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APPLICATION OF MULTI-CRITERIA DECISION MAKING METHODS FOR MENU SELECTION

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Abstract: Nutritional information on menus can assist customers in making healthier eating choices. One technique being utilized to tackle the rise of overweight and obesity is the use of nutritional information on menus. Menu engineering strategies can be used to improve sales of generally healthier and higher margin items. For today's food and beverage companies, menu engineering has become essential. Companies must continually evaluate their menus in order to keep up with changing customer demands and the conditions of the competitive market. Menu engineering's core involves comparing the effectiveness of each menu. At this point, correct decision-making under numerous factors is thought to be a very challenging procedure. To evaluate alternatives according to many features, several Multi-Criteria Decision-Making (MCDM) approaches have been created. The main novelty of this paper is that four MCDM methods, including Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), Fuzzy TOPSIS, VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), and Fuzzy VIKOR, are employed to evaluate menu options. Comparative analysis of MCDM methods is another contribution of this study. The process of evaluating and selecting healthier menu alternatives can become challenging and time-consuming. This study pointed out how crucial it is to conduct comparative analysis using various MCDA methods and to carefully determine the right ones when addressing the issue of selecting the best menu, taking into account the values of the criterion in fuzzy numbers.

Keywords: Menu engineering, Menu selection, Multi-criteria, Decision-making approaches

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1. Introduction

Describing the most nutritious menu items in less appealing words may promote the idea that healthy foods aren't delicious or indulgent, undermining customers' choice of healthier eating options. Much can be done to make healthy selections appealing, and further research is needed to understand how changing descriptions in restaurant settings might impact food choice, metabolism, satisfaction, and overall attitudes about healthy eating (Turnwald et al., 2017). Efficient communication is critical in providing significant and relevant nutrition information that reflects the healthiness of a menu item. Moreover, offering more nutrition information may be necessary to foster positive perceptions of the promoted menu item and purchase intent among customers. Restaurant management can encourage consumers to choose healthier menu items by displaying calorie, fat, and cholesterol information on the menu board or through advertising healthy choices (Jeong and Jang, 2016).

Researchers should prioritize long-term prevention of chronic diseases such as cancer and cardiovascular disease among the general population (Detopoulou et al., 2022). For instance, menu calorie labeling may contribute to public health promotion and the prevention of chronic diseases (Jia et al., 2023). Additionally, dietary fiber plays a crucial role in maintaining good health and preventing noncommunicable diseases (Sampaio et al., 2017). Excessive sodium consumption, often associated with restaurant foods, has been linked to an increased risk of cardiovascular disease (Wolfson et al., 2018). Many are unaware that reducing salt intake is one of the easiest and quickest ways to improve our health. In the UK alone, just 1 fewer "pinch" of salt per day can save almost 4,000 heart attacks and strokes annually (World awareness weeks). Alonso et al. (2021) presented that by 2050, there would be 87 870 fewer cases of premature ischemic heart disease and 126 010 fewer cases of premature stroke, compared to the health gains in the base-case analysis, if larger population salt intake reductions were achieved by 2030, as advised by the World Health Organization (WHO). Consequently, numerous researchers have investigated issues related to dietary habits. One of the main aims of this study is to evaluate the most preferred menus of a local restaurant according to six important criteria. It is very difficult to evaluate the six criteria, including calories, cholesterol, fiber, saturated fat, sodium, and sugar, for each menu at the same time. At this point, the advantages of using

MCDM methods are emphasized in this study.

