Scientific Journal of Informatics
Vol. 13, No. 3, August 2026

p-ISSN 2407-7658 https://journal.unnes.ac.id/journals/sji e-ISSN 2460-0040

Business Intelligence Dashboard for Outdoor Equipment Rental Bundling Recommendations Using FP-Growth

Ahmad Zaki Azizi[1]*, Febrian Murti Dewanto[2], Aris Tri Jaka Harjanta[3]
[1,2,3]Informatics Department, Universitas Persatuan Guru Republik Indonesia Semarang, Indonesia

Abstract.
Purpose: This study aims to address the underutilization of transaction data in the outdoor equipment rental industry by developing an integrated Business Intelligence (BI) dashboard using the FP-Growth algorithm to generate product bundling recommendations and support data-driven decision-making.
Methods: A quantitative approach based on the Knowledge Discovery in Databases (KDD) framework was employed using 596 rental transactions from Batas Outdoor Rental recorded between January and May 2026. The data were preprocessed and transformed into a binary matrix using TransactionEncoder. FP-Growth was applied with a minimum support of 2% (0.02), while association rules were generated using a minimum confidence of 30% (0.30) and validated with a lift threshold of 1.20.
Results: A quantitative approach based on the Knowledge Discovery in Databases (KDD) framework was employed using 596 rental transactions from Batas Outdoor Rental recorded between January and May 2026. The data were preprocessed and transformed into a binary matrix using TransactionEncoder. FP-Growth was applied with a minimum support of 2% (0.02), while association rules were generated using a minimum confidence of 30% (0.30) and validated with a lift threshold of 1.20.
Novelty: This study integrates FP-Growth-based transaction analysis with an interactive BI dashboard specifically for outdoor equipment rentals. Unlike previous studies focusing primarily on product combinations or promotional packages, the proposed approach provides an end-to-end decision-support framework connecting transaction analysis, automated bundling recommendations, and interactive visualization.

Keywords: Business Intelligence, FP-Growth, Association Rule Mining, Product Bundling, Outdoor Equipment Rental

Received June 2026 / **Revised** August 2026 / **Accepted** August 2026

INTRODUCTION

Transaction data has evolved into a vital strategic asset for organizations because it provides valuable insights into business performance, customer behavior, and market dynamics [1], [2]. Business Intelligence (BI) functions as an analytical mechanism for transforming organizational data into actionable information that supports data-driven decision-making [3], [4]. To maximize the utilization of transaction data, organizations increasingly rely on analytical dashboards that consolidate complex operational metrics into interactive visual representations [5], [6]. These dashboards facilitate the monitoring of key performance indicators and support managers in interpreting business information more efficiently, thereby enabling faster and more informed decision-making[7], [8]. The deployment of such advanced analytical capabilities is particularly relevant to the outdoor equipment rental industry, a sector characterized by transactional patterns that differ from conventional retail environment [9], [10]. Unlike ownership-based retail transactions, rental transactions involve the temporary use of equipment, and customers may select multiple items according to the requirements of particular outdoor activities and rental periods [11], [12]. Consequently, comprehending these distinct rental patterns enables service providers to mitigate logistical miscommunication, streamline operational efficiency, and leverage historical behavioral insights [13], [10]. This understanding empowers rental operators to formulate targeted promotional strategies, such as product bundling, based on observed rental patterns [14], [15].

[1]*Corresponding author.
Email addresses: 22670050@upgris.ac.id (Azizi), febrianmd@upgris.ac.id (Dewanto), aristrijaka@upgris.ac.id (Harjanta)
DOI: 10.15294/sji.v13i3.57444

To conduct a granular examination of consumer behavior, Market Basket Analysis (MBA) is frequently employed to uncover associative relationships among products co-occurring within individual transactions [16], [17]. Among various data mining techniques, the Frequent Pattern Growth (FP-Growth) algorithm demonstrates superior computational effic2iency by utilizing a compact FP-Tree structure [18], [19]. This architectural advantage avoids the resource-intensive candidate generation process inherent in traditional association models [20], [21]. This characteristic makes FP-Growth suitable for identifying recurring product combinations that can support cross-selling and product bundling [22], [23]. In the context of outdoor equipment rental, identifying such combinations can provide insights into the products that are frequently rented together and can support the formulation of activity-oriented rental packages based on actual transaction patterns.

Despite extensive scholarly attention toward visual analytics and association rule mining, many existing studies have predominantly focus on conventional retail environments, while the application of data mining and Business Intellignece integration in the outdoor equipment rental domain remains comparatively limited [24]. Furthermore, previous studies have utilized association algorithms to identify rental patterns and construct recommendation systems [9], [12], Although these studies and product bundling, integration of rental transaction analysis, automated bundling recommendations, and comprehesive managerial visualization remains an opportunity for further development [25], [6]. To address these gaps, this study proposes the development of an integrated Business Intelligence dashboard that incorporates the FP-Growth algorithm to systematically analyze customer rental patterns [7]. By extracting frequent itemsets from historical transaction data, the system translates complex association rules into relevant, automated product bundling recommendations directly within an intuitive visual interface [26], [27]. The primary objective of this research is to augment strategic, data-driven decision-making within the outdoor equipment rental ecosystem through the synthesis of advanced data mining and interactive visual analytics [5], [4]. Implementing this intelligent dashboard provides managers with analytical information that can support the formulation of promotional strategies, inventory planning, and service improvement [28]. Ultimately, this study provides a practical framework for integrating FP-Growth-based transaction analysis with Business Intelligence visualization, enabling micro, small, and medium enterprises (MSMEs) to leverage historical rental data as a basis data-driven promotional and operational decision-making [29], [22].

METHODS

This study adopts a quantitative-experimental research design with a Knowledge Discovery in Databases (KDD) approach. The research process was conducted systematically through several stages, including data collection, data preprocessing, pattern discovery using the FP-Growth algorithm, association rule generation, and visualization through a Business Intelligence Dashboard. This approach was adopted to identify frequent rental patterns from historical transaction data and generate product bundling recommendations that can support business decision-making in outdoor equipment rental services. Based on the research workflow is illustrated in Figure 1.

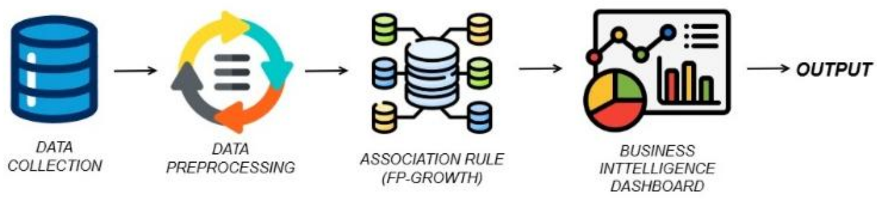

Figure 1. Research workflow

Dataset collection

The dataset used in this study consists of 596 historical rental transactions obtained directly from Batas Outdoor Rental. The dataset contains transaction information, including transaction date, customer, total payment, profit, and rental item details. The data were processed and analyzed using Python and PostgreSQL to identify rental patterns and generate bundling recommendations. The collected transactions were used as the primary data source for the subsequent preprocessing, association rule mining, and dashboard development stages.

Data preprocessing

Before applying the FP-Growth algorithm, the collected transaction data were preprocessed to ensure that the data were suitable for association rule mining. The preprocessing stage consisted of reviewing the transaction records, removing irrelevant attributes that were not required for pattern mining, checking the consistency of product names, and ensuring that each transaction contained identifable rental items. Missing or incomplete records that could not provide valid information for transaction analysis were excluded from the data mining dataset. The rental item details were then grouped according to their transaction identifiers so that each transaction represented a set of products rented together. This process was necessary to ensure that the resulting transaction structure accurately represented customer rental combinations before being transformed into a binary transactional matrix.

FP-Growth and association rule mining

The extraction of associative rental patterns from the historical transaction dataset was performed using the Frequent Pattern Growth (FP-Growth) algorithm[30], [24]. This data mining technique provides an efficient approach for identifying frequent itemsets by constructing a compact FP-Tree structure and avoiding the repeated candidate-generation process required by traditional association rule mining approaches. Prior to executing the algorithm, the preprocessed operational records were transformed into a binary transactional matrix using a transaction encoding technique. In this representation, each row corresponds to an individual rental transaction, while each column represents a unique outdoor equipment item. A value of 1 indicates that an item was included in a particular transaction, whereas a value of 0 indicates that the item was not included. This representation enables the FP-Growth algorithm to systematically identify combinations of equipment that frequently occur within the rental transactions.

To identify significant frequent itemsets, an initial minimum support threshold of 0.02, or 2%, was established[31]. The support metric measures the proportion of transactions containing a specific item combination relative to the total number of transactions. The 2% threshold was selected based on the characteristics of the rental transaction dataset, which contains 596 transactions with diverse combinations of outdoor equipment. With this threshold, an itemset must occur in at least approximately 12 transactions to be considered a frequent pattern. This threshold was selected to retain recurring equipment combinations that may be relevant for bundling recommendations while excluding combinations with insufficient occurrence in the dataset. The support value for an itemset X is calculated by dividing the number of transactions containing X by the total number of transactions, as formulated in Equation (1):

$$Support(X) = \frac{Total\ Transactions\ Containing\ X}{Total\ Transactions} \quad (1)$$

The selection of the 2% minimum support threshold was further examined through a sensitivity analysis using alternative support values of 1%, 3%, and 5%, while maintaining a minimum confidence of 30% and a minimum lift of 1.20. The results of the sensitivity analysis are presented in Table 1.

Table 1. Sensitivity analysis of minimum support threshold

Minimum Support	Approx. Minimum Transactions	Frequent Itemsets	Association Rules
1%	6	1,217	5,507
2%	12	293	625
3%	18	154	245
5%	30	64	74

As presented in Table 1, increasing the minimum support threshold resulted in a substantial reduction in both frequent itemsets and association rules. At a 1% threshold, the analysis generated 1,217 frequent itemsets and 5,507 association rules, whereas increasing the threshold to 3% reduced the results to 154 frequent itemsets and 245 association rules. At a 5% threshold, only 64 frequent itemsets and 74 association rules were generated. In comparison, the 2% threshold produced 293 frequent itemsets and 625 association rules. These results indicate that the 2% threshold provides a balance between retaining recurring equipment combinations and limiting the number of association rules requiring further interpretation. Therefore, the minimum support threshold of 2% was retained for the subsequent association rule mining process.

Following the extraction of frequent itemsets, association rules were generated to determine conditional relationships among rented products. The strength of these rules was evaluated using a minimum confidence threshold of 0.30, or 30%[32]. Confidence measures the conditional probability that an item or itemset Y occurs in a transaction when another item or itemset X is already present. The confidence value is calculated by dividing the support of the combined itemset X ∪ Y by the support of the antecedent item X, as expressed in Equation (2):

$$Confidence = \frac{Support\ (X\ \cup\ Y)}{Support\ (X)} \tag{2}$$

In practical terms, Equation (2) determines the proportion of transactions containing the antecedent X that also contain the consequent Y. For example, a confidence value of 30% indicates that at least 30% of transactions containing the antecedent also contain the corresponding consequent. The selection of the 30% confidence threshold was further evaluated through a sensitivity analysis using alternative confidence values of 20%, 40%, and 50%, while maintaining a minimum support of 2% and a minimum lift of 1.20. The results of the sensitivity analysis are presented in Table 2.

Table 2. Sensitivity analysis of minimum confidence threshold

Minimum Support	Minimum Confidence	Assoctiation Rules
2%	20%	831
2%	30%	625
2%	40%	488
2%	50%	366

As presented in Table 2, increasing the minimum confidence threshold progressively reduced the number of association rules. At a confidence threshold of 20%, 831 association rules were generated, while the 30% threshold resulted in 625 rules. Increasing the threshold to 40% and 50% reduced the number of rules to 488 and 366, respectively. Although a higher confidence threshold provides a stricter criterion for conditional relationships, it also reduces the number of potentially relevant rental patterns retained for further analysis. Based on these results, the 30% confidence threshold was retained as a moderate criterion that limits weaker associations while preserving a broader range of potentially meaningful relationships among rental products.

