ENHANCING RESTAURANT DINING EXPERIENCE: DESIGN AND EVALUATION OF A MOBILE APP FOR PERSONALIZED MENU ITEM SELECTION IN RESTAURANTS

A Paper
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

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In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Computer Science

March 2023

Fargo, North Dakota

North Dakota State University
Graduate School

Title

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

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ABSTRACT

Picking the right food item from a restaurant menu can be challenging for people, specially for those who are unfamiliar with local cuisine and those with specific dietary requirements. Existing menus often lack essential information, making it difficult for diners to make quick and confident decisions. In this paper, we propose a mobile app that offers a user-friendly interface to allows users rank menu items based on their preferences and concerns. Using personalized ranking algorithms, the app analyzes the ingredients and nutritional content of menu items, providing users with valuable information to make informed choices. Preliminary tests suggest that the app is easy to use and effective in providing relevant information to users. Overall, the proposed system has the potential to improve the dining experience of individuals with various dietary needs and preferences.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my advisor Dr. Jen Li, for her unwavering support, guidance, and valuable insights throughout this research. I am grateful for her encouragement and for always push me to the boundaries of my research.

I would also like to thank my committee members Dr. Jun Kong and Dr. Indranil SenGupta for their invaluable time and to show interest in my work.

I extend my heartfelt appreciation to my lab mates Wordh Ul Hasan and Maryam Sadat Amiri Tehrani Zadeh, who have been instrumental in providing their support and insightful discussions. Their hard work in developing the algorithm of the mobile app is notable. Their contributions have been invaluable, and I couldn't have completed this project without them.

Last but not least, I want to thank my husband, parents and in-laws who have been a constant source of love, support, and motivation throughout my academic journey. Their support, encouragement, and belief in me have kept me going through the ups and downs of my research work.

I am truly grateful for everyone who has played a role in my research work, and I couldn't have done it without their help and support.

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LIST OF ABBREVIATIONS

MCDM ....Multi-Criteria Decision Making

ICT ....Information and Communication Technology

PDA...Personal Digital Assistants

QR Code..Quick Response Code

AI ....Artificial Intelligence

OCR ....Optical Character Recognition

NLP ....Natural Language Processing

AHP...Analytic Hierarchy Process

TOPSIS ....Technique for Order of Preference by Similarity to Ideal Solution

SQL ....Structured Query Language

UI ....User Interface

FAQ...Frequently Asked Questions

BMI ....Body Mass Index

SWRL ....Semantic Web Rule Language

PV ....Prerow value

IRB ....Institutional Review Board

1. INTRODUCTION

Eating out at restaurants has become a ubiquitous part of modern society. However, choosing a suitable meal from a restaurant menu can be a challenging for many individuals. 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.

To address these issues, we propose a personalized menu decoder system that can help people to understand menu items, screen menus containing restricted ingredients, and identify appropriate menu items based on the user's personal preferences and health concerns. Our system utilizes a comprehensive knowledge graph of food and nutrition to help users understand menu items, filter menus containing ingredients, and identify appropriate options based on their personal preferences and health concerns. The system employs multi-criteria decision-making

(MCDM) techniques to integrate various user preferences and constraints, along with their views, to rank menu items and provide personalized recommendations.

The proposed system builds upon existing research in the areas of food informatics, dietary recommendation systems, and knowledge graphs. Previous studies have focused on developing recommendation systems for specific dietary restrictions or preferences, such as vegetarian or gluten-free diets [2][3]. Other studies have utilized knowledge graphs to model food and nutrition information to help users make informed decisions about their food choices [4]. However, our system differs from previous work by providing a personalized menu decoding system that combines knowledge graphs with MCDM techniques to rank menu items based on a user's preferences and constraints.

The personalized menu decoder system has been evaluated with a use case study and usability study. The use case study involved creating a personalized menu for a user with dietary restrictions, while the usability study evaluated the system's ease of use and usefulness. The usability study was conducted with 40 participants from diverse background such as, vegetarian, vegan, Muslim, Hindu, people with dietary restrictions due to health conditions. However, 33 participants completed the survey. The results of the use case study demonstrate that the proposed system is effective in creating personalized menus that meet the user's dietary restrictions. The results of the usability study suggest that the proposed system is easy to use and useful for identifying appropriate menu items based on the user's personal preferences and health concerns.

Disclaimer: This project was a collaborative effort, with different team members contributing to different aspects of the project. While two team members were primarily responsible for the system design and functionalities, the author's major contribution was focused on designing and implementing the user interface and conducting the usability study and analyzing the results.

This paper is organized in the following sections: Chapter 2 presents the relevant background information and related works. Chapter 3 outlines the design of the personalized menu decoder system. Chapter 4 presents the Use Case and Usability study, Study results and analysis. Finally, Chapter 5 concludes the paper.

2. LITERATURE REVIEW

In this section we provide an overview of the factors contributing to the increasing trend of dining out, such as changes in lifestyle, globalization, work patterns, culture, time limitations, socialization etc. It also discusses the challenges individuals face when making food selection decisions, including unfamiliarity with menu items, dietary restrictions, and health concerns. The section reviews existing technology research in the area of food selection decisions. Additionally, it explores the limitations of existing approaches and highlights the need for a personalized menu decoder system that integrates user preferences and constraints to provide tailored recommendations.

2.1. Background

To start with, understanding the choices of foods one could make while dining out, we must understand the facts behind the decision-making process driving towards eating out. During the last few years, the restaurant industry has grown more rapidly than ever before. Statistics show that expenditure on eating out in US households has increased significantly in the last few decades. As a result, Food and drink sales only in the US restaurants reached over 773 billion US dollars in 2019 which was only around 280 billion during 1999[5].

2.1.1. Cuisine and Cross-Cultural Food Perception

One of the primary concepts of the ongoing restaurant industry is 'Cuisine.' It refers to a cooking method using distinct ingredients, and techniques associated with a culture or geographic location. Often it is influenced by the availability of local ingredients, climate, native traditional cooking habits, religious or sumptuary laws, culinary culture exchange, etc. 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

[6]. Joel et al. represented implicit trade patterns in global cuisines for more that 50 countries. Their findings include the economic gains through the cross-cultural cuisine restaurants in US and how it impacts to resemble migration patterns more than food trade patterns based on the availability of ingredients in the origin country [7]. Hitti et al. said many are unwilling to devote a significant percentage of their time to cooking, thus they want to taste different cuisines [8][13].

2.1.2. Factors Influencing Dining Out Behaviors and Preferences

Factors that drive people to dine out are complex and varied. Knutson et al in their studies suggest that dining out is associated with social status and is often viewed as a way to celebrate a special occasion [8]-[10]. Others suggest that people dine out as a way to enjoy leisure or family time. Often the main motivation is time saving as it allows to avoid the hassle of cooking and cleaning up afterward [11]-[13]. Additionally, dining out during lunchtime is more common, and many diners cite convenience and quick service as important factors in their decision to eat out [9]. This is likely since many people are unable to return home for meals due to a lack of knowledge or skills necessary to prepare the foods they enjoy. In a study by Hitti et al., they explored people's feeling intimidated by the complexity of cooking and preference to dine out to enjoy a wider variety of dishes that they may not be able to prepare at home [10]. These findings suggest that dining out serves a variety of purposes for people, including socializing, convenience, and the opportunity to enjoy a wider variety of foods.