Yamamoto et al. (2005) found that most adolescents' meal ordering behavior remained unchanged when calorie and fat content information was added to menus. Nevertheless, promoting the provision of nutrition information is advisable because it lead some adolescents to reduce their calorie and fat intake without imposing any adverse financial effects on the restaurants. Gerend (2009) examined the dietary choices of college students in relation to the availability of calorie information on fast-food menus. Elbel et al. (2009) investigated how menu calorie labels influence consumer decisions regarding fast food. In their study involving low-income and minority consumers, calorie labeling increased both the calorie information and the number of individuals reporting that this information influenced their food choices. Dumanovsky et al. (2010) assessed awareness of calorie content on fast-food menus. Obbagy et al. (2011) found that most chefs believed that restaurant dishes could be significantly reduced in calorie content without customers noticing. They emphasized the need for collaboration between chefs and public health experts to make appealing low-calorie menu options more accessible. Dowray et al. (2013) explored the impact of calorie content labeling, combined with information about the physical activity required to burn those calories, on meal choices from a fast-food menu. Respondents generally selected lower-calorie meals when presented with this information, suggesting that the distance-to-walk label was particularly effective.

Hobin et al. (2022) demonstrated that listing calories for both alcoholic and non-alcoholic beverages on restaurant menus increased customer awareness of calorie content. Jia et al. (2023) investigated the relationship between menu calorie labels, dietary quality, and weight status, exploring whether this relationship varied among different groups. While calories provide a measure of food consumption, they do not reflect nutritional value comprehensively. Considerations such as protein and fiber content, sugar, salt, and fat levels are equally important. For instance, reducing total fat intake without addressing saturated fat may not significantly impact low-density lipoprotein cholesterol (LDL-C) levels (Nicolosi et al., 2001). Therefore, it is advisable to consider multiple criteria when evaluating dietary choices.

In Hwang and Lorenzen (2008), the participants found menus that included calories, macronutrients, and fat content to be the most useful and reliable. They also perceived menus with more nutritional information as more appealing. Furthermore, the disclosure of nutritional information influenced participants' overall sentiments about menu items and their attitudes toward nutrition. Bruemmer et al. (2012) audited menu items to document changes resulting from King County's menu labeling regulation. Certain menu items were redesigned to improve nutrition profiles by reducing energy, saturated fat, and sodium content. Patel et al. (2016) assessed restaurant companies and their recipes. They found that acceptable ingredient changes led to reductions of up to 26% in calories and up to 31% in sodium per serving. Most menu items in restaurants experienced slight decreases in calories, fat, saturated fat, and sodium, which were considered acceptable. Cantu-Jungles et al. (2017) conducted a meta-analysis on sodium, total fat, saturated fat, and carbohydrates, finding no significant impact of menu labeling on U.S. adults' nutrient choices in restaurants. Huang et al. (2022) observed that menu items at large chain restaurants in the USA contained higher absolute levels of energy, fat, saturated fat, and sugar compared to the UK. Inter-country variations were especially notable in children's meal items for sodium and saturated fat.

Scourboutakos et al. (2014) found that displaying sodium information on restaurant menus led to significantly lower salt intake among customers compared to those who only had access to calorie information. However, the extent of the reduction varied depending on the type of restaurant. These results suggest that menu labeling can influence the nutrient composition of diners' choices when eating out, particularly when sodium information is provided alongside calorie information. Rudelt et al. (2014) recommended that individuals aiming to limit their sodium intake should exercise caution when making menu choices at fast-food establishments. Hobin et al. (2016) conducted an experimental study to explore whether various menu labeling formats, which provide information on calorie and sodium content, influence parents' choices. Menu labeling that includes calorie and sodium information may reduce the demand for fast food children's meals and help parents choose healthier food options for their kids. Wolfson et al. (2018) demonstrated that although the sodium content of newly introduced items decreased on average, foods on U.S. chain restaurant menus still tend to have excessive sodium levels. In Byrd et al. (2018), customers' menu choices were assessed based on the calorie and sodium contents of the items. The study found that, even with taste preferences considered, the menu displaying the sodium warning symbol did not significantly differ from the other menu conditions. Byrd and Almanza (2021) indicated that policies mandating sodium menu labeling may not achieve the expected outcome of encouraging customers to choose lower-sodium items. Sisti et al. (2023) also demonstrated that the sodium content of menu items remained unchanged after the implementation of sodium warning icon legislation, underscoring the challenges associated with reducing sodium levels in restaurant offerings.

