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User-Centric Diet Recommender Systems with Human-Recommender System Interaction (HRI) based Serendipity Aspect

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Abstract−Currently, obesity is on the rise globally with predictions to continue rising until 2030. Adopting a healthy diet and increasing physical activity are key strategies to reduce the risk of obesity. However, there are significant challenges in adhering to a diet, including the monotony of food choices and difficulty in maintaining motivation. This research aims to develop a user-centered dietary recommendation system that addresses these challenges by introducing serendipity into the diet planning process. Serendipity in this context refers to generating unexpected yet relevant food recommendations, thereby enhancing user engagement and satisfaction. The system uses content-based recommendation techniques, including TF-IDF, Cosine Similarity, and K-Means clustering, to provide personalized dietary suggestions based on individual health profiles, calorie needs, and food preferences. The evaluation of the system involved user testing with 11 participants, where user satisfaction was measured using a Likert scale. Most users (mode of 5 out of 5) expressed strong satisfaction with the recommender system. Additionally, A/B testing demonstrated an improvement in user engagement and dietary adherence, with more mode values of 5 in the evaluation of the second version of the web where users could adjust the similarity values. The evaluation of the system demonstrated that incorporating serendipity into recommendations significantly improves user experience and adherence to dietary plans. The findings highlight the potential of serendipity to transform dietary adherence, making the dieting process more enjoyable and sustainable.

Keywords: Content-Based Recommendation System; Serendipity; TF-IDF; Cosine Similarity; K-Means

1. INTRODUCTION

Obesity is a critical global issue, with more than 2 billion adults affected and projections indicating a continued rise until 2030 [1], [2]. This condition is characterized by excessive body fat accumulation and results from an imbalance between caloric intake and energy expenditure[3]. Obesity significantly increases the risk of various diseases, making it a severe public health concern [2]. The Body Mass Index (BMI) is a widely used metric to evaluate obesity, with a BMI of 30 kg/m² or higher indicating obesity [4], [5]. Addressing obesity requires adopting healthy dietary habits and increasing physical activity. The Dietary Guidelines for Americans (DGA) emphasize the importance of regulating calorie intake and choosing nutritious foods to maintain an ideal weight [6]. However, managing nutrient balance is challenging, highlighting the need for effective dietary strategies [7]. One approach to achieve this balance is calculating daily caloric needs using Basal Metabolic Rate (BMR) and Total Daily Energy Expenditure (TDEE) [8].

Dietary recommendation systems can be crucial in managing caloric intake and promoting healthy eating habits. Traditional recommendation systems focus on accuracy, sometimes translating to user satisfaction [9]. Recent studies suggest that the effectiveness of recommendation systems is significantly influenced by human interaction rather than merely algorithmic precision [10]. Serendipity, providing unexpected yet relevant recommendations, is crucial for enhancing user engagement and satisfaction by delivering surprising results that evoke positive emotional responses [11].

Several studies have contributed to developing dietary recommendation systems in the past five years. For instance, Agapito et al. [12] proposed DIETOS, a recommender system for adaptive diet monitoring and personalized food suggestions based on individual health profiles and real-time questionnaires. Hamdollahi Oskouei and Hashemzadeh [13] developed FoodRecNet, a comprehensively personalized food recommendation network that integrates various dietary and health factors for practical recommendations. Mat Baseri and Saad [2] introduced a dietary monitoring system using decision tree techniques to help control obesity by classifying food calories and providing dietary guidelines. Yuan and Luo [7] explored a personalized diet recommendation system using K-means clustering and collaborative filtering algorithms to enhance nutritional balance and user satisfaction. Lastly, Trang Tran et al. [1] provided an overview of recommender systems in the healthy eating domain, emphasizing the challenges and opportunities in incorporating user preferences and health data for better dietary recommendations. These studies focused on improving algorithmic accuracy but did not adequately address user experience. However, their study did not fully explore human interaction, and no user evaluations were conducted. So, this research proposes the development of a user-centered diet recommendation system. The system considers the user's calorie intake and favorite foods, so the recommendations generated can generate serendipity to improve the user experience [14] [15].

While these studies have made significant contributions to the field, there remains a notable gap in addressing user interaction and satisfaction, mainly through the lens of serendipity. Serendipity in recommender systems involves providing users with unexpected yet relevant recommendations that meet their needs and introduce an element of surprise and delight. This concept is essential for dietary recommendation systems, as it can lead to more engaging and satisfying user experiences.

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The urgency of this research lies in its potential to significantly enhance the effectiveness of dietary recommendation systems by addressing a critical gap in user engagement and satisfaction. Current systems often fall short in maintaining long-term user adherence due to their focus on algorithmic precision without considering the user's experience [11]. Given the growing obesity epidemic and the need for sustainable dietary habits, developing a recommendation system that not only meets nutritional needs but also keeps users engaged and motivated is crucial. By introducing serendipity, this research aims to make dietary recommendations more enjoyable and diverse, thereby improving adherence and overall health outcomes.

This research aims to bridge the gap identified in the existing literature by developing a user-centered dietary recommendation system incorporating serendipity. The proposed system leverages a content-based approach, considering users' caloric needs and food preferences to generate personalized recommendations. By focusing on human interaction with the system, this study seeks to enhance the user experience and satisfaction. The system is designed to provide a personalized food catalog, specifying the number of calories for breakfast, lunch, and dinner. User feedback, collected through a Likert scale, will be used to evaluate the serendipity aspect of the recommendations.

In addressing the identified research gaps, this study proposes a comprehensive framework for evaluating and enhancing serendipity in dietary recommendation systems. By integrating user preferences and caloric needs with a content-based recommendation approach, the system aims to deliver personalized and unexpected dietary suggestions. The evaluation of serendipity will involve collecting user ratings and comments on the recommendations, providing valuable insights into the system's effectiveness and user satisfaction.

In summary, this research addresses two main problems: developing a dietary recommendation system that enhances user satisfaction through serendipity and evaluating the serendipity aspect of the recommendations. The study aims to contribute to the field by providing insights into the importance of human interaction in dietary recommendation systems and offering a novel approach to incorporating serendipity into these systems. Several studies, such as Agapito et al.'s DIETOS [12], Hamdollahi Oskouei and Hashemzadeh's FoodRecNet [13], and Yuan and Luo's personalized diet recommendation system [7], have made significant contributions to the development of dietary recommendation systems but have primarily focused on algorithmic accuracy rather than user experience. This research builds on these foundations by emphasizing user engagement and satisfaction through unexpected yet relevant recommendations. The goal is to improve the user experience and effectiveness of dietary recommendation systems by introducing elements of surprise and delight, thereby encouraging healthier eating habits and addressing the global challenge of obesity.

2. RESEARCH METHODOLOGY

2.1 Research Stages

In this research, a diet recommendation system is developed on a web application focusing on serendipity in diet food recommendations. After the data is collected, pre-processing includes case-folding, data cleaning, lemmatization, stop word removal, and filtering. Next, the processed data will generate relevant food candidates using cosine similarity and TF-IDF techniques. The second stage involves re-ranking, where the combined foods will be further analyzed using the K-Means clustering method and the help of the Google Image API to provide more varied and exciting final food recommendations. In the final stage, these food recommendations will be tested through A/B testing by users, where users provide feedback through a serendipity questionnaire. The results of this feedback are then analyzed to assess the effectiveness and surprise level of the recommendations provided by the system. The flowchart of this system design can be seen in Figure 1.

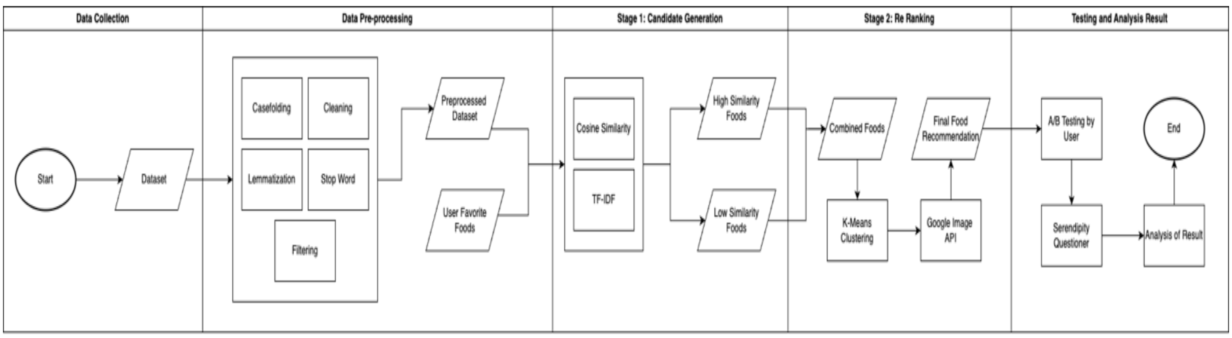

Figure 1. System Flowchart Design

Figure 1 shows the development of the dietary recommendation system, which adopts a comprehensive approach to encourage serendipity in food suggestions. Starting with data collection, it aggregates a rich dataset from user inputs and existing databases, covering recipes, ingredient profiles, nutritional content, and user health information. This foundational phase is critical for personalizing food recommendations. In the subsequent

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preprocessing phase, the dataset undergoes several refinement procedures, such as case-folding, data cleaning, lemmatization, stop word elimination, and data filtering, to ensure its integrity and uniformity and lay the groundwork for precise analysis. The system then employs cosine similarity and TF-IDF methods to identify and prioritize food items according to user preferences and nutritional needs. Cosine similarity assesses the likeness between items based on ingredient profiles, while TF-IDF evaluates ingredient significance in recipes against their dataset frequency. This results in a preliminary list of suited food candidates. These candidates are refined through K-Means clustering and incorporating Google Image API, enriching the recommendations with diversity and compelling visual appeal. This re-ranking procedure ensures that the suggestions are pertinent, varied, and engaging. User feedback gathered from interactions with two application versions—one with standard and another with serendipitous recommendations—via a serendipity-focused questionnaire and A/B testing aids in comparing user satisfaction levels. This feedback is critical for analyzing the recommendations' effectiveness and serendipity. The final stage involves a thorough assessment of user feedback to enhance the recommendations' surprise element and effectiveness and ensure that future iterations of the system better meet user expectations. The process outlined in Figure 1, from meticulous data collection to the detailed analysis of user feedback, is designed to enhance the personalization and serendipity of dietary recommendations, aiming to improve user satisfaction and adherence to dietary suggestions.

2.2 Data

This research utilizes a dataset from Kaggle. This dataset contains 522,517 recipes with details such as cooking time, servings, ingredients, nutritional values, cooking steps, and total calories. An explanation of each column that will be used can be seen in Table 1.

Table 1. Data

Name	Description
Name	Title of the food recipe
Description	Description of the food recipe
Recipe Ingredient Parts	Recipe ingredients
Recipe Instructions	Steps to make
Keywords	Keywords of the food recipe
Images	Image URL for the food recipe
Calories	Number of calories in food
Fat Content	Fat content
Saturated Fat Content	Saturated fat content
Cholesterol Content	Cholesterol content
Sodium Content	Sodium content
Carbohydrate Content	Carbohydrate content
Fiber Content	Fiber content
Sugar Content	Sugar content
Protein Content	Protein content

Based on Table 1, the Name column contains the title of each food recipe. The Description column provides a brief overview of the recipe. The RecipeIngredientParts column lists the ingredients required. The RecipeInstructions column outlines the preparation steps. The Keywords column includes relevant keywords for search and categorization. The Images column provides URLs to food images. Nutritional information is captured in the Calories, FatContent, SaturatedFatContent, CholesterolContent, SodiumContent, CarbohydrateContent, FiberContent, SugarContent, and ProteinContent columns.

2.3 Preprocessing

Quality data is required to produce quality recommendations. Therefore, data processing must be done before the data can be used effectively. The data preprocessing steps include data cleaning, case folding, lemmatization, and stop word removal.

a. Data Cleaning
   Essential data processing processes include identifying, rectifying, and removing inaccurate and incomplete data in the data set. At this stage, special characters and terms are also removed [16]. The data cleaning process can be seen in Table 2 below.