2.1.3. Key Attributes for Decision Making at a Restaurant

According to Shahzadi et al., customer satisfaction partially mediates the association between major restaurant features and behavioral intentions [15]. Customers' judgments of restaurant quality are significantly influenced by their budget, taste, and preferences [14][15]. In a study by Peter et al., it was found that the combination of ingredients was the most significant attribute for customers, and a significant number of participants mentioned avoidance of certain foods and how the ingredients were produced [14]. Cost is another important factor that influences customers' restaurant choices. Price and improved quality are two clear elements in judging the worth of the services supplied [16]-[19]. Some researchers have found that customers' choices are influenced by low-calorie, low-fat, and healthier items, despite the higher cost for those options [20]-[22]. Therefore, attributes related to food ingredients, nutrition, health, and cost can be considered as the key factors in customers' menu choices at restaurants. These findings suggest that restaurants need to carefully consider their menu offerings and pricing strategies to meet the diverse needs and preferences of their customers.

2.2. Existing Technology

Restaurant Menu Enhancement of ICT facilities, wide availability of faster and easy to access internet connection and modern digital marketing policies worked as catalyst in digitalizing different business sectors. Restaurants are no different. Restaurants have been adopted and yet adopting significant amount of technology inclusion and digitalization's. Many researchers are successfully contributing for the improvement in this section. Here we briefly discuss about some existing technology and how we are proposing a more personalized system.

2.2.1. Digitalization of Restaurant Menu and Customer Services

Restaurants are investing heavily in adopting new digital technology that will help them to increase their productivity and provide better customer service in areas such as ordering meals, booking tables, checking dish availability, and accepting and processing orders. In restaurants, technology inclusions have an impact on customer service and communication between waiters, clients, and the kitchen [28]. Currently, waiters use personal digital assistants

(PDAs) to digitize customer orders and automatically connect them to the kitchen. In certain circumstances, diners use table displays to place their own orders, lessening room staff from having to maintain track of them and letting them to focus only on serving clients [25]. Furthermore, due to COVID – 19 epidemic restaurant's menu and meals have been made widely available via different Mobile applications and web platforms. Uses of easy to access technology such as QR coder scanning have been also gained popularity while designing a framework. Kincaid et al. described the use of self-ordering and intelligent systems capable of handle customers as a trending experiment [26]. Different research works around globe including qualitative and quantitative studies explored the factors and customer perceptions while choosing a menu item [14][15].

An interesting work by Chittaro et al. explored how the placement of a digital mounted display can impact someone's decision making while choosing an item [27]. Various studies have investigated the use of personal preferences to recommend restaurants to individual customers. Zhang et al. [9] developed a method that combines group correlations and customer preferences using probability linguistic terms to describe group preferences. The authors then applied a similarity measurement to cluster customers with similar preferences. Fakhri et al. [10] proposed a restaurant recommendation system based on collaborative filtering techniques that rely on user ratings. To calculate the proximity between users, the researchers used similarity measures based on user rating and user attributes.

2.2.2. Necessity of Restaurant Menu Ranking and Our Approach

While previous research and technology interventions have made significant progress in exploring the impact of technology on the restaurant industry and understanding customer preferences when choosing menu items [9], these studies have not fully leveraged the necessity to improve menu item ranking. Many of these studies focus on traditional methods such as surveys or statistical analysis to identify factors affecting customer choices[14][15]. Some studies have explored the use of digital technology to enhance the ordering process[25][26][28]. While these methods can provide valuable insights, they are still limited in their ability to capture the complex relationships between different menu items and customer preferences.

Our approach of implementing Artificial Intelligence particularly knowledge graph has the potential to significantly enhance the experience of diners by assisting them in selecting menu items according to their preferences. Also, to the best of our knowledge there are no systems to help users to choose the best meals catering their needs and preferences in a particular restaurant.

3. SYSTEM DESIGN

Our system design consists of a user-friendly mobile application that enables users to scan the menu of a restaurant. The scanned menu image is then decoded trough Optical Character Recognition (OCR), and the extracted text is processed using Natural Language Processing (NLP). A knowledge graph is then implemented to filter out restricted food ingredients and Multicriteria Decision Making (MCDM) more particularly AHP and TOPSIS is used to rank the menu based on the user's preferences. This design allows for a seamless and personalized experience for users, while also ensuring that their dietary needs and restrictions are taken into account.

3.1. User Interface Design

The user interface design of the mobile app was created using Figma, Figma is a web-based user interface design tool. And the app was developed using Flutter, an open-source cross-platform app development kit by Google. The server was implemented using Springboot, which uses microservice architecture for web applications, and the system used a SQL database. The app has standard sign-up and login. During sign-up, users are prompted for additional information such as important factors, general health information, and preferences. On the home page, the user can scan a restaurant menu, and the app displays the top 3 ranked items according to the user's preferences, as well as other recommended items after filtering restricted food ingredients or based on the user's preferences. The full menu is also available without any filtering. When a user selects an item from the list, the app provides details such as ingredients and calories, and the user can change their preferences and choices anytime from the app’s settings menu.

3.1.1. Welcome

The welcome page is the initial screen that appears when the user opens the app. It has two main buttons: Login and Sign up. The Login button directs the user to the login page where they can enter their credentials to access their account. The Sign-up button takes the user to the sign up page where they can create a new account. This page serves as a gateway for the user to access the functionalities of the app.

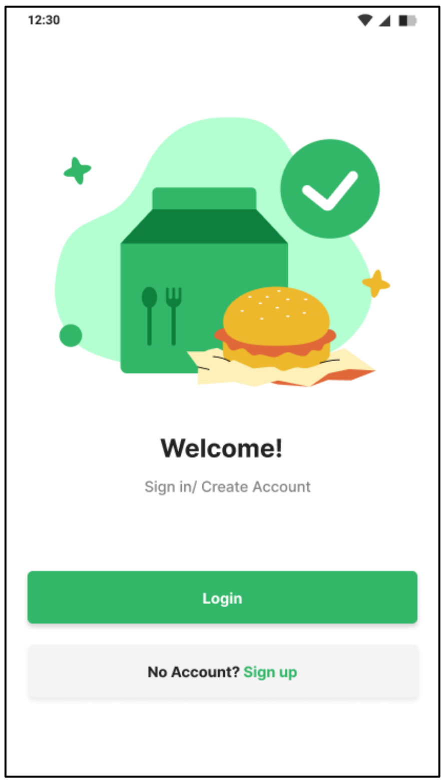

Figure 1. Welcome Page of the App.

3.1.2. Signup

The Signup page is the initial page of the app where new users can create an account to access the features of the app. The user needs to provide their Name, Email, and Password to register an account. Additionally, the page also offers the option to sign up with Google Account for convenience. Once the user submits the registration form, their information is stored securely in the database, and they are redirected to a login survey.

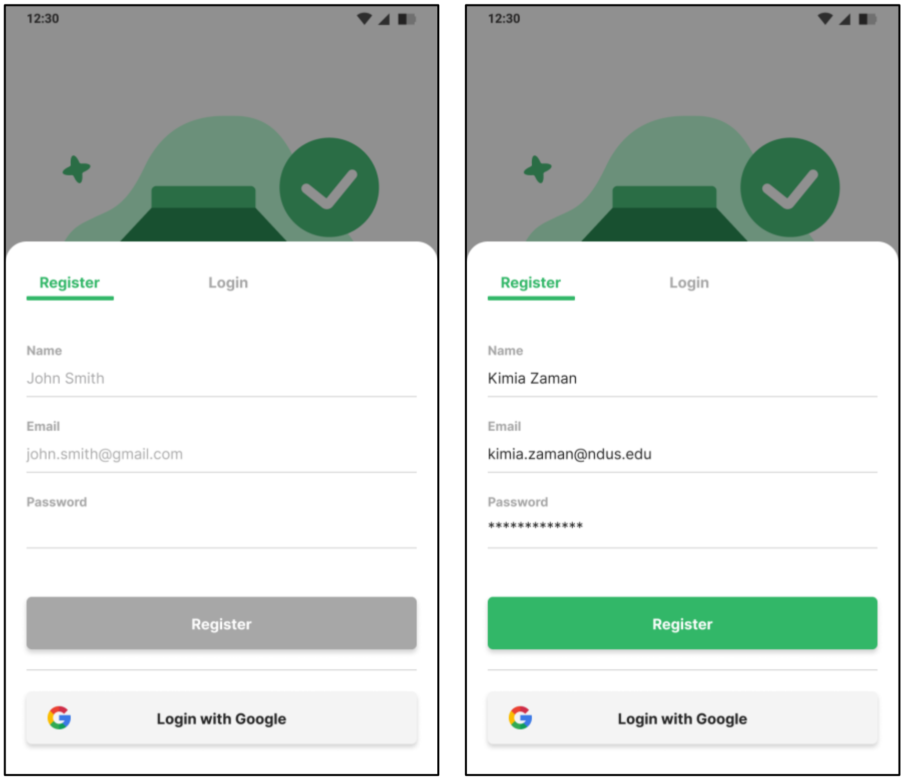

Figure 2. Sign-up Page of the App.

3.1.3. Login

The login page of the app allows users to enter their email and password to log in to their account. Users can also choose to log in with their Google account. If the user enters the wrong email or password, a warning message will pop up to inform them of the error. In case a user forgets their password, they can reset it by clicking the "forgot password" option. This will redirect them to an authentication process such as, they will receive a password reset link on their registered email, from where they can reset their password.

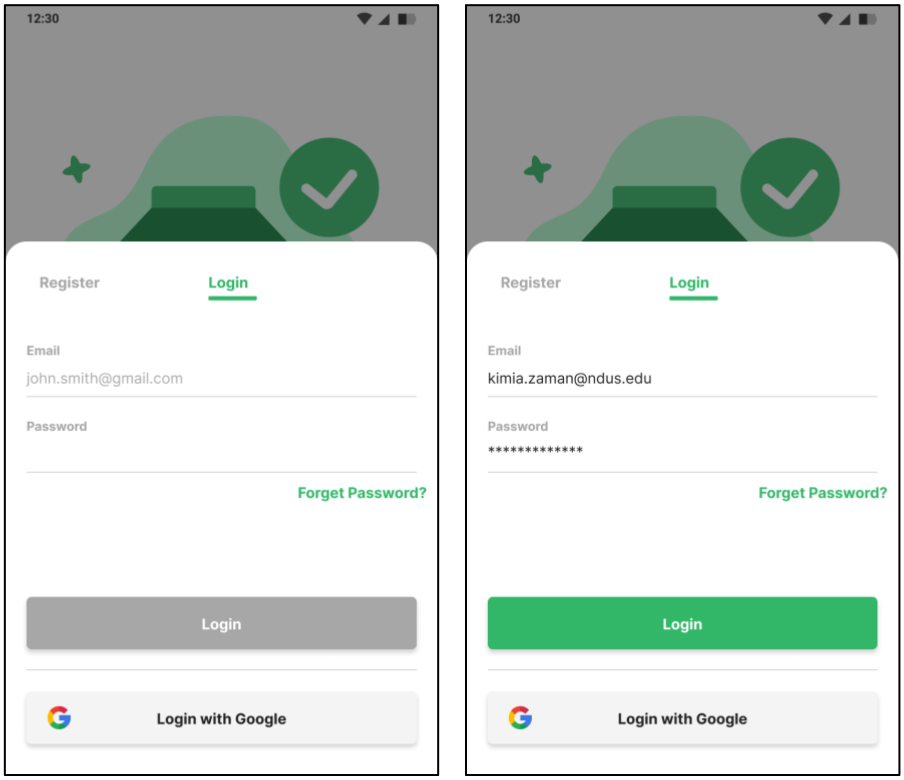

Figure 3. Login Page of the App.

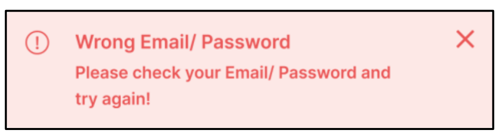

Figure 4. Pop-up Warning for Wrong Email/ Password.

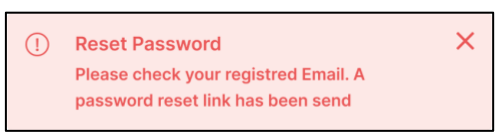

Figure 5. Pop-up Confirmation Message for Password Reset Link Sent.

3.1.4. Signup Survey

The Signup Survey is designed to gather important information about the user's preferences and health-related data. It comprises three sections. The first section allows users to rank the importance of several attributes such as cost, religious constraint, health constraint, food allergies, personal choices, nutrition, and calories on a scale of Very Important, Important, Neutral, Less Important, Not Important. In the second section, users are asked to provide general information like gender, height, weight, and activity level. The third section focuses on the user's preferences related to cost, food restrictions due to religious or health constraints, allergies, calories, and favorite food items. The Likert scale is used to determine the user's cost preference, while a drop-down menu allows the user to choose their favorite food items.

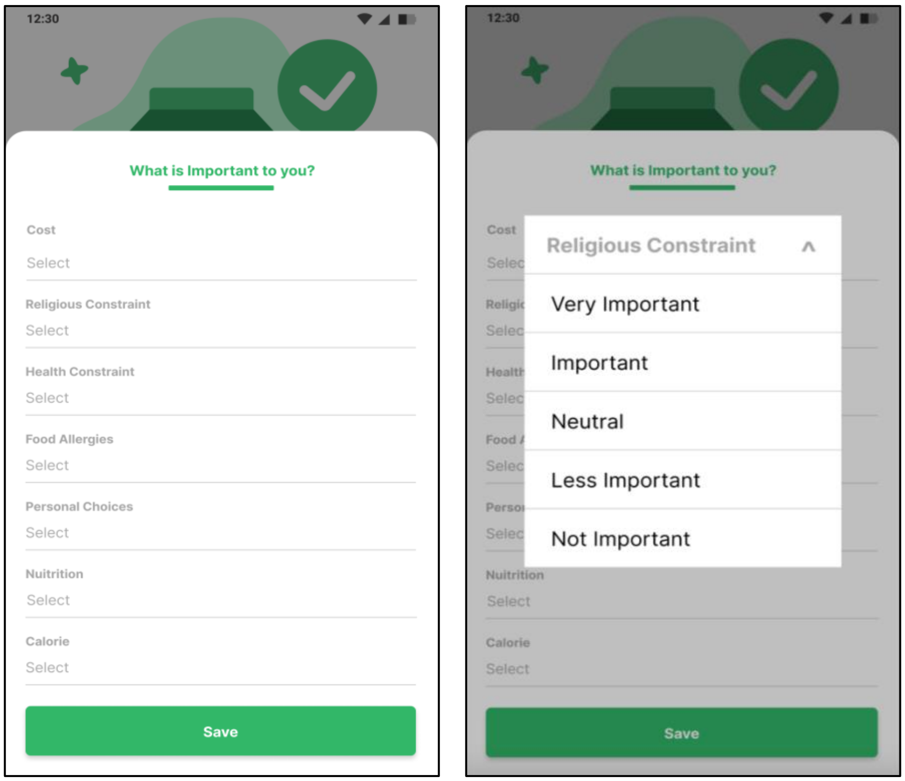

Figure 6. Signup Survey 1: ‘What is important to you’ Without and With Popup Dropdown Menu.

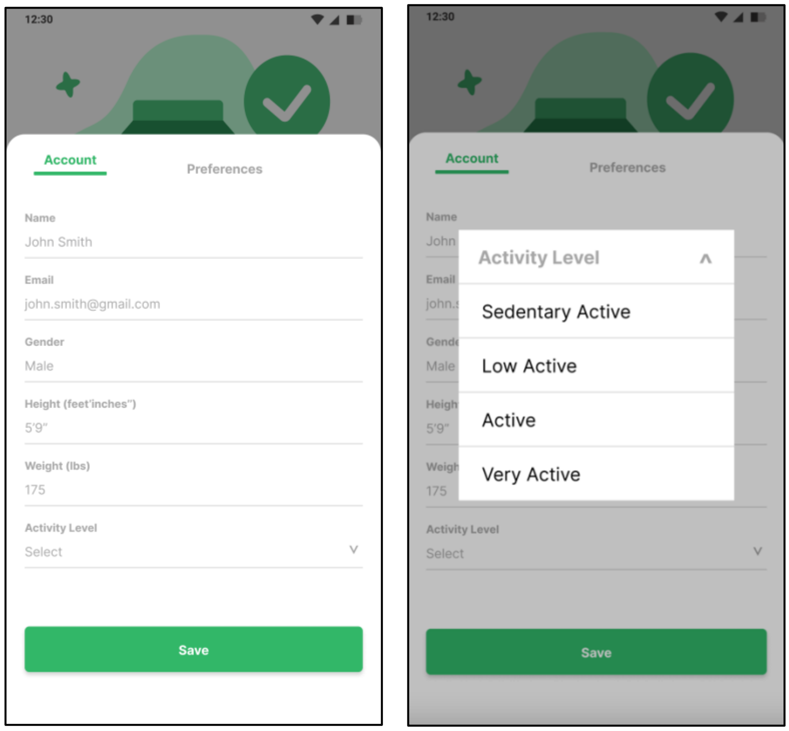

Figure 7. Signup Survey 2: General Information.

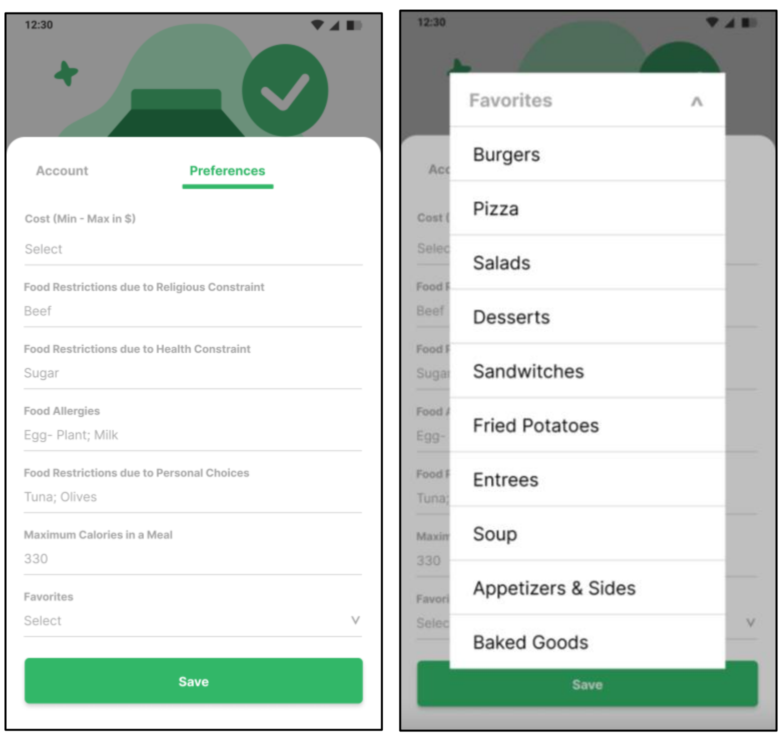

Figure 8. Preferences Without and With Popup Dropdown Menu.

3.1.5. App Home

The home page of the app serves as the main screen for users to access different features and functionalities. Users can scan a QR code or take a picture of the menu by tapping on the scan icon. Users can manually locate and select a restaurant by tapping the local restaurants navigate icon located in the upper left corner of the screen. Once a restaurant is selected, users can access the full menu by tapping the menu icon located at the bottom of the screen. Additionally, users can browse commonly asked questions about the app, restaurants, and nutrition from the FAQ icon located next to the menu. Users can also access and change their general and preference information by tapping the profile icon located in the lower right corner of the screen. Overall, the home serves as a central hub for users to access different features and functionalities, making it easy for them to find the information they need and navigate the app effectively.

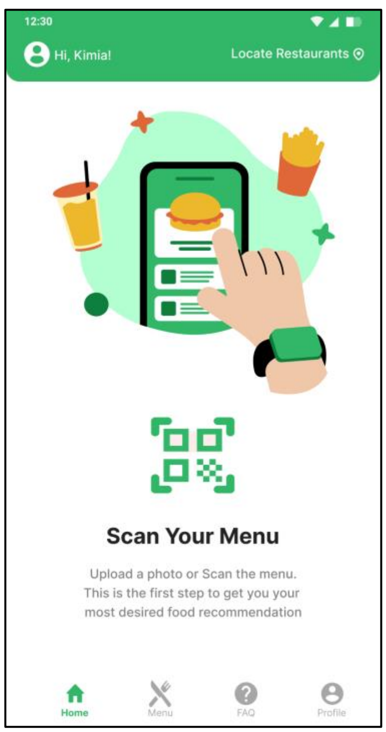

Figure 9. App Home.

3.1.6. Menu Recommendation

The menu recommendation is the key feature of the app that provides personalized recommendations to the users based on their informed preferences. When a user scans or uploads a menu, they are automatically redirected to this page where they can see the top three recommended items. These recommendations are based on the user's preferences such as cost, dietary restrictions, and personal choices that were provided during the signup survey. Users can see the details of each item such as its name, photo, calorie count, and nutritional values by tapping on the item. In addition to the recommendations, the menu recommendation page also displays a beautiful interface including the name, operation hours, and location of the restaurant. Users can view all the recommended items by tapping the "See all recommended items" button, which will display an enhanced menu with more items along with the top three recommendations. Again, users can see the details of each item such as its name, photo, calorie count, and nutritional values by tapping on the item.

Furthermore, users are also able to see the unfiltered menu with all available items. This feature allows users to explore the full menu of the restaurant and find other items that they might be interested in. Overall, the menu recommendation page is a useful tool for users to discover new and personalized menu items that fit their preferences.

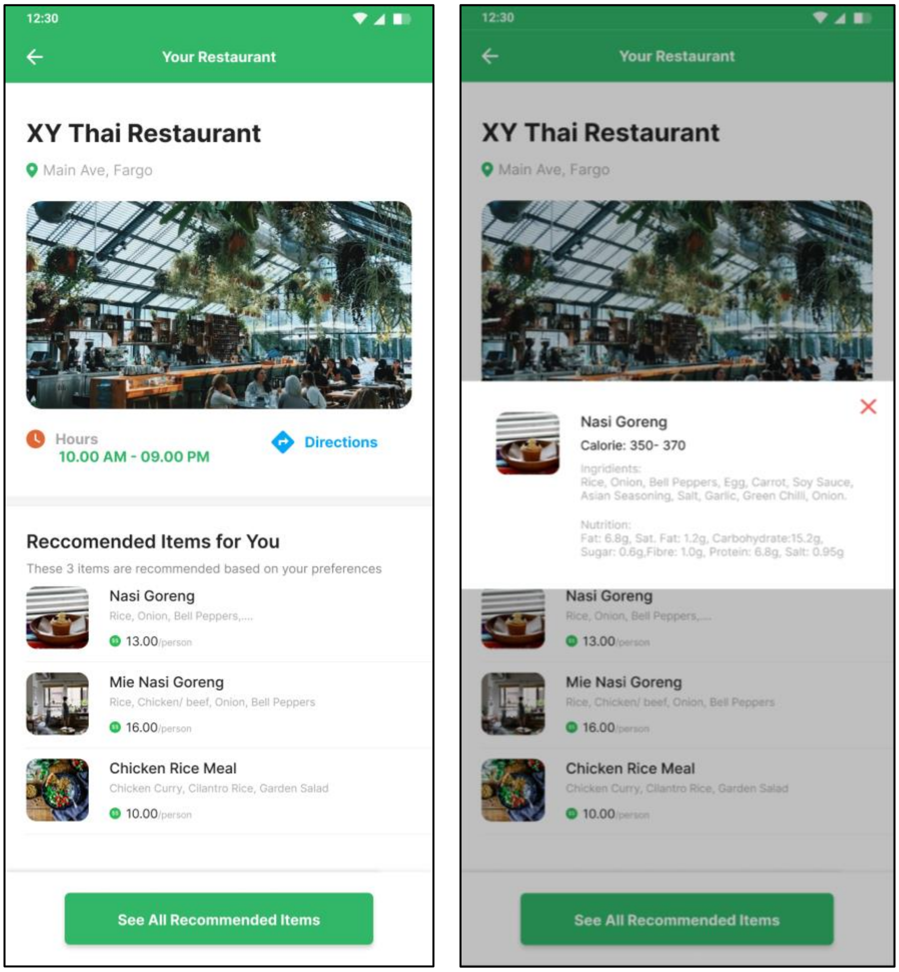

Figure 10. Top 3 Menu Recommendation and Selected Item Details Popup.

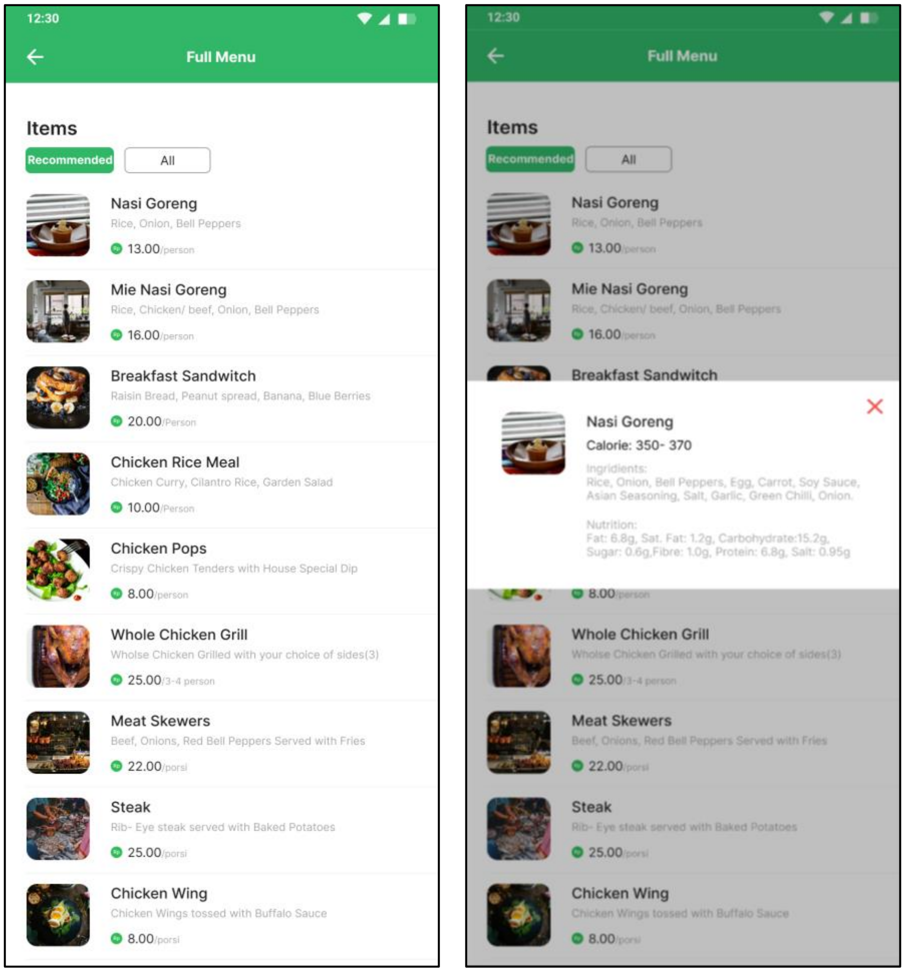

Figure 11. Full Menu Recommendation and Item Details Popup.

3.2. System Architecture and Functionality

Although this is not the focus of my research work, for the completeness of the paper, we describe the technical details of our personalized restaurant menu recommendation system's architecture and functionality in this section. The system uses multi-criteria decision making (MCDM) and the analytic hierarchy process-technique for order preference by similarity to ideal solution (AHP-TOPSIS) to provide personalized menu recommendations for diners. The system's architecture and functionality are designed to be user-friendly, efficient, and effective in providing personalized menu recommendations based on the user's dietary restrictions, special dietary preferences, health conditions, cultural and religious practices, and taste preferences.

We begin by discussing the overall architecture of the system and how it processes user input to generate personalized menu recommendations. We then describe the MCDM and AHP-TOPSIS algorithms used by the system to rank menu items based on the user's preferences and concerns. We also discuss the data sources and preprocessing steps used by the system to generate the required data inputs for the MCDM and AHP-TOPSIS algorithms.

3.2.1. System's Knowledgebase

The knowledge base of the system contains the user's profile and background knowledge of food, nutrition, and food constraints. We utilize ontology to represent concepts and relationships as it provides a machine-understandable logic nature. Our high-level food and nutrition ontology is extended with detailed information from the USDA database. The user's profile information, including gender, age, BMI, health concerns, food allergies, and flavor preferences, is also represented as an ontology. Rules and regulations related to food and nutrition constraints are defined and applied to the ontologies. We convert diet guidelines for patients with diet-related chronic diseases, such as obesity, diabetes, cardiovascular disease, hypertension, etc., into semantic rules. For instance, the 2015-2020 Dietary Guidelines for Americans suggest that individuals with (pre)hypertension should consume no more than 1500 mg of sodium per day. This rule can be represented with Semantic Web Rule Language (SWRL):

Person(?user) ^

hasHypertension(?user,true) ->

hasDailySodiumLimit(?user,1500)

3.2.2. Restaurant Menu Item Recognition

The process of identifying the restaurant and menu items begins with capturing a photo of the menu using the mobile app described in the system architecture. Optical Character

Recognition (OCR) is used to extract the menu items from the image, however, not all items can be identified from a single image and the menu image may not provide all the necessary information. To address this, a pre-existing dataset can be used for matching with the restaurant image. In our experiments, we collected a dataset from the Department of Health and Mental Hygiene New York, [29] which is an online collection of nutrition and menu information from top restaurant companies. S Hesam et al. [28] proposed a scalable machine learning approach for matching restaurant menus to crowdsourced food data by studying the problem of matching a structured restaurant menu item to a large crowdsourced dataset. By using OCR, we can extract the Restaurant Name, Menu section name, and Item name from the image, which are then used to generate a query for retrieving data from the dataset for all the restaurant menu items. This data is then used to generate recommendations for our restaurant menu.

3.2.3. Menu Filtering

The menu items that violate essential restrictions will be eliminated as a primary step. These obligatory constraints may include medical restrictions, nutritional rules, and other cultural or religious limitations. Users will be inquired about any health-related restrictions, and accordingly, all menu items that include ingredients conflicting with their allergies or dietary preferences will be excluded. Additionally, vegetarian users' meals will not contain any animal products, and hypertensive users' meals will be restricted to low sodium intake. Those who are lactose intolerant will not be served dairy products. Furthermore, users will be asked to specify any ingredients they want to avoid due to their religious beliefs or personal choices. Once the unqualified menu items are eliminated, the remaining ones will be prioritized according to the user's preferences.

3.2.4. Menu Ranking

Our proposed approach for ranking menu items integrates two decision-making techniques: the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This approach takes into account multiple preferences, such as price, religious and nutritional preferences, personal preferences, and favorites, to rank menu items. In addition, religion-based factors can be considered as either a constraint or a preference for different users.

First, we use AHP to determine the criteria for decision-making and prepare a questionnaire to ask users to rate the importance of each criterion. A pairwise comparison matrix is created using these ratings and normalized to obtain the weight of each criterion.

Then, we use TOPSIS to rank the menu items based on the determined criteria. The criteria considered in our approach include cost, favorites, religious preferences, nutrition, personal preferences, menu item rating, popularity, and time to serve the dish.

Our proposed approach provides a systematic and efficient way to rank menu items that meet the user's preferences and constraints. This approach can be used by restaurants and food service providers to enhance the user experience by providing personalized menu recommendations.

4. SYSTEM EVALUATION

System evaluation was done in two phases- Use case study and usability study.

Use case study was designed to identify and analyze user requirements and expectations and finally generate an appropriate recommendation based on their need. The use case study helped in evaluating the recommendation engine of the app and refining it based on the persona's preferences.

The usability study was designed to evaluate the app's user interface and functionality. It involved a usability survey with around 40 participants. The study collected feedback on the usability, user experience, and overall satisfaction of the app. It also collected user's expectations from the app to identify, usability issues and area for improvement.

The following sections elaborated more about the use case study and usability study of the app.

4.1. Use Case Study

The use case study was designed to evaluate the functionality of the system based on specific user's preferences. In this study, a popular American restaurant 'Olive Garden' was chosen as an example. We considered 377 menu items including appetizers, entrees, soups, salads, dessert and beverages to generate recommendations. We imagined two personas Alice and Bob. The details of each persona are listed in table 1 and table 2.

Table 1. Persona: Alice.

PERSONA	ALICE
BASIC INFORMATION	
AGE	25
GENDER	Female
HEIGHT	5 feet
WEIGHT	130 lbs.
ACTIVITY LEVEL	No data available
PREFERENCES	
COST	$0 - $20
RELIGIOUS CONSTRAINTS	Pork, Alcohol
HEALTH CONSTRAINTS	Diabetes Type-II
PERSONAL CHOICES	None
FOOD ALLERGIES	Eggs
MAX. CALORIES	650
FAVORITE FOODS	Chicken, Shrimp, Eggplant, Celery
IMPORTANCE	
COST	Important
RELIGIOUS CONSTRAINTS	Very Important
HEALTH CONSTRAINTS	Very Important
PERSONAL CHOICES	Neutral
FOOD ALLERGIES	Very Important
MAX. CALORIES	Important

Table 2. Persona: Bob.

PERSONA	**BOB**
BASIC INFORMATION	
AGE	55
GENDER	Male
HEIGHT	6 feet
WEIGHT	190 lbs
ACTIVITY LEVEL	No data available
PREFERENCES	
COST	$0 - $50
RELIGIOUS CONSTRAINTS	None
HEALTH CONSTRAINTS	Hypertension
PERSONAL CHOICES	None
FOOD ALLERGIES	None
MAX. CALORIES	650
FAVORITE FOODS	Beef, Pork, Seefood
IMPORTANCE	
COST	Not Important
RELIGIOUS CONSTRAINTS	Not Important
HEALTH CONSTRAINTS	Very Important
PERSONAL CHOICES	Important
FOOD ALLERGIES	Not Important
MAX. CALORIES	Very Important

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 3.

Table 3. Ranked top 5 menu items based on Alice's preferences.

Menu Item	Healthy 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

The table 3 consists of seven columns, where the first column lists the names of the meals. The second column is called "Healthy Index," which is determined based on PV [30] values and indicates how well the meal meets the recommended nutrition criteria. The values range from 0 (low grade) to 1 (high grade). The third column shows the cost of each meal. The fourth column displays the ratings given by consumers. The fifth column lists the main ingredients used in the meals, while the sixth column shows the number of calories per serving. Lastly, the preference score is calculated using the TOPSIS method and ranges between 0 and 1.

After taking Alice's dietary restrictions and preferences into account, certain menu items were removed from consideration. For example, meals containing eggs or exceeding the recommended carbohydrate limit were excluded. Similarly, dishes containing pork were removed due to religious constraints. A ranking of the remaining menu items was done based on Alice's preference score, calculated using the TOPSIS approach and pairwise comparison matrix. The preference scores range from 0 to 1, with higher values indicating greater preference. The top 5 food items, based on Alice's dietary preferences, are listed in Table 3. Alice prioritizes healthier food over her favorite ingredients, resulting in the top four food items not containing her favorite foods but having high health rankings. These popular food items also have higher weighted preference scores.

Table 4. Ranked top 5 menu items based on Bob’s preferences.

Menu item	Ingredients	Healthy Index	Cost	Rating	Calories	Preference score
Spaghetti w/ Meat Sauce	Mini Pasta Bowl, Meat Sauce	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

The columns in this table represent the same information as the previous table, but they are ordered according to Bob's priority preferences. Bob values his favorite foods over cost and rating. As he has hypertension, he is advised to limit his sodium intake to 1500 mg, so meals like 'Cheese Ravioli w/ Meat Sauce' and 'Braised Beef & Tortelloni' have been excluded because they exceed this limit. Bob prioritizes his favorite ingredients over a healthier diet or popular dishes. The top-ranked food has a meat sauce and lower health score, but it includes Bob's favorite ingredient, giving it a higher preference weighted score than the second-ranked food, which is more popular and has a higher health score, but does not include his favorite ingredient.

4.2. Usability Study

Our research study focuses on understanding the user experience while dining out and also the usability of a proposed system designed to rank and recommend menu items at a restaurant based on a customer's preferences. We conducted surveys with forty participants through an online survey link. Our survey questions were designed with a combination of demographic information, 5-point Likert scale and few open-ended questions. The study was approved by the Institutional Review Board (IRB) of the North Dakota State University, indicating that ethical guidelines for conducting research with human participants were followed. Participants were recruited through personal contacts of the researchers, researcher's Facebook profile and using university' graduate list-serv. The sample size was 40 individuals, but the analysis only included 33 complete responses. The gender distribution of the participants was 21 males and 12 females, and their ages ranged from 18 to 44. Moreover, 7 participants held Ph.D. degrees, 11 had Masters, 13 had Bachelors, 1 had College, and 1 had High-School degree.

In the following sections, we discuss the participant recruitment, data collection and moderation, and research ethics.

4.2.1. Study Design

Our study focused on understanding the participants traditional experiences, behaviors, decision making factors etc. while they choose a food item at a restaurant. Then we showed them our proposed design, a mobile application interface and its possible features through a pre recorded video. Finally, we asked them about their thought on our proposed design through some standard usability questions. Our survey included 3 unidentifiable demographic questions, 10 experience based Likert scales, a video explaining the user experience of our proposed app, 6 usability Likert scales and 5 open ended questions. Our study followed a combination of quantitative and qualitative research method.

4.2.2. Participant Recruitment

Participants were recruited through known circles of the authors using convenience sampling. The purpose of the study, participants privacy and other information behind the research were explained to each participant before the sessions. Informed consent was obtained from all participants before starting the study. Participants were free to skip any questions or the survey at any point they feel uncomfortable to answer. The survey link was circulated among known persons to the researchers and also through social media advertisements. All the participants were 18 years and above.

4.2.3. Research Ethics

All the participants were adults and gave written consent in the study. Our strategies, policies, and permissions were discussed in detail in the first page of the survey for transparency. It was mentioned that participants had the right to skip any questions or to skip the survey at any point if they are not comfortable with the questions. All our collected data are secured and stored in a private drive with access to the researchers only. IRB was obtained for this study.

4.2.4. Data Analysis and Results

All the study questions were in English and circulated among the people with intermediate to expert proficiency in English language. Survey results were analyzed using quantitative data analysis methods by gathering numerical data and generalizing it to make conclusions about a particular phenomenon. We also did a Descriptive statistical analysis and Chi square test as statistical tests on our survey data.

4.2.4.1. Numerical Data Analysis and Results

In our study, we examined the dining out habits of the participants. Our survey results reveal that a majority of the participants sometimes dine out (59%), while 31% of the respondents dine out occasionally and rest of the of the participants claimed that they dine out a lot. However, no participant said they never dine out. We further examined the participants' experience of selecting a meal from a restaurant menu. The findings indicate that only 4 out of

33 respondents never experienced difficulty understanding a restaurant menu. On the contrary, the rest of the participants, i.e., 29, admitted to having difficulties understanding a restaurant menu, either occasionally or sometimes. In the study, we also inquired about specific constraints such as religion, health, food allergies, and personal choices that may restrict individuals from selecting particular meals. Our results indicate that 30 participants have concerns about violating at least one of these four constraints while only three never had any such concerns. The users' concerns regarding violating a diet constraint when eating in a restaurant are illustrated in Fig. 12.

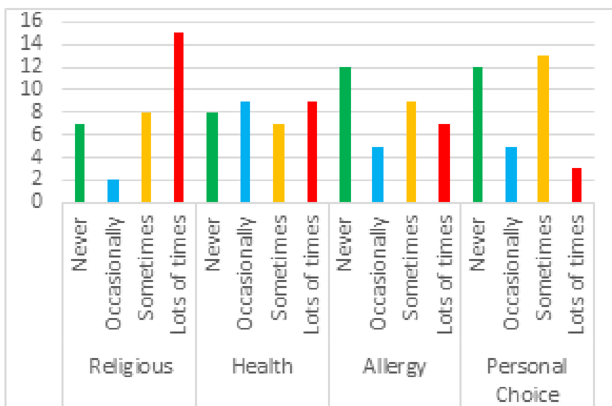

Figure 12. The Users' Concerns Regarding Violating a Diet Constraint When Eating at a Restaurant.

In the study, we further explored how participants deal with the problems they face while selecting a meal from a restaurant menu. The survey results reveal that 31 participants either search online, ask the waiter or waitress about a menu item or ingredient that is unfamiliar to them, or simply avoid an item that is new to them.

In the second phase of the study, we gathered feedback about the proposed app interface through a standard Likert scale. The results show that a vast majority of the participants (30 out of 33) felt that the app was helpful, and 23 respondents claimed that they would like to use the app frequently. Moreover, 29 participants found the app interface very simple and easy to use, while only three were neutral, and one participant stated that the system design is unnecessarily complicated. The results of our usability survey responses are illustrated in Figures 13 to 16 which suggest that users perceive our system to be user-friendly, easy to use, and helpful, and they would like to use it.

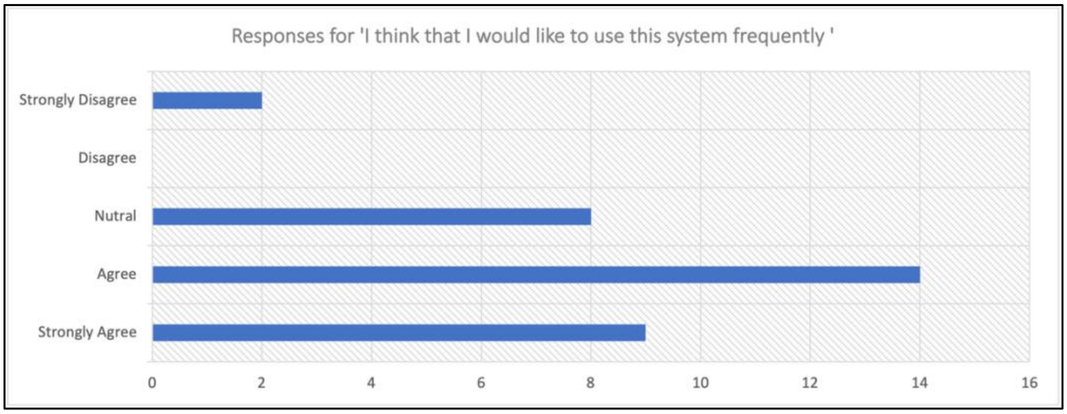

Figure 13. Responses for “I think that I would like to use the system frequently”.