State and local governments can contribute to creating a healthier food supply and population by supporting efforts to reduce sodium levels through systemic and environmental reforms (Alexander et al., 2021). Bowers and Suzuki (2014) found that menu labeling, intended to encourage shifts in dietary and health behaviors, was associated with positive changes. Those who used menu labels reported meeting recommended exercise guidelines, consuming more fruits, and drinking less soda compared to those who did not use menu labeling. Sigala et al. (2022) assessed the impact of menu added-sugar warning labels on customer behavior. Falbe et al. (2023) reported that the likelihood of ordering high-added-sugar menu items decreased with the presence of added-sugar warning labels, and participants' awareness of items containing more than 50% of the daily recommended added sugar amount improved.

This study contributes to a better understanding of menu selection and the most effective ways to evaluate six important criteria: calories, cholesterol, fiber, saturated fat, sodium, and sugar. This study also contributes to the literature by conducting a field experiment at a local restaurant to examine menu choices in a real-world environment. While this study deals with choosing the best menu by considering the criteria values, it has made a comparative analysis using various MCDM methods. For the problem of menu selection, two different fuzzy MCDM methods—fuzzy TOPSIS and fuzzy VIKOR—are proposed. In both cases, both quantitative and qualitative decision factors can be evaluated as subjectively as necessary. Tom et al. (2015) used calories, cholesterol, fiber, saturated fat, sodium, and sugar for restaurant menu evaluation. As in the study of Tom et al. (2015), six criteria, including calories, cholesterol, fiber, saturated fat, sodium, and sugar, are used. This study focuses on

- determine and evaluate alternatives considering six criteria,
- propose fuzzy TOPSIS and fuzzy VIKOR,
- present comparison analyses of proposed MCDM methods, TOPSIS, and VIKOR,
- analyze the results, considering six criteria for ten menu alternatives.

The paper is structured as follows: the proposed methods are explained in the "Proposed Methodology" section. The "Results and Discussion" section assesses the findings using four different methods. Finally, the "Conclusion" section summarizes the contribution of the study and offers suggestions for further research.

2. Materials and Methods

The food and beverage sector is among the fastest growing sectors due to economic developments. The rapid increase in the number of those operating in this sector worldwide has led to fierce competition in this field, and businesses have chosen to focus more on customer requests and needs day by day (İpek and Göktürk, 2021). At this point, one of the phenomena required to meet customer requests and needs in businesses is the menu engineering process (Mutlu et al., 2022).

Menu management took what enterprising chefs had used intuitively for years and turned it into a computerized, scientific model that everyone could understand. The gastronomic value and inventiveness of dishes are highly valued by all menu planners in menu engineering (Morrison, 1996). Menu engineering is a methodological alternative that allows the analysis of the dishes offered by a restaurant, making it possible to determine the financial profitability and popularity of the gastronomic offer in order to correct, improve, and maintain the menu (Juliana et al., 2021; Hermida and Aráuz, 2023). Menu engineering may periodically make the decision to formulate a strategy based on the results of menu sales that occur within a given period of time. It is necessary to understand the solutions and follow-up to increase the sales of the next menu (Ardiansyah, 2020).

Kwong (2005) found that menu engineering and design were crucial in enhancing the profitability of Asian restaurants. Many of the evaluated main course products in the study were classified as unpopular and/or unprofitable, and it was discovered that the sampled menus had little commercial impact. To create a menu recommender, Tan et al. (2012) determined that the MCDM method was successful with a number of innovative algorithms and a database of client knowledge. The restaurant menu evaluation and selection problem has been successfully solved as an MCDM problem by Tom et al. (2015). To rank the menu items according to the customer-selected priority criteria, they created a fuzzy MCDM model. Tom and Annaraud (2017) determined that the fuzzy MCDM method can be successfully used to assess the contribution margin and popularity index and to choose the best strategy.