Table 2. Data Cleaning

Column	Before	After
RecipeIngredientParts	c("blueberries", "granulated sugar", "vanilla yogurt", "lemon juice")	blueberries, granulated sugar, vanilla yogurt, lemon juie

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RecipeInstructions	c("Toss 2 cups berries with sugar.", "Let stand for 45 minutes, stirring occasionally.", "Transfer berry-sugar mixture to food processor.", "Add yogurt and process until smooth.", "Strain through fine sieve. Pour into baking pan (or transfer to ice cream maker and process according to manufacturers' directions). Freeze uncovered until edges are solid but centre is soft. Transfer to processor and blend until smooth again.", "Return to pan and freeze until edges are solid.", "Transfer to processor and blend until smooth again.", "Fold in remaining 2 cups of blueberries.", "Pour into plastic mold and freeze overnight. Let soften slightly to serve.")	Toss 2 ups berries with sugar., Let stand for 45 minutes, stirring oasionally., Transfer berry-sugar mixture to food proessor., Add yogurt and proess until smooth., Strain through fine sieve. Pour into baking pan or transfer to ie ream maker and proess aording to manufaturers' diretions. Freeze unovered until edges are solid but entre is soft. Transfer to proessor and blend until smooth again., Return to pan and freeze until edges are solid., Transfer to proessor and blend until smooth again., Fold in remaining 2 ups of blueberries., Pour into plasti mold and freeze overnight. Let soften slightly to serve.

Based on Table 2, the data were cleaned by removing punctuation marks, symbols, and special characters, which aimed to prevent noise and make the text easier to understand.

b. Case Folding

Case Folding aims to equalize each character in the text to lowercase or uppercase. This process converts all character formats found in the data set to lowercase [17]. Case Folding process can be seen in Table 3 below.

Table 3. Case Folding

Column	Before	After
Name	Low-Fat Berry Blue Frozen Dessert	lowfat berry blue frozen dessert
RecipeIngredientParts	blueberries, granulated sugar, vanilla yogurt, lemon juie	blueberries, granulated sugar, vanilla yogurt, lemon juie
RecipeInstructions	Toss 2 ups berries with sugar., Let stand for 45 minutes, stirring oasionally., Transfer berry-sugar mixture to food proessor., Add yogurt and proess until smooth., Strain through fine sieve. Pour into baking pan or transfer to ie ream maker and proess aording to manufaturers' diretions. Freeze unovered until edges are solid but entre is soft. Transfer to proessor and blend until smooth again., Return to pan and freeze until edges are solid., Transfer to proessor and blend until smooth again., Fold in remaining 2 ups of blueberries., Pour into plasti mold and freeze overnight. Let soften slightly to serve.	toss 2 ups berries with sugar, let stand for 45 minutes, stirring oasionally, transfer berrysugar mixture to food proessor, add yogurt and proess until smooth, strain through fine sieve pour into baking pan or transfer to ie ream maker and proess aording to manufaturers diretions freeze unovered until edges are solid but entre is soft transfer to proessor and blend until smooth again, return to pan and freeze until edges are solid, transfer to proessor and blend until smooth again, fold in remaining 2 ups of blueberries, pour into plasti mold and freeze overnight let soften slightly to serve

Based on Table 3, the data initially included capital letters. Thus, in this stage, all capital letters in the text were converted to lowercase.

c. Lemmatization

Lemmatization is the process of returning a word to its base form, such as the base word in the dictionary. This technique is used in information retrieval to overcome the problem of lexical mismatch, making it easier to search and analyze text data [16]. Table 4 below shows this.

Table 4. Lemmatization

Column	Before	After

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Name	lowfat berry blue frozen dessert	lowfat berry blue frozen dessert
RecipeIngredientParts	blueberries, granulated sugar, vanilla yogurt, lemon juie	blueberry, granulated sugar, vanilla yogurt, lemon juie
RecipeInstructions	toss 2 ups berries with sugar, let stand for 45 minutes, stirring oasionally, transfer berrysugar mixture to food proessor, add yogurt and proess until smooth, strain through fine sieve pour into baking pan or transfer to ie ream maker and proess aording to manufaturers diretions freeze unovered until edges are solid but entre is soft transfer to proessor and blend until smooth again, return to pan and freeze until edges are solid, transfer to proessor and blend until smooth again, fold in remaining 2 ups of blueberries, pour into plasti mold and freeze overnight let soften slightly to serve	toss 2 ups berry sugar, let stand 45 minutes, stirring oasionally, transfer berrysugar mixture food proessor, add yogurt proess smooth, strain fine sieve pour baking pan transfer ie ream maker proess aording manufaturers diretions freeze unovered edge solid entre soft transfer proessor blend smooth again, return pan freeze edge solid, transfer proessor blend smooth again, fold remaining 2 ups blueberries, pour plasti mold freeze overnight let soften slightly serve

Based on Table 4, the data before the lemmatization process included words in various forms. Therefore, at this stage, words in the text were converted to their base forms.

d. Stop Word Removal

Stop word removal is a process in natural language processing that aims to eliminate frequently appearing words that do not significantly contribute to understanding the text’s meaning, such as conjunctions and prepositions [16]. This research utilizes the English stop word list from the Natural Language Toolkit (NLTK), as shown in Table 5 below.

Table 5. Stop Word Removal

Column	Before	After
Name	lowfat berry blue frozen dessert	lowfat berry blue frozen dessert
RecipeIngredientParts	blueberries granulated sugar vanilla yogurt lemon juie	blueberry granulated sugar vanilla yogurt lemon juie
RecipeInstructions	toss 2 ups berries with sugar let stand for 45 minutes stirring oasionally transfer berrysugar mixture to food proessor add yogurt and proess until smooth strain through fine sieve pour into baking pan or transfer to ie ream maker and proess aording to manufaturers diretions freeze unovered until edges are solid but entre is soft transfer to proessor and blend until smooth again return to pan and freeze until edges are solid transfer to proessor and blend until smooth again fold in remaining 2 ups of blueberries pour into plasti mold and freeze overnight let soften slightly to serve	toss 2 ups berry sugar let stand 45 minute stirring oasionally transfer berrysugar mixture food proessor add yogurt proess smooth strain fine sieve pour baking pan transfer ie ream maker proess aording manufaturers diretions freeze unovered edge solid entre soft transfer proessor blend smooth return pan freeze edge solid transfer proessor blend smooth fold remaining 2 ups blueberry pour plasti mold freeze overnight let soften slightly serve

Based on Table 5, the stop word removal stage aimed to eliminate common words that do not significantly contribute to understanding the text’s meaning, such as conjunctions and prepositions.

2.4 TF-IDF

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Term frequency (TF) is calculated by comparing the number of words in a document to the number of words in the document. In contrast, Inverse Document Frequency (IDF) is a calculated or weighted value for a word. When the IDF value is high, the word value becomes less important. Here is how to calculate the IDF value [18].

$$TF - IDF(t,d) = tf_{t,d} \text{ x} \log\left(\frac{N}{df_t}\right) \quad (1)$$

represents the total number of occurrences of the t (favorite food) in the document d, N represents the total number of documents in the dataset, and dft represents the number of documents containing the t (favorite food).

2.5 Cosine Similarity

Cosine similarity is a method used to measure the similarity between two objects, in this case, documents or items, which is highly relevant in recommendation systems. This method is a traditional method that is often used and combined with TF-IDF. Cosine similarity is a measure of similarity between two vectors obtained from the value of multiplying the cosine angle between the two vectors being compared [18]. The following is the cosine similarity equation:

$$\cos\alpha = \frac{a \times b}{|a| \times |b|} \quad (2)$$

2.6 K-Means Clustering

K-Means is an unsupervised learning algorithm used to classify/group objects based on their attributes/features, where K is a positive integer [19]. The grouping in this recommender system is determined by the number of favorite foods the user enters. It is used to classify the final food results so that the food produced varies according to user input.

2.7 Recommender System Development

The developed diet recommendation system has several components integrated to provide users with personalized and relevant food recommendations. The development of this system begins with creating a use case diagram to visualize the interaction between the user and the system. This use case diagram shows various activities that can be performed by the user, such as filling in personal health data, entering favorite foods, and selecting diet foods that the system has recommended. The leading actor in this system is the user, who interacts with the recommendation system to get dietary advice that suits his needs and preferences. The use case diagram can be seen in Figure 2.

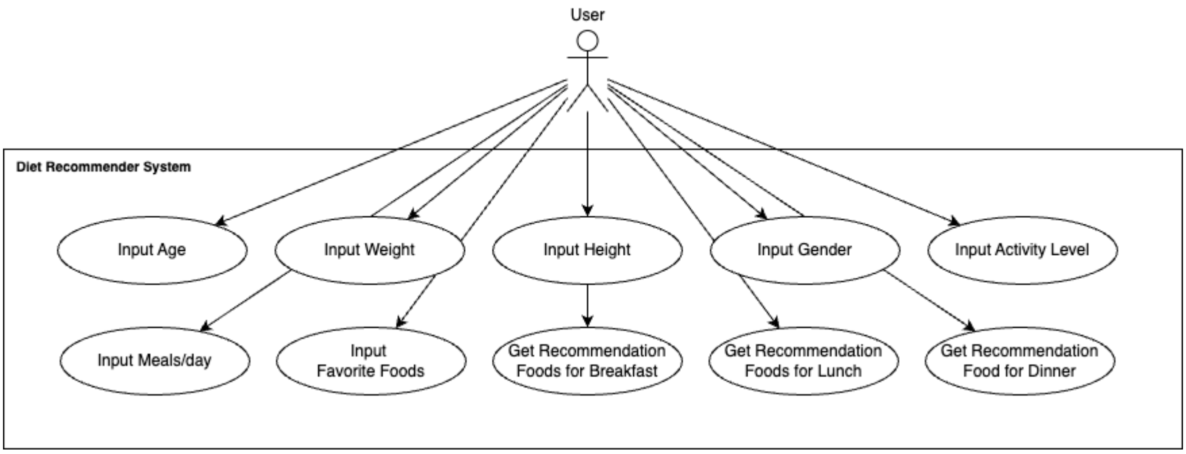

Figure 2. Use Case Diagram

The use case diagram in Figure 2 illustrates the interaction between the user and the diet recommendation system. As the primary actor, the user can perform several activities: inputting personal health data (age, weight, height, gender, activity level, meals per day, and favorite foods) and receiving food recommendations for breakfast, lunch, and dinner. This diagram visualizes the user's role in entering information and obtaining personalized dietary advice from the system.

Next, a deployment diagram was created to illustrate the physical architecture of the system. This diagram shows how the software components are placed on the available hardware and how communication occurs between them. The frontend was developed using React and deployed on a web server that can be accessed by users through a browser. The backend is developed using Fast API and serves as an API server that handles requests from the frontend and communicates with the machine learning model deployed in a virtual machine. Deployment diagram can be seen in Figure 3.

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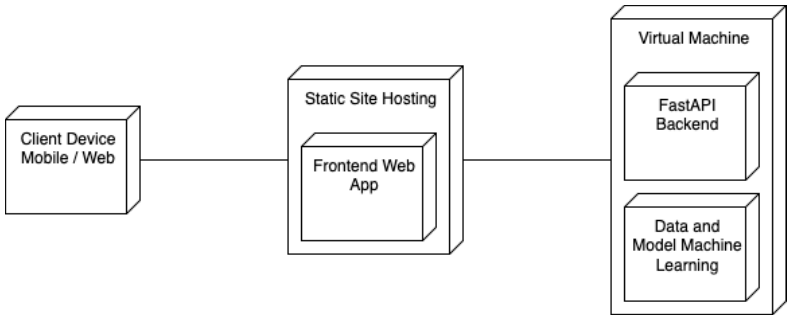

Figure 3. Deployment Diagram

The deployment diagram in Figure 3 shows the physical architecture of the diet recommendation system. The frontend, developed using React, is hosted on a static site and accessed by users through a browser. The backend, developed using FastAPI, handles requests from the frontend and communicates with the machine learning model stored on a virtual machine. The virtual machine also contains the data and model storage, ensuring efficient data processing and model management.

Some screenshots of the web user interface are included to represent the developed system visually. The main page gives users access to fill in their health data. Furthermore, the user can enter his/her favorite food. Based on the profile data, the user can request dietary food recommendations. The system will generate a list of foods customized to the user's daily calorie needs, calculated using TDEE (Total Daily Energy Expenditure). The user can then select breakfast, lunch, and dinner meals from the recommended list on the meal selection page. The process of generating serendipity is obtained from the process of combining foods that have high and low cosine similarity scores so that the result of the recommendations given by the user is a combination of foods that are very compatible with the user's favorite foods and foods that are less compatible with the user's favorite foods but still have a small cosine similarity value.

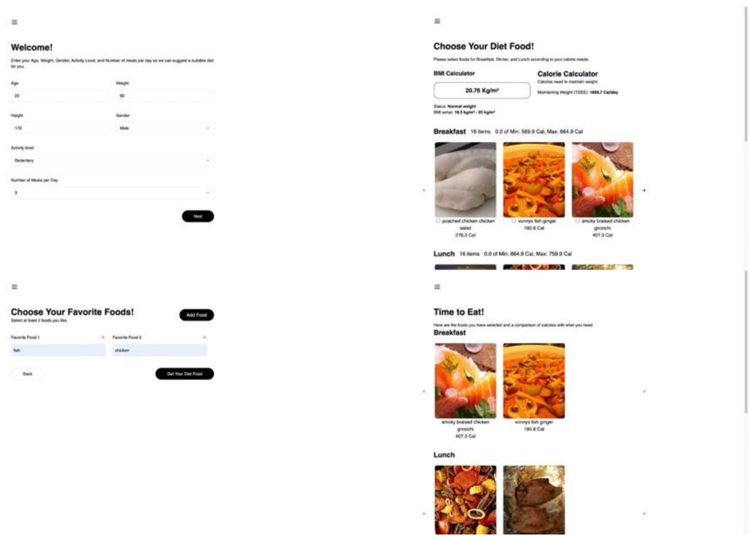

Figure 4. Website Version 1

The screenshots in Figure 4 illustrate the web interface of the developed diet recommendation system. The main page allows users to input their health data, such as age, weight, height, gender, activity level, and meals per day. Users can also enter their favorite foods. Based on this profile data, the system generates personalized dietary recommendations tailored to the user’s daily calorie needs, calculated using Total Daily Energy Expenditure (TDEE). Users can select breakfast, lunch, and dinner meals from the recommended list. The system introduces serendipity by combining foods with varying cosine similarity scores, resulting in recommendations that include highly compatible and slightly less compatible but still relevant food options.

The author conducted A/B testing of two web versions in this research. In the first version, users do not need to set high and low similarity food values. In the second version, users can set high and low similarity values to provide feedback on whether the recommendations produced are better in the evaluation. This test was conducted to understand whether additional control on the similarity parameter can increase user satisfaction with the recommendations generated.

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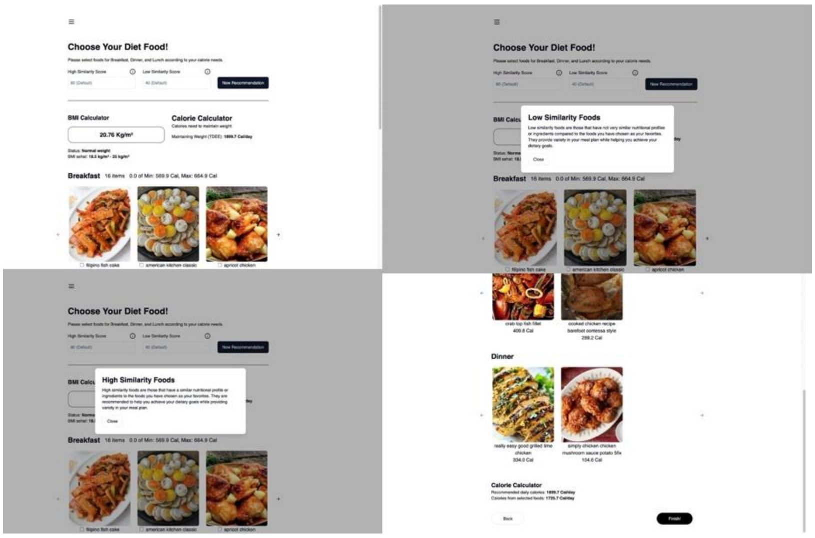

Figure 5. Website Version 2

The screenshots in Figure 5 illustrate the second version of the diet recommendation system's web interface. This version allows users to adjust the similarity scores for their food recommendations, choosing between high and low similarity. The interface includes BMI and calorie calculators and presents food options for breakfast, lunch, and dinner based on the user's profile. High-similarity foods closely match the user's preferences, while low-similarity foods are less like the user's preferences. This version aims to enhance user engagement by allowing customization of recommendation parameters.

With this approach, the developed diet recommendation system not only provides personalized and relevant advice but also introduces the element of serendipity, i.e., unexpected yet relevant recommendations, so that users get a more exciting and varied experience in carrying out their diet program.

3. RESULT AND DISCUSSION

This section summarizes the experimental results of the web application that has been created. This research measures the effectiveness and performance of the diet recommendation system. The evaluation assessed how the system could meet user needs and produce relevant and serendipitous recommendations. The evaluation process involved quantitative Likert scale testing, A/B testing to compare system variations, and user feedback analysis on the recommendations' usability, relevance, and surprise element. The results of this evaluation form the basis for further improvement and optimization of the developed diet recommendation system.

3.1 User Satisfaction Test Results

Testing was carried out on 11 people who were doing or going on a diet. Respondent criteria are adjusted to the domain that researchers will evaluate. The users obtained were seven men and four women. Most users are 18-24 years old, with varying body weight and activity levels.

