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Implementation Of A Personalized Healthy Food Menu Recommendation System Using Content-Based Filtering Based On User Profiles

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ABSTRACT

This study implemented a personalized healthy food menu recommendation system using content-based filtering and cosine similarity. The system translated user characteristics, dietary goals, preferences, allergies, and health-related restrictions into menu attributes. The pilot dataset contained 10 healthy menus represented by 15 binary attributes. Recommendation performance was evaluated offline using 10 controlled user-profile scenarios with realistic age, sex, weight, height, and activity values. Basal metabolic rate and total daily energy expenditure were calculated with the Mifflin-St Jeor equation. After allergen filtering, 94 user-menu candidate pairs were assessed. Reference relevance labels were determined before ranking based on meal-category compatibility, absence of allergen conflicts, and fulfillment of at least two target attributes. At a cut-off of three recommendations, the system achieved macro Precision@3 of 0.7000, Recall@3 of 0.9167, F1@3 of 0.7481, nDCG@3 of 0.8948, and Hit Rate@3 of 1.0000. All 10 functional test cases passed, and no allergen-conflicting menu appeared in the final top-three results. The findings indicated that the system produced relevant and traceable recommendations, although the small pilot dataset limited generalizability.

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1. Introduction

Health is a crucial factor in supporting quality of life and human productivity. Changes in modern lifestyles, such as low physical activity, increased consumption of foods high in sugar, salt, and fat, and low fruit and vegetable consumption, contribute to an increased risk of non-communicable diseases. The World Health Organization explains that non-communicable diseases remain the leading cause of death globally [1]. In Indonesia, the 2023 Indonesian Health Survey also showed that indicators of non-communicable diseases and behavioral risk factors remain a significant concern in health development [2].

Consumption patterns that do not align with the principles of balanced nutrition are one of the problems associated with this condition. The Balanced Nutrition Guidelines emphasize the importance of consuming a variety of foods, practicing good hygiene, physical activity, and regularly monitoring body weight [3]. However, in daily practice, people often experience difficulty translating energy and nutrient needs into daily menu choices. This difficulty is compounded by the varying nutritional needs of each individual.

A person's energy and nutrient needs are influenced by age, gender, weight, height, physical activity level, dietary goals, food preferences, allergies, and certain health conditions. Therefore, a general menu recommendation approach may not be suitable for all users. Digital systems that can create user profiles and match them to menu attributes can be a helpful tool in providing more personalized recommendations.

Several studies in Indonesia have shown that digital applications can be used to support dietary management. Erlansyah and Dea developed an Android-based diet guide application that helps users manage food intake and exercise [4]. Labib et al. developed a nutrition recommendation system based on user profiles and exercise activities [5]. Haryana et al. demonstrated that a self-assessment diet application can be used as a nutritional support tool for overweight and obese adolescents [6]. This research demonstrates that user profile data can be utilized to support nutritional recommendations or support.

In terms of food recommendation systems, Pangestu et al. implemented content-based filtering to recommend healthy foods based on user calorie needs [7]. Almas et al. used content-based filtering and K-Nearest Neighbors for food recommendations based on nutritional needs [8]. Sholeh et al. designed an Indonesian food recommendation system based on nutritional content using knowledge-based filtering [9]. While this research is relevant, there is still room for development in user-profile-based healthy menu recommendation systems that combine estimated energy needs, preferences, dietary restrictions, and menu attributes in a single recommendation flow.

Based on these research issues and gaps, this study implements a personalized healthy menu recommendation system using a user-profile-based content-based filtering method. The novelty of this research lies not only in the use of content-based filtering, but also in the integration of the user's personal profile, estimated daily energy needs, food preferences, allergies or dietary restrictions, and health conditions into a single, transparently explainable recommendation model. The system builds a user profile from physical data and preferences, calculates energy needs using BMR and TDEE, maps menu items to nutritional attributes and health tags, and then calculates similarity using cosine similarity. Furthermore, the system adds a menu filtering mechanism based on allergies or dietary restrictions so that menu items with incongruent ingredients can still be eliminated even if they have a certain similarity value. The main contribution of this research is the design and implementation of a web-based healthy menu recommendation system that not only displays menu rankings but also demonstrates the rationale for recommendations through matching attributes between the user profile and the menu. Thus, the system developed can be used as an initial tool in selecting a healthy menu that is more personal, targeted, and traceable, without being intended as a medical diagnostic tool.

2. Research methodology

This research uses a web-based recommendation system development approach. The research flow is structured chronologically so that the implementation process of content-based filtering can be tested from initial data to recommendation results. The research stages are shown in Figure 1.

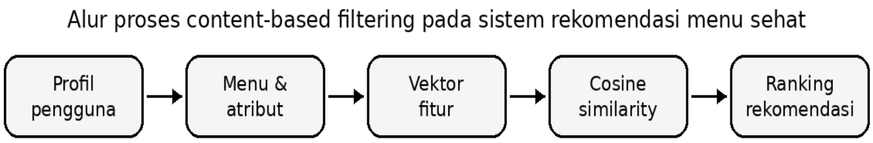

Figure 1. Content-based filtering process flow in the healthy menu recommendation system

2.1. Data Acquisition and Instrumentation

The data used consisted of primary and secondary data. Primary data was obtained through observations of user needs in selecting healthy menu items and interviews with a nutrition resource person, Novita Pratiwi, S.Gz. The interview was conducted to obtain input regarding user profile parameters, energy requirement calculations, menu attribute categories, and limitations that should be considered in healthy menu recommendations. This primary data was used to determine system requirements, user profile attributes, menu attributes, and menu filtering rules based on allergies or dietary restrictions.

The interview with Novita Pratiwi, S.Gz. indicated that a user profile should at least include age, gender, weight, height, physical activity, dietary goals, food preferences, allergies or dietary restrictions, and specific health conditions. The resource person also suggested that the system should not only compare calories but also consider menu characteristics such as high protein, low sugar, low fat, vegetarian, and the content of potentially allergenic ingredients such as milk or nuts. This input was used to develop menu attributes and user profiles in the content-based filtering process.

Validation was carried out by asking the resource person to review the suitability of the attributes used in the initial dataset and the menu filtering rules. Validation results were used to ensure that the 15 binary attributes A1-A15 could be used as initial representations of menus and user profiles. Tag A15 is defined as support for fat and/or sugar restriction, not as a clinical diagnosis label. Secondary data was obtained from nutritional guidelines, recommendation system literature, previous research, and scientific sources on energy requirement calculations and content-based filtering methods [3], [7]-[15].

The research instruments included observation sheets, interview guides, menu master data, user profile designs, functional test scenarios, and recommendation evaluation scenarios. The pilot dataset actually used in the calculations consisted of 10 menus (M1-M10) and 15 binary attributes (A1-A15), resulting in 150 item attribute values. Evaluation was conducted on 10 controlled test profiles. These profiles were test scenarios, not patient or respondent data, and were compiled with values for age, weight, height, and activity within realistic ranges.

2.2. User Profile and Energy Needs

A user profile is created from data on age, gender, weight, height, physical activity level, dietary goals, food preferences, allergies or dietary restrictions, and certain health conditions. Daily energy requirements are calculated by estimating the Basal Metabolic Rate (BMR) using the Mifflin-St Jeor equation, then multiplied by the activity factor to obtain the Total Daily Energy Expenditure. (TDEE) [16] [17].

$$\text{BMR male} = 10W + 6.25H - 5A + 5 \tag{1}$$

$$\text{BMR female} = 10W + 6.25H - 5A - 161 \tag{2}$$

$$\text{TDEE} = \text{BMR} \times \text{activity factors} \tag{3}$$

In this calculation, W represents the user's body weight measured in kilograms, H represents the user's height measured in centimeters, and A represents the user's age expressed in years. These three variables serve as the primary inputs required for estimating the individual's daily energy requirements using the selected calculation method. To improve the accuracy of the estimation, the calculation also incorporates an activity factor. The activity factor is adjusted according to the user's reported level of physical activity, ranging from a sedentary lifestyle to highly active daily routines. By taking the user's activity level into account, the formula can provide a more realistic estimate of the total amount of energy the body requires each day. After the calculation is completed, the resulting value is referred to as the Total Daily Energy Expenditure (TDEE). This TDEE value represents the estimated number of calories the user needs to maintain their current body weight under their current lifestyle and activity conditions. The calculated TDEE is then used as the user's daily energy target within the system. In addition, the TDEE value becomes one of the key components stored in the user's profile, allowing it to be utilized for personalized recommendations, nutritional planning, and other features that rely on an accurate estimate of the user's daily energy requirements.

2.3. Content-Based Filtering Procedure

A content-based filtering method is used to match user profiles with menu attributes. The recommended items are healthy food menu items, while item features consist of menu category, energy, protein, fat, carbohydrate content, main ingredients, preferences, allergies, and health condition tags. Each menu item is represented in an attribute vector. User profiles are also represented in the same vector to calculate the similarity level.

The similarity value is calculated using cosine similarity because this technique can measure the closeness of two vectors based on the direction or pattern of their attributes [12], [13], [18]. The cosine similarity equation is shown in Eq. (4).

$$\text{Sim}(U, M) = (U \cdot M) / (\|U\| \, \|M\|) \tag{4}$$

U is the user profile vector, M is the menu vector, U • M is the dot product, while ||U|| and ||M|| are the lengths of each vector. The menu with the highest similarity value is placed at the top of the recommendation order.

2.4. Recommendation Algorithm

Table 1. Healthy menu recommendation algorithm

No.	Procedure
1	Input user profile: age, gender, weight, height, activity level, dietary goals, preferences, allergies, and health conditions.
2	Calculate the user's BMR and TDEE using Equations (1), (2), and (3).
3	Retrieve menu data and menu attributes from the database.
4	Preprocess: energy category normalization, preference mapping, allergy mapping, and health condition tag generation.
5	Construct a user profile vector and a vector for each menu item.
6	Calculate the similarity between the user profile and each menu item using Equation (4).

No.	Procedure
7	Filter out menu items that conflict with allergies or dietary restrictions.
8	Sort menu items by the highest similarity value.
9	Display a list of menu recommendations to the user.

The algorithm table shows that recommendations are not generated directly from menu names, but through profiling, attribute mapping, similarity calculations, and sorting of results.

2.5. Testing Method

Testing was conducted in two forms. First, functional testing used 10 scenarios to examine registration, login, profile input, energy calculation, menu management, recommendation process, ranking, allergy filtering, and result display. Second, offline evaluation was conducted on 10 test profiles and 10 menus, or 100 profile-menu pairs before filtering. After removing menus with conflicting allergies, 94 candidate pairs were actually counted. Relevance labels were determined before the ranking process based on three criteria: mealtime category matching, no allergy conflicts, and at least two non-category target attributes being met. Performance was reported on the top three recommendations using Precision@3, Recall@3, F1@3, normalized discounted cumulative gain (nDCG@3), and Hit Rate@3. Precision@3 is the proportion of relevant menu items in the top three results; Recall@3 is the proportion of all relevant menu items successfully found; F1@3 is the harmonic mean of precision and recall; nDCG@3 takes into account the position of relevant menu items; and Hit Rate@3 is one if at least one relevant menu item appears in the top three results.

3. Results and Discussion

3.1. Identification of Problems and System Needs

Problem identification results indicate that users often experience difficulty determining healthy menus that meet their body's needs. This difficulty arises because users must consider numerous factors, such as calorie needs, dietary goals, nutritional content, food preferences, allergies, and health conditions. In the manual process, users typically select menus based on general estimates without structured calculations. This can lead to menu selections that are less aligned with the user's energy needs and consumption limits.

Table 2. Requirements for a healthy menu recommendation system

Actor	Needs	Description
User	Filling out your profile	Users enter their age, gender, weight, height, activity level, dietary goals, preferences, allergies, and health conditions.
User	Viewing energy estimates	The system displays BMR and TDEE as an overview of daily energy requirements.
User	Viewing recommendations	The system displays menus based on the highest similarity score.
Admin	Managing menu data	The admin sets the menu name, ingredients, category, nutritional value, and health tags.
System	Calculating recommendations	The system generates profile and menu vectors, calculates cosine similarity, and then performs ranking.

Based on these needs, the system is designed as a healthy menu recommendation system, not a medical diagnosis system. The system provides initial menu suggestions based on the match between the user profile and menu attributes.

3.2. Interview Results and Nutrition Validation

Interviews were conducted with a nutrition expert, Novita Pratiwi, S.Gz., to obtain initial validation of user profile parameters, menu attributes, and menu filtering rules used in the recommendation system. The interview results indicated that the system needs to consider the user's physical data to estimate energy needs, dietary goals to determine the direction of recommendations, food preferences to improve menu suitability, and allergies or dietary restrictions to prevent inappropriate menu items from being displayed as recommendations..

Table 3. Interview results and system utilization

Aspects	Resource person input	System Utilization	Validation
User profile	Age, gender, weight, height, activity level, dietary goals, preferences, allergies, and health conditions should be considered.	Used as user profile input and the basis for generating profile vectors.	match
Daily energy	Energy requirements should be calculated so that menu items aren't selected solely based on name or taste.	The system calculates BMR and TDEE as user energy targets.	match
Menu attributes	Menu items should be labeled with items such as moderate calorie, high protein, low sugar, low fat, vegetarian, dairy, and nut-based.	Used as item attributes in content-based filtering.	match
Restrictions/allergies	Menu items containing prohibited ingredients should be filtered out, even if they share other attributes.	The system gives a not recommended status to menus that conflict with allergies.	match

3.3. Menu Data Collection and User Characteristics

The pilot dataset in this study consists of 10 healthy menus coded M1-M10. Each menu item has a mealtime category, energy value, and descriptive tags, which are then mapped to 15 binary attributes A1-A15. Therefore, the data size used in the evaluation is 10 menu items, 15 features, and 10 test profiles. This data is used to demonstrate the content-based filtering process in a traceable manner, from item representation to ranking results. This dataset is not intended to represent the entire variety of daily menus in Indonesia.

Table 4. Initial dataset of healthy food menus

Code	Menu	Category	Calories	Tags
M1	Brown rice with grilled chicken and vegetables	Afternoon	520	High protein, low sugar
M2	Banana and almond oatmeal	Morning	390	High fiber, vegetarian
M3	Gado-gado with light peanut sauce	Afternoon	480	High vegetable, vegetarian
M4	Steamed fish with broccoli and potatoes	Evening	430	High protein, low fat
M5	Clear chicken and vegetable soup	Evening	350	Low fat, low sugar
M6	Stir-fried tempeh and tofu with vegetables	Afternoon	450	Vegetarian, vegetable protein
M7	Vegetable salad with boiled egg	Morning/Afternoon	320	Low calories, high protein
M8	Grilled chicken with fresh vegetables and brown rice	Afternoon	560	High protein, low sugar
M9	Fruit and yogurt smoothie	Morning	300	High in fiber, contains milk
M10	Capcay with tofu and gravy	Evening	330	High vegetable, vegetarian

The ten items in Table 4 have different combinations of attributes. All these combinations are mapped to the same feature space as the user profile. Numerical nutritional values available in the application are still stored as menu data, but the content-based filtering evaluation in this study uses the energy categories and binary tags listed in Table 5 so that calculations can be reproduced directly.

3.4. Data Preprocessing and Attribute Selection

Data preprocessing involves selecting relevant attributes and simplifying menu values into quantifiable features. Calorie values are not only stored as numbers but also categorized as low, medium, or high based on user needs. Preferences and restrictions are mapped to binary features such as vegetarian, high-protein, low-sugar, low-fat, dairy, or nut-containing..

Table 5. Recommended healthy menu attributes

Code	Attributes	Description
A1	Morning Category	Menu suitable for breakfast
A2	Afternoon Category	Menu suitable for lunch
A3	Evening Category	Menu suitable for dinner
A4	Low Calories	Relatively low energy
A5	Moderate Calories	Moderate energy
A6	High Protein	Moderately high protein
A7	Low Fat	Relatively low fat
A8	Low Sugar	Suitable for sugar restrictions
A9	Vegetarian	Does not contain meat
A10	High Fiber	Contains vegetables/fruit/high fiber
A11	Plant-Based Protein	Plant-based protein sources
A12	Contains Milk	Screening is required for dairy allergies
A13	Contains Nuts	Screening is required for nut allergies
A14	Suitable for Weight Loss Diets	Supports a calorie deficit
A15	Fat/Sugar Restrictions	Menu labeled low-fat and/or low-sugar; not a clinical diagnosis label

The attributes in the table are used to create item representations. This attribute mapping is a crucial part of content-based filtering because the system requires similar features in user profiles and menus to calculate similarity scores.

3.5. User Profile Creation and Menu Representation

An example user scenario is used to demonstrate the calculation process. The user is a 22-year-old female, weighing 60 kg, 160 cm tall, light activity level, weight loss goal, milk allergy, prefers high-protein menus, and limits fat and sugar intake. Based on the Mifflin-St Jeor equation, the user's BMR is $10(60) + 6.25(160) - 5(22) - 161 = 1329$ kcal. With a light activity factor of 1.375, TDEE = $1329 \times 1.375 = 1827.38$ kcal per day. The system then prioritizes low-to-moderate calorie, high-protein, low-sugar, and dairy-free menus.

Table 6. Example of user profile

Components	Value
Gender	Female
Age	22 years old
Weight	60 kg
Height	160 cm
Activity	Light
Goals	Losing weight
Preferences	High protein, low sugar
Allergies	Milk

Components	Value
Health Restrictions	Limiting fat and sugar intake
Target Menu	Low/moderate calories, high protein, no dairy

The profile is then transformed into active attributes A5, A6, A8, A14, and A15, which are moderate in calories, high in protein, low in sugar, suitable for weight loss goals, and supportive of fat/sugar restriction. The allergy attribute is not assigned a positive weight to the vector, but is used as a hard filter. Therefore, menu items containing milk (A12) are excluded before the final results are displayed.

Table 7. Representation of active attributes of profiles and menus

Data	Active attribute code	Active Attributes
Profil pengguna	A5, A6, A8, A14, A15	Moderate calories, high protein, low sugar, suitable for diets, fat/sugar restriction
M1	A2, A5, A6, A8, A14, A15	Lunch, moderate calories, high protein, low sugar, suitable for diets, fat/sugar restriction
M2	A1, A5, A9, A10, A13, A14	Morning, moderate calories, vegetarian, high fiber, nuts, suitable for diets
M3	A2, A5, A9, A10, A13	Lunch, moderate calories, vegetarian, high fiber, nuts
M4	A3, A5, A6, A7, A14, A15	Evening, moderate calories, high protein, low fat, suitable for diets, fat/sugar restriction
M5	A3, A4, A7, A8, A14, A15	Lunch, low calories, low fat, low sugar, suitable for diets, fat/sugar restriction
M6	A2, A5, A9, A11, A14	Lunch, moderate calories, vegetarian, plant-based protein, suitable for diets
M7	A1, A2, A4, A6, A14, A15	Morning/afternoon, low calories, high protein, suitable for diets, fat/sugar restriction
M8	A2, A5, A6, A8, A14, A15	Lunch, moderate calories, high protein, low sugar, suitable for diets, fat/sugar restriction
M9	A1, A4, A10, A12, A14	Morning, low calories, high fiber, milk, suitable for diets
M10	A3, A4, A9, A10, A11, A14	Evening, low calories, vegetarian, high fiber, plant-based protein, suitable for diets

The vector representation table uses active attribute codes to maintain readability and prevent the table from expanding. Systematically, these attribute codes are still represented as binary vectors. Active attributes are assigned a value of 1, and inactive attributes are assigned a value of 0.

3.6. Similarity Calculation

The similarity calculation is performed after the user profile and all menus are in the same attribute space. For example, the user profile has active attributes A5, A6, A8, A14, and A15. Menu M1 has active attributes A2, A5, A6, A8, A14, and A15. The same attributes between the profile and M1 are A5, A6, A8, A14, and A15 so the dot product is 5. The length of the profile vector is square root 5, while the length of the M1 vector is square root 6. The similarity value is calculated as follows:

$$\mathrm{Sim}(U, M1) = 5 / (\sqrt{5} \times \sqrt{6}) = 0.91 \tag{5}$$

The same calculation was performed on the entire menu. Menu items containing allergens, such as milk, were assigned a non-recommended status, even if they shared other attributes. The calculation results are shown in Table 8.

Table 8. Results of cosine similarity calculations

Code	Matching attributes	Number of menu attributes	Similarity	Status
M1	5	6	0.91	Recommended
M8	5	6	0.91	Recommended

Code	Matching attributes	Number of menu attributes	Similarity	Status
M4	4	6	0.73	Recommended
M7	4	6	0.73	Recommended
M5	4	6	0.73	Recommended
M6	2	5	0.40	Low alternative
M10	2	6	0.37	Low alternative
M2	2	6	0.37	Need to check for nuts
M3	1	5	0.20	Need to check for nuts
M9	2	5	0.40	Not recommended: milk

These results show that the M1 and M8 menus get the highest similarity values because they have the most attributes in common with the user profile. Menu M9 tidak direkomendasikan karena mengandung susu, sesuai dengan pantangan pengguna. This shows that the system not only calculates similarity, but also performs filtering based on user profile constraints.

3.7. Recommended Menu Ranking

Table 9. Results of menu recommendation ranking

Ranking	Code	Menu	*Similarity*	Results
1	M1	Brown rice with grilled chicken and vegetables	0.91	Main
2	M8	Grilled chicken with red rice and vegetables	0.91	Main
3	M4	Steamed fish with broccoli and potatoes	0.73	Alternative
4	M7	Vegetable salad with boiled egg	0.73	Alternative
5	M5	Clear chicken and vegetable soup	0.73	Alternative

The ranking table shows that the system displays the menu with the highest similarity score as the primary recommendation. M1 and M8 both achieved a similarity score of 0.91 because they satisfy the required nutritional attributes, including moderate calorie content, high protein, low sugar, suitability for weight loss, and compliance with fat and sugar restrictions. These characteristics make them the most appropriate recommendations for the user's profile. Meanwhile, M4, M7, and M5 are presented as alternative recommendations because they satisfy most, but not all, of the target attributes, resulting in lower similarity scores than the primary recommendations.

3.8. Web-Based System Implementation

The system is implemented as a web-based application with two actors: a general user and an administrator. General users can create accounts, fill in profile data, view energy requirement calculations, and view a list of menu recommendations. Administrators can manage menu data, nutritional values, menu attributes, and user data. Features are implemented to support a structured recommendation process from input to output.

Table 10. Features of web-based system implementation

Actor	Features	Description
User	Registration and login	Creating an account and logging in to the system
User	Profile input	Filling in physical data, activity, preferences, allergies, and health conditions
User	Energy estimation	Viewing BMR and TDEE results
User	Menu recommendations	Viewing menu lists based on similarity

Actor	Features	Description
Admin	Manage menu	Adding and editing menu data and nutritional values
Admin	Manage attributes	Determining menu tags for the recommendation process
System	CBF calculation	Creating vectors, calculating similarity, and ranking

The implementation results indicate that the system flow operates according to the specified requirements. User profile data entered into the system are successfully processed into recommendation attributes that represent the user's nutritional needs and preferences. These attributes are then used to calculate similarity values and generate suitable menu recommendations. Based on the similarity results, the system displays the most relevant menu options for the user. This implementation ensures that each stage of the recommendation process is clear, consistent, and systematic. As a result, the entire recommendation workflow can be easily explained and traced, beginning with the user's input, continuing through the attribute processing and similarity calculation, and ending with the final menu recommendations presented by the system.

3.9. Functional Testing

Table 11. Functional test results

No.	Features	Scenario	Expected Results	Status
1	Registration	User enters account details	Account saved	Successful
2	Login	User enters email and password	Login to dashboard	Successful
3	Profile Input	User enters physical data and preferences	Profile saved	Successful
4	Energy Calculation	System calculates BMR and TDEE	Energy value displayed	Successful
5	Manage Menu	Admin adds menu items and nutritional values	Menu saved	Successful
6	Manage Attributes	Admin sets menu tags	Attributes saved	Successful
7	Recommendati ons	System calculates cosine similarity	Similarity value displayed	Successful
8	Menu Ranking	System sorts menu items	Menu displayed according to ranking	Successful
9	Allergy Filter	Profile has a milk allergy	Sequenced menus are not recommended	Successful
10	Recommended Results	User opens the recommendations page	Menu list displayed	Status

The results of the functional testing demonstrate that all key features of the system operate as expected and perform their intended functions successfully. Each core feature was tested to ensure that it responded correctly to user input and produced the expected outputs under normal operating conditions. The testing process confirmed that the system was able to execute its primary functions consistently without significant errors or unexpected behavior. In addition to verifying the functionality of the system, the testing also evaluated the recommendation process to determine whether it generated appropriate results for different user profiles. The findings indicate that the recommendation results are not determined solely by similarity values or matching scores. Instead, the system also considers important user profile constraints, including dietary restrictions and allergies, when selecting suitable recommendations. By incorporating these personal limitations into the recommendation process, the system is able to filter out options that may not be appropriate for a particular user. This approach improves the overall quality and relevance of the recommendations while reducing the possibility of suggesting unsuitable items. As a result, the recommendations generated by the system are safer, more personalized, and more accurate because they are based on both similarity calculations and the specific information provided by each user during the input process.

3.10. Recommendation Performance Evaluation

The offline evaluation used ten test profiles P1-P10. The BMR and TDEE values in Table 12 were calculated directly using Equations (1)-(3), not randomly filled in. Five profiles were female and five were male, with ages 22-45 years, weight 52-85 kg, height 158-178 cm, and activity factor 1.20-1.55. These ranges were chosen to produce a reasonable variation in energy needs and menu attribute targets for the system testing.

Table 12. Test profile and energy requirement calculation results

Profile	Gender/ Age	BB/TB	Activity factors	BMR (kkal)	TDEE (kkal)
P1	P/22	60 kg/160 cm	1,375	1329,00	1827,38
P2	L/26	68 kg/172 cm	1,550	1630,00	2526,50
P3	P/35	72 kg/158 cm	1,375	1371,50	1885,81
P4	P/28	55 kg/165 cm	1,200	1280,25	1536,30
P5	L/30	80 kg/175 cm	1,550	1748,75	2710,56
P6	P/24	52 kg/158 cm	1,375	1226,50	1686,44
P7	L/45	85 kg/170 cm	1,200	1692,50	2031,00
P8	P/32	65 kg/162 cm	1,550	1341,50	2079,33
P9	L/38	74 kg/178 cm	1,375	1667,50	2292,81
P10	P/40	70 kg/160 cm	1,200	1339,00	1606,80

Each user profile is first analyzed and then mapped to an active attribute based on the information provided by the user. This mapping process allows the system to identify the most relevant characteristics that will be used during the recommendation procedure. After the active attributes have been determined, relevance labels are generated independently from the cosine similarity scores. In other words, the relevance of a menu item is not determined solely by the similarity calculation. Instead, the system applies additional criteria to ensure that the recommended menu items are appropriate for the user's profile and dietary requirements. First, each menu item must correspond to the appropriate mealtime category, such as breakfast, lunch, or dinner. Second, the menu item must successfully pass the allergy filter so that foods containing ingredients that could trigger the user's allergies are excluded from the recommendations. Finally, each menu item must satisfy at least two non-categorical target attributes before it is considered relevant. These additional conditions help improve the quality and suitability of the recommendations generated by the system. As illustrated in Table 13, the list of reference items considered relevant is not always identical to the top three menu items ranked by cosine similarity. Consequently, the calculated precision and recall values are not automatically perfect, reflecting the influence of these additional relevance criteria.

Table 13. Profile vector, relevant menu, and top-3 recommendation results

Profile	Active profile attributes	Allergy filter	Relevant menu	Top-3 system
P1	A1,A4,A6,A14,A15	A12	M7	M7,M1,M4
P2	A2,A5,A6,A8,A14	-	M1,M6,M7,M8	M1,M8,M6
P3	A3,A4,A7,A8,A14	-	M4,M5,M10	M5,M10,M4
P4	A1,A5,A9,A10,A14	A13	M9	M6,M9,M10
P5	A2,A5,A9,A11,A14	-	M1,M3,M6,M8	M6,M3,M1
P6	A3,A4,A9,A10,A11	-	M10	M10,M3,M6
P7	A2,A5,A6,A7,A15	-	M1,M7,M8	M1,M4,M8
P8	A1,A4,A10,A14	A12	M2,M7	M10,M2,M7
P9	A3,A5,A6,A7,A14	-	M4,M5	M4,M1,M5
P10	A2,A5,A8,A9,A10	A13	M1,M6,M8	M6,M1,M8

Table 14. Results of the evaluation of the performance of recommendations at K = 3

Profile	Precision@3	Recall@3	F1@3	nDCG@3	Hit Rate@3
P1	0,3333	1,0000	0,5000	1,0000	1,0000
P2	1,0000	0,7500	0,8571	1,0000	1,0000
P3	1,0000	1,0000	1,0000	1,0000	1,0000
P4	0,3333	1,0000	0,5000	0,6309	1,0000
P5	1,0000	0,7500	0,8571	1,0000	1,0000
P6	0,3333	1,0000	0,5000	1,0000	1,0000
P7	0,6667	0,6667	0,6667	0,7039	1,0000
P8	0,6667	1,0000	0,8000	0,6934	1,0000
P9	0,6667	1,0000	0,8000	0,9197	1,0000
P10	1,0000	1,0000	1,0000	1,0000	1,0000
Macro average	**0,7000**	**0,9167**	**0,7481**	**0,8948**	**1,0000**

Based on Table 14, the average Precision@3 macro of 0.7000 indicates that 70% of the menus in the top three recommendations meet the relevance criteria. The Recall@3 of 0.9167 indicates that most relevant menus were successfully found, while the F1@3 of 0.7481 indicates a fairly good balance between precision and completeness of the results. The nDCG@3 value of 0.8948 shows that relevant menus are generally placed at the top positions. A Hit Rate@3 of 1.0000 means that all profiles found at least one relevant menu in the top three results. All allergy conflicts in scenarios P1, P4, P8, and P10 were successfully removed from the final results. The imperfect precision value occurs mainly because the dataset size is small and some menus have similar attributes but different mealtime categories.

3.11. Analysis, Implications, and Limitations

The evaluation results show that content-based filtering is capable of placing relevant menu items at the top of the list, but its performance should be interpreted as a pilot test result. The dataset only consists of 10 menu items and 15 binary attributes, so the diversity of ingredients, portion sizes, sodium, actual sugar, micronutrients, and cultural dietary variations are not represented. The 10 profiles used represent a controlled test scenario, not real users; therefore, this study did not measure user satisfaction, dietary adherence, or health impacts. Relevance labels were also generated from predefined attribute rules, not independently assessed by multiple nutrition experts.

Another limitation is that all attributes were assigned the same binary weight. This approach facilitates reproducibility of calculations, but fails to reflect the fact that allergies, energy needs, preferences, and health conditions can have varying levels of importance. Future research should expand the dataset, include more comprehensive portion sizes and numeric nutrient content, involve more than one nutrition expert to establish ground truth, test real users with satisfaction instruments, and compare feature weighting and hybrid methods.

From a methodological perspective, content-based filtering is suitable for new systems because recommendations can be generated without a significant rating or transaction history. The system only requires user profiles and menu attributes. Once user interaction data is available, a hybrid approach can be considered so that the system reflects more than just the attributes specified by the administrator.

For administrators, the attribute structure makes menu data easier to manage and navigate. Each recommendation can be explained by matching attributes and the reason for the exclusion, particularly in cases of allergy conflicts. This transparency is a practical advantage over models that simply generate scores without justification.

For users, the system can be used as an initial tool for filtering and sorting menu options. The recommendations are not intended to be diagnostic or a substitute for consulting a nutritionist, especially for users with certain medical conditions, severe allergies, or clinical dietary therapy needs.

4. Conclusion

This study successfully implemented a personalized healthy food menu recommendation system using user profile-based content filtering. The pilot dataset consisted of 10 menus represented by 15 binary attributes. Evaluation was conducted on 10 realistic test profiles and resulted in 94 candidate pairs after allergy filtering. For the top three recommendations, the system achieved macro averages of Precision@3 of 0.7000, Recall@3 of 0.9167, F1@3 of 0.7481, nDCG@3 of 0.8948, and Hit Rate@3 of 1.0000. All 10 functional tests were successful, and there were no conflicting menus with allergies in the final results. These results indicate that the system is capable of generating relevant and searchable recommendations at the pilot scale. However, the generalizability of the results is still limited by the size of the dataset, the use of equally weighted binary attributes, and the lack of real-user evaluation and multi-expert validation.

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