After implementing activity-based costing, Linassi et al. (2016) discovered that the majority of menu items have negative operational profits. Particularly in labor-intensive production systems, the adoption of activity-based costing improves the accuracy of the effective cost of each menu item. DiPietro (2017) examined the changing and evolving segments of the food service industry, restaurant operations, service quality in food service, restaurant financing, food service marketing, food safety and health, and the increasing role of technology in the industry. The results of Hamdallah and Srouji (2018) studies showed that the modified balanced scorecard approach, which includes both financial and non-financial perspectives, positively affects menu management in health-care centers in Jordan. Fang (2020) found that integrated a slack-based measure and data envelopment analysis model can be used to improve the financial performance and sustainability of the menu in chains of Chinese and Japanese restaurants. Hermida and Aráuz (2023) determined that menu engineering methodology in a restaurant located in the city of Ibarra can be used to increase the profitability of catering services, improve kitchen resources, and improve service quality. Lai et al. (2020) discussed the management of menu profitability in the restaurant industry. Technology advancement has led to the creation of methods that can be used to manage menu profitability.

Menu engineering describes particular methods for assessing the performance of individual menu items so that strategic choices can be made. In order to choose imprecise and strategic options, decision makers utilize menu engineering against manually created target values (Tom et al., 2017). There are several methods for menu engineering, and companies have different preferences depending on what they need. In order to develop a more effective decision-making tool, this study used fuzzy MCDM models to identify the options for a strategy. MCDM methods for menu management are given in Table 1. The comparative use of four different methods (TOPSIS, fuzzy TOPSIS, VIKOR, and fuzzy VIKOR) in menu management makes a significant contribution to the literature.

Table 1. MCDM methods for menu management

Author(s)	Fuzzy based MCDM	MAIRCA*	BWM*	TOPSIS	AHP*	VIKOR
Tom, Wibowo, and Grandhi (2015)	√					
Tom and Annaraud (2017)	√					
Nerisafitra and Putri (2017)				√		
Arsić et al. (2019)		√	√			
Ho et al. (2022)					√	
This study	√			√		√

*AHP= analytic hierarchy process, MAIRCA= multi attributive ideal-real comparative analysis, BWM= best-worst method

A precise understanding of the criterion weights and assessments is assumed in traditional MCDA approaches. However, there are some instances in the real world where it is impossible to use precise expressions. At this point, variables that are imprecisely expressed by fuzzy TOPSIS and fuzzy VIKOR can be created using linguistic values.

Unquestionably, one of the most critical actions a person can take is making decisions, encompassing a broad range of alternatives. The study of decision-making delves into how decisions are made and how they can be improved. Essentially, it involves determining the best alternative or ranking them by preference (Arora et al., 2022). Effective decision-making can be exceptionally challenging in various situations. When dealing with group decision-making, the complexity increases because it necessitates gaining consensus within the group. Therefore, numerous Multiple-Criteria Decision-Making (MCDM) techniques have been developed and are favored by decision-makers for evaluating options based on various criteria (Cevikcan et al., 2009). MCDM methods rely on engineering expertise, intuition, and past experiences. Fuzzy logic-based MCDM approaches are gaining popularity among researchers due to their capacity to compare multiple criteria and potential alternatives using natural language linguistic terms, which align with human subjective cognition (Alpay and Iphar, 2018).

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) is a straightforward and widely used method for addressing problems related to ranking and selecting alternatives. It excels at handling MCDM issues because it can accommodate decision-makers' fuzzy opinions and perceptions. Moreover, the TOPSIS method is adept at managing uncertainties that often arise in real-world scenarios characterized by fuzziness (Arora et al., 2022). The proposed approach is described as a sequence of sequential steps.

Step 1. Create a decision matrix and construct the normalized decision matrix

Decision matrix, which includes m alternatives connected to n criteria, is assessed using the TOPSIS approach. A_i denotes the i[th] alternative considered. In order to enable comparison across the attributes, this procedure attempts to convert the various attribute dimensions into nondimensional attributes. It is possible to calculate an element r_{ij} of the normalized decision matrix R as (equation 1);

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{1}$$

The numerical result of the i[th] alternative in relation to the j[th] criterion is denoted by x_{ij}.