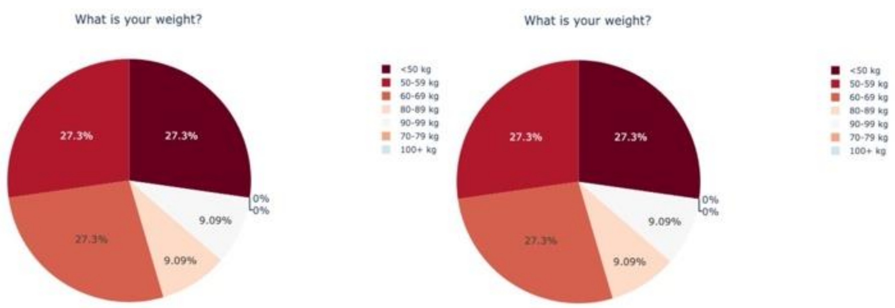

Figure 6. Distribution of user weight and user activity level data

The pie charts in Figure 6 illustrate the distribution of user weight among the 11 respondents participating in the study. Most users fall into the 60-79 kg weight range, with an equal distribution of 27.3% in each main category. This visual representation helps to understand the diversity in user weight.

The test was carried out quantitatively by testing two versions of the website built for respondents and asking them to fill out a questionnaire in the form of a Likert scale.

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Table 6. The Score for the Likert scale

Criteria	Score Weight	
Strongly Disagree	SD	1
Disagree	D	2
Neutral	N	3
Agree	A	4
Strongly Agree	SA	5

Table 6 shows the scoring system for the Likert scale used in the questionnaire. The scale ranges from 1 to 5, with "Strongly Disagree" (SD) scoring one and "Strongly Agree" (SA) scoring 5. This scoring system was used to quantify respondents' feedback.

The weight per question in Table 8, Table 9, Table 10, and Table 11 is calculated by calculating the Likert scale score based on Table 6 and question-based on Table 7 multiplied by the number of respondents who chose that scale. After each scale is calculated, the sum is done, and the weight for the question is obtained.

Table 7. Questionnaire

Question	Number
How easy was it to use this diet recommendation system?	1
How satisfied is the user with the system design?	2
How intuitive is the user interface?	2
How easy is it to find the desired food?	4
How useful were the food recommendations in supporting dietary needs?	5
How relevant are the recommended foods to the user's health profile and food preferences?	6
How often are foods found that had not been considered before but fit into the user's diet?	7
How often do the food recommendations result in discovering fun new variations in the user's diet?	8
How often do food recommendations inspire the desire to try new foods?	9
How easy was it to use the customization features on this system?	10
How satisfied are users with the recommendation results after adjusting?	11
How often is food found that matches user preferences after customizing?	12
How often do the food recommendations after customization lead to discovering new, enjoyable variations in diet?	13
How often does the customization feature help discover interesting new foods?	14
How often are new foods discovered through recommendations that were never considered before?	15
How often do food recommendations surprisingly match preferences, even if the food is new?	16
How often do food recommendations provide options that differ from usual but remain interesting?	17
How often are new and exciting combinations of ingredients found through the recommendation system?	18

Table 7 lists the questionnaire questions used to evaluate various aspects of the diet recommendation system. Each question corresponds to a specific number, ranging from ease of use to the relevance and novelty of the food recommendations. As seen in Tables 8 to 11, the weights for each question were calculated by multiplying the number of respondents who chose each Likert scale option (from Table 6) by the corresponding score and summing the results.

Table 8. User Satisfaction Weight Calculation

	1		2		3		4	
Likert scale	Respondent	Result Scale	Respondent	Result Scale	Respondent	Result Scale	Respondent	Result Scale
SD	0 x 1	0	0 x 1	0	0 x 1	0	0 x 1	0
D	0 x 2	0	0 x 2	0	0 x 2	0	0 x 2	0

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ISSN 2685-3310 (media online)
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N	3 x 3	9	1 x 3	3	2 x 3	6	4 x 3	12
A	2 x 4	8	5 x 4	20	5 x 4	20	2 x 4	8
SA	6 x 5	30	5 x 5	25	4 x 5	20	5 x 5	25
Weight		**47**		**48**		**46**		**45**

Table 8 shows how user satisfaction weights are calculated based on the Likert scale responses. Each respondent's choice is multiplied by the corresponding Likert scale score, and the results are summed to obtain the total weight for each question. This process quantifies user satisfaction for questions 1 through 4.

Table 9. Web Version 1 Weight Calculation

	5		**6**		**7**		**8**	
Likert scale	**Respondent**	**Result Scale**	**Respondent**	**Result Scale**	**Respondent**	**Result Scale**	**Respondent**	**Result Scale**
SD	0 x 1	0	0 x 1	0	0 x 1	0	0 x 1	0
D	0 x 2	0	0 x 2	0	0 x 2	0	0 x 2	0
N	1 x 3	3	2 x 3	6	5 x 3	15	3 x 3	9
A	4 x 4	16	3 x 4	12	2 x 4	8	2 x 4	8
SA	6 x 5	30	6 x 5	30	4 x 5	20	6 x 5	30
Weight		**49**		**48**		**43**		**47**

	9	
Likert scale	**Respondent**	**Result Scale**
SD	0 x 1	0
D	0 x 2	0
N	0 x 3	0
A	4 x 4	16
SA	7 x 5	35
Weight		**51**

Table 9 shows the weight calculations for Web Version 1 based on the Likert scale responses for questions 5 through 9. Each respondent's choice is multiplied by the corresponding Likert scale score, and the results are summed to determine the total weight for each question. This process quantifies user satisfaction and feedback for Web Version 1.

Table 10. Web Version 2 Weight Calculation

	10		**11**		**12**		**13**	
Likert scale	**Respondent**	**Result Scale**	**Respondent**	**Result Scale**	**Respondent**	**Result Scale**	**Respondent**	**Result Scale**
SD	0 x 1	0	0 x 1	0	0 x 1	0	0 x 1	0
D	0 x 2	0	0 x 2	0	0 x 2	0	0 x 2	0
N	3 x 3	9	1 x 3	3	3 x 3	9	1 x 3	3
A	2 x 4	8	3 x 4	12	5 x 4	20	6 x 4	24
SA	6 x 5	30	7 x 5	35	3 x 5	15	4 x 5	20
Weight		**47**		**50**		**44**		**47**

	14	
Likert scale	**Respondent**	**Result Scale**
SD	0 x 1	0
D	0 x 2	0
N	1 x 3	3
A	2 x 4	8
SA	8 x 5	40
Weight		**51**

Table 10 shows the weight calculations for Web Version 2 based on the Likert scale responses for questions 10 through 14. Each respondent's choice is multiplied by the corresponding Likert scale score, and the results are summed to determine the total weight for each question. This process quantifies user satisfaction and feedback for Web Version 2.

Table 11. Serendipity Evaluation Weight Calculation

	15		**16**		**17**		**18**	

Building of Informatics, Technology and Science (BITS)
Volume 6, No 2, September 2024, Page: 1020−1033
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v6i2.5754

Likert scale	Respondent	Result Scale	Respondent	Result Scale	Respondent	Result Scale	Respondent	Result Scale
SD	0 x 1	0	0 x 1	0	0 x 1	0	0 x 1	0
D	0 x 2	0	0 x 2	0	0 x 2	0	0 x 2	0
N	0 x 3	0	3 x 3	9	2 x 3	6	3 x 3	9
A	5 x 4	20	4 x 4	16	3 x 4	12	1 x 4	4
SA	6 x 5	30	4 x 5	20	6 x 5	30	7 x 5	35
Weight		**50**		**45**		**48**		**48**

Table 11 shows the weight calculations for evaluating serendipity based on the Likert scale responses for questions 15 through 18. Each respondent's choice is multiplied by the corresponding Likert scale score, and the results are summed to determine the total weight for each question. This process quantifies user feedback on the serendipity aspect of the recommendations.

We meticulously calculated each question's median and mode values in our study. This approach was chosen because the Likert scale, which categorizes responses in an ordinal manner, is best analyzed through these statistical measures [20]**.** This method accurately interprets our data's central tendencies and most frequent responses, providing insightful conclusions about the participants' attitudes and perceptions.

Table 12. Median and Mode of User Satisfaction Weight Calculation

Question	Median	Mode
1	5	5
2	4	5
3	5	5
4	4	5

Table 12 shows the median and mode values for user satisfaction weight calculations. The median represents the middle value, and the mode indicates each question's most frequently occurring value. These measures help summarize user satisfaction effectively.

Table 13. Median and Mode of Web Version 1 Weight Calculation

Question	Median	Mode
5	5	5
6	5	5
7	4	3
8	5	5
9	5	5

Table 13 shows the median and mode values for the weight calculations of Web Version 1. The median is the middle value, and the mode is the most frequently occurring value for each question, summarizing user feedback for this website version.

Table 14. Median and Mode of Web Version 2 Weight Calculation

Question	Median	Mode
10	5	5
11	5	5
12	4	4
13	5	4
14	4	5

Table 14 presents the median and mode values for the weight calculations of Web Version 2. The median is the middle value, and the mode is the most frequently occurring value for each question, summarizing user feedback for this website version.

Table 15. Median and Mode of Serendipity Evaluation Weight Calculation

Question	Median	Mode
15	5	5
16	4	5
17	4	4
18	5	5

Table 15 shows the median and mode values for the weight calculations of the serendipity evaluation. The median represents the middle value, and the mode indicates the most frequently occurring value for each question, summarizing the user feedback on serendipity.

3.2 Analysis of the Test Results

In this section, we analyze the user testing and A/B testing results of the User-Centered Dietary Recommendation system. This analysis is organized to address the following key aspects:

3.2.1 User Satisfaction

User satisfaction was measured using Likert scales on various parameters, including the usefulness of the recommendations, relevance to the user's health profile, novelty of the recommendations, and the serendipity aspect of the recommended items. The data from Table 8 and Table 12 show that most users were satisfied and found the diet recommendation system easy to use. The relevance of the recommended items to users' health profiles and food preferences also scored high (Table 9).

3.2.2 Serendipity Evaluation

Serendipity is a crucial aspect of the system, aiming to provide users with unexpected yet relevant recommendations. This aspect was evaluated based on user feedback on how often they found the recommendations surprising and enjoyable (Table 11). Users frequently reported discovering new food items that suited their dietary needs and preferences. The system's ability to combine items with high and low cosine similarity significantly contributed to positive evaluations, as evidenced by high ratings in the serendipity aspect (Table 15).

3.2.3 A/B Testing Comparison Analysis

A/B testing compared two versions of the recommendation system to evaluate the impact of user control over similarity parameters. In version one, the user had no control over the similarity settings, whereas in version two, the user could set high and low similarity thresholds. The results from Table 9 and Table 10 show that giving control to users increases satisfaction and perceived relevance of the recommendations. The analysis revealed that users preferred the system version, which allowed them to set similarity parameters, making the recommendations feel more personalized and in line with their expectations.

4. CONCLUSION

In this study, researchers developed a user-centered dietary recommendation system with a serendipity aspect based on human recommendation system interaction. This research uses content-based recommendation, TF-IDF, Cosine Similarity, and K-Means techniques to generate personalized and relevant food recommendations for users. The system was tested through user A/B testing. The test results show that the recommendations provided by the system help support users' dietary needs, with high average scores on usability and relevance. Serendipity, or the ability to provide unexpected yet relevant recommendations, was also evaluated through user feedback. Most users reported finding surprising new foods that matched their preferences, improving their overall dietary experience. A/B testing compared two system versions, with the second version giving users more control over setting similarity parameters. The results showed that users preferred the version with these additional controls, as it made the recommendations feel more personalized and in line with their expectations. Statistical analysis of the test data confirmed that the diet recommendation system effectively provided relevant and engaging recommendations, increasing user satisfaction and engagement. Including user control over recommendation parameters further enhances performance and user experience. This research proves that the developed dietary recommendation system can provide personalized and effective dietary solutions, considering serendipity aspects to enhance user engagement and satisfaction. The researcher recommends that the system be continuously developed and optimized based on user feedback to achieve better results in the future.

REFERENCES

[1] T. N. Trang Tran, M. Atas, A. Felfernig, and M. Stettinger, "An overview of recommender systems in the healthy food domain," *J Intell Inf Syst*, vol. 50, no. 3, pp. 501–526, Jun. 2018, doi: 10.1007/s10844-017-0469-0.

[2] M. F. Mat Baseri and A. F. Saad, "Dietry Monitoring System Using Decision Tree to Control Human Obesity," *International Journal of Artificial Intelligence*, vol. 10, no. 1, pp. 9–20, Jun. 2023, doi: 10.36079/lamintang.ijai-01001.485.