Furthermore, the lift ratio was employed as an additional validation metric to evaluate the strength of an association relative to the expected co-occurrence of the antecedent and consequent. Lift compares the observed confidence of an association rule with the expected occurrence of the consequent when the items are assumed to occur independently. An association rule is considered to have a positive association when its lift value is greater than 1.0[33]. The lift ratio is calculated by dividing the confidence of the rule by the support of the consequent item Y, as expressed in Equation (3):

$$Lift\ (X\ \rightarrow Y) = \frac{Confidence\ (X \rightarrow Y)}{Support\ (Y)} \tag{3}$$

Through the application of Equation (3), the strength of the relationship between products can be evaluated. A lift value exceeding 1.0 indicates that the antecedent and consequent occur together more frequently than would be expected if they were independent. In this study, a minimum lift threshold of 1.20 was applied as an additional filtering criterion to retain association rules with stronger positive relationships. Therefore, the final association rules were selected based on a minimum support of 2%, minimum confidence of 30%, and minimum lift of 1.20. Based on these criteria, a total of 625 valid association rules were obtained. The resulting rules served as the analytical foundation for formulating data-driven product bundling recommendations. These extracted insights were subsequently integrated into the interactive Business Intelligence dashboard to facilitate monitoring and support objective promotional decision-making for the rental business.

Business intelligence dashboard

The association rules generated from the FP-Growth process were subsequently integrated into the Business Intelligence dashboard as the final stage of the research workflow. First, the frequent itemsets and association rules that satisfied predefined support, confidence, and lift criteria were selected for further processing. Second, the selected association rules were analyzed to identify relationships among rental products and were transformed into product bundling recommendations. Third, the resulting transaction data, association rules, and bundling recommendations were organized according to relevant indicators, including rental performance, product relationships, and recommendation results. Finally, these structured analytical outputs were delivered to the visualization environment and presented through the Business Intelligence dashboard. This process enabled the FP-Growth output to be transformed into actionable information that supports the interpretation of rental patterns and product bundling opportunities for promotional and operational decision-making.

The Business Intelligence dashboard was developed using a full-stack architecture consisting of a React-based frontend and a Flask-based backend. React was used to develop the user interface, while Vite was utilized as the build tool. Recharts was employed to create interactive visualizations for rental trends, transaction information, and analytical results, while React Force Graph 2D was used to visualize the relationships among the association rules generated by the FP-Growth algorithm. SCSS was used for interface styling, React Router DOM was employed to manage dashboard navigation, and Axios was utilized to facilitate communication between the frontend and the backend RESTful API. On the backend side, Flask was used as the Python-based web framework to provide transaction and analytical data through the RESTful API, while PostgreSQL was utilized as the relational database for storing transaction data and other relevant business information. The psycopg2-binary library was used to establish the connection between Flask and PostgreSQL, while python-dotenv was utilized to manage environment variables and application configuration. Through this architecture, the FP-Growth results were delivered from the backend to the React-based dashboard and presented through interactive visualizations, enabling the analytical findings to be interpreted as product bundling opportunities for the outdoor equipment rental business.

RESULT AND DISCUSSION

This section presents the results obtained from the implementation of the proposed Business Intelligence Dashboard and the FP-Growth algorithm on historical rental transaction data. The analysis begins with an overview of the dataset characteristics, followed by frequent itemset discovery, association rule generation, bundling recommendation analysis, and dashboard implementation. The findings are then interpreted to demonstrate how transaction data can be transformed into actionable business insights for outdoor equipment rental decision-making.

Dataset overview

The dataset analyzed in this study was obtained from Batas Outdoor Rental and consists of 596 historical rental transactions collected between January and May 2026. The dataset contains transaction information, including transaction date, customer information, total payment, profit, and detailed rental items. These data were utilized to identify rental patterns and generate product bundling recommendations through the FP-Growth algorithm. To better understand the scope of the analyzed data, the main characteristics of the rental transaction dataset are presented in Table 3.

Table 3. Dataset characteristics

Parameter	Value
Observation Period	January – May 2026
Total Transactions	596
Distinct Customers	492
Distinct Products	58
Total Revenue	Rp 61,313,430
Average Transaction Value	Rp 102,875

As presented in Table 3, the dataset includes 596 rental transactions involving 492 distinct customers and 58 different rental products. During the observation period, the transactions generated a total revenue of Rp 61,313,430 with an average transaction value of Rp 102,875. The diversity of products and customer activities provides sufficient variability for discovering meaningful rental patterns through association rule mining. To further examine rental activity over time, the monthly transaction distribution is presented in Figure 2.

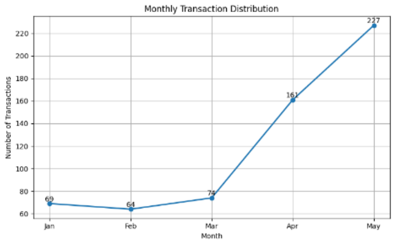

Figure 2. Monthly rental transaction distribution

The monthly transaction distribution shown in Figure 2 also indicates an increasing rental activity towards May 2026. This pattern indicates that rental activity varied across the observation period rather than remaining constant. The increase in transaction volume towards May also provides contextual information for interpreting the subsequent rental patterns, as variations in demand may influence the frequency with which particular equipment combinations appear in the transaction data. In addition to transaction volume, product rental frequency was analyzed to identify the most popular rental items. The results are presented in Figure 3.

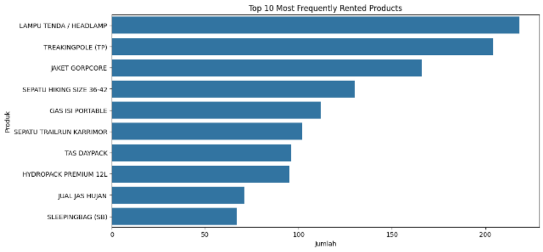

Figure 3. Top 10 most frequently rented products

The results shown in Figure 3 indicate that Lampu Tenda / Headlamp was the most frequently rented product, followed by Trekking Pole and Matras Spon. These products represent equipment commonly used across multiple outdoor activities and may therefore serve as potential anchor products for bundling recommendations. Their high rental frequency provides an initial indication of customer demand; however, high individual rental frequency alone does not establish that products are frequently rented together. Therefore, further analysis using FP-Growth is required to identify recurring combinations among these products.

Frequent itemset analysis

The FP-Growth algorithm was applied to the preprocessed rental transaction dataset to identify frequent itemsets representing products that are commonly rented together. By discovering recurring combinations of rental items, the analysis provides insights into customer rental behavior and serves as the foundation for generating association rules and bundling recommendations. The mining process identified several frequent itemsets that met the minimum support threshold of 0.02. These itemsets reveal that customers tend to rent products in groups that correspond to specific outdoor activities, such as camping, hiking, and outdoor cooking. Rather than renting individual products independently, customers often select complementary equipment that collectively supports a particular activity.

Table 4. Top frequent itemsets generated by FP-Growth

Itemset	Support
LAMPU TENDA / HEADLAMP, TREKKINGPOLE (TP)	0.191275
JAKET GORPCORE, TREKKINGPOLE (TP)	0.162752
JAKET GORPCORE, LAMPU TENDA / HEADLAMP	0.144295
SEPATU HIKING SIZE 36-42, TREKKINGPOLE (TP)	0.139262
JAKET GORPCORE, SEPATU HIKING SIZE 36-42	0.122483
LAMPU TENDA / HEADLAMP, SEPATU HIKING SIZE 36-42	0.107383
JAKET GORPCORE, LAMPU TENDA / HEADLAMP, TREKKINGPOLE (TP)	0.102349
LAMPU TENDA / HEADLAMP, SEPATU TRAILRUN KARRIMOR	0.100671
HYDROPACK PREMIUM 12L, TREKKINGPOLE (TP)	0.093960
HYDROPACK PREMIUM 12L, LAMPU TENDA / HEADLAMP	0.092282

As presented in Table 4, the combination of Trekking Pole and Lampu Tenda / Headlamp achieved the highest support value of 0.191275, followed by Jaket Gorpcore and Trekking Pole with a support value of 0.162752. The recurring presence of trekking poles, lighting equipment, hiking shoes, and outdoor jackets indicates that customers tend to select complementary equipment rather than renting products independently. These combinations are consistent with equipment requirements for hiking and camping activities. From a bundling perspective, products with relatively high co-occurrence can serve as suitable components for packages because their joint appearance in transactions reflects recurring customer rental behavior. The frequent itemsets therefore provide the foundation for generating association rules that further evaluate the strength of these relationships.

Association rule analysis

The frequent itemsets identified by the FP-Growth algorithm were subsequently used to generate association rules. These rules provide deeper insights into the relationships between rental products by measuring how frequently products appear together and the strength of their associations. In this study, a total of 625 association rules were generated based on the predefined support, confidence, and lift criteria. To provide an overview of the generated association rules, descriptive statistics of the support, confidence, and lift values are presented in Table 5.

Table 5. Summary statistics of association rules

Metric	Minimum	Maximum	Mean
Support	0.0201	0.1913	0.0344
Confidence	0.3000	0.9333	0.5467
Lift	1.2294	16.5556	3.7361

The results in Table 5 indicate that the generated association rules exhibit varying levels of association strength. The support values range from 0.0201 to 0.1913, with a mean of 0.0344, indicating that the identified product relationships generally represent recurring but relatively specialized rental patterns. Confidence ranges from 0.3000 to 0.9333, with a mean value of 0.5467, indicating varying levels of conditional association between antecedent and consequent products. Meanwhile, lift values range from 1.2294 to 16.5556, with a mean of 3.7361. Since lift values greater than 1 indicate positive association, these results demonstrate that the identified product relationships occur more frequently than would be expected under independent occurrence. The relatively high mean lift therefore indicates that several rental products exhibit meaningful relationships that can be considered when developing data-driven bundling strategies. To further investigate the strongest relationships among rental products, the top association rules ranked by lift value are presented in Table 6.

Comparison with previous studies

To contextualize the association rule mining results, the findings of this study were compared with previous studies that applied Apriori and FP-Growth algorithms in outdoor equipment rental, recommendation, promotional package, and product bundling contexts. The comparison considers the business context, algorithm used, analytical objective, and main contribution of each study. The comparison is presented in Table 6.

Table 6. Comparison with previous studies

Study	Business Context	Algorithm	Main Objective	Main Contribution
Rizal et al.	Outdoor equipment rental	Apriori + K-Means	Identify rental product patterns	Identification of associations among rental products after transaction clustering
Elfreda and Usman	Outdoor equipment rental	Apriori	Develop a recommendation system	Generation of rental product recommendations based on association patterns
Gusti et al.	Scooter motorcycle workshop	FP-Growth	Determine promotional packages	Identification of product combinations for promotional package determination
Andriana et al.	Product promotion and bundling	FP-Growth	Develop smart bundling recommendations	Development of data-driven product bundling based on transaction history
This study	Outdoor equipment rental	FP-Growth	Analyze rental patterns and generate bundling recommendations	Integration of association rules and bundling recommendations into a Business Intelligence dashboard

The comparison in Table 6 demonstrates that association rule mining has previously been applied to rental recommendation and product bundling problems, although the analytical objectives and implementation approaches differ. In the outdoor equipment rental context, K-Means clustering combined with the Apriori algorithm has been applied to identify relationships among rental products [9]. Apriori has also been utilized to support recommendation systems for outdoor equipment rental services [12]. In other business contexts, FP-Growth has been applied to determine promotional packages and identify product combinations for smart bundling [14], [15]. These studies demonstrate the applicability of association rule mining for identifying product relationships and supporting recommendation or bundling strategies. However, the existing applications differ in terms of business context and system integration, particularly in the integration of rental transaction analysis, automated bundling recommendations, and Business Intelligence visualization.

Compared with these previous studies, the present study applies FP-Growth directly to historical outdoor equipment rental transactions and extends the analytical process by integrating the resulting association rules with automated product bundling recommendations and a Business Intelligence dashboard. This integration connects transaction pattern discovery with visual business analysis and practical bundling recommendations within a centralized environment. Therefore, the contribution of this study is not limited to identifying frequently associated rental products, but also includes the transformation of the resulting analytical patterns into information that can be interpreted and utilized for promotional and operational decision-making.

The quantitative results should nevertheless be interpreted in relation to the characteristics of each dataset and the parameter settings used in the respective studies. The number of generated association rules and the magnitude of lift values cannot be directly interpreted as measures of algorithmic superiority because transaction volume, product diversity, support thresholds, confidence thresholds, and filtering criteria may differ across studies. Therefore, the comparison presented in Table 6 is intended to contextualize the analytical approach and research contribution rather than to establish direct performance superiority. In the present study, the FP-Growth configuration generated 625 valid association rules with a mean lift of 3.7361 from 596 historical rental transactions. These results indicate that the selected configuration was able to identify a substantial number of positively associated rental product combinations within the analyzed dataset.
To further examine the strongest relationships identified by the FP-Growth algorithm, the association rules with the highest lift values are presented in Table 7.

Table 7. Top association rules by lift value

Antecedent	Consequent	Support	Confidence	Lift
Sleeping Bag, Gas Isi Portable	Tenda 4/5 Person, Matras Spon, Lampu Tenda / Headlamp	0.0201	0.6667	16.56
Tenda 4/5 Person, Matras Spon, Lampu Tenda / Headlamp	Sleeping Bag, Gas Isi Portable	0.0201	0.5000	16.56
Matras Spon, Sleeping Bag, Gas Isi Portable	Tenda 4/5 Person, Lampu Tenda / Headlamp	0.0201	0.7500	15.41
Sleeping Bag, Gas Isi Portable	Tenda 4/5 Person, Lampu Tenda / Headlamp	0.0218	0.7222	14.84
Gas Isi Portable, Lampu Tenda / Headlamp, Sleeping Bag	Tenda 4/5 Person, Matras Spon	0.0201	0.8000	14.45

The strongest association rule, with (Sleeping Bag, Gas Isi Portable) as the antecedent and (Tenda 4/5 Person, Matras Spon, Lampu Tenda / Headlamp) as the consequent, achieved a lift value of 16.56 and a confidence value of 66.67%. This result indicates that customers who rent a sleeping bag and portable gas are more likely to also rent a tent, sleeping mat, and lighting equipment than would be expected from independent rental behavior. The relationship reflects a broader activity-readiness pattern, in which customers select complementary equipment required for an outdoor activity. The combination can therefore be interpreted as a potential camping-oriented bundling opportunity.

However, this rule has a support value of 0.0201, corresponding to approximately 12 transactions out of the 596 transactions analyzed. Therefore, the high lift value should be interpreted cautiously. Although the rule demonstrates a strong association within the observed transactions, its relatively low support indicates that the combination represents a relatively specialized rental pattern rather than a general customer preference. Consequently, the rule may be considered for targeted bundling or cross-selling strategies, while further validation using additional rental transactions and observation periods would be beneficial before adopting it as a permanent promotional package.

Bundling recommendations analysis

The validated association rules were subsequently transformed into product bundling recommendations based on the relationships identified among rental products. The generated recommendations were organized into activity-oriented categories to make the analytical results more understandable and applicable for managerial decision-making. The recommendations include hiking, camping, cooking, survival, and premium-oriented bundles.

Table 8. Top bundling recommendations

Bundle Name	Category	Confidence	Lift
Starter Camping Bundle	Camping	67%	16.56
Family Camping Bundle	Camping	45%	14.48
Camp Explorer Bundle	Camping	37%	12.20
Hiking Essentials Bundle	Hiking	40%	9.93
Weekend Camping Bundle	Camping	53%	9.63

The generated recommendations demonstrate that camping and hiking represent prominent activity-oriented rental patterns within the analyzed transactions. The Starter Camping Bundle, with a confidence of 67% and a lift of 16.56, represents the strongest recommendation among the generated bundles, followed by the Family Camping Bundle with a lift of 14.48. These results indicate that the statistical relationships discovered by FP-Growth can be translated into packages that are easier for managers and customers to understand. Instead of presenting individual association rules, the system groups related equipment according to potential activity requirements, providing a more practical basis for promotional planning and cross-selling. The presence of other categories, such as cooking and survival, also indicates that bundling opportunities are not limited to the dominant camping and hiking activities.

Business intelligence dashboard implementation

The validated rental patterns, association rules, and bundling recommendations were subsequently integrated into the Business Intelligence Dashboard to transform the analytical results into an interactive decision-support environment.

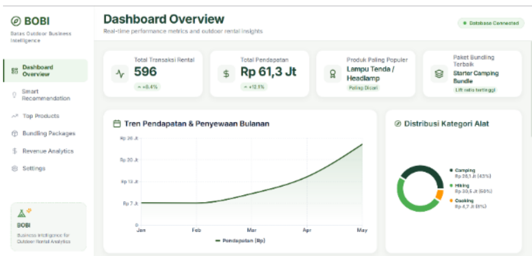

Figure 4. Dashboard overview

Figure 4 presents the main dashboard interface, which summarizes key indicators related to rental transactions, revenue, product performance, and bundling recommendations. By consolidating these indicators within a single interface, the dashboard allows managers to obtain an overview of business performance without manually examining individual transaction records.

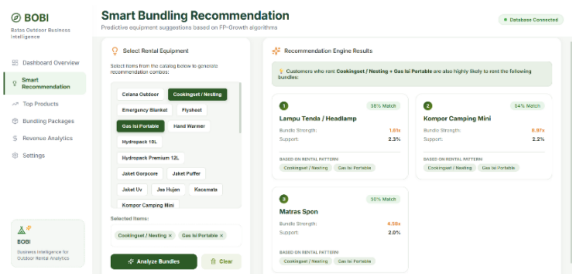

Figure 5. Smart recommendation module

Figure 5 illustrates the recommendation module, which assists users in identifying complementary rental products based on the association rules generated by FP-Growth. By selecting one or more products, the system generates related product recommendations together with their corresponding confidence and lift values. This functionality enables managers to identify potential cross-selling opportunities and supports the formulation of product combinations based on observed customer rental behavior.

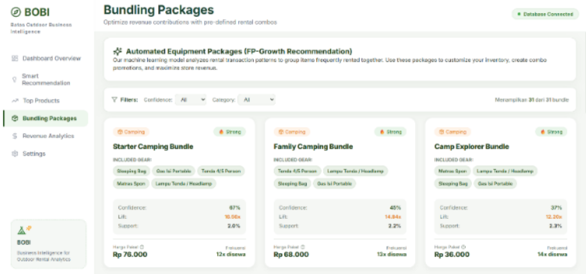

Figure 6. Bundling recommendation dashboard

Figure 6 presents the bundling recommendation dashboard, which displays recommended rental packages together with relevant analytical metrics, including support, confidence, and lift. These metrics provide transparency regarding the strength of each recommendation and assist managers in evaluating the suitability of proposed bundles for promotional packages or standard rental offerings. The dashboard also provides analytical visualizations that support monitoring of business performance, including revenue trends, product popularity, and rental activity indicators. Through this integration, the FP-Growth results are transformed from statistical association rules into visual and actionable information that can support cross-selling, promotional planning, inventory management, and operational decision-making.

User Acceptance Testing (UAT)

User Acceptance Testing (UAT) was conducted to evaluate whether the developed Business Intelligence Dashboard could be used effectively and meet the practical needs of its intended users. The evaluation focused on three main aspects, namely interface, usability, and effectiveness. The interface aspect evaluated the clarity and presentation of dashboard elements, the usability aspect evaluated the ease of navigation and interaction with the system, while the effectiveness aspect evaluated the usefulness of the analytical information and product bundling recommendations in supporting business decision-making.

A total of five respondents participated in the evaluation. The respondents were selected based on their relevance to the use of the developed Business Intelligence Dashboard in the outdoor equipment rental context. The respondents were asked to interact with the dashboard and evaluate its interface, usability, and effectiveness based on their experience using the system. The evaluation instrument consisted of 15 questions, with five questions assigned to each evaluation aspect.

Each respondent's answer was assigned a score using a five-point Likert scale. “Strongly Agree” (SA) was assigned a score of 5, “Agree” (A) was assigned a score of 4, “Neutral” (N) was assigned a score of 3, “Disagree” (D) was assigned a score of 2, and “Strongly Disagree” (SD) was assigned a score of 1.

Table 9. User Acceptance Testing (UAT) results

No	Aspect	Question	SA	A	N	D	SD	Total
1.	Interface	Q1	20	2	0	0	0	24
		Q2	20	4	0	0	0	24
		Q3	10	12	0	0	0	22
		Q4	15	4	3	0	0	22
		Q5	10	12	0	0	0	22
2.	Usability	Q6	20	4	0	0	0	24
		Q7	10	12	0	0	0	22
		Q8	15	4	3	0	0	22
		Q9	10	8	3	0	0	21
		Q10	20	4	0	0	0	24
3.	Effectiveness	Q11	20	4	0	0	0	24
		Q12	10	12	0	0	0	22
		Q13	15	4	3	0	0	22
		Q14	10	12	0	0	0	22
		Q15	20	4	0	0	0	24

From Table 9, the total score for each question was obtained by summing the weighted scores from the five Likert categories. For example, Q1 obtained a score of 20 from the Strongly Agree category and 4 from the Agree category, resulting in a total score of 24. The maximum score for each question was 25, obtained from five respondents selecting the highest Likert score of 5.

To determine the level of user acceptance for each evaluation aspect, the percentage was calculated using the following formula:

$$Percentage = \frac{Obtained\ Score}{Maksimum\ Score} \times 100\% \quad (4)$$

Interface

The interface aspect consists of five questions, namely Q1 to Q5. The total score was obtained by summing the scores of all five questions:

$$24 + 24 + 22 + 22 + 22 = 114$$

The maximum score for the interface aspect was obtained from five respondents, five questions, and the highest Likert score of 5:

$$5 \times 5 \times 5 = 125$$

Therefore, the percentage for the interface aspect was calculated as follows:

$$Percentage = \frac{114}{125} \times 100\% = 91.20\% \quad (5)$$

The result indicates that the interface aspect achieved a score of 91.20%, which falls into the Very Good category. This result indicates that the respondents considered the dashboard interface clear, understandable, and appropriately presented for accessing the information provided by the system.

Usability

The usability aspect consists of five questions, namely Q6 to Q10. The total score obtained from these questions was:

$$24 + 22 + 22 + 21 + 24 = 113$$

The maximum score for the usability aspect was 125. Therefore, the percentage for the usability aspect was calculated as follows:

$$Percentage = \frac{113}{125} \times 100\% = 90.40\% \quad (6)$$

Effectiveness

The effectiveness aspect consists of five questions, namely Q11 to Q15. The total score obtained from these questions was:

$$24 + 22 + 22 + 22 + 24 = 114$$

The maximum score for the interface aspect was 125. Therefore, the percentage for the effectiveness aspect was calculated as follows:

$$Percentage = \frac{114}{125} \times 100\% = 91.20\% \quad (7)$$

The result indicates that the effectiveness aspect achieved a score of 91.20%, which falls into the Very Good category. This result indicates that the analytical information and product bundling recommendations provided through the dashboard were considered useful for understanding rental patterns and supporting promotional and operational decision-making.

Based on the results of the UAT, the interface aspect achieved a percentage of 91.20%, while the usability aspect achieved 90.40% and the effectiveness aspect achieved 91.20%. All three aspects fall within the Very Good category based on the evaluation criteria. To determine the overall level of user acceptance, the average percentage of the three evaluation aspects was subsequently calculated as follows:

$$Average = \frac{91.20+90.40+91.20}{3} = 90.93\% \quad (8)$$

The evaluation categories used to determine the level of user acceptance are presented in Table 10.

Table 10. Evaluation categories

Percentage	Category
81%-100%	Very Good
61%-80%	Good
41%-60%	Fair
21%-40%	Poor
0%-20%	Very Poor

Based on the calculated average, the overall user acceptance score of the developed Business Intelligence Dashboard was 90.93%, which falls into the Very Good category. This result indicates that the dashboard was well accepted by the evaluated users in terms of interface, usability, and effectiveness. The interface evaluation shows that the dashboard provides a clear and understandable presentation of information, while the usability evaluation indicates that the main dashboard features can be accessed and operated easily. Furthermore, the effectiveness evaluation indicates that the analytical information and product bundling recommendations are considered useful for interpreting rental patterns and supporting promotional and operational decision-making.

Overall, the UAT results provide user-based evidence that the integration of FP-Growth analysis into the Business Intelligence Dashboard can be practically utilized to present rental patterns, product relationships, and bundling recommendations in an accessible form. The findings support the practical applicability of the developed dashboard as a decision-support tool for outdoor equipment rental management.

CONCLUSION

This study developed a Business Intelligence Dashboard integrated with the FP-Growth algorithm to analyze historical rental transaction patterns and generate product bundling recommendations for outdoor equipment rental businesses. Using 596 historical rental transactions, FP-Growth identified 625 valid association rules based on the selected support, confidence, and lift criteria, resulting in 31 meaningful product bundling recommendations, particularly for camping and hiking activities. The analytical results were integrated into a web-based dashboard with interactive visualizations of rental performance, product relationships, association rules, and bundling recommendations, supporting promotional planning, cross-selling, inventory management, and operational decision-making. The integration of the React-based frontend, Flask backend, PostgreSQL database, and FP-Growth process provides an end-to-end framework for transforming historical transactions into actionable business insights. User Acceptance Testing (UAT) involving five respondents produced an overall acceptance score of 90.93%, categorized as Very Good, with interface, usability, and effectiveness scores of 91.20%, 90.40%, and 91.20%, respectively. These results demonstrate that the proposed dashboard is well accepted and provides practical support for interpreting rental patterns and making data-driven decisions. Future research may incorporate larger and longer-period datasets, customer segmentation, predictive analytics, and real-time recommendation capabilities to improve the robustness and personalization of rental recommendations.

REFERENCES

[1] Adebunmi Okechukwu Adewusi, Ugochukwu Ikechukwu Okoli, Ejuma Adaga, Temidayo Olorunsogo, Onyeka Franca Asuzu, and Donald Obinna Daraojimba, "BUSINESS INTELLIGENCE IN THE ERA OF BIG DATA: A REVIEW OF ANALYTICAL TOOLS AND COMPETITIVE ADVANTAGE," *Computer Science & IT Research Journal*, vol. 5, no. 2, pp. 415–431, Feb. 2024, doi: 10.51594/csitrj.v5i2.791.

[2] A. Bany Mohammed, M. Al-Okaily, D. Qasim, and M. Khalaf Al-Majali, "Towards an understanding of business intelligence and analytics usage: Evidence from the banking industry," *International Journal of Information Management Data Insights*, vol. 4, no. 1, p. 100215, 2024, doi: https://doi.org/10.1016/j.jjimei.2024.100215.

[3] H. Shafa, "Artificial intelligence-driven business intelligence models for enhancing decision-making in us enterprises," *ASRC Procedia: Global Perspectives in Science and Scholarship*, vol. 1, no. 1, pp. 771–800, Apr. 2025, doi: 10.63125/b8gmdc46.

[4] G. P. Selvarajan, “The Role of Machine Learning Algorithms in Business Intelligence: Transforming Data into Strategic Insights,” *International Journal of Advanced Research and Interdisciplinary Scientific Endeavours*, vol. 1, no. 7, pp. 391–400, Dec. 2024, doi: 10.61359/11.2206-2440.

[5] M. A. Rahman and M. S. Alam, “HOW INTERACTIVE DASHBOARDS IMPROVE MANAGERIAL DECISION-MAKING IN OPERATIONS MANAGEMENT,” *American Journal of Advanced Technology and Engineering Solutions*, vol. 1, no. 01, pp. 122–146, Feb. 2025, doi: 10.63125/cqm5jk84.

[6] N. Hasimah, A. Rahman, M. Zool, and F. Basir, “User-Centered Analytics Dashboard Design for Effective Business Management Decisions,” *International Journal of Advanced Research in Computational Thinking and Data Science Journal homepage*, vol. 9, no. 1, pp. 12–21, Feb. 2026, [Online]. Available: https://karyailham.com.my/index.php/ctds/index

[7] P. S. A. Malla and P. L. Sirisha, “Data-driven business decision making: leveragingpredictive analytics and BI dashboards,” *Scientiarum: A multidisciplinary journal*, vol. 1, no. 4, pp. 21–27, Jan. 2026, doi: 10.54646/SAPARS.2025.18.

[8] Imeldawaty Gultom, Eka Pandu Cynthia, and Alabbas Hussein Saeed, “Visualization and Analysis of Employee Performance Data Using a Power BI-based Business Intelligence Dashboard,” *Journal of Computer Science Artificial Intelligence and Communications*, vol. 1, no. 2, pp. 46–51, Dec. 2025, doi: 10.64803/jocsaic.v1i2.19.

[9] R. Rizal, M. Al Husaini, D. Rizal Nursamsi, and M. M. Rizki, “Implementation of the Apriori Algorithm on Outdoor Equipment Rental Transaction Data Based on Clustering Using the K-Means Algorithm,” *International Journal of Applied Information Technology) J. Appl. Inf. Technol*, vol. 08, no. 02, 2024, doi: 10.25124/ijait.v8i2.6367.

[10] M. A. Amirullah, A. Eviyanti, H. . Setiawan, and N. Atiyanti, “Web-based Outdoor Equipment Rental Information System AT in Outdoors,” *Repository Antis Publisher*, vol. 2, Jan. 2024, doi: 10.61796/jaide.v2i1.1480.

[11] S. Nayak, Sonia, and Y. K. Sharma, “Efficient Machine Leaning Algorithms for Sentiment Analysis In Car Rental Service,” in *2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES)*, Greater Noida, India: EEE, Apr. 2023, pp. 452–463. doi: 10.1109/CISES58720.2023.10183435.

[12] R. P. Elfreda and M. L. L. Usman, “Implementation of Agile Method and Apriori Algorithm for Recommendation System in Outdoor Equipment Rental Services,” *Jurnal Teknik Informatika (Jutif)*, 2026, [Online]. Available: https://jutif.if.unsoed.ac.id/index.php/jurnal/article/view/5567

[13] M. Karunanithi, P. Chatasawapreeda, and T. A. Khan, “A predictive analytics approach for forecasting bike rental demand,” *Decision Analytics Journal*, vol. 11, p. 100482, 2024, doi: https://doi.org/10.1016/j.dajour.2024.100482.

[14] I. Gusti *et al.*, “Implementation of FP-Growth Algorithms for Promo Package Determination in a Scooter Motorcycle Workshop Business,” *Journal of Applied Informatics and Computing (JAIC)*, vol. 9, no. 3, pp. 2548–6861, Jun. 2025, doi: 10.30871/jaic.v9i3.9499.

[15] A. Dara Andriana, M. Fadiel, U. Dewi Widianti, G. Catur Pamuji, and G. Tri Mardiani, “Optimizing Product Promotion with Smart Bundling: An FP-Growth and IT-Enabled Analytical Framework,” in *Proceeding of International Conference on Informatics, Engineering, Science & Technology (INCITEST)*, Bandung, 2025.