Step 2. Construct the weighted normalized decision matrix

A set of weights from the decision maker is incorporated into the decision matrix. The computation of this matrix involves multiplying each column of the matrix R by the corresponding weight, w_j. Weighted normalized decision matrix is denoted as v.

Step 3. Determine ideal and negative ideal solutions

The two created alternatives, A^* and A^-, stand for the ideal solution, which is the most preferred alternative, and the least preferable solution, which is the negative-ideal solution, respectively.

Step 4. Calculate the separation measure

The n-dimensional Euclidean distance can be used to calculate the distance between each alternative. Each alternative's distance from the ideal is provided by (equation 2);

$$s_{i^*} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^*\right)^2} \tag{2}$$

$i = 1,2,\dots,m$

Each alternative's distance from the negative ideal is provided by (equation 3);

$$s_{i^-} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2} \quad (3)$$

$i = 1,2, \ldots , m$

Step 5. Calculate the relative closeness to the ideal solution

The relative closeness of A_i with respect to A^* is defined as (equation 4);

$$c_{i^*} = \frac{s_{i^-}}{(s_{i^*} + s_{i^-})} \quad (4)$$

$0 < c_{i^*} < 1,\ i = 1,2, \ldots , m$

Step 6. Rank the preference order

The descending order of c_{i^*} can be used to rank a group of alternatives in order of preference. A detailed information of TOPSIS can be found in Hwang and Yoon (1981). Incorporating the steps mentioned above, the fuzzy extension of the TOPSIS method is depicted in Figure 1 (Papathanasiou and Ploskas, 2018).

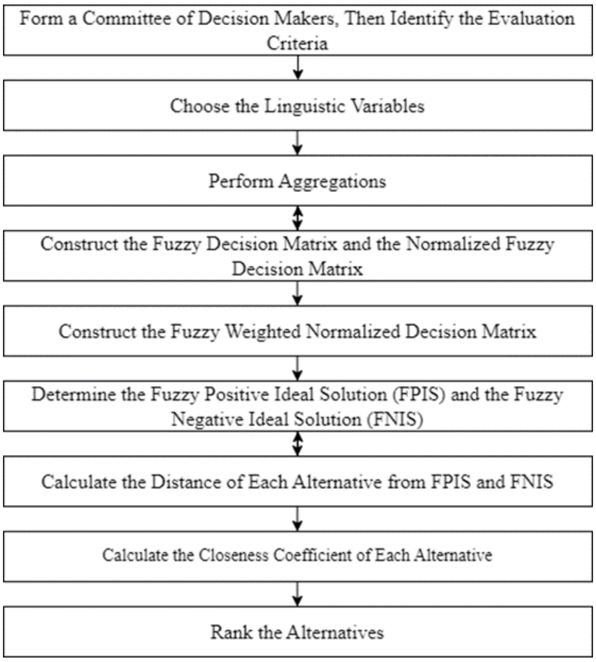

Figure 1. Fuzzy TOPSIS (Papathanasiou and Ploskas, 2018).

Each method has a separate procedure for normalizing. Vector normalization is used by TOPSIS, but linear normalization is used by VIKOR (Sarı, 2018). On the other hand, both the TOPSIS and VIKOR methods operate on a fundamental principle: they employ an aggregating function to determine the proximity of a solution to the ideal one. The fuzzy TOPSIS method identifies a solution that is the closest to the ideal and furthest from the negative ideal solution. Meanwhile, the fuzzy VIKOR method seeks a compromise solution that maximizes group utility for the majority while minimizing it for the opponents (Umamaheswari and Kumari, 2014). The VIKOR and fuzzy VIKOR methodologies are outlined in Figure 2 and Figure 3, including the maximum desirability (Si), lack of desirability (Ri), and VIKOR index (Qi).