[3] I. Lovita, M. Hendrianingtyas, and R. Triwardhani, "Hubungan resting metabolic rate (RMR) dan komposisi tubuh dengan kadar HbA1c pada obesitas," *Intisari Sains Medis*, vol. 10, no. 1, Apr. 2019, doi: 10.15562/ism.v10i1.345.

[4] M. Bastien, P. Poirier, I. Lemieux, and J.-P. Després, "Overview of Epidemiology and Contribution of Obesity to Cardiovascular Disease," *Progress in Cardiovascular Diseases*, vol. 56, no. 4, pp. 369–381, Jan. 2014, doi: 10.1016/j.pcad.2013.10.016.

[5] I. E. Young, A. Poobalan, K. Steinbeck, H. T. O'Connor, and H. M. Parker, "Distribution of energy intake across the day and weight loss: A systematic review and meta-analysis," *Obesity Reviews*, vol. 24, no. 3, p. e13537, Mar. 2023, doi: 10.1111/obr.13537.

Building of Informatics, Technology and Science (BITS)
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ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v6i2.5754

[6] P. J. Huth, V. L. Fulgoni, D. R. Keast, K. Park, and N. Auestad, “Major food sources of calories, added sugars, and saturated fat and their contribution to essential nutrient intakes in the U.S. diet: data from the national health and nutrition examination survey (2003–2006),” *Nutr J*, vol. 12, no. 1, p. 116, Dec. 2013, doi: 10.1186/1475-2891-12-116.

[7] Z. Yuan and F. Luo, “Personalized Diet Recommendation Based on K-means and Collaborative Filtering Algorithm,” *J. Phys.: Conf. Ser.*, vol. 1213, no. 3, p. 032013, Jun. 2019, doi: 10.1088/1742-6596/1213/3/032013.

[8] E. E. M. Da Rocha, V. G. F. Alves, and R. B. V. Da Fonseca, “Indirect calorimetry: methodology, instruments and clinical application:,” *Current Opinion in Clinical Nutrition and Metabolic Care*, vol. 9, no. 3, pp. 247–256, May 2006, doi: 10.1097/01.mco.0000222107.15548.f5.

[9] D. Kotkov, J. A. Konstan, Q. Zhao, and J. Veijalainen, “Investigating serendipity in recommender systems based on real user feedback,” in *Proceedings of the 33rd Annual ACM Symposium on Applied Computing*, Pau France: ACM, Apr. 2018, pp. 1341–1350. doi: 10.1145/3167132.3167276.

[10] S. Fazeli, H. Drachsler, M. Bitter-Rijpkema, F. Brouns, W. V. D. V. Brouns, and P. B. Sloep, “User-Centric Evaluation of Recommender Systems in Social Learning Platforms: Accuracy is Just the Tip of the Iceberg,” *IEEE Trans. Learning Technol.*, vol. 11, no. 3, pp. 294–306, Jul. 2018, doi: 10.1109/TLT.2017.2732349.

[11] S. M. McNee, J. Riedl, and J. A. Konstan, “Making recommendations better: an analytic model for human-recommender interaction,” in *CHI ’06 Extended Abstracts on Human Factors in Computing Systems*, Montréal Québec Canada: ACM, Apr. 2006, pp. 1103–1108. doi: 10.1145/1125451.1125660.

[12] G. Agapito *et al.*, “DIETOS: A dietary recommender system for chronic diseases monitoring and management,” *Computer Methods and Programs in Biomedicine*, vol. 153, pp. 93–104, Jan. 2018, doi: 10.1016/j.cmpb.2017.10.014.

[13] S. Hamdollahi Oskouei and M. Hashemzadeh, “FoodRecNet: a comprehensively personalized food recommender system using deep neural networks,” *Knowl Inf Syst*, vol. 65, no. 9, pp. 3753–3775, Sep. 2023, doi: 10.1007/s10115-023-01897-4.

[14] M. De Gemmis, P. Lops, G. Semeraro, and C. Musto, “An investigation on the serendipity problem in recommender systems,” *Information Processing & Management*, vol. 51, no. 5, pp. 695–717, Sep. 2015, doi: 10.1016/j.ipm.2015.06.008.

[15] D. Kotkov, A. Medlar, and D. Glowacka, “Rethinking Serendipity in Recommender Systems,” in *Proceedings of the 2023 Conference on Human Information Interaction and Retrieval*, Austin TX USA: ACM, Mar. 2023, pp. 383–387. doi: 10.1145/3576840.3578310.

[16] R. Hendrawan, Adiwijaya, and S. Al Faraby, “Multilabel Classification of Hate Speech and Abusive Words on Indonesian Twitter Social Media,” in *2020 International Conference on Data Science and Its Applications (ICoDSA)*, Bandung, Indonesia: IEEE, Aug. 2020, pp. 1–7. doi: 10.1109/ICoDSA50139.2020.9212962.

[17] Rianto, A. B. Mutiara, E. P. Wibowo, and P. I. Santosa, “Improving the accuracy of text classification using stemming method, a case of non-formal Indonesian conversation,” *J Big Data*, vol. 8, no. 1, p. 26, Dec. 2021, doi: 10.1186/s40537-021-00413-1.

[18] M. W. Putri, A. Muchayan, and M. Kamisutara, “Sistem Rekomendasi Produk Pena Eksklusif Menggunakan Metode Content-Based Filtering dan TF-IDF,” *JOINTECS*, vol. 5, no. 3, p. 229, Sep. 2020, doi: 10.31328/jointecs.v5i3.1563.

[19] S. Bandyopadhyay, S. S. Thakur, and J. K. Mandal, “Product recommendation for e-commerce business by applying principal component analysis (PCA) and K-means clustering: benefit for the society,” *Innovations Syst Softw Eng*, vol. 17, no. 1, pp. 45–52, Mar. 2021, doi: 10.1007/s11334-020-00372-5.

[20] H. Boone and D. Boone, “Analyzing Likert Data,” *JOE*, vol. 50, no. 2, Apr. 2012, doi: 10.34068/joe.50.02.48.