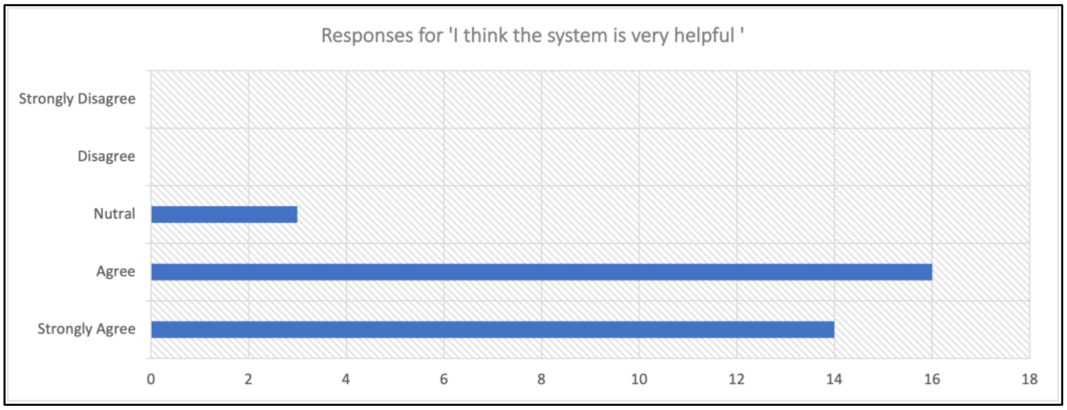

Figure 14. Responses for “I think the system is very helpful”.

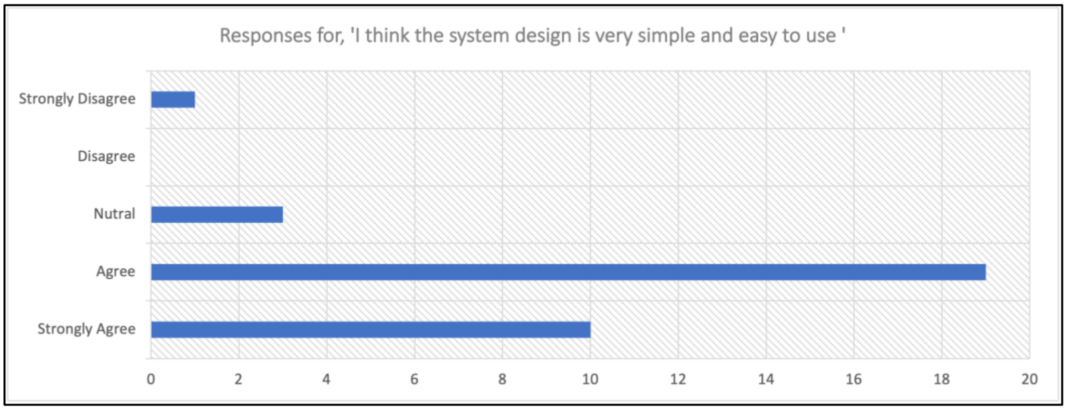

Figure 15. Responses for “I think the system design is very simple and easy to use”.

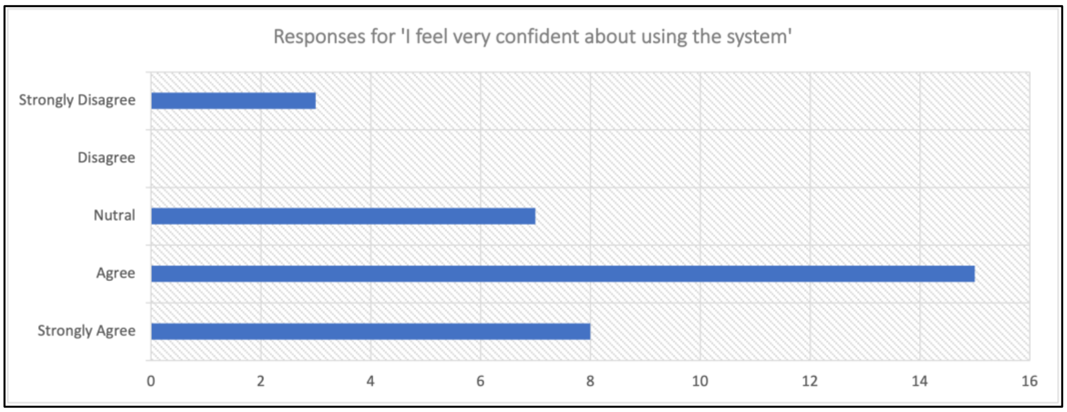

Figure 16. Responses for “I feel very confident about using the system”.

4.2.4.2. Statistical Data Analysis and Results

We did Statistical testing to make inferences about population parameters based on sample data. It helped us to determine the degree of uncertainty and the level of confidence we can place in our results. We used Descriptive statistics for analyzing data, which provides a summary of the central tendency, dispersion, and shape of a dataset. It helps to describe and understand the characteristics of a sample, making it easier to interpret and draw conclusions. distribution of responses across categories is different from what would be expected by chance.

To perform the descriptive statistical analysis on the given data, we can calculate the mean and standard deviation for each statement. The formulas for mean and standard deviation are:

Mean, $\mu = \frac{\sum x_i}{N}$ x_i is each value from the responses, N is the total no. of responses

Standard deviation, $\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}}$

Here, x_i is each value from the responses, N is the total no. of responses

Using these formulas, we can calculate the mean and standard deviation for each question, as shown in the table below:

Table 5. Mean and standard deviation for usability survey responses.

Statements	**Mean**	**Standard Deviation**
I think that I would like to use this system frequently.	3.68	1.94
I think the system is very helpful.	4.16	0.67
I think the system design is very simple and easy to use.	4.05	1.03
I feel very confident about using the system.	3.63	1.85
I found the system unnecessarily Complex.	2.47	1.96
I think that I would need the support of a technical person to be able to use this system.	2.26	1.98

The table above shows the mean and standard deviation for each statement. The mean represents the average value of each response, while the standard deviation represents the degree of variability or dispersion of the responses around the mean.

Based on the descriptive analysis, we can see that the participants had relatively high levels of agreement with first four statements, with mean scores ranging from 3.68 to 4.16. This suggests that the participants found the system to be useful, easy to use, and instilled confidence in them.

Question 5 and 6 on the other hand, had a much lower mean score of 2.47 and 2.26, indicating that majority of the participants does not find the system complex while some of them did and might need technical support to use the system.

Overall, the descriptive statistical analysis results indicate that the potential users have given positive feedback about the overall system.

However, we did not use ANOVA and t-tests as statistical data analysis methods as these are used to analyze differences between groups based on continuous data, and they assume normality and equal variances. They are not appropriate for analyzing categorical data or ordinal data with a limited number of response options. In the case of our data, the responses are categorical, so ANOVA and t-tests would not be appropriate.

5. CONCLUSION

Choosing a meal from a restaurant menu can be a challenging task for many people, especially when they are not familiar with the food options or are concerned about their dietary restrictions or health requirements. The traditional methods of menu selection, such as asking the waiter or searching online, are time-consuming and may not provide satisfactory results.

Therefore, to address this issue and enhance the user experience of dining out, we have proposed a personalized menu ranking approach. Our approach has been implemented as a mobile app prototype, which has been tested for its usability and effectiveness. Our proposed system is not only feasible but also highly effective in enhancing the user experience of dining out. Our user-friendly and easy to use system provides customized recommendations based on individual dietary restrictions and preferences, allowing users to make informed decisions quickly and easily. Overall, our research has shown that personalized menu ranking can be a powerful tool for enhancing the dining experience of customers.

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