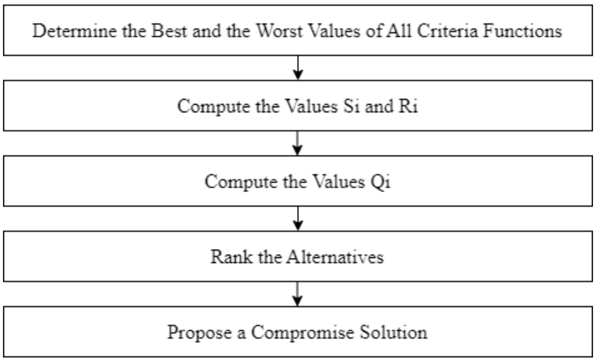

Figure 2. VIKOR (Papathanasiou and Ploskas, 2018)

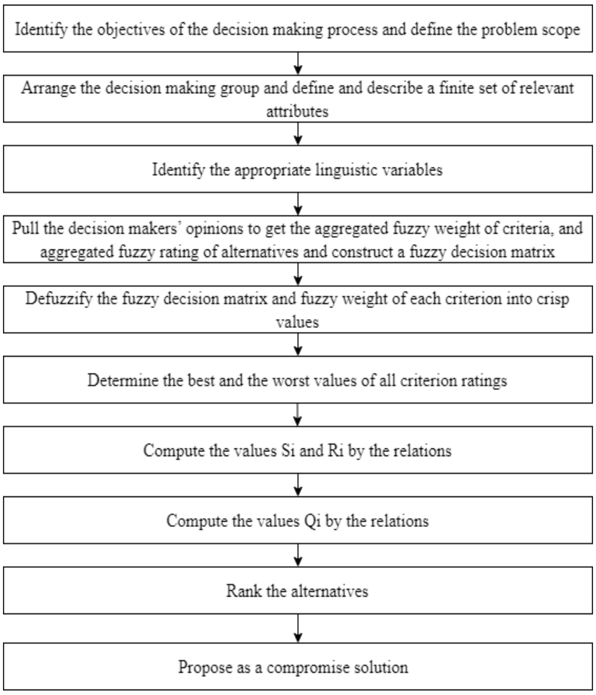

Figure 3. Fuzzy VIKOR (Sanayei et al., 2010).

The most important methods for resolving issues in the real world are TOPSIS and VIKOR, which are applied to discrete alternative challenges. They are capable of identifying the right alternative right away. They reduce the need for pairwise comparisons, and the process may not be greatly impacted by the capacity limitation. They can be applied to a wide range of alternatives and attributes. When objective or quantitative data are available, they are suitable to use. Based on an aggregating function that stands for "closeness to the ideal," they are created (Alsalem et al., 2018). TOPSIS and VIKOR methods were used in this study due to their many advantages. The real world occasionally presents situations in which using precise expressions is not possible. At this point, fuzzy TOPSIS and fuzzy VIKOR can be used to provide a better solution. This study contributes to the literature by comparing these four methods.

3. Results and Discussion

A "healthy menu" has emerged as a crucial idea for the survival and success of the restaurant industry. Given the growing significance of healthiness in the restaurant sector, it has emerged as one of the most difficult academic problems (Hur and Jang, 2015). In this paper, four MCDM methods are used to evaluate ten alternatives, considering six important criteria, including calories, cholesterol, fiber, saturated fat, sodium, and sugar. The menu content of ten alternatives is presented in Table 2. The most preferred menu content by the local restaurant was taken into account. Menu contents were designed for university students and employees. Alternatives were evaluated by four different dietitians, considering six criteria. The importance of the criteria weights for TOPSIS and VIKOR is given in Table 3. In Table 3, calorie weight is greater than other criteria.

Table 2. Menu content of alternatives

	Menu content
Alternative 1	Lentil Soup, Chicken Leg, Pasta With Sauce, Ayran
Alternative 2	Beef Stew, Rice, Cacik, Shambali Dessert
Alternative 3	Roast Meatballs, Bulgur Rice, Salad, Seasonal Fruit
Alternative 4	Creamy Carrot Soup, