Integrating Decision Support System to Food Choices for Better Digital Customer Experience

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Abstract

Consumers have conflicting demands and search for different personalized tools to help their decisions in the digital world. This study aims to develop a personalized decision support system for food choices. The developed Goal Programming model creates optimal menu alternatives according to consumers' hunger levels, dietary status, allergen restrictions, corresponding to personal needs, and price/speed preferences regarding service performance. These alternatives help consumers find the right foods, reducing wasted time and improving well-being. A pilot customer satisfaction survey evaluates the digital customer experience. The results show that the developed food recommendation system increased online customer satisfaction and experience.

Keywords: *Decision Support System, Customer Experience, Goal Programming*

1. Customer Experience in the Digital World and Food Suggestion Systems

Today's digitalization process, the use of internet technologies in all areas of life, the extraordinary increase in the use of mobile platforms such as tablet computers and smartphones, the development of online social networks and the increase in broadband connection speed have brought a very different dimension to retail sales (Laudon & Traver, 2017). The integration of digitalization activities into businesses' business models has led to significant changes in the way businesses do business and the unique value proposition provided to their customers (Parviainen et al., 2017). The critical success factor in experience creation is not the use of technology to improve the functions and features of products and services, but rather the use of technology in activities that facilitate people's experiences, simplify purchasing decisions, and provide personalized content (Prahalad & Ramaswamy, 2003).

Consumers' search for diversity enables them to add pleasure, fun and excitement to their lives and causes them to seek such an experience in their consumption preferences (Solomon, 2013). Especially in product categories that appeal to the senses and emotions such as food and beverage and restaurant selection, consumers tend to seek a variety that they will enjoy more than a utilitarian approach (Van Trijp, Hoyer, & Inman, 1996). During this search, people may be indecisive many times while performing consumption activities (Festinger, 1957). Especially the choice of food is a complex decision that people face every day, with many variables affecting the selection process. When ordering food digitally or researching recipes, people make the choice that maximizes their benefits and provides the most value to them according to various factors (Myunga, McCoolb, & Feinsteinc, 2008). Although quality, speed, price, and taste are the most important factors affecting food choice, health issues, ethical approaches, mood, hunger level, physiological rewards, depression, and weight control are also important (Connors et al.,2001).

Food choice is a multidimensional, situational, dynamic and complex decision process that has attracted the attention of many disciplines (Sobal & Bisogni, 2009) and different models have been developed (Gains, 1994; Story et al., 2002). Today's consumer's behavior of using many online or offline channels when ordering food (omni), increased competition, the existence of a consumer mass that seeks speed in service and delivery and cannot be patient (Lynch, 2018), generation Y and Generation Z consumers' interest in the digital world, their preference for simplicity, ease and convenience, and the importance they attach to the experience of their purchases further increase the importance of a system that is more personalized, takes into account many personal variables, and offers the best set of alternative suggestions in the food selection problem.

These digital systems, which can make life so much easier, serve as recommendation systems in order to offer more personalized experiences in line with the needs and expectations of the individual with the increase in competition. The food recommendation systems developed in the literature are generally personalized for diabetes and chronic diseases, based on the energy density of foods and recommending healthier meals, or as a guide to help people to eat daily according to their profile (Lo et al., 2008; Ge et al., 2015; Rehman et al., 2017; Subramaniyaswamy et al., 2019). However, people's decision to choose or prefer daily meals requires a holistic perspective as it is a complex decision (Sobal & Bisogni, 2009) that can vary depending on many variables such as hunger levels, dietary status and price/speed.

This study aims to create a digital personalized food recommendation system based on people's hunger status, dietary status, price and speed expectation, and desired food restrictions. This study differs from the health or diabetes-oriented food recommendation systems developed in the literature, which are the main variables affecting food choice, such as hunger, dietary status, price and speed constraint (Connors et al., 2001; Myunga et al., 2008), as a holistic structure and responds to the personal needs of all users when they need to make a food choice by offering the best solution alternatives. In the first phase of the study, a mathematical model for the food recommendation system is developed and made available online. In the second phase, the impact of this digital tool on customer experience is measured.

2. Metadology

In this study, Goal Programming, which is one of the multi-criteria decision-making methods, is used to present the most appropriate menu alternative from the food list by considering the personal preferences of the people in their food choices. Goal Programming, as an extension of linear programming, aims to minimize the deviations of conflicting objectives from their goals (Charnes et al., 1955; Charnes & Cooper, 1961). There are many studies on nutrition and food recommendation systems using goal programming in the literature (Pasic et al., 2012; Omotesho & Muhammad-Lawa, 2010). For example, Pasic et al. (2012) developed a goal programming optimization model to meet the daily nutritional needs of individuals. Omotesho and Muhammad-Lawa (2010) used goal programming to develop an optimal food plan for rural households in Nigeria. Kumar jain et al. (2020) used weighted goal programming method to meet the vitamin needs of people from the foods they consume daily. Lestari et al. (2020) developed a goal programming model that aims to minimize deviations in calorie and nutrient content at optimal costs for children aged 4-6 years. Dhoruri et al. (2017) used the goal programming method to regulate the amount of calories, protein, fat and carbohydrates and minimize costs for patients with high blood sugar. It has been observed that there are models based on linear programming in the field of nutrition in the literature, but they usually include energy-based diet and health-themed topics under budget constraints. In this study, unlike the studies in the literature (Kim et al., 2009; Freyne et al., 2010; Faiz et al., 2014; Banerjee et al., 2019), in addition to considering dietary status under the health theme, it is aimed to develop a tool based on meeting personal expectations by considering rational variables such as price and speed determined by the user together with subjective variables such as hunger level and dietary status.

The previously developed mathematical model algorithm by the authors is embedded in the background of the http://offermefood.com/ website. React.js 17 with EcmaScript 6 standards is used for the frontend and Backend is coded as REST with Web Api 2 in .Net Framework 4.6 for the website. A pilot study is conducted to measure the success of the developed model in addressing users' constraints and preferences. After using the system for a certain period of time on the web site, users are able to evaluate the compatibility of the food recommendations with their own preferences and constraints, and to assess their willingness to recommend the model to others. The sample size is determined as 100 people for the pilot survey using convenience sampling method (Reynolds et al., 1993). The satisfaction statements to be used in the questionnaire are prepared by utilizing the statements in satisfaction scales with proven validity and reliability in the literature (Doll et al., 1995; Downing, 1999; Sindhuja & Dastidar, 2009, Wixom & Todd, 2005). The questionnaire form consists of dimensions such as "content", "ease of use", "compatibility", "responsiveness/timeliness", "tendency to use" and "attitude", which are most frequently used in satisfaction scales in the literature mentioned above. The statements in the questionnaire form are measured with a 5-point Likert scale and the collected data are analyzed using SPSS 22.0 program.

2.1.Mathematical Model

The following presents the model’s parameters, decision variables, and models.

Parameters

x_n: the amount of food component subject to the n[th] request
os: The number of daily meals of the user

$$\boldsymbol{xc}\ (the\ amount\ of\ requested\ calorie): \begin{cases} 66.432 + 13.75(w) + 5(h) - 6.755(a), \\ \quad for\ men \\ 655.09 + 9.56(w) + 1.85(h) - 4.68(a), \\ \quad for\ women \end{cases}$$

(Harris–Benedict principle of the base energy expenditure equation)
w: user weight (kg)
h: user height (cm)
a: user age

$$\boldsymbol{pro}: \begin{cases} 0.1, \text{if hunger level is low} \\ 0.225, \text{if hunger level is middle} \\ 0.35, if\ \text{hunger level}\ is\ high \end{cases}$$

$$\boldsymbol{fib}: \begin{cases} 25\ (mg),\ \ \text{if hunger level is low} \\ 30\ (mg), \text{if hunger level is middle} \\ 35\ (mg), if\ \text{hunger level}\ is\ high \end{cases}$$

xt: maximum acceptable preparation time for the menu
xf: maximum acceptable price for the menu
z^c: the number of foods requested from food category c
y_{kn}: the amount of food component subject to the n[th] request in food k
yc_k: the calorie of food k
yp_k: the amount of protein in food k
yl_k: the total amount of fiber in food k
yt_k: the preparation time for food k
yp_k: the price for food k

Decision variables

$$\boldsymbol{a_k^c}: \begin{cases} 1,\ \ selection\ of\ food\ k\ in\ category\ c \\ 0,\ \ otherwise \end{cases}$$

$\boldsymbol{dc^+}, \boldsymbol{dc^-}, \boldsymbol{dp^+}, \boldsymbol{dp^-}, \boldsymbol{dl^+}, \boldsymbol{dl^-}, \boldsymbol{d_n^+}, \boldsymbol{d_n^-}$ deviation variables

Mathematical Model

$$\boldsymbol{Min}\ \ (\boldsymbol{dc^+} + \boldsymbol{dc^-}) + \boldsymbol{4} * (\boldsymbol{dp^+} + \boldsymbol{dp^-}) + \boldsymbol{2} * (\boldsymbol{dl^+} + \boldsymbol{dl^-}) \qquad (1)$$

$$\boldsymbol{Min}\ \sum_{\boldsymbol{n}}^{\boldsymbol{N}} (\boldsymbol{d_n^+} + \boldsymbol{d_n^-}) \qquad (2)$$

Subject to:

$$\sum_{\boldsymbol{k}}^{\boldsymbol{K}} \boldsymbol{a_k^c} \le \boldsymbol{z^c} \qquad \forall\, \boldsymbol{c},\ \ \boldsymbol{c} = \boldsymbol{1..C} \qquad (3)$$

$$\sum_{\boldsymbol{c}}^{\boldsymbol{C}} \sum_{\boldsymbol{k}}^{\boldsymbol{K}} \boldsymbol{y_{kn}} * \boldsymbol{a_k^c} + \boldsymbol{d_n^+} - \ \boldsymbol{d_n^-} = \boldsymbol{x_n} \qquad \forall\, \boldsymbol{n},\ \ \boldsymbol{n} = \boldsymbol{1..N} \qquad (4)$$

$$\sum_c^C \sum_k^K \boldsymbol{yc_k * a_k^c + dc^+ - dc^- = xc\ /os} \tag{5}$$

$$\sum_c^C \sum_k^K \boldsymbol{yp_k * a_k^c + dp^+ - dp^- = pro * (\frac{xc}{4*os})} \tag{6}$$

$$\sum_c^C \sum_k^K \boldsymbol{yl_k * a_k^c + dl^+ - dl^- = fib} \tag{7}$$

$$\max_t(\boldsymbol{yt_k * a_k^c}) \leq \boldsymbol{xt} \qquad \forall\, \boldsymbol{c},\ \ \boldsymbol{c = 1..C},\ \forall\, \boldsymbol{k},\ \ \boldsymbol{k = 1..K} \tag{8}$$

$$\sum_c^C \sum_k^K \boldsymbol{yf_k * a_k^c \leq xf} \qquad \forall\, \boldsymbol{k},\ \ \boldsymbol{k = 1..K} \tag{9}$$

$$\boldsymbol{a_k^c} \in \{\boldsymbol{0, 1}\} \qquad \forall\, \boldsymbol{c},\ \ \boldsymbol{c = 1..C},\ \ \forall\, \boldsymbol{k},\ \ \boldsymbol{k = 1..K} \tag{10}$$

$$\boldsymbol{d_c^+, d_c^-, d_p^+, d_p^-, d_l^+, d_l^-, d_n^+, d_n^-, \geq 0} \qquad \forall\, \boldsymbol{n},\ \ \boldsymbol{n = 1..N} \tag{11}$$

The purpose of the mathematical model is to respond to the user's diet and hunger. While trying to meet the hunger preference with protein and fiber and meet the diet preference with calories, the model ensures that the components have equal weight (1 g protein = 4 calories (Gupta, 2019); 1 g fiber = 2 calories (Garvey, 2016)). The model's second priority is to minimize the gap between the user's food content preferences and the contents of the suggested menu. Constraint (3) ensures that the number of dishes to be served from each category of food in the recommended menu does not exceed the number requested by the user. Constraint (4) shows that each component (the amount of vitamin C, magnesium, etc.) to be selected by the user must be included in the recommended menu similarly. Constraint (5) ensures that the recommended menu meets the number of calories that the user should take in a meal. Constraints (6) and (7) also require that the recommended menu contain a sufficient amount of protein and fiber in case of hunger. Constraint (8) requires that the menu's preparation time be determined by the food with the longest preparation time on the menu. Constraint (9) ensures that the total cost of the recommended menu does not exceed the user's budget. Additional constraints are included in (10) and (11).

Dataset of the model is obtained from secondary sources. The food categories and definitions of the meals used in the design of the food recommendation system based on the study of Merdol (2018). The prices of the ingredients of the meals are checked from a local retailer catering to the middle-income level. For the speed variable, which is among the rational preferences of consumers during food choices, the cooking time predicted in the recipes is used. Food components are obtained from the food composition chart (Bell et al., 2011).

3. Findings

Before measuring users' system experience, data on the intensity of internet usage and frequency of online food ordering provide information about their profiles. Table 1 shows that 61.7% of the participants who participated in the pilot survey to measure satisfaction and customer experience with the food recommendation system developed high Internet users, 36.2% of the participants order food online more than twice a week, and 68.1% order food online at least once a week.

Table 1. Intensity of internet use and frequency of ordering food online

	n	**Valid Percentage**
Internet Usage Intensity		
Low	**2**	**2,1**

Middle	**34**	**36,2**
High	**58**	**61,7**
Total	**94**	**100**
Frequency of Online Food Ordering		
Every day	**5**	**5,3**
1 per week	**25**	**26,6**
2 or more per week	**34**	**36,2**
1 per month	**21**	**22,3**
Never	**9**	**9,6**
Total	**94**	**100**

Doll and Torkzadeh (1988)'s "End-User Computing Satisfaction" 12-item scale is used to measure the participants' satisfaction with the food suggestion system. According to the one-sample t-test results of the participants' statements, it is seen that all of them are different from the test value of "Undecided (3)" and the statements are valid. When the participants evaluated the system in terms of content, 82.9 percent of the participants stated that the system asked for information about their health, hunger, etc., and 73.4 percent stated that the food recommendations offered by the system are compatible with their needs. In addition, 82.9 percent of the participants stated that the system worked properly, and 71.3 percent are satisfied with the food menus offered. When they evaluated the system in terms of format, many of the participants stated that the meal recommendations are clear and useful for them. In addition to these, it is seen that most of the participants have a positive opinion in terms of the ease of use and speed of the system.

Table 2 shows the cognitive and emotional online customer experience evaluations of the participants, which were created by utilizing the scales of Frow and Payne (2007), and Martin, and others (2015) to measure the customer experience of the system. Accordingly, it is found that most of the participants evaluated both cognitive and emotional experience positively.

Table 2. Online customer experience findings

	Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Completely Agree**	**Average**	**t**	**p**	**Cronbach Alpha**
COGNITIVE EXPERIENCE									
The meal suggestions provided by the system were in line with my needs	-	7 (7,4)	13 (13,8)	53 (56,4)	21 (22,3)	3,94	11,151	0,000	
The speed at which the system worked was good.	-	1 (1,1)	6 (6,4)	34 (36,2)	53 (56,4)	4,47	21,473	0,000	

I know that the personal information I entered into the system is safe.	1 (1,1)	2 (2,1)	20 (21,3)	37 (39,4)	34 (36,2)	4,07	11,967	0,000	
EMOTIONAL EXPERIENCE									
The system made my food selection decision easier.	2 (2,1)	-	7 (7,4)	38 (40,4)	47 (50)	4,36	16,478	0,000	
I liked the system visually.	3 (3,2)	5 (5,3)	15 (16)	36 (38,3)	35 (37,2)	4,01	9,595	0,000	0,800
I enjoyed using the system.	2 (2,1)	2 (2,1)	7 (7,4)	35 (37,2)	48 (51,1)	4,32	14,779	0,000	
I was happy that the recommended meals were customized for me.	-	5 (5,3)	9 (9,6)	36 (38,3)	44 (46,8)	4,27	14,531	0,000	

4. Conclusion and Discussion

Digitalization and rapid technological advancement have increased the bounds for developing customer experiences, and competition has reached the highest levels. Activities that simplify the purchasing decision by increasing the personal experience of today's consumers and offering personalized content come to the fore. In the food and beverage sector, it has become important to create a variety that customers will enjoy and to bring innovative solutions in cases of indecision to create customer experience. Especially food selection is a complex problem that people face every day, with many variables affecting the selection process. Consumers frequently search the internet for both food orders and homemade food recipes, and it is known that users are indecisive. Although quality, speed, price and taste are the most important factors affecting food choice, health issues, ethical approaches, mood, hunger level, physiological rewards, depression and weight control also come to the fore. In the literature, food recommendation systems have been developed to meet one or more of these (Lo et al., 2008; Ge et al., 2015; Rehman et al., 2017; Subramaniyaswamy et al., 2019). The developed food recommendation systems generally include personalized systems for diabetes and chronic diseases, based on the energy density of foods and recommending healthier meals, or as a guide to help people with their daily nutrition according to their profile. However, the decision to select or choose a daily meal requires a holistic perspective as it is a complex decision (Sobal & Bisogni, 2009) that can vary depending on many variables such as hunger levels, dietary status and price/speed. Another important issue is that the developed system should be tested, used and evaluated by the customers themselves. This study creates a digital tool that covers the hunger status, diet status, price expectation, speed expectation and desired nutrient constraints. In the study, a web-based software is implemented to ensure that the most appropriate menu is created in line with the conflicting demands of people in food selection. Goal programming was chosen to realize different goals at the same time and the algorithm was coded with React.js 17 and .Net Framework 4.6. The website offermefood.com is available on the internet to demonstrate the developed model. Users could find three different personalized menu alternatives with respect to their preferences.

According to the survey results, the participants are generally satisfied with the system, both cognitively that the system facilitated their food selection decisions and is compatible with their current needs, and that the system made them happy, and they enjoyed the system. However, according to the literature (Frow & Payne, 2007; Sobal & Bisogni, 2009), this system is insufficient in terms of creating the feeling of being in a "flow" of customer experience on online platforms. Accordingly, it would be useful to develop the system to create more unique experiences and to measure the experience in this sense. In future studies, disease, allergen and undesirable ingredient types and food component options can be increased, the food database can be expanded, and artificial intelligence-based recommendation systems can be tested by learning personal preferences. In addition, to further customize users' preferences, it would be beneficial for the continuity of the system to save their previous preferences and data and to show differentiated menus in subsequent uses.

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