
Automatic Menu Recommendation for Industrial Catering Using Constraint-Based Filtering, K-Means Clustering, and Apriori Association Rule Mining

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Abstract

Industrial catering services that supply daily meals to factory workers face recurring operational challenges, particularly in planning menus that are balanced in terms of cost, ingredient availability, and nutritional variety. Manual menu planning is time-consuming and often results in inconsistent decisions, especially when ingredient stocks fluctuate daily. This study presents the design and implementation of an automatic daily menu recommendation system for Puteri Catering, an industrial catering service in Sidoarjo, East Java, Indonesia. The system integrates three complementary approaches: Constraint-Based Filtering to validate menu candidates against current ingredient stock and budget limits, K-Means Clustering to categorize menus into three cost groups (Cheap, Moderate, and Expensive) based on their production cost per serving (HPP), and Apriori Association Rule Mining to discover frequent menu combination patterns from historical transaction data. The system was developed using the Laravel 11 framework with a MySQL database, while the machine learning components were implemented in Python using the Scikit-learn and MLxtend libraries. The dataset used consists of 43 menu items, 62 raw ingredients, and 60 historical daily transactions. Evaluation results show that K-Means clustering achieved a Silhouette Score of 0.5794, indicating a good separation between clusters. The Apriori algorithm successfully generated 83 association rules, with the strongest rule being Rawon → Mendol with a confidence of 88.9% and a lift of 3.56. Functional testing using the Black Box method across 47 test cases covering 9 system modules yielded a 100% success rate. The system successfully generates three menu package recommendations per day, each with automatic ingredient stock deduction, providing a practical and data-driven solution for daily operational planning in industrial catering services.

1. Introduction

Menu planning in industrial catering services is a critical operational task that directly affects production efficiency, cost control, and worker satisfaction. Unlike restaurant settings where customers choose their own meals, industrial catering such as services supplying daily meals to factory workers requires the management

to plan a complete menu package every day, covering main dishes, vegetables, and complementary items, within a defined budget and based on available ingredient stocks [1]. When this process is done manually, it tends to be time-consuming, inconsistent, and prone to errors, particularly when ingredient availability changes daily.

Puteri Catering is an industrial catering service based in Sidoarjo, East Java, Indonesia, that supplies daily meal boxes to factory workers. The catering currently manages 43 menu items across three categories, namely main dishes (Lauk), vegetables (Sayur), and complementary items (Pelengkap), with daily serving volumes ranging from 50 to 80 portions. Prior to this research, menu planning was performed manually by the owner each morning, without considering real-time ingredient stock levels or systematic cost analysis. This approach frequently resulted in suboptimal decisions and missed opportunities to optimize the production cost per serving (Harga Pokok Produksi/HPP).

Previous studies have explored data mining and machine learning approaches for food menu analysis and recommendation. Several works applied the Apriori algorithm to identify frequent menu or product combinations from transaction data, differing mainly in the retail or culinary context studied, ranging from consumer shopping trends to light snack sales [2],[3],[4],[5],[6], while others used K-Means Clustering to group menus or food products based on sales levels or pricing characteristics [7],[8],[9],[10]. Constraint-based recommender systems have also been studied as an effective approach for filtering candidates based on hard constraints such as budget and availability[11]. Beyond recommender-system approaches, multi-objective optimization methods have also been applied to menu planning problems in institutional food service settings such as schools and hospitals, primarily to satisfy nutritional and cost objectives [12]; however, such approaches typically rely on detailed nutritional data structures rather than historical transaction patterns and are not designed for the daily, stock-constrained, budget-driven decision context of industrial catering operations. However, most of these studies addressed only one aspect of the problem, either pattern discovery, clustering, or filtering, and were conducted in general food retail or small culinary business contexts, without considering the operational complexities specific to industrial catering, such as daily stock validation and multi-component menu packages [13],[1].

This study addresses these limitations by designing and implementing an integrated automatic menu recommendation system for Puteri Catering. The proposed system combines three complementary approaches in a sequential pipeline. First, Constraint-Based Filtering validates menu candidates against real-time ingredient stock and daily budget constraints. Second, K-Means Clustering groups menus into three cost categories, namely Cheap, Moderate, and Expensive, based on their HPP per serving. Third, Apriori Association Rule Mining extracts frequent menu combination patterns from 60 historical daily transactions to refine the recommendation output. The final output consists of three recommended menu packages per day, one from each cost category, allowing the catering administrator to choose the package that best fits the day's operational conditions.

The system was developed as a web-based application using the Laravel 11 framework, MySQL database, and Python-based machine learning scripts utilizing Scikit-learn and MLxtend libraries. To the best of the authors' knowledge, this is among the first studies to integrate constraint-based filtering, K-Means clustering, and Apriori mining into a unified daily menu recommendation pipeline specifically designed for the industrial catering context.

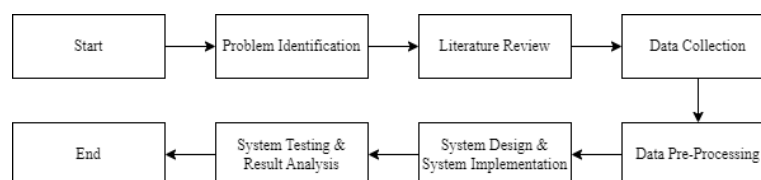


Figure 1. Research Flow Diagram

The system was developed as a web-based application and tested using real operational data from Puteri Catering. The following subsections describe each component of the proposed method in detail.

2. Research Method

This study follows a sequential development approach that begins with data collection and system design, followed by algorithm implementation, system development, and functional testing. Figure 1 illustrates the overall research flow. The system was developed as a web-based application and tested using real operational data from Puteri Catering. The following subsections describe each component of the proposed method in detail.

2.1 Data Collection

The data used in this study were collected directly from Puteri Catering, Pasuruan, East Java, Indonesia. The dataset consists of three main components. First, menu data comprising 43 menu items categorized into three groups: 19 main dishes (Lauk), 11 vegetable dishes (Sayur), and 13 complementary items (Pelengkap). Second, ingredient data comprising 62 raw ingredients along with their unit prices, which are used to calculate the production cost per serving (HPP). Third, historical transaction data comprising 60 daily transaction records from April to June 2025, each containing the menu combination served, the number of portions, and the date of service.

2.2 System Architecture

The proposed system is built using a three-tier architecture consisting of a frontend layer, a backend layer, and a machine learning layer. The frontend is developed using Bootstrap 5 as a responsive web interface accessible through any standard browser. The backend is built using the Laravel 11 framework with PHP, handling all business logic, routing, and database operations. The database uses MySQL to store all master data and transaction records across six main tables, namely tb_bahan (ingredients), tb_menu (menus), tb_komposisi (recipe compositions), tb_stok (ingredient stocks), tb_hpp (production costs), and tb_transaksi (daily transactions). The machine learning layer consists of three Python scripts that are executed by the Laravel backend using the shell_exec function, with results returned in JSON format for further processing. The system has been deployed using a split-hosting architecture, with the Laravel application hosted on Rumahweb shared hosting and the Python machine learning scripts served as a Flask REST API on the Railway cloud platform; the deployed system is publicly accessible at <https://puteri-catering.site>.

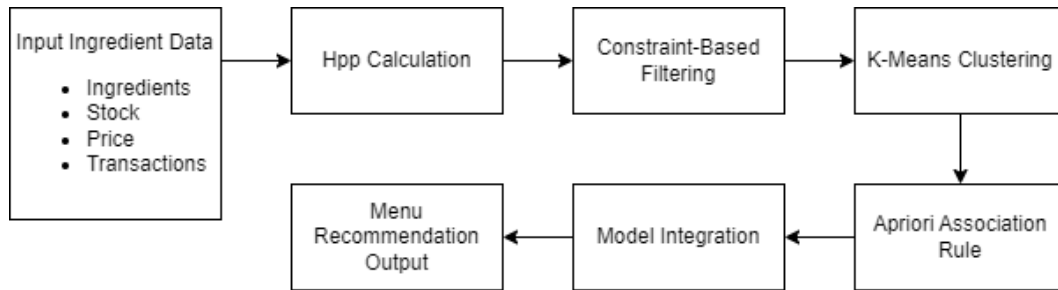


Figure 2. System Architecture Diagram

2.3 HPP Calculation

The production cost per serving (HPP) for each menu item is calculated using a Python script (hitung_hpp.py) that reads ingredient compositions from the database and computes the total material cost per portion. The formula used is as follows:

$$HPP_{material} = \sum (Q_i \times P_i) \quad (1)$$

In addition to material costs, an overhead cost is added to each serving to account for basic operational expenses that are not included in the recipe. The overhead rules applied in this system are: (a) main dishes and

vegetable dishes are charged an overhead of Rp 1,750 per serving, representing the cost of steamed rice (0.1 kg × Rp 14,000), basic cooking oil (0.02 liters × Rp 15,000), and basic seasoning (0.005 kg × Rp 10,000); (b) complementary items are charged no overhead (Rp 0) as they are self-contained and do not require rice; and (c) Nasi Kuning (yellow rice) is charged an overhead of Rp 350 per serving only, since the rice ingredient is already included in its composition; this overhead therefore comprises only basic cooking oil (0.02 liters × Rp 15,000 = Rp 300) and basic seasoning (0.005 kg × Rp 10,000 = Rp 50). The final HPP value is rounded to the nearest hundred to conform to the smallest currency denomination commonly used in Indonesia, as expressed in Equation (2):

$$HPP_{final} = \text{round} \left(\frac{(HPP_{material} + \text{Overhead})}{100} \right) \times 100 \quad (2)$$

2.4 HPP Constraint-Based Filtering

Constraint-Based Filtering is the first stage of the recommendation pipeline. It validates all active menu items against two hard constraints before they are considered as recommendation candidates. The first constraint checks whether the ingredient stock is sufficient for the requested number of portions, as expressed in Equation (3):

$$S_i \geq Q_i \times N \quad (3)$$

where i denotes each ingredient required by the menu. The second constraint checks whether the total HPP of a menu package does not exceed the budget limit set by the administrator, as expressed in Equation (4):

$$HPP_{Lauk} + HPP_{Sayur} + HPP_{Pelengkap} \leq B \quad (4)$$

Menu items that fail either constraint are excluded from the candidate pool. Only menus that pass both constraints proceed to the next stage.

2.5 K-Means Clustering

K-Means Clustering is applied to group the menu items that passed the filtering stage into three cost categories based on their HPP values. The number of clusters $K=3$ was determined using the Elbow Method, which identifies the point of diminishing returns in the within-cluster sum of squares (WCSS) as K increases. The algorithm is implemented using the Scikit-learn library with parameters $n_clusters=3$, $random_state=42$, and $n_init=10$ to ensure reproducibility [7],[8].

The clustering process begins by initializing three centroids randomly. Each menu is then assigned to the nearest centroid based on the Euclidean distance of its HPP value, as expressed in Equation (5):

$$d(x, c) = |HPP_{menu} - HPP_{centroid}| \quad (5)$$

The centroids are updated iteratively until convergence. After clustering, the clusters are sorted by centroid value so that the cluster with the lowest centroid is labeled Cheap (Murah), the middle cluster is labeled Moderate (Sedang), and the highest is labeled Expensive (Mahal). The quality of the clustering result is evaluated using the Silhouette Score, defined in Equation (6):

$$s(i) = \frac{(b(i) - a(i))}{\max(a(i), b(i))} \quad (6)$$

where $a(i)$ is the mean intra-cluster distance of data point i and $b(i)$ is the mean nearest-cluster distance. A score closer to 1.0 indicates well-separated clusters.

2.6 Apriori Association Rule Mining

Apriori Association Rule Mining is applied to discover frequent menu combination patterns from the 60 historical transaction records. The algorithm is implemented using the MLxtend library with a minimum support of 0.1 (10%) and a minimum confidence of 0.3 (30%) [2],[5].

The support of an itemset X is defined in Equation (7):

$$\text{support}(X) = \frac{\text{frequency}(X)}{\text{total}_{\text{transactions}}} \quad (7)$$

The confidence of a rule $X \rightarrow Y$ is defined in Equation (8):

$$\text{confidence}(X \rightarrow Y) = \frac{\text{support}(X \cup Y)}{\text{support}(X)} \quad (8)$$

The lift of a rule $X \rightarrow Y$, which measures the strength of association beyond random co-occurrence, is defined in Equation (9):

$$\text{lift}(X \rightarrow Y) = \frac{\text{confidence}(X \rightarrow Y)}{\text{support}(Y)} \quad (9)$$

A lift value greater than 1 indicates that the co-occurrence of X and Y is not coincidental and that the rule carries meaningful information. The association rules generated by Apriori are used in the final recommendation stage to prioritize menu combinations that are historically consistent with Puteri Catering's serving patterns.

2.7 Recommendation Generation and System Testing

The final recommendation is generated by integrating the outputs of all three preceding stages. From the pool of individual menu items that passed Constraint-Based Filtering, the system randomly generates 200 valid menu package combinations, each consisting of one main dish, one vegetable dish, and one complementary item. These combinations are then ranked by their total package HPP, and the packages with the lowest, median, and highest total HPP values are selected to represent the Cheap, Moderate, and Expensive packages, respectively. It should be noted that this package-level HPP ranking is performed independently of the item-level K-Means clustering described in Section 2.5; the clustering output instead characterizes the overall cost distribution of the menu catalog for the administrator, while the final package classification relies on ranking the total HPP of the randomly generated valid combinations. Association rules from the Apriori stage are subsequently applied to prioritize, among combinations within the same rank, those that match historically frequent patterns.

The system was tested using the Black Box Testing method, which evaluates functional correctness by verifying that system outputs match expected results for a given set of inputs, without examining internal code logic [14]. A total of 47 test cases were designed across 9 system modules, covering authentication, dashboard, ingredient management, menu management, stock management, automatic recommendation, manual menu selection, transaction history, and reporting modules.

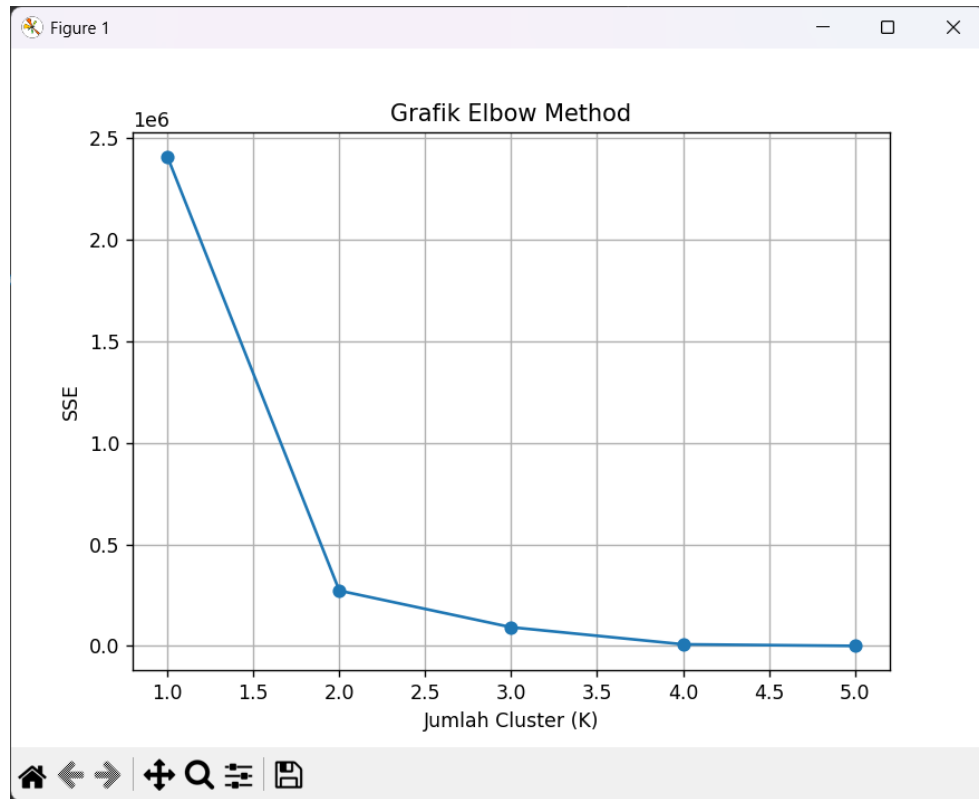


Figure 3. Elbow Method Result for Determining Optimal K

3. Result and Discussions

This study follows a sequential development approach that begins with data collection and system design, followed by algorithm implementation, system development, and functional testing. Figure 1 illustrates the overall research flow.

The system was developed as a web-based application and tested using real operational data from Puteri Catering. The following subsections describe each component of the proposed method in detail.

3.1 HPP Calculation Results

The HPP calculation was successfully performed for all 43 active menu items in the Puteri Catering database. Table 1 presents a summary of the HPP results grouped by menu category.

Table 1. Summary of HPP Calculation Results by Category

Menu Category	Number of Items	Minimum HPP	Maximum HPP	Average HPP
Main Dish (Lauk)	19	Rp 2,600	Rp 9,800	Rp 4,997
Vegetable (Sayur)	11	Rp 2,100	Rp 5,100	Rp 2,936
Complementary (Pelengkap)	13	Rp 400	Rp 2,500	Rp 1,254
Total	43	Rp 400	Rp 9,800	Rp 3,229

The lowest HPP is held by Kerupuk Udang (dried shrimp crackers) at Rp 400 per serving, while the highest HPP belongs to Empal Daging (braised beef) at Rp 9,800 per serving. The wide HPP range across all 43 menus demonstrates sufficient price diversity to support meaningful clustering and to accommodate various budget levels set by the administrator. The overhead component of Rp 1,750 per serving for main dishes and

vegetables was found to contribute significantly to the total HPP, particularly for low-material-cost items such as Tempe Goreng (fried tempeh), where overhead accounts for approximately 67% of the final HPP (Rp 1,750 out of Rp 2,600).

3.2 K-Means Clustering Results

K-Means Clustering with K=3 was applied to the HPP values of all 43 menus. The algorithm converged after several iterations and produced three well-separated clusters as summarized in Table 2.

Table 2. K-Means Clustering Results

Cluster	Category	Centroid HPP	Number of Menus	Percentage
1	Cheap (Murah)	Rp 1,823	26	60.5%
2	Moderate (Sedang)	Rp 4,492	13	30.2%
3	Expensive (Mahal)	Rp 8,700	4	9.3%

The Cheap cluster (centroid Rp 1,823) is dominated by complementary items, vegetable dishes, and tempeh or tofu-based main dishes. The Moderate cluster (centroid Rp 4,492) consists mainly of chicken, egg, and fish-based dishes. The Expensive cluster (centroid Rp 8,700) contains exclusively beef-based dishes, namely Ayam Goreng Telor, Daging Sunduk (Sate), Daging Kelapa, and Empal Daging.

The quality of the clustering result was evaluated using the Silhouette Score. The obtained value of 0.5794 indicates a Good separation between clusters, as values in the range of 0.50 to 0.70 are generally considered to reflect reasonably well-defined cluster structures [7],[8]. This confirms that the choice of K=3 is appropriate for the HPP distribution of Puteri Catering's menu dataset, as shown by the Elbow Method result in Figure 3. Figure 4 illustrates the distribution of menus across the three clusters.

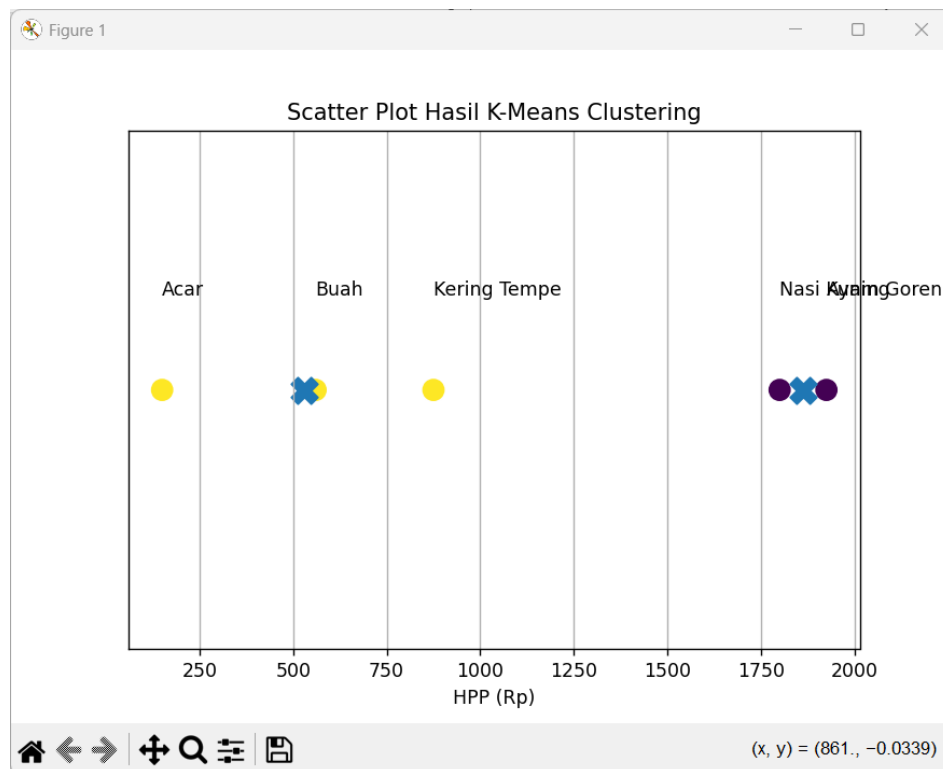


Figure 4. K-Means Clustering Result

3.3 Apriori Association Rule Mining Results

The Apriori algorithm was applied to 60 historical daily transaction records. With a minimum support of 0.1 and a minimum confidence of 0.3, the algorithm identified 15 frequent itemsets and generated a total of 83 association rules. Table 3 presents the 10 strongest rules ranked by lift value.

Table 3. Top 10 Association Rules by Lift Value

Antecedent	Consequent	Support	Confidence	Lift
Rawon	Mendol	15.0%	88.9%	3.56
Rawon	Kerupuk Udang	15.0%	88.9%	3.20
Pecel, Urap-urap	Bakwan Sayur	11.7%	87.5%	3.15
Pecel, Urap-urap	Peyek Kacang	11.7%	87.5%	3.15
Ayam Bakar	Sayur Asem	10.0%	85.7%	3.06
Empal Daging	Kerupuk Udang	10.0%	83.3%	3.00
Tongkol Balado	Dadar Jagung	10.0%	80.0%	2.88
Bali Telor	Lodeh Rebung	13.3%	80.0%	2.67
Ayam Goreng Telor	Buah Semangka	18.3%	78.6%	2.48
Daging Sunduk (Sate)	Acar	10.0%	75.0%	2.50

The strongest rule found is Rawon (a black beef soup made with keluak/black nut spice) → Mendol (a fried fermented-soybean patty) with a confidence of 88.9% and a lift of 3.56, meaning that when Rawon appears in a transaction, there is an 88.9% probability that Mendol also appears, and this co-occurrence is 3.56 times more likely than random chance. This pattern is consistent with the culinary tradition of East Java, where Rawon is conventionally served with Mendol and Kerupuk Udang as accompaniments [2],[5]. All rules with a lift value above 1 confirm that the discovered associations are statistically meaningful and not coincidental.

3.4 Recommendation System Results

The integrated recommendation system generates three menu packages per request, each representing a different cost level. Table 4 presents an example of recommendation output generated for 60 portions with a budget limit of Rp 10,000 per serving.

Table 4. Example of Recommendation Output (60 Portions, Budget Rp 10,000/serving)

Package	Main Dish (Lauk)	Vegetable (Sayur)	Complementary (Pelengkap)	Total HPP	Package
Cheap	Tempe Goreng (Rp 2,600)	Sayur Bayam (Rp 2,600)	Kerupuk Udang (Rp 500)	Rp 5,700	Cheap
Moderate	Ayam Goreng (Rp 4,100)	Sayur Sop (Rp 2,700)	Buah Jeruk (Rp 700)	Rp 7,500	Moderate
Expensive	Rawon (Rp 6,300)	Tauge Kemangi (Rp 2,200)	Mendol (Rp 700)	Rp 9,200	Expensive

The system successfully produces three distinct packages with a consistent cost ordering of Cheap less than Moderate less than Expensive. All three packages satisfy the ingredient stock constraint for 60 portions. The recommendation output also reflects the Apriori rules, as the Expensive package contains the combination of Rawon and Mendol, which was identified as the strongest association rule with a confidence of 88.9%.

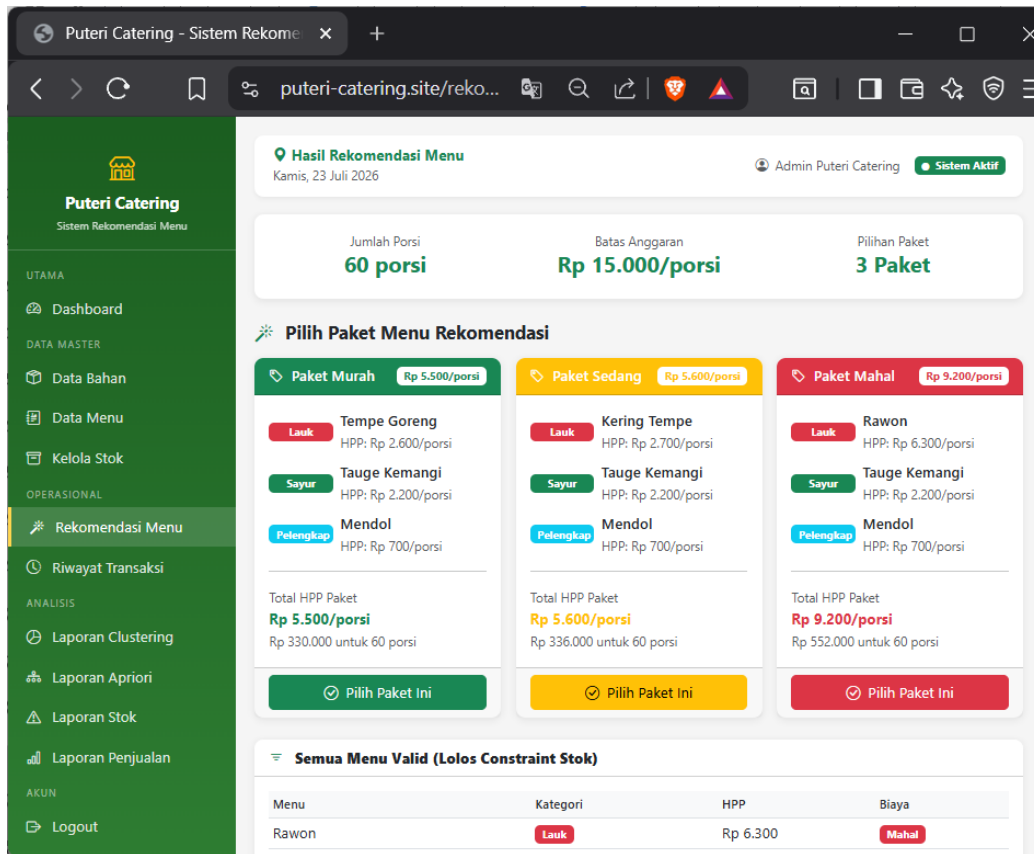


Figure 5. Screenshot of Recommendation System Interface Showing Three Menu Packages

3.5 Black Box Testing Results

Functional testing was conducted using the Black Box Testing method across 47 test cases covering 9 system modules. Table 5 summarizes the testing results by module.

Table 5. Black Box Testing Results Summary

No	Module	Number of Test Cases	Passed	Failed	Success Rate
1	Authentication	6	6	0	100%
2	Dashboard	3	3	0	100%
3	Ingredient Management	5	5	0	100%
4	Menu Management	5	5	0	100%
5	Stock Management	6	6	0	100%
6	Automatic Recommendation	8	8	0	100%
7	Manual Menu Selection	7	7	0	100%
8	Transaction History	3	3	0	100%
9	Reports and Analytics	4	4	0	100%

All 47 test cases across all 9 modules passed successfully, yielding an overall success rate of 100%. The authentication module correctly handled both valid and invalid login attempts, including empty field validation and unauthorized access prevention. The automatic recommendation module verified that the three generated packages consistently maintain the correct cost ordering and that ingredient stocks are automatically deducted

after a package is selected. The manual menu selection module confirmed that the system enforces the minimum requirement of at least one item from each category before allowing a transaction to be saved.

These results collectively demonstrate that the proposed hybrid system, integrating Constraint-Based Filtering, K-Means Clustering, and Apriori Association Rule Mining, provides a functional, reliable, and operationally practical solution for daily menu planning in industrial catering services.

3.6 Discussion

The clustering and association rule mining results obtained in this study can be further contextualized against comparable studies in the literature. For K-Means clustering, the Silhouette Score of 0.5794 achieved in this study falls within the “Good” separation range. Prior studies applying K-Means to group food or beverage menus by sales level [7],[8],[9],[10] generally did not report a quantitative cluster validity metric such as the Silhouette Score, focusing instead on descriptive cluster interpretation. In a broader retail context, K-Means was applied with Silhouette Score evaluation to a larger customer segmentation dataset (2,000 records, 7 attributes) and obtained an optimal Silhouette Score of only 0.43 at $k = 4$, categorized as indicating a “weak” cluster structure [15]. The comparatively higher Silhouette Score obtained in this study suggests that HPP, as a single continuous cost variable, produces more clearly separated clusters than multi-attribute customer segmentation, consistent with the general observation that clustering quality tends to degrade as dimensionality and attribute heterogeneity increase.

For Apriori association rule mining, the strongest rule identified in this study (Rawon $\rightarrow$ Mendol, confidence 88.9%, lift 3.56) demonstrates a substantially stronger association than comparable rules reported in related food and retail transaction studies. Previous Apriori-based menu recommendation studies [2],[3],[4],[5],[6] reported confidence values in a broadly comparable range but did not consistently report lift as a complementary validity measure. In general retail transaction datasets, a strongest-rule confidence of 60.5% and lift of 2.70 was reported from 30,000 supermarket transactions [16], while a maximum lift of only 1.655 was reported from the widely used Groceries dataset [17]. The substantially higher confidence and lift values obtained in this study can be attributed to the smaller, more homogeneous, and culturally consistent transaction dataset of Puteri Catering, where menu combinations are strongly shaped by established regional culinary conventions, such as Rawon being conventionally served with Mendol, rather than the more heterogeneous and loosely correlated purchasing behavior typical of general retail or grocery transactions.

Regarding the positioning of this study relative to prior constraint-based and knowledge-based recommender system research, a constraint-based recommender system leveraging RDF knowledge graphs was proposed for the vehicle purchase domain, demonstrating the effectiveness of explicit constraint modeling for identifying relevant recommendations, but without incorporating pattern discovery or clustering techniques [11]. Similarly, recent advances in knowledge-based and knowledge-graph-enhanced recommendation emphasize semantic reasoning and graph embeddings but likewise do not integrate clustering-based cost categorization or association-rule-based combination discovery within a single pipeline [18],[19]. A systematic review of food recommender systems observed that most existing food recommendation approaches rely on a single machine learning technique, most commonly content-based or collaborative filtering [20], and noted the general absence of studies addressing multi-component menu package construction under real-time operational constraints such as stock and budget [1]. Related food recommender studies published since this review, such as the hybrid KNN-SVD approach [21] and the multi-criteria food and restaurant recommender [22], similarly focus on single-item recommendation rather than multi-component package assembly, while the two-stage clustering-and-association-rule approach [23] and the collaborative-filtering-with-clustering-and-association-rule method [24] each combine two of the three techniques used in this study but do not incorporate constraint-based filtering against real-time stock and budget data, nor address the multi-component package structure characteristic of industrial catering menus. In this context, the present study extends beyond [11] and [1] by demonstrating that constraint-based filtering, K-Means clustering, and Apriori association rule mining can be effectively integrated into a single sequential pipeline that simultaneously enforces operational feasibility through constraints, cost categorization through clustering, and historically informed combination selection

through association rules for multi-component menu packages, a combination not previously addressed in the reviewed literature. In terms of operational forecasting, machine learning-based demand forecasting models have also been proposed to reduce food waste in catering services [25], suggesting a complementary direction for future integration with the present recommendation pipeline.

4. Conclusions and Future Works

This section presents the conclusions drawn from the design, implementation, and testing of the automatic menu recommendation system, along with recommendations for future development.

4.1 Conclusions

This study has successfully designed and implemented an automatic daily menu recommendation system for Puteri Catering, an industrial catering service supplying meal boxes to factory workers in Sidoarjo, East Java, Indonesia. The system integrates three complementary algorithmic approaches in a sequential pipeline to address the operational challenges of daily menu planning.

The following conclusions are drawn from the results of this study. First, the integration of Constraint-Based Filtering, K-Means Clustering, and Apriori Association Rule Mining into a unified recommendation pipeline proves effective in generating daily menu packages that simultaneously satisfy budget constraints, ingredient stock availability, and historical combination patterns. The system successfully produces three distinct menu packages per day, namely Cheap, Moderate, and Expensive, with a consistent cost ordering confirmed across all test scenarios.

Second, K-Means Clustering with $K=3$ successfully categorized all 43 menu items into three cost groups based on HPP values, achieving a Silhouette Score of 0.5794, which indicates a good cluster separation. The resulting centroids of Rp 1,823, Rp 4,492, and Rp 8,700 per serving for the Cheap, Moderate, and Expensive clusters respectively provide meaningful and interpretable groupings that align with the actual pricing structure of Puteri Catering's menu offerings.

Third, the Apriori algorithm successfully extracted 83 association rules from 60 historical transaction records, with the strongest rule being Rawon $\rightarrow$ Mendol with a confidence of 88.9% and a lift of 3.56. These rules reflect culturally consistent menu combination patterns from East Javanese culinary tradition and effectively guide the recommendation system toward combinations that are both cost-efficient and contextually appropriate.

Fourth, functional testing using the Black Box method across 47 test cases covering 9 system modules yielded a 100% success rate, confirming that all system features operate correctly according to their specifications.

4.2 Future Works

Several directions for future development are identified based on the limitations observed during this study. First, the transaction dataset used for Apriori mining currently consists of 60 simulated records. As the system accumulates real daily transaction data from Puteri Catering's operations, the discovered association rules are expected to become more accurate and reflective of actual serving patterns, improving recommendation quality over time.

Second, the HPP values in the current system are static and based on ingredient prices at the time of research. A periodic price update mechanism, such as weekly or monthly price revision, should be incorporated to ensure that cost calculations remain accurate as market prices fluctuate.

Third, the current system requires the administrator to manually input the number of portions each day. Future development could incorporate a short-term demand forecasting model based on historical portion data to assist the administrator in estimating daily requirements, reducing manual input and improving operational planning efficiency.

Fourth, the system's user interface is currently optimized for desktop use. Developing a mobile-responsive interface or a dedicated mobile application would extend the system's accessibility, allowing administrators to

manage menu planning and monitor stock status directly from smartphones, which is particularly relevant for small catering businesses where operational tasks are often handled on the go.

Fifth, future work could explore the use of more advanced recommendation techniques, such as collaborative filtering or deep learning-based approaches, to further improve the personalization and accuracy of menu recommendations.

5. Declarations

Author Contributions

Elang Rezky Pratama: Conceptualization, Methodology, Software, Data Curation, Writing – Original Draft. Yulian Findawati: Supervision, Validation, Writing – Review & Editing. Cindy Taurusta: Validation, Methodology. Yunianita Rahmawati: Investigation, Formal Analysis.

Funding

This research received no external funding.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The operational data from Puteri Catering supporting this research are not publicly available due to enterprise privacy, but are available from the corresponding author on reasonable request.

Use of Artificial Intelligence (AI)

No AI tools were used in the preparation of this manuscript.

Ethical Clearance

This research is classified as low risk; therefore, the authors provide a self-declaration of ethical compliance.

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