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Eat This, Not That! – a Personalised Restaurant Menu Decoder That Helps You Pick the Right Food

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Abstract— **Picking the right food from a restaurant menu sometimes is not an easy thing for many people: visitors who are not familiar with local restaurants' meal names and their ingredients, people with religious diet constraints, patients with nutrition requirements, and people with special diet preferences. It is not easy for these diners to choose meals from restaurant menus as they do not provide enough information for the diners to make decisions in a brief period. In this paper, we propose an AI-empowered personalized restaurant menu decoder app that can help users make wise choices from any menu in any restaurant. With an easy-to-use interface, the app can quickly rank the restaurant's menu items based on the user's preferences and concerns. Preliminary test results have demonstrated the good usability of the proposed system.**

Keywords—Artificial Intelligence, multi-criteria decision making, Semantic Web, AHP, TOPSIS, Food Recommendation, Restaurant Menu Recommendation

I. Introduction

In a fast-paced society, we eat out more often at restaurants than we would like to admit. However, choosing a good meal from the multiple options on a restaurant menu is not always an easy task. Imagine a visitor opening the menu at a local restaurant, but being overwhelmed with strange and confusing meal names and ingredients, this problem is more viable for minority people, new immigrants, or tourists. Other than unfamiliarity with food, many people have religious dietary restrictions, medical or personal dietary preferences, etc. Currently, 10% of Americans identify themselves as vegetarian, vegan, or vegetarian-inclined, while 7% of Americans suffer from food allergies to the "Big 8": milk, peanuts, shellfish, tree nuts, eggs, fish, soy, and/or wheat [1]. That is a total of 17% of Americans who have to be a little pickier about where they eat, and there are plenty more diets that fit under the "special menu" umbrella such as Asian, Diabetic, Gluten-free, Hindu believers, Kosher, Low- Cal, Low- Fat, Low- Sodium, Muslim Believers, etc. These constraints make picking the right food from the menu even more difficult. Restaurant menus are created to attract people's attention to the taste, but not to tell them whether the meals are healthy or not. Although many restaurant menus provide meal calory information, it is not sufficient to let people make decisions if they have food-related health issues.

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To solve the aforementioned issues, we proposed a personalized menu decoder system that can help people to understand menu items, screen menus containing forbidden ingredients, and identify appropriate menu items based on user's personal preferences and health concerns. The menu decoder system was implemented based on a comprehensive knowledge graph that provides foundational knowledge about food and nutrition. Healthy eating guidelines can be implemented as logical rules over the knowledge graph. We employed the technique of multi-criteria decision making (MCDM) to integrate various users' preferences and constraints information and user views to rank menu items. The proposed system has been evaluated with a use case study and usability study. The results demonstrate the feasibility of the system.

The result of the paper is organized as follows: Section II presents the background knowledge and related work. Section III describes the design of the menu decoder. Section IV provides the evaluation study and analysis. Finally, Section V concludes the paper.

II. Related Work

Restaurant food is normally influenced by the availability of local ingredients, climate, native traditional cooking habits, religious or sumptuary laws, culinary culture exchange, etc.[2] . Natalie et al. did a cross-cultural qualitative study among American and Australian participants to understand the perception and representation of adopting food cultures through restaurant chains [3]. Shahzadi et al's study findings suggest that the association between major restaurant features and behavioral intentions is partially mediated by customer satisfaction [4]. Customers' judgments of the importance and performance of a restaurant's quality appear to be significantly different based on their budget, taste, and preferences [4], [5]. Peter et al. in their study results found that 'The combination of ingredients is the most significant attribute while at least 30% of their participants mentioned 'Avoidance of certain food' and how 'the ingredients of the dish was produced' [5]. Cost is another important factor. Price and improved quality are two clear elements in judging the worth of the services supplied [6]–[8]. Some researchers found that customers' choices are influenced by low-calorie, low-fat,

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healthier items despite the higher cost of those options [9]–[11]. Therefore, attributes related to food ingredients, nutrition, health, cost, etc. can be considered the key attributes of choosing a menu at restaurants.

A healthy and balanced diet is crucial to maintaining people's physical health. Meanwhile, people's food preferences and health conditions should also be considered in their food choice. To serve this purpose, personalized food recommendations based on various personal requirements have been researched. For example, many research works integrate the context of geographic location in food and restaurant recommendation. In [12], the authors recommend healthy food in the user's vicinity. In [13], researchers create a probabilistic model to include the geographic influence on restaurant recommendations. Another context factor for food recommendations is time. In their research, S. Sanjo and M. Katsurai [14] recommend recipes based on their time-related popularity. More context factors and user profiles are integrated for recipe recommendations in [15].

Researchers have considered individual customers' personal preferences to recommend restaurants. For instance, Zhang et al. [16] proposed a restaurant recommendation method that combines group correlations and customer preferences. They used probability linguistics terms to describe group preferences, and then apply a similarity measurement to cluster customers with similar preferences. Fakhri et al. [17] proposed a restaurant recommendation system using collaborative filtering techniques that are based on ratings given by users. User rating-based similarity and user attribute-based similarity have been used to calculate the proximity between users.

In summary, although there is various research on recommending or planning food/meals and research on recommending restaurants, to the best of our knowledge there are no systems to help users to choose the best meals in a particular restaurant. This is the motivation for our research.

III. System Design

A. System Overview

Fig. 1 shows the architecture of the proposed system. It is implemented as a mobile app. After a user installs the app, a short survey about the user's basic information and diet preferences, concerns, and restrictions will be provided to the user. This input serves as the user profile knowledge. To start using the app, a user needs to take a picture of the restaurant menu. Through Optical Character Recognition (OCR) [18] and using crowd sousing techniques, the menu items can be extracted. The extracted menu items will be processed to get key information such as meal name, ingredients, price, etc. Then menu items will be filtered based on the mandatory constraints of the user's diet profile, for example, removing items with ingredients that the user is allergic to, or meals violating a health constraint. This process is enabled through ontology-assisted rule-based reasoning. Then an MCDM-based ranking algorithm is applied to rank menu items based on the user's preferences. The ranked menu items are provided to the user for his/her reference. The details of the system's components are presented in the following sections.

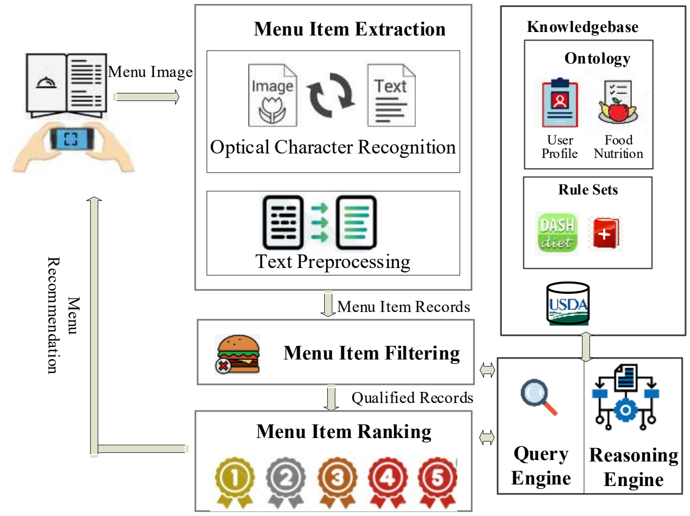

Fig. 1. System Architecture

B. Knowledge Preparation

The system's "brain" is a knowledge base including the user's profile and background knowledge about food, nutrition, and rules about food constraints and healthy eating. We adopt ontology to represent concepts and relationships between them, because of ontology's machine-understandable logic nature. Specifically, we defined a high-level food and nutrition ontology that was further extended with detailed information from the USDA database. User's profile information including gender, age, BMI, health concerns, food allergy, flavor preferences, etc. is also represented as ontology.

Rules and regulations regarding food and nutrition constraints can be defined and applied to the ontologies. Diet guidelines for patients with diet-related chronic diseases, such as obesity, diabetes, cardiovascular disease, hypertension, etc., are converted into semantic rules. For example, the 2015-2020 Dietary Guidelines for Americans recommend the sodium intake for people with (pre)hypertension should be within 1500 mg per day. This guideline can be converted to a rule represented by the Semantic Web Rule Language (SWRL):

Person(?user) ^
hasHybertension(?user, true) ->
hasDailySodiumLimit(?user,1500)

C. Restaurant & Menu Item Recognition

To recognize the restaurant and menu items, a user needs to take pictures of the menu pages. OCR technique is then applied to the picture to extract menu items. Not all menu items can be extracted from a single image and not all information can be gathered from the menu image alone. To solve this problem, we employed a prepopulated dataset as an auxiliary tool to get the menu items. For our prototype, we collected data from the Department of Health and Mental Hygiene New York [19], a searchable online collection of nutrition and menu information from the nation's leading restaurant companies. We employed the matching mechanism proposed by Salehian et al. [18], to match restaurant menus to crowdsourced food data. The matching algorithm uses Markov Decision Process to get candidate food data. Then it applied a Convolutional Neural

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network to rank the candidates and select the best one. Through these processes, menu items with detailed ingredients can be obtained.

D. Menu Filtering

Menu items that violate mandatory constraints will be removed first. The mandatory constraints include medical constraints, nutrition rules, and other unconditional cultural and religious constraints. The users will be asked about health-related constraints, for example, if a user is allergic to eggs, all items with egg ingredients need to be removed. For a vegetarian user, all items with animal products must be eliminated. For a user with hypertension, meals with sodium beyond the limitation should be removed. For a user who is lactose intolerant, all dairy products will be removed. And then users will also be asked about ingredients they want to avoid either because of strict religious practices they follow or personal choices that they want to avoid. After removing the unqualified menu items, the rest items will be ranked based on the user's preferences.

E. Menu Ranking

We propose an approach that integrates the Analytic Hierarchy Process (AHP) & the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [20] to realize the MCDM for menu items ranking. Users' multiple preferences, such as favorite items, price, religious preferences, nutritional preferences, and personal preferences will be considered to rank the menu items. For different people, a religion-based diet can be a constraint or can be a preference. We filtered menu items based on religious constraints in the Menu Filtering stage, but religion-based factors can also be considered as preferences in this stage for some users.

We propose an AHP-TOPSIS a decision-making technique in which several criteria are reviewed, and various options are defined depending on all the criteria. The outcome of the deconstruction of the choices is the formation of a hierarchy that can be easily understood and analyzed independently. The hierarchy's elements are then assessed by comparing them to one another in terms of the impact they have on the element in the hierarchy. AHP Follows step by step process as follows:

1. *Determine the criteria for decision making*
2. *Prepare the questionnaire to ask users which criteria are more important using a scale of 1 to 9 also known as Saaty's fundamental scale [21].*
3. *Create a pairwise comparison matrix using the importance score.*
4. *Divide each column by its column sum*
5. *Calculate the n^{th} root of the products and their sum*
6. *Normalize the n^{th} root of the products to obtain the weights. This is known as eigenvector ω*

We get the weights of each criterion using AHP methods. Now we utilize TOPSIS to rank the alternatives. The TOPSIS steps are as follows

1. *Evaluation of alternatives by normalized decision matrix*
2. *Determine the positive and negative ideal solution*
3. *Calculate the separation measures based on the weight matrix*
4. *Calculate the relative closeness to the ideal solution*
5. *Rank the preference order*

The criteria we have considered to rank the menu items include cost, favorites, religious preferences, nutrition, personal preferences, menu item rating, popularity, and time to serve the dish. Then the AHP-TOPSIS algorithm will perform on a wide range of criteria. Fig. 2 shows how AHP-TOPSIS is applied to the menu items to rank them in our current system design.

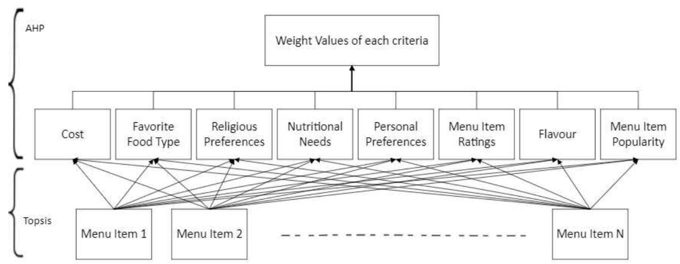

Fig. 2: Applying AHP-TOPSIS algorithm on the filtered menu items

IV. Evaluation

We implemented the proposed system as a mobile app, MenuDecoder, Fig.3 shows the interfaces of MenuDecoder. It was implemented using Flutter [22], an open-source cross-platform app development kit provided by Google. We used Springboot [23] application to implement the server. It uses microservice architecture for developing web applications. Our system used a SQL Database. We evaluated the app using use case studies and usability studies.

A. Use Case Study

For the use case study, we have chosen one popular US restaurant "Olive Garden" as our example restaurant. Olive garden's menu in our case has 377 menu items including appetizers, entrees, soups, salad, dessert, and beverages.

In this use case, we assume two users who use our system to help them pick meals at Olive Garden. A female user, Alice, has the following basic information: age: 25, height: 5 feet, weight: 130 pounds, health problem: type II diabetes. Religious constraint: no pork and alcohol. Her favorite foods include chicken, shrimp, eggplant, and celery. She is allergic to eggs. Based on her preference survey, the cost is important, she favors meals within $20; nutrition is very important as she cares about her health; meal rating and popularity are important because she cares about the reviews from the social media. Favorite food is neutral in this case.

Based on Alice's basic physical information, her mandatory food constraints, and preferences, our system made the following recommendations, i.e., ranked menu items, as shown in Table I.

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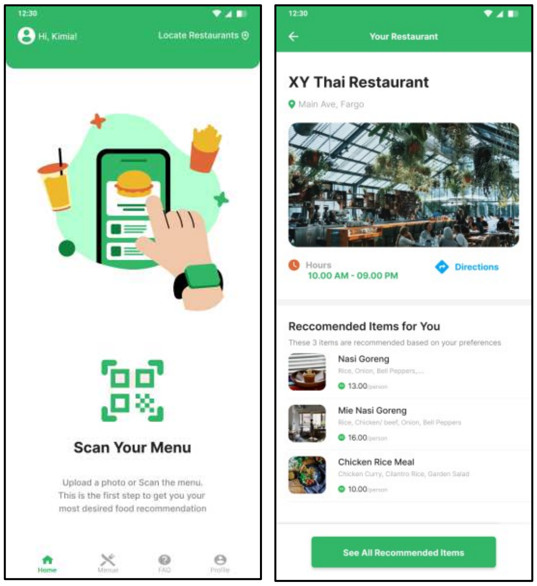

Fig. 3: Interface of the prototype app.

Table I. Ranked top 5 menu items based on Alice's preferences

Menu item	Heathy Index	Cost	Rating	Ingredients	Calories	Preference score
Lasagna Classico	*0.77*	*$17.79*	*4.6/5*	*Lasagna*	*640*	*0.99*
Lasagna	*0.77*	*$17.79*	*4/5*	*Lasagna*	*640*	*0.97*
Ravioli di Portobello	*0.62*	*$15.99*	*4.2/5*	*Ravioli, Mushrooms, Smoked Cheese, Sundried Tomato Sauce*	*570*	*0.95*
Shrimp Scampi	*0.63*	*$19.99*	*4.2/5*	*Garlic Sauce, Shrimp, Asparagus, Tomatoes, Angel Hair Pasta*	*500*	*0.95*
Fettuccine Alfredo Mini Pasta Bowl	*0.28*	*$15.99*	*4.3/5*	*Alfredo sauce, Mini Pasta*	*500*	*0.85*

In the first table, the first column represents the name of each meal. Second, we have the "Healthy Index", which is derived from PV values [24]. Using this metric, we can determine how close the nutrition of the meal is to the optimal nutrition recommendation. 0 is the lowest grade and 1 is the highest grade. On the Cost column, you will find the price of each item. On the Rating column, you will find the ratings given by consumers. The fifth column shows the primary ingredients, and the sixth column indicates the total number of calories per serving. The preference score is calculated in a TOPSIS manner and ranges between zero and one.

Based on Alice's mandatory constraints, certain menu times are removed from consideration. For example, all meals containing eggs are removed because Alice is allergic to eggs. As Alice has diabetes, based on the diet recommendation of diabetes [25], Alice's Carbohydrate should be not more than 60 grams per meal. Therefore, menu items like 'Five Cheese Ziti al Forno, Dinner' and 'Chicken Scampi, Dinner' are removed because their Carbohydrate value exceeds this limit. Also, because of Alice's religious constraints, meals such as Shrimp Carbonara and Chicken Carbonara are removed because they contain pork. The ranking is based on Alice's preference score (last column in Table I) which is computed by the TOPSIS approach and pairwise comparison matrix. Weighted preferences are calculated in the range between 0 and 1, the higher the value the better. The top-5 foods are listed in Table I. The column in Table I reflects Alice's diet preferences. Alice prioritizes healthier food over her favorite foods. As a result, we see that the top four foods do not have her favorite ingredients, but their health ranking is high. Thus, they have higher weighted preferences scores. In addition, these are popular foods that everyone is often quoted as recommending.

Another user, Bob, has the following basic information: age: 55, height: 6 feet, weight: 190 pounds, health problem: hypertension. He has no religious constraints or allergies. He is strict on his diet for hypertension control. His favorite foods include beef, pork, and seafood. Based on his preference survey, the cost is not important at all. He prefers to eat meals that have his favorite food. Other than hypertension control, he is not too strict on food nutrition when he eats in a restaurant. He does not care about food popularity and rating at all.

Based on Bob's basic physical information, his mandatory food constraints, and preferences, our system made the following recommendations, i.e., ranked menu items, as shown in Table II. We can see the columns in Table II are different from the columns in Table I, as Bob has different preferences than Alice. Each recommendation is personalized based on the user's preferences.

The description of this table column is the same as the previous table, except that the order of columns is different. Bob's priority preferences are used to determine the order of the columns. For example, favorite foods are of higher priority than cost and rating. According to the American Heart Association recommendation, Bob is recommended not to exceed 1500 mg sodium because of his hypertension. Due to this, many menu items such as 'Cheese Ravioli w/ Meat Sauce' and 'Braised Beef & Tortelloni' containing his favorite ingredient have been removed, because their sodium value exceeded this limit. The ingredients in Bob's favorite meals matter more than a healthier diet or popularity. We can see that the first food, which has a meat sauce and a lower health score and lower popularity, has a higher preference weighted score than the second food, which has higher popularity and a higher health score, but no favorite ingredient.

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Table II. Ranked top 5 menu items based on Bob's preferences

Menu item	Ingredients	Heathy Index	Cost	Rating	Calories	Preference score
Spaghetti w/ Meat Sauce Mini Pasta Bowl	Meat Sauce, Mini Pasta	0.23	$12.99	4.5	280	0.95
Lasagna Classico, Lunch	Lasagna	0.77	$17.79	4.6	640	0.93
Lasagna	Lasagna	0.77	$17.79	4	640	0.92
Ravioli di Portobello, Lunch	Ravioli, Mushrooms, Smoked Cheese & Sundried Tomato Sauce	0.62	$15.99	4.2	570	0.92
Shrimp Scampi	Garlic Sauce, Shrimp, Asparagus, Tomatoes & Angel Hair Pasta	0.63	$19.99	4.2	500	0.92

From these two cases, we can see that our system respects users' diet constraints and preferences. It can accurately remove unqualified meals based on users' health, religion, and other constraints and intelligently order menu items based on the multiple (conflicting) preferences of users.

B. *Usability Study*

We designed a qualitative usability study focusing on collecting feedback, insights, and findings on how people like the app. This study was approved by the Institutional Review Board (IRB) of the North Dakota State University. Participants were recruited through the research team members' personal Facebook websites and the university's graduate student email list. We demonstrated the app to the participants and surveyed them with a set of questions to study their experiences. 40 objects participated in our test while 33 of them completed the survey. Therefore, we only analyzed the results based on 33 complete responses. Out of 33 participants 21 were male and 12 were female, all the participants were aged between 18- 44 and 7 participants had *Ph.D.*, 11 had *Masters*, 13 had *Bachelors*, 1 had *College,* and 1 had *High-School* degree.

First, we use a set of survey questions to justify the rationale for the research, i.e., why the research is being conducted. Our results show that around 59% of the study participants *Sometimes* dine out, around 31% said they dine out *Occasionally* while the rest said they dine out a *Lots of times*. Now we tried to understand, from those who experience eating out at a restaurant, whether they may have difficulty in picking a meal from the restaurant menu. Based on the survey results, only 4 out of 33 respondents said they *never* have difficulty understanding a restaurant menu, while the rest 29 participants said they have difficulty understanding a restaurant menu either *Occasionally* or *Sometimes*. We specifically asked about 4 types of constraints in our study, such as religion, health, food allergy, and personal choices; Only 3 out of 33 participants said they never had any concerns about violating any of these constraints, and the rest 30 participants said they at least have concerns about violating one of these four constraints. Fig. 4 shows the results about users' concerns regarding violating a diet constraint when they eat in a restaurant.

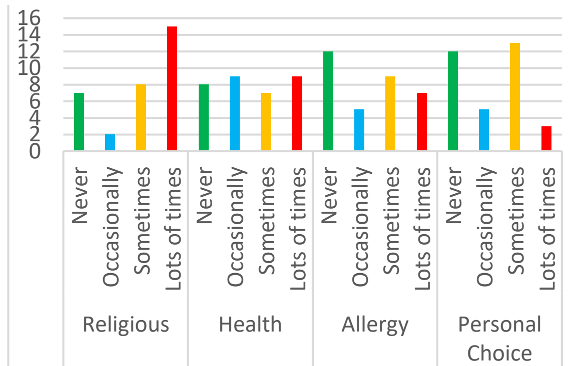

Fig. 4: Concerns about eating in a restaurant regarding violating a diet constraint

We understand that people do have problems when they order food from a menu. We asked how they deal with these problems. According to our study result, 31 participants said that they either search online or ask the waiter/waitress about a menu item or ingredient they are unknown to them, or they simply avoid an item that is unfamiliar to them.

In the second phase of the study, we collected users' feedback about the proposed app interface through a standard Likert scale. 30 out of 33 participants felt this app was helpful, and 23 claimed that they would like to use the app frequently. 29 participants found the interface very simple and easy to use while only 3 were neutral and 1 said the system design is unnecessarily complicated. Figures 5 – 8 illustrate the results of our usability survey responses. People think our system is user-friendly, easy to use, and helpful, and they would like to use it.

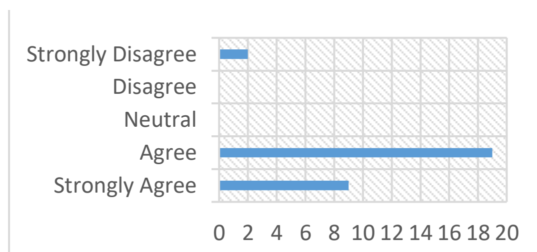

Fig 5: Responses for "I think that I would like to use this system frequently"

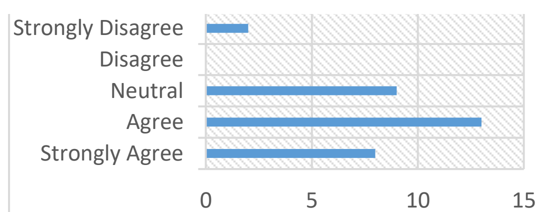

Fig 6: Responses for "I think the system is very helpful"

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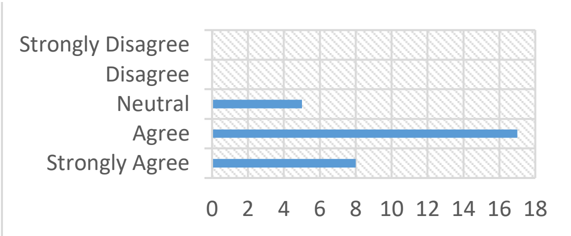

Fig 7: Responses for "I think the system design is very simple and easy to use."

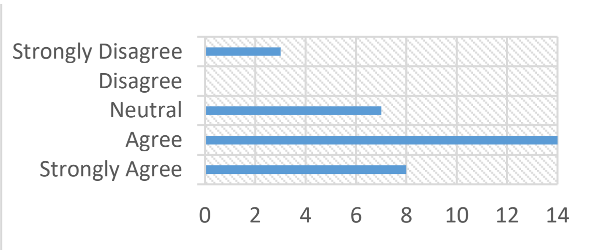

Fig 8: Responses for "I feel very confident about using the system."

V. Conclusions

Choosing the right meal from a restaurant menu can be stressful and frustrating. People may not be familiar with food on the menu, or do not know if the food items are good for their health or violate their diet constraints. To address these issues and help people to choose the most appropriate food items based on their personal needs, we propose an AI-enabled menu ranking approach. It uses knowledge about food, nutrition, healthy eating, medical rules, and users' diet constraints and preferences to rank and recommend menu items to the users. A prototype was implemented as a mobile app. Experiments in terms of use case and usability tests performed on the mobile app justify the feasibility and effectiveness of the proposed system.

Acknowledgment

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