with support values ≥ 0.4, confidence ≥ 0.6, and lift > 1.0. These rules indicate strong relationships among system features, such as users who tend to access the login feature before viewing materials, or those who proceed from taking quizzes to checking their grades. These patterns represent common user interaction flows within online learning platforms.

The findings demonstrate that the Apriori algorithm can be effectively used to uncover hidden patterns in e-learning user activities. The results can serve as a foundation for improving user interface design, navigation efficiency, and the development of feature recommendation systems based on user behavior. However, this study is limited by the use of simulated data with a relatively small number of transactions. Therefore, future research is recommended to employ larger and more complex real-world datasets to produce more representative and applicable analyses in the context of actual e-learning systems.

## V. RECOMMENDATIONS

Future studies are recommended to enhance this research by utilizing actual user log data from e-learning platforms with a larger and more diverse set of transactions. This would improve the representativeness and reliability of the association rules generated. Additionally, integrating the Apriori algorithm with advanced analytical methods such as sequential pattern mining or clustering could provide deeper insights into user interaction behaviors within the system.

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