[16] S. Chopvitayakun, W. Jitsakul, and N. Aukkanit, “Analyzing Purchase Behavior Using FP Growth Technique to Find Association Rules,” in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Dec. 2024, pp. 106–111. doi: 10.1145/3678610.3678618.

[17] J. Prayitno, B. Saputra, S. A. Rahayu, and T. Hariguna, “Market Basket Analysis Using FP-Growth Algorithm to Design Marketing Strategy by Determining Consumer Purchasing Patterns,” *Journal of Applied Data Sciences*, vol. 4, no. 1, pp. 38–49, Jan. 2023.

[18] Zulham, I. Rusydi, and N. Hidayah, “APPLICATION OF DATA MINING IN GROCERY SALES USING THE FP-GROWTH ALGORITHM,” in *Proceedings The 1st Annual Dharmawangsa International Conference*, 2023.

[19] M. Patil and T. Patil, “Apriori Algorithm against Fp Growth Algorithm: A Comparative Study of Data Mining Algorithms,” in *Proceedings of the 7th International Conference on Innovations and Research in Technology and Engineering (ICIRTE-2022)*, Mumbai, May 2022. doi: 10.2139/ssrn.4113695.

[20] T. Lakshika and A. Caldera, "Association Rules for Knowledge Discovery From E-News Articles: A Review of Apriori and FP-Growth Algorithms," *Advances in Science, Technology and Engineering Systems Journal*, vol. 7, no. 5, pp. 178–192, 2022, doi: 10.25046/aj070519.

[21] S. R. Karimah and E. D. Udayanti, "Comparison of Apriori and FP-Growth Algorithms in Market Basket Analysis for Online Book Sales," *Journal of Applied Informatics and Computing (JAIC)*, vol. 10, no. 1, pp. 566–574, Feb. 2026, doi: 10.30871/jaic.v10i1.11921.

[22] S. Marwah, N. Rahaningsih, I. Ali, and I. Wiguna Marthanu, "FP-Growth for Data-Driven Purchase Pattern Analysis and Product Recommendations at Flanetqueen Store," *Journal of Artificial Intelligence and Engineering Applications*, vol. 5, no. 2, pp. 2808–4519, Feb. 2026, doi: 10.59934/jaiea.v5i2.1850.

[23] U. M. Wulandari, A. T. Suseno, and M. Kholilurrahman, "Market Basket Analysis Using FP-Growth and Apriori on Distro Store Sales Transaction," *MATICS: Jurnal Ilmu Komputer dan Teknologi Informasi (Journal of Computer Science and Information Technology)*, vol. 17, no. 1, pp. 12–18, Mar. 2025, doi: 10.18860/mat.v17i1.28820.

[24] H. Hairani and J. Ximenes Guterres, "Exploring Customer Purchasing Patterns: A Study Utilizing FP-Growth Algorithm on Supermarket Transaction Data," *International Journal of Engineering and Computer Science Applications (IJECSA)*, vol. 3, no. 1, pp. 33–42, Mar. 2024, doi: 10.30812/ijecsa.v3i1.3874.

[25] E. Kannout, M. Grodzki, and M. Grzegorowski, "Towards Addressing Item Cold-Start Problem in Collaborative Filtering by Embedding Agglomerative Clustering and FP-Growth into the Recommendation System," *Computer Science and Information Systems*, vol. 20, no. 4, pp. 1343–1366, Sep. 2023, doi: 10.2298/CSIS221116052K.

[26] C. Uripto and P. Mayang, "Analisis Pola Pembelian Produk Digital Menggunakan Metode FP-Growth untuk Optimalisasi Strategi Bundling pada Marketplace Online," *Jurnal Ilmu Komputer Al Muslim*, vol. 5, no. 1, Apr. 2026.

[27] Fariz, E. D. Wahyuni, and T. L. I. Sugata, "Implementation of the FP-Growth Algorithm for Bundling Strategy and Store Layout Redesign at Toko Kasih Ibu," *JURNAL TEKNOLOGI DAN OPEN SOURCE*, vol. 8, no. 2, pp. 482–494, Nov. 2025, doi: 10.36378/jtos.v8i2.4673.

[28] N. F. Fahrudin, R. Maulana, and M. M. Barmawi, "Optimasi Bundling Produk Toko Roti berbasis Waktu menggunakan Algoritma FP-Growth," *Rekayasa Hijau: Jurnal Teknologi Ramah Lingkunga*, vol. 8, no. 3, pp. 297–308, Dec. 2024, doi: 10.26760/jrh.v8i3.297-308.

[29] M. Pancić, D. Ćućić, and H. Serdarušić, "Business Intelligence (BI) in Firm Performance: Role of Big Data Analytics and Blockchain Technology," *Economies*, vol. 11, no. 3, Mar. 2023, doi: 10.3390/economies11030099.

[30] I. D. Putri, Yuhandri, and R. Hardianto, "Application of the FP-Growth Algorithm in Consumer Purchasing Pattern Analysis," *Journal of Computer Science and Information Technology*, vol. 10, no. 2, pp. 44–49, Apr. 2024, doi: 10.35134/jcsitech.v10i2.99.

[31] Zulfa Hana Aqliyah, Rudi Kurniawan, and Tati Suprapti, "FP-Growth Algorithm for Association Model Optimization in Household Sales Data," *Journal of Artificial Intelligence and Engineering Applications (JAIEA)*, vol. 4, no. 2, pp. 830–838, Feb. 2025, doi: 10.59934/jaiea.v4i2.760.

[32] Z. U. Rizqi, "Implementasi Association Rule-Market Basket Analysis dalam Menentukan Strategi Product Bundling pada Usaha Ritel," *Performa: Media Ilmiah Teknik Industri*, vol. 21, no. 2, p. 113, Sep. 2022, doi: 10.20961/performa.21.2.30156.

[33] X. Li and M. F. Rosas, "Career Recommendation System Design Based on FP-growth Algorithm," in *Proceedings of the 3rd International Conference on Internet Technology and Educational Informatization, ITEI 2023, November 24–26, 2023, Zhengzhou, China*, Zhengzhou: European Alliance for Innovation, Apr. 2024. doi: 10.4108/eai.24-11-2023.2343709.