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Implementation of Agile Method and Apriori Algorithm for Recommendation System in Outdoor Equipment Rental Services

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Abstract

Drop Outdoor Purwokerto faces inefficiencies in its outdoor equipment rental process, where customers are required to visit the store directly to check item availability, often resulting in miscommunication and suboptimal transaction management. To address this issue, this study aims to design and develop a web-based outdoor equipment rental information system that enables real-time availability checking and efficient online booking. The system is developed using the Agile methodology to accommodate dynamic user requirements and iterative system improvements. In addition, the Apriori algorithm is implemented to analyze historical rental transaction data and generate item recommendations based on association rule mining. The analysis results indicate that several outdoor equipment items exhibit strong association patterns, with the highest lift value exceeding 1, signifying meaningful relationships beyond random co-occurrence. These patterns are utilized as the basis for the recommendation feature within the system. Functional testing using Black Box Testing shows that all system features operate as expected, achieving a 100% success rate across tested scenarios, including transaction processing, cart management, and recommendation display. The findings demonstrate that integrating the Agile development approach with Apriori-based data mining can effectively support data-driven decision-making in outdoor equipment rental services. This study contributes to the development of recommendation systems for small and medium-sized rental businesses by highlighting the practical application of association rule mining on rental transaction data, which exhibits characteristics distinct from conventional retail datasets.

Keywords : *Agile Method, Apriori Algorithm, Outdoor Equipment Rental System, Recommendation System.*

1. INTRODUCTION

The increasing popularity of outdoor recreational activities has led to significant growth in demand for outdoor equipment rental services. In Indonesia, this trend is particularly evident among urban communities seeking cost-efficient access to camping and hiking equipment without the need for ownership. Drop Outdoor Purwokerto is one such rental service provider offering various equipment, including tents, sleeping bags, stoves, and hiking accessories [1], [2]. However, despite the growing demand, many small-scale rental businesses still rely on manual transaction and inventory management processes, which limits operational efficiency and service quality.

One of the main challenges faced by outdoor equipment rental services is the lack of real-time access to item availability and transaction information. Customers are often required to visit the store physically to confirm availability, which can result in miscommunication, booking conflicts, and sudden order cancellations [3], [4]. From the service provider's perspective, manual inventory tracking and fragmented transaction records increase the risk of data inconsistency and reduce the ability to analyze customer behavior effectively. Previous studies have shown that limited information transparency and inefficient transaction management can negatively affect customer satisfaction and business sustainability [3].

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A web-based rental information system offers a potential solution to these challenges by enabling real-time inventory monitoring, automated transaction recording, and centralized data management [5], [6]. Beyond operational efficiency, transaction data generated by such systems can be utilized to extract valuable insights into customer rental behavior. Unlike conventional retail transactions, outdoor equipment rental data exhibits unique characteristics: transactions are usage-based rather than ownership-based, items are often rented in functional combinations (e.g., tents with stoves or ground mats), and rental duration plays a significant role in transaction structure. These characteristics differentiate rental-based datasets from typical retail purchase data and require contextual interpretation.

Association rule mining, particularly using the Apriori algorithm, has been widely applied in retail environments to identify co-purchase patterns and support recommendation systems. However, many existing studies focus on static retail datasets and treat the algorithm as a standalone analytical component. Limited attention has been given to the application of Apriori in rental-based transaction contexts, especially within small and medium-sized enterprises (SMEs), where transaction volumes are moderate and system integration plays a crucial role in operational decision-making [7], [8], [9].

This study addresses this gap by implementing the Apriori algorithm within a fully integrated, web-based outdoor equipment rental system developed using the Agile methodology. Rather than merely applying Apriori as an analytical add-on, this research emphasizes seamless integration between live transaction processing and association-rule analysis. Transaction data generated through real user interactions is directly utilized to form frequent itemsets and association rules, which are then translated into actionable product recommendations within the system interface [7], [8], [9].

The novelty of this research lies in two key aspects. First, it explores the application of association-rule mining in a rental-based outdoor equipment domain, where item combinations are driven by activity needs rather than impulsive buying behavior. Second, it demonstrates a practical, end-to-end system implementation in which recommendation logic is dynamically derived from transaction data and made accessible to both users and administrators. By combining Agile-based system development with integrated data mining, this study aims to improve rental management efficiency, reduce miscommunication, and support data-driven decision-making for small-scale outdoor equipment rental services [7], [8], [9].

2. METHOD

This study employs a combination of data mining and software engineering approaches to develop a web-based outdoor equipment rental system with an integrated recommendation feature. The Apriori algorithm is utilized to extract association patterns from rental transaction data, while the Agile methodology is applied to support adaptive system development. The Apriori Algorithm is applied to discover associative patterns am The Apriori Algorithm is a data mining technique used to identify association rules from a set of transactional data. The analysis is conducted by identifying frequent itemsets, which are combinations of items that frequently appear together, based on two main parameters: support (the frequency of occurrence of an item combination within all transactions) and confidence (the probability that an item will be purchased along with another item)[10].

The Apriori Algorithm is applied to discover associative patterns among items within transaction data. The Apriori process consists of several main stages[10]:

a. Preprocessing Data

This stage is conducted prior to executing the Apriori Algorithm. The purpose is to ensure that transaction data is properly prepared for the association analysis. Several procedures are typically carried out, including:

1. Data Cleaning: Removing duplicate, incomplete, or irrelevant transaction records.

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2. Data Transformation: Converting transaction data into a suitable format, such as item-based transaction structures where each record represents one transaction containing a list of purchased items.
3. Item Normalization: Standardizing product name formatting to ensure consistency in the Item Name field before being processed by the Apriori algorithm. This step is essential because minor differences in spelling, capitalization, or phrasing may cause the system to treat identical items as distinct entities.
4. For instance, transaction data may contain variations such as "sepatu tracking", "Sepatu Tracking", and "sepatu Tracking", all referring to the same product. Without normalization, the algorithm will treat these entries as separate items, leading to inaccurate association analysis.

Final Dataset Preparation: Structuring data into itemsets to facilitate further processing by the Apriori algorithm.

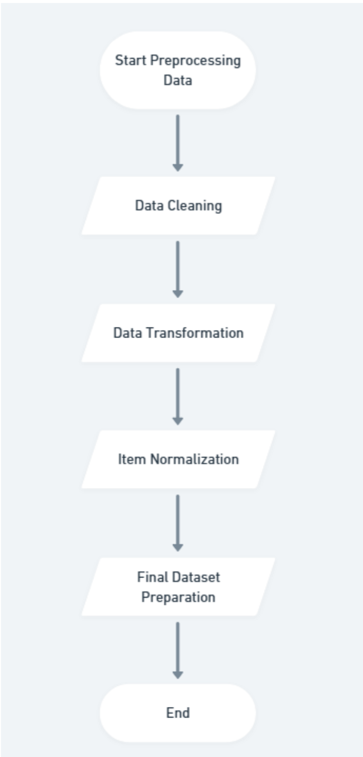

Figure 1. Data Preprocessing Flow Diagram

b. Formation of Frequent Itemsets
Determining itemsets that meet the minimum support threshold using the following formula:

$$Support\ (\mathrm{A}) = \frac{Number\ of\ Transactions\ Containing\ A}{Total\ Number\ of\ Transactions} \quad (1)$$

c. Formation of Association Rules
From the frequent itemsets, association rules are generated that meet the minimum confidence threshold using the following formula:

$$Confidence\ (\mathrm{A} \rightarrow \mathrm{B}) = \frac{Support\ (A \cup B)}{Support\ (A)} \quad (2)$$

Where A is the antecedent and B is the consequent.

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d. *Lift* Determination

Lift is used to measure the strength of the association between item A and item B. If the lift value is greater than 1, the relationship between A and B is considered positive, meaning they frequently appear together.

$$Lift\ (A \rightarrow B) = \frac{Support\ (A \cup B)}{Support\ (A)\ x\ Support\ (B)} \quad (3)$$

e. Rule Evaluation

The generated rules are evaluated to determine the strength of the relationships between the associated items.

The Agile methodology is a software development approach that emphasizes flexibility, collaboration, and iterative and incremental development[11]. This approach enables the development team to quickly adapt to changes in user requirements and conduct repeated evaluations at each stage of development. The stages of the Agile method applied in this research include:

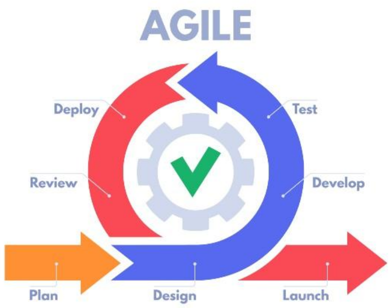

Figure 2. Agile Flow Diagram

a. Planning: Determining the system's functional and non-functional requirements, including identifying key features such as transaction management and product recommendation.
b. Design: Developing the system interface design and database structure that supports transaction data processing.
c. Development: Implementing the system in stages based on feature priority, such as the login module, item management, rental transactions, and integration of the Apriori algorithm.
d. Testing: Conducting testing on each module to ensure the system functions according to user requirements and that product recommendations align with transaction patterns.
e. Review and Iteration: Evaluating test results to improve deficiencies before proceeding to the next stage.

With the Agile approach, the system development process can be carried out more adaptively to changes in user requirements, resulting in a more responsive system that aligns with real-world usage contexts[11].

3. RESULTS

This section presents the research results, including the system design stages, system development using the Agile method, and the implementation of the Apriori algorithm in transaction data analysis. The research findings are presented in the form of descriptions, tables, and figures to illustrate the performance of the developed system. System development using the Agile method provides flexibility in iterative improvement, enabling system refinements based on stakeholder feedback[12]. Agile-based development has also been shown to improve collaboration and accelerate value delivery on software

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projects, especially in small-scale industries[13]. Furthermore, the implementation of the Apriori algorithm successfully generated association patterns between rental products that frequently appear together within transactions, supporting the development of relevant product recommendation features[14]. This analytical approach aligns with current trends in data-driven decision-making to enhance operational services and business performance[15].

3.1. Results of Apriori Algorithm Implementation

This web-based outdoor equipment procurement system is designed not only to manage inventory and process rental transactions but also to analyze customer purchasing or rental patterns. The analysis utilizes the Apriori algorithm to identify relationships among products that are frequently rented together. The implementation of the Apriori algorithm involves several stages, including the formation of frequent itemsets, calculation of support, and the creation of association rules. The results of this analysis are used to provide product recommendations to users based on previous transaction patterns. Consequently, the system functions not only as a transaction management platform but also as a decision-support tool for promotion strategies and inventory management. Recent studies have shown that Apriori-based analysis is effective in discovering co-purchase patterns and supporting recommendation and bundling features in transaction systems[16], [17], [18].

3.1.1. Transaction Dataset

The transaction data were extracted from the rental transaction records of Drop Outdoor Purwokerto for the period October–November 2024. The dataset consists of 245 rental transactions stored in CSV format. Each transaction record contains a transaction ID, rental date, and a set of rented items. This dataset was preprocessed and used as the input for association rule mining using the Apriori algorithm.

Table 1. Transaction Sample Data on October 2024

Tanggal Transaksi	Hari	Jenis Transaksi	Nama Barang	Jumlah	Harga per Hari	Durasi (Hari)	Tanggal Kembali	Total Harga
2024-10-01	Tuesday	Sewa	Tenda 6p	1	60.000	1	2024-10-02	60.000
2024-10-01	Tuesday	Sewa	Sepatu Tracking uk 40	1	20.000	1	2024-10-02	20.000
2024-10-01	Tuesday	Sewa	Sepatu Tracking uk 38	1	20.000	3	2024-10-04	60.000
2024-10-01	Tuesday	Sewa	Tas Carrier 45L	1	20.000	2	2024-10-03	40.000
2024-10-01	Tuesday	Sewa	Sepatu Tracking uk 38	1	20.000	1	2024-10-02	20.000
2024-10-01	Tuesday	Sewa	Headlamp	1	5.000	1	2024-10-02	5.000
2024-10-01	Tuesday	Sewa	Headlamp	3	-	-	-	135.000
2024-10-01	Tuesday	Sewa	Matras	2	-	-	-	80.000
2024-10-01	Tuesday	Sewa	Sleeping Bag	2	-	-	-	300.000
2024-10-01	Tuesday	Sewa	Sepatu Tracking uk 38	1	20.000	2	2024-10-04	40.000

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3.1.2. *Data Pre Processing*

Before applying the Apriori algorithm, the transaction data was preprocessed to ensure quality and consistency so that the resulting associations would be valid. The process began by reading the CSV file, which uses a semicolon (;) as the delimiter. The column parsing was configured accordingly, and the date column was converted to the datetime type. A snippet of the raw data is shown in Figure 3.1, representing the initial dataset format before cleaning. Next, data cleaning was performed by removing duplicate rows and entries with missing critical values, such as missing item names or transaction dates, as these could interfere with the calculation of itemset frequencies and reduce the quality of the resulting rules. Proper data preprocessing has been shown to be essential in association-rule mining implementations to avoid misleading patterns and ensure valid rule extraction[19].

index	Tanggal Transaksi;Hari;Jenis Transaksi;Nama Barang;Jumlah;Harga per Hari;Durasi (Hari);Tanggal Kembali;Total Harga
0	2024-10-01;Tuesday;Sewa;Tenda 6p;1;60000;1;2024-10-02;60000
1	2024-10-01;Tuesday;Sewa;Sepatu Tracking uk 40;1;20000;1;2024-10-02;20000
2	2024-10-01;Tuesday;Sewa;Sepatu Tracking uk 38;1;20000;3;2024-10-04;60000
3	2024-10-01;Tuesday;Sewa;Tas Carrier 45L;1;20000;2;2024-10-03;40000
4	2024-10-01;Tuesday;Sewa;Sepatu Tracking uk 38;1;20000;1;2024-10-02;20000

Show 25 per page

Figure 3. Dataset Before Preprocessing Stage

The transaction data for October 1, 2024, shows that several items were rented on that day under the transaction type 'Rental'. On this date, users rented various outdoor equipment items, including a 6P Tent for one day, Tracking Shoes size 40, Tracking Shoes size 38, and a 45L Carrier Bag. Each transaction was recorded with complete details, including the quantity of items, the rental price per day, and the return date. For example, renting the 6P Tent was charged at IDR 60,000 per day for 1 day, so the total price was calculated as quantity × price per day × duration. The rental patterns on this date indicate that users tend to rent multiple items in a single transaction, especially equipment that is used together during outdoor activities, such as tents, hiking footwear, and supporting gear. This transaction data later serves as input to the Apriori algorithm to analyze product associations.

The next step is product name normalization to standardize the format of item categories. Normalization involves removing extra spaces, trimming whitespace at the beginning or end, converting capitalization to a consistent format (e.g., Title Case), and applying manual mapping for spelling variations or abbreviations (e.g., tenda 6p → Tenda 6P, sepatu tracking uk38 → Sepatu Tracking Uk 38). This normalization process is crucial because the Apriori algorithm treats each unique string as a separate item. If a product is written inconsistently, it will be considered a different item, leading to inaccurate support and confidence values and biased association outcomes. Proper data preprocessing and normalization have been identified as essential steps in data-mining pipelines to ensure valid association rule results[20], [21]. The normalized dataset is shown in Figure 3.2, ready for the frequent itemset formation stage.

	Tanggal Transaksi	Hari	Jenis Transaksi	Nama Barang	Jumlah	Harga per Hari	Durasi (Hari)	Tanggal Kembali	Total Harga
0	2024-10-01	Tuesday	Sewa	Tenda 6p	1	60000.0	1.0	2024-10-02	60000
1	2024-10-01	Tuesday	Sewa	Sepatu Tracking uk 40	1	20000.0	1.0	2024-10-02	20000
2	2024-10-01	Tuesday	Sewa	Sepatu Tracking uk 38	1	20000.0	3.0	2024-10-04	60000
3	2024-10-01	Tuesday	Sewa	Tas Carrier 45L	1	20000.0	2.0	2024-10-03	40000
4	2024-10-01	Tuesday	Sewa	Sepatu Tracking uk 38	1	20000.0	1.0	2024-10-02	20000

Figure 4. Dataset After the Normalization Stage

After ensuring data consistency, the next step is to transform and aggregate the data into a transaction format, where each transaction is represented as a single row containing a list of rented items. In this dataset, each Transaction Date is treated as a unique transaction, so all items with the same date are combined into one itemset entry. This approach is used because the dataset does not provide a

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specific transaction ID. However, in future implementations, if a specific transaction ID is available (e.g., Invoice Number or Receipt ID), grouping should be based on that ID to avoid merging different transactions that happen to occur on the same date.

This process results in a data structure in the form of a list of lists, where each list element represents a single transaction containing the set of items rented together. This format is essential for processing frequent itemsets using the Apriori algorithm, as it analyzes co-occurrence within transactions rather than individual items. An example of the aggregated structure is shown in Figure 3.3 as the final dataset before support calculation begins.

	Tanggal Transaksi	Barang yang Disewa
0	2024-10-01	[Tenda 6P, Sepatu Tracking Uk 40, Sepatu Track...
1	2024-10-02	[Sepatu Tracking Uk 38, Sepatu Tracking Uk 40,...
2	2024-10-03	[Matras, Tas Carrier 60L, Tas Mini 12L, Tas Mi...
3	2024-10-04	[Matras, Tenda 6P, Gas Refill, Sepatu Tracking...
4	2024-10-05	[Tenda 6P, Jaket Outdoor L, Jaket Outdoor L, M...

Figure 5. Dataset After Transformation into Transaction Format

Before applying the algorithm, each itemset is also cleaned from internal duplicates (for example, if an item appears multiple times in a single transaction due to input errors, only one occurrence is considered for the association analysis), because Apriori counts presence rather than quantity. This step ensures that the support calculation reflects the proportion of transactions containing the itemset, rather than the number of units sold.

The final preprocessing step is to encode the data in a binary format (one-hot encoding) using a transaction encoder, where each column represents a unique item, and each row represents a transaction with Boolean values (True/False or 1/0). This binary matrix format is required by many Apriori implementations (e.g., the mlxtend library) to efficiently compute item combination frequencies. A snippet of the encoded matrix is shown in Figure 3.4. The use of one-hot encoding as a transformation step before association rule mining has been shown in recent research to be effective and necessary for correct frequent itemset generation[22].

During the entire preprocessing stage, intermediate output files (e.g., transaksi_cleaned.csv and transaksi_encoded.csv) were also generated for documentation and reproducibility, as shown in Figure 3.5. Additionally, brief statistical checks—such as the total number of final transactions, the number of unique items, and the item frequency distribution—were conducted to verify that the preprocessing objectives were met. In this study's dataset (October–November 2024), preprocessing yielded 245 clean transactions with n unique items, ready for Apriori analysis.

With this preprocessing workflow, the quality of input data for the Apriori algorithm is ensured: normalization reduces item-name fragmentation, aggregation by transaction preserves the shopping cart context, and encoding formats the data for correct support and confidence calculations. These steps are crucial because inconsistencies or dirty data would produce misleading frequent itemsets and association rules, rendering them ineffective for business decision-making[23].

	Baterai	Cooking Set	Flysheet 3x5	Gas Camping	Gas Refill	HT	Hamoock	Headlamp	Jaket Outdoor L	Jaket Outdoor M	...	Sepatu Tracking uk 40	Sepatu Tracking uk 42	Sleeping Bag	Tas Carrier 45L	Tas Carrier 60L	Tas Daypack 20L	Tas Mini 12L	Tenda 2p	Tenda 4p	Tenda 6p
0	False	False	False	False	False	False	False	True	False	False	...	True	False	True	True	False	False	False	False	False	True
1	False	False	False	True	False	False	False	True	False	False	...	True	False	False	False	False	False	False	False	False	True
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	True	True	False	True	False	False	False
3	False	False	False	False	True	False	False	False	False	False	...	False	True	False	False	False	False	False	False	False	True
4	True	False	False	False	False	False	False	True	True	False	...	False	False	True	False	False	False	True	False	False	True

5 rows × 27 columns

Figure 6. Dataset After Transformation into Binary Format

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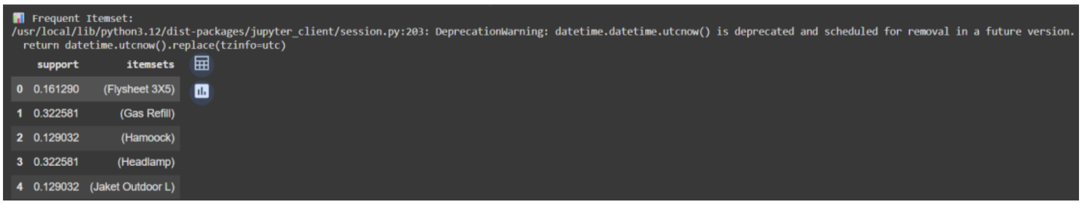
	Tanggal	Transaksi	Itemset
0	2024-10-01		[Tenda 6P, Sepatu Tracking Uk 40, Sepatu Track...
1	2024-10-02		[Sepatu Tracking Uk 38, Sepatu Tracking Uk 40,...
2	2024-10-03		[Matras, Tas Carrier 60L, Tas Mini 12L, Tas Mi...
3	2024-10-04		[Matras, Tenda 6P, Gas Refill, Sepatu Tracking...
4	2024-10-05		[Tenda 6P, Jaket Outdoor L, Jaket Outdoor L, M...

Figure 7. Final Dataset After Preprocessing Stage

3.1.3. *Frequent Itemset*

This stage represents the initial step in applying the Apriori algorithm after the transaction data has been converted into binary form. The objective is to identify item combinations that most frequently occur together in outdoor equipment rental transactions. This process involves calculating the support value for each item or item combination.



```
Frequent Itemset:
/usr/local/lib/python3.12/dist-packages/jupyter_client/session.py:203: DeprecationWarning: datetime.datetime.utcnow() is deprecated and scheduled for removal in a future version.
  return datetime.utcnow().replace(tzinfo=utc)
```

	support	itemsets
0	0.161290	(Flysheet 3X5)
1	0.322581	(Gas Refill)
2	0.129032	(Hamoock)
3	0.322581	(Headlamp)
4	0.129032	(Jaket Outdoor L)

Figure 8. Frequent Itemset

The support value represents the proportion or frequency of an item's occurrence relative to the total number of transactions and is calculated using the formula:

$$Support\ (A)\ = \frac{Number\ of\ Transactions\ Containing\ A}{Total\ Number\ of\ Transactions} \qquad (4)$$

The higher the support value, the more frequently the item appears in transactions. Items with support values exceeding the minimum support threshold are retained as frequent itemsets. Based on the calculations, the five items with the highest support values are presented in the following table:

Table 2. Frequent Itemset

No	Itemset	Support
1	Flysheet 3x5	0.161290
2	Gas Refill	0.322581
3	Hamoock	0.1229032
4	Headlamp	0.322581
5	Jaket Outdoor L	0.129032

From the table above, it can be seen that the items "Gas Refill" and "Headlamp" have the highest support value of 0.322581, meaning that approximately 32% of all transactions include the rental of these two products. This indicates that these items have high demand and are frequently rented by customers.

Meanwhile, the items "Hamoock," "Flysheet 3x5," and "Outdoor Jacket L" have lower support values, ranging between 12 and 16%. Although they are not as popular as the first two items, their support values still indicate that these products are rented relatively often and can be included in subsequent association rules.

These frequent itemsets provide an initial overview of the products customers favor most. This information can be used to determine stock levels or the number of units to prepare, identify opportunities for rental bundles (e.g., Headlamp + Gas Refill), and develop promotion strategies based

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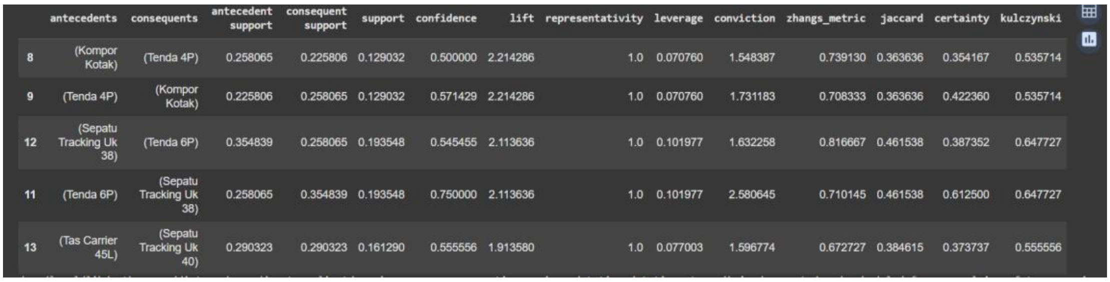
on products that are often used together. The use of association-rule mining in Indonesian retail contexts has proven effective for informing stock planning, bundle offerings, and marketing strategies based on actual transaction patternsIm[24].

3.1.4. *Asociation Rules*

The next stage after forming frequent itemsets is generating association rules. The purpose of this stage is to identify relationships between products that frequently appear together in a single transaction. Association rules are represented in the form of implications:

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

which can be interpreted as: if a customer rents item A, they are likely to rent item B as well. In this analysis, each rule is evaluated using several key metrics, including support, confidence, and lift.



	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_metric	jaccard	certainty	kulczynski
8	(Kompor Kotak)	(Tenda 4P)	0.258065	0.225806	0.129032	0.500000	2.214286	1.0	0.070760	1.548387	0.739130	0.363636	0.354167	0.535714
9	(Tenda 4P)	(Kompor Kotak)	0.225806	0.258065	0.129032	0.571429	2.214286	1.0	0.070760	1.731183	0.708333	0.363636	0.422360	0.535714
12	(Sepatu Tracking Uk 38)	(Tenda 6P)	0.354839	0.258065	0.193548	0.545455	2.113636	1.0	0.101977	1.632258	0.816667	0.461538	0.387352	0.647727
11	(Tenda 6P)	(Sepatu Tracking Uk 38)	0.258065	0.354839	0.193548	0.750000	2.113636	1.0	0.101977	2.580645	0.710145	0.461538	0.612500	0.647727
13	(Tas Carrier 45L)	(Sepatu Tracking Uk 40)	0.290323	0.290323	0.161290	0.555556	1.913580	1.0	0.077003	1.596774	0.672727	0.384615	0.373737	0.555556

Figure 9. Asociation Rules

Based on the calculations, several of the strongest association rules were obtained, as shown in the following table:

Table 3. Asociation Rules

No	Antecedent	Consequent	Support	Confidence	Lift
1	Kompor Kotak	Tenda 4P	0.129032	0.500000	2.214286
2	Tenda 4P	Kompor Kotak	0.129032	0.571429	2.214286
3	Sepatu Tracking UK 38	Tenda 6P	0.193548	0.545455	2.113636
4	Tenda 6P	Sepatu Tracking UK 38	0.193548	0.750000	2.113636
5	Tas Carrier 45L	Sepatu Tracking UK 40	0.161290	0.555556	1.913580

The results above indicate that:

a. The rule (Tenda 6P → Sepatu Tracking Uk 38) has a confidence of 0.75 and a lift of 2.11, meaning that approximately 75% of customers who rent a Tenda 6P also rent Sepatu Tracking Uk 38. A lift value greater than 2 indicates a strong, significant relationship between the two items.
b. Similarly, the rule (Tenda 4P → Kompor Kotak) and its reverse show a lift of 2.21, indicating a high interrelation between these two products—customers who rent a Tenda 4P often also require a Kompor Kotak for camping activities.
c. The rule (Tas Carrier 45L → Sepatu Tracking Uk 40) has a lift close to 1.9, showing that renting a Tas Carrier is often accompanied by renting Sepatu Tracking, although the strength of this association is slightly lower compared to the first two rules.

Overall, these association rules reveal customer behavior patterns in renting outdoor equipment. This information can be utilized by the service provider to:

a. Offer bundled rental packages (e.g., Tenda + Kompor Kotak or Tenda 6P + Sepatu Tracking).
b. Design strategies for product placement in displays or implement automatic recommendation systems on the rental website/application.

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c. Determine stock procurement priorities based on product associations.

Thus, applying the Apriori algorithm to the outdoor equipment rental dataset provides valuable insights into customer rental patterns and supports data-driven business decision-making.

3.2. *Implementation Results of the Website*

The website implementation results indicate that the outdoor equipment rental system successfully processes transactions directly through the web interface. During testing, several product rentals—such as tents, tracking shoes, and headlamps—were simulated through the catalog page. Each successfully processed transaction is automatically recorded in the database, including the transaction date, item type, quantity, and total price. These transactions are stored in a standardized format, making them ready for input into the Apriori analysis. The trial demonstrates that each rental or purchase on the website directly affects the dataset structure, which, in turn, influences support calculation, frequent itemset formation, and association rule generation. Thus, the integration between the transaction system and the Apriori analysis process works effectively, producing rental patterns that reflect actual user activity on the website.

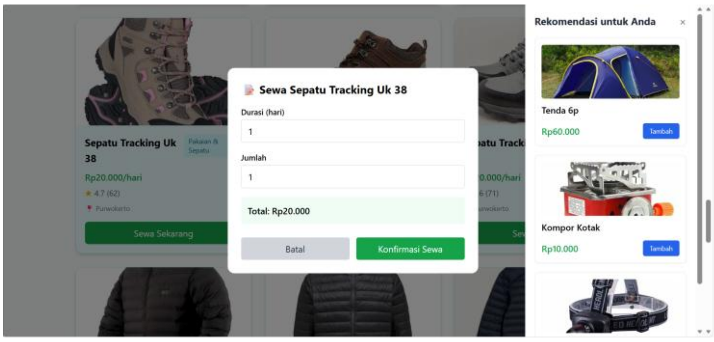

Figure 10. Rental of Tracking Shoes UK 38

The Tracking Shoes UK 38 has a lift value of 2.113636 with the 6P Tent, indicating a strong association between these two items. Additionally, the Tracking Shoes UK 38 also shows a relationship with the Box Stove with a lift value of 1.12723, and a similar association with the Headlamp at a lift of 1.12723. Lift values above 1 for all three combinations indicate that these items tend to appear together in transactions and have a positive association, which can be considered when designing recommendations or product bundling strategies.

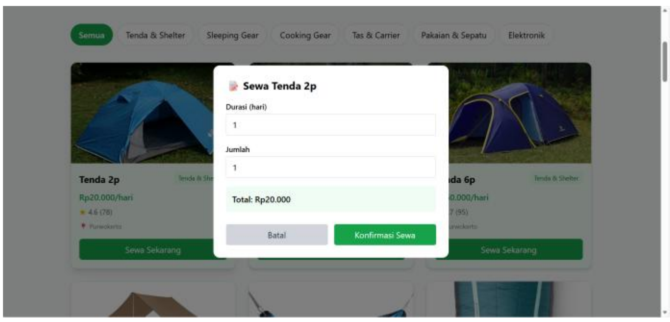

Figure 11. Rental of 2P Tent

On the other hand, the 2P Tent does not exhibit a lift value above 1. This means the association between the 2P Tent and other products in consumer purchasing patterns is weak. In other words, the presence of the 2P Tent in a transaction does not increase the likelihood that other items will be rented together, so its correlation with other products is minimal or nonexistent. Therefore, the system does not display any recommendations for the 2P Tent.

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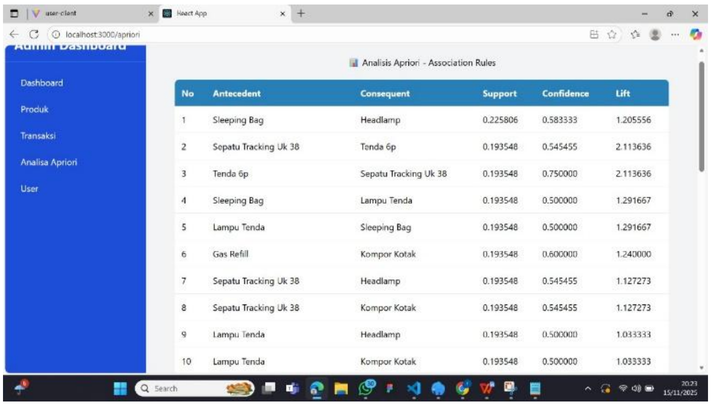

Figure 12. Admin Dashboard

The admin dashboard page is designed as the main information hub, displaying the results of the Apriori algorithm processing in a comprehensive manner. On this page, the system presents the list of formed itemsets along with their support, confidence, and lift values generated from the purchase pattern analysis. This visualization allows the admin to quickly understand which items are frequently purchased together and the strength of the relationships between products. In addition, the dashboard shows the generated association rules, making it easier for the admin to identify the most relevant product recommendations. The concise, structured layout helps the admin evaluate, monitor, and make data-driven decisions to improve sales strategies.

On this dashboard page, each association rule result is accompanied by key columns with specific meanings in the analysis process. The Antecedent column indicates the initial item or the first item purchased by the user, while the Consequent represents the item likely to be purchased together with the antecedent. The Support value shows the percentage of total transactions that include both items; for example, a support of 0.225806 means that approximately 22.6% of transactions involve both a sleeping bag and a headlamp. Confidence indicates the likelihood that a user will purchase the consequent after purchasing the antecedent. For instance, a confidence value of 0.583333 means that users who rent a sleeping bag have a 58.3% chance of also renting a headlamp. Finally, Lift measures the strength of the relationship between two items compared to random purchase behavior. A lift value greater than 1 indicates a positive association, equal to 1 indicates independence, and less than 1 suggests a weak or infrequent combination.

4. DISCUSSION

The discussion in this study focuses on the analysis of results from the implementation of the Apriori algorithm, the development of the web-based rental system, and the interpretation of outdoor equipment rental patterns derived from transaction data processing. Through this discussion, a deeper understanding is gained of customer behavior, the relevance of the Apriori algorithm to recommendation systems, and the effectiveness of integrating the transaction system with data analysis.

4.1. Discussion of Apriori Analysis Results

The Apriori algorithm was applied to the rental transaction dataset to identify frequent purchase patterns and relationships among items ordered by customers. This analysis aims to understand customer behavior from transaction history to generate accurate, relevant product recommendations. From the calculation results, it was found that the combination of Tent and Ground Mat is one of the item pairs with the highest occurrence frequency. This is evidenced by a support value of 22.22%, indicating that approximately one-fifth of all transactions included both items together.

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Furthermore, the confidence value reached 71.43%, showing that when a customer rents a Tent, there is a 71.43% chance they will also rent a Ground Mat. This figure indicates a strong and relatively consistent tendency in customer behavior. This consistency is reinforced by a lift value of 1.19, which indicates that the relationship between the two items is not coincidental but reflects a positive association that occurs more frequently than random chance. Therefore, the association rule {Tent} → {Ground Mat} can serve as a valid basis for product recommendation features. A recent Indonesian study using the Apriori algorithm on retail transaction data showed similar patterns, confirming that frequent itemset and association-rule mining are effective in uncovering meaningful product associations for recommendation and inventory management[25].

A deeper interpretation of support, confidence, and lift provides insight into the quality of the generated association rules. Support reflects the popularity of the item pair across the entire transaction dataset, confidence indicates the strength of the directional relationship from the antecedent to the consequent, and lift measures the extent to which the relationship occurs due to actual association rather than by chance. These three metrics serve as the system's reference for determining whether a rule is suitable for implementation as a recommendation.

Additionally, to facilitate the admin's understanding of the analysis results, the system dashboard displays several key columns: Antecedent, Consequent, Support, Confidence, and Lift, each of which carries operational significance as follows:

a. Antecedent: The item that is first purchased or rented by the user.
b. Consequent: The item that tends to be purchased or rented together with the antecedent.
c. Support: The percentage of all transactions that contain both items together. For example, a value of 0.225806 means approximately 22.6% of transactions include the combination of a sleeping bag and a headlamp.
d. Confidence: The likelihood that a user will rent the consequent after renting the antecedent. For instance, a confidence of 0.583333 indicates a 58.3% chance that a user who rents a sleeping bag will also rent a headlamp.
e. Lift: Measures the strength of the relationship between items compared to random co-occurrence. A lift greater than 1 indicates a positive association, lift equal to 1 indicates independence, and lift less than 1 indicates a weak or negative association.

Using this information structure, the admin can directly assess the quality of each association rule, evaluate its relevance, and determine which rules are suitable for implementation as recommendations on the website. The system's ability to display analysis results in real time also facilitates monitoring the algorithm's performance and supports data-driven decision-making.

From a business perspective, these findings have strategic value. Strong rental patterns, such as Tent and Ground Mat combinations, can be leveraged to create product bundling strategies, like a "beginner camping set" package. Additionally, management can plan stock procurement more accurately based on historical demand combinations. If the relationships between items are strong and stable over time, bundle promotions or combined purchase discounts can be offered to increase rental conversion rates.

Thus, the Apriori algorithm analysis not only provides technical benefits for developing a recommendation system but also delivers business insights that can enhance operational efficiency and revenue potential. This analysis underscores that data mining in the context of outdoor equipment rentals can lead to more informed decisions aligned with customer needs.

4.2. Discussion on Web-Based Recommendation System Implementation

The implementation of the web-based recommendation system in this study aims to integrate the outdoor equipment rental transaction process with purchase pattern analysis using the Apriori algorithm.

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The system is built with a web-based architecture, allowing both admins and users to conduct transactions directly through a responsive interface. On the frontend, the interface is designed to be easily accessible, providing a clear interaction flow from item selection to rental to checkout. On the backend, the system employs database-driven data management, recording all transactions as the foundation for Apriori algorithm calculations.

The Apriori algorithm is implemented directly in the backend, where incoming transaction data is processed and stored in a normalized database. The system then performs pattern extraction (frequent itemsets) and generates association rules based on support, confidence, and lift values. This process runs periodically or as needed by the admin, ensuring that the system's recommendations always reflect the most recent transaction data. Furthermore, this implementation ensures that each new transaction can update detected patterns, making the recommendations dynamic and adaptive.

From a data-flow perspective, when a user conducts a rental transaction, the system records the selected item combination as a single transaction entry. This data serves as input to the Apriori module. The Apriori algorithm was chosen for implementation due to its effectiveness in extracting item combination patterns in datasets with a moderate number of transactions, such as outdoor equipment rentals. Additionally, Apriori produces association rules that are easy to interpret and can be directly used as the basis for product recommendations.

The system's recommendation function works by taking the antecedent of the item currently being viewed or rented by the user and matching it with the pre-generated association rules. If the lift and confidence values meet the minimum thresholds, the system displays items strongly associated with the selected item. This ensures that recommendations are not based on assumptions but on historically verified patterns. Conversely, if an item's lift value is below 1, the system does not display a recommendation because the item's relationships are considered weak or insignificant.

4.3. Discussion on Website Testing Results Using Black Box Testing

To ensure that all system functionality operates according to user requirements, testing was conducted using the Black-Box Testing method. This approach focuses on examining the system's inputs and outputs without considering the internal code structure. Testing was performed on the Drop Outdoor Rental web application, built with a React frontend and a Flask backend, following scenarios that simulate real user workflows. These scenarios included item selection by renters, cart management, checkout processing, and transaction verification by the admin.

The testing process was conducted in a local development environment using a laptop with an Intel Core i5 processor, 8 GB RAM, and Windows 11 operating system. The web application was accessed using Google Chrome browser version 120. The backend service was executed using Flask framework, while the frontend was deployed locally using React. Testing was performed by simulating both user and administrator roles under normal network conditions.

The Black Box Testing approach ensures that critical features consistently function as expected from the end-user perspective. During testing, inputs such as selecting multiple items, adjusting rental durations, or applying checkout procedures were monitored to verify that the system responded correctly, recorded transactions accurately, and updated the database for subsequent Apriori analysis. The results indicated that the system handled all tested scenarios reliably, with no functional errors in transaction processing, item management, or data recording.

Overall, the testing demonstrates that the implemented web application meets functional requirements and provides a stable, user-friendly platform for both renters and administrators. The successful execution of Black Box Testing confirms that the system can support seamless rental operations while maintaining data integrity, enabling accurate pattern analysis, and delivering consistent recommendations through the integrated Apriori algorithm.

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Table 4. List of Test Cases and Testing Results

No	Test Case Description	Test Step	Test Data	Expected Result	Status
1.	Adding Item to Cart	1. Open the Main Page 2. Click "Rent Now" on a product 3. Fill in the duration & quantity 4. Click "confirm rental"	Product: Tenda 2P Duration: 1 day Quantity: 1	1. A success notification appears 2. The cart icon count increases 3. The item appears on the cart page	Pass
2.	Checkout Process	1. Open the cart 2. Click "Proceed to Checkout" 3. Fill out the form completely 4. Click "Confirm Rental"	Name: Raditya WhatsApp Number: 085866569894 Address: Jl. Merdeka	1. Redirected to the success page 2. Order ID is displayed 3. Data is saved in the database	Pass
3.	Empty Form Validation	1. On the checkout page, leave the form empty 2. Click "Confirm Rental"		Appear message"⚠️ Fill in personal details!"	Pass
4.	Cart Persistence	1. Add an item to the cart 2. Refresh the page 3. Reopen the cart		The item remains in the cart after refreshing the page.	Pass
5.	Admin Viewing Transactions	1. Open the admin/transactions page 2. Search for the latest transaction		The transaction data appears completely (including name, items, and total).	Pass
6.	Apriori Recommendations	1. Click "Rent Now" on Sepatu Tracking UK 38		A sidebar displaying product recommendations appears (Tenda 4P, Kompor Kotak, Headlamp).	Pass

The test results indicate that all test cases passed, meaning each function produced the expected output. In the first test case, the system successfully added items to the cart, evidenced by the increased cart icon count, a success notification, and the item appearing on the cart page. The checkout process ran smoothly, redirecting users to a success page and storing all transaction data in the database. Validation on the checkout page also worked correctly, as warning messages appeared when users attempted to submit empty forms.

Additionally, cart persistence tests showed that items remained in the cart even after refreshing the page, indicating that data storage mechanisms are stable. On the admin side, all user transactions were fully displayed on the admin dashboard, enabling proper monitoring. Testing of the Apriori-based recommendation feature demonstrated that the system displayed recommendations based on the association patterns. For example, when a user views the product detail page for "Sepatu Tracking Ukuran 38," the system automatically suggests items such as Tenda 4P, Kompor Kotak, and Headlamp, which have positive lift values relative to that item.

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The successful execution of all Black Box Testing scenarios indicates that the system's core functionalities are reliable and aligned with user requirements. More importantly, the correct recording of transaction data ensures that the Apriori algorithm receives valid input for association analysis. This reliability is crucial, as inaccurate transaction records could directly affect the quality of generated recommendations. Therefore, the testing results not only validate system usability but also confirm the robustness of the data pipeline supporting the recommendation mechanism.

Overall, the Black Box Testing confirms that the integration of transaction features with the Apriori analytics module works as intended. The system is not only functionally stable but also capable of generating accurate, data-driven recommendations. These findings support the conclusion that the system is ready for operational use and can provide a consistent, informative, and user-expected experience.

4.4. Discussion and Research Gap Analysis

Previous studies on Apriori-based recommendation systems predominantly focus on retail sales environments or theoretical algorithm performance. In contrast, this study addresses a specific operational context, namely outdoor equipment rental services, which involve unique constraints such as limited stock, rental duration, and seasonal demand.

The findings indicate that Apriori is effective when adapted to rental-based transactional data, especially when combined with Agile development practices. This research bridges the gap between algorithmic recommendation models and practical rental management systems, contributing to both information system development and applied data mining domains.

4.5. Consumer Behavior Interpretation

Beyond numerical evaluation, the association patterns identified through the Apriori algorithm also reflect meaningful consumer behavior in outdoor equipment rental services. The frequent co-occurrence of items such as tents, ground mats, trekking shoes, and portable cooking equipment indicates that customers tend to rent equipment in functional sets rather than as individual items.

This pattern suggests that a significant portion of users are likely beginner or casual outdoor enthusiasts who prefer complete and practical equipment combinations for short-term activities, such as weekend camping or family-oriented outdoor trips. For instance, the strong association between tents and ground mats implies a fundamental need for comfort and basic shelter, which aligns with first-time or non-professional campers.

Similarly, recommendations generated for items such as trekking shoes accompanied by tents and portable stoves may indicate users preparing for light hiking or mixed camping–trekking activities. These findings demonstrate that the Apriori-based recommendation system does not merely rely on algorithmic calculations but captures realistic usage contexts and rental behavior patterns, making the recommendations relevant and user-oriented.

4.6. Business Implications and System Limitations

From a managerial perspective, the identified association rules provide actionable insights for rental business operations. Frequently rented item combinations can be utilized to design bundled rental packages, such as beginner camping sets or family outdoor packages, which may simplify the rental process and increase transaction value. Furthermore, understanding recurring itemset patterns enables more effective inventory and stock planning, ensuring that high-demand items are available simultaneously to prevent incomplete rentals.

However, this study also has several limitations that should be considered. The transaction dataset used in this research is relatively limited in size and time span, which may restrict the generalizability of the discovered patterns. Additionally, the Apriori algorithm is sensitive to the selection of minimum

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support and confidence thresholds, which can influence the quantity and quality of generated association rules.

Another limitation is that this research does not incorporate temporal or seasonal factors, such as peak holiday periods or weather conditions, which may significantly affect outdoor equipment rental behavior. Despite these limitations, the findings demonstrate that Apriori remains effective for extracting meaningful patterns in rental-based transaction data when applied within an integrated web-based system.

5. CONCLUSION

This study successfully designed and implemented a web-based outdoor equipment rental information system for Drop Outdoor Purwokerto by integrating the Agile development methodology and the Apriori algorithm. The developed system effectively addresses key operational challenges, particularly limited access to real-time inventory information and frequent miscommunication during the rental process, which previously required customers to visit the store directly.

The application of the Apriori algorithm on rental transaction data proved effective in identifying meaningful item associations that reflect actual customer behavior in outdoor equipment rentals. Unlike conventional retail transactions, rental data exhibit distinctive characteristics such as bundled equipment usage, dependency among complementary items, and constraints related to usage duration. By capturing these characteristics, the recommendation system was able to provide relevant and contextual item suggestions, thereby helping users prepare complete equipment sets and reducing the risk of incomplete rentals.

A key contribution of this research lies in the seamless integration of association rule mining into an operational rental system. Rather than treating Apriori as a standalone analytical method, this study demonstrates its practical implementation within a real-world service platform. This integration supports more efficient rental management, improves recommendation accuracy, and enhances the overall user experience, particularly for small-scale rental businesses (UMKM) that require simple yet data-driven decision support tools.

From a system development perspective, the Agile methodology enabled iterative refinement through continuous stakeholder feedback, ensuring that system features such as inventory monitoring, transaction validation, and recommendation relevance remained aligned with real operational needs. This confirms that Agile is a suitable development approach for dynamic service-based information systems where requirements evolve rapidly.

Despite these contributions, this study has several limitations. The dataset used is relatively limited in size and time span, and the Apriori algorithm is sensitive to parameter thresholds, which may affect the generalizability of the generated rules. Therefore, future research is recommended to explore alternative algorithms such as FP-Growth for performance comparison, utilize larger and longer-term datasets, and incorporate temporal or seasonal analysis to better capture demand fluctuations in outdoor equipment rentals. Additionally, future studies may evaluate the system’s impact on business performance and user satisfaction over extended operational periods.

Overall, this research demonstrates that Apriori-based recommendation systems, when integrated with an Agile-developed web platform, can significantly improve operational efficiency, recommendation relevance, and service quality in outdoor equipment rental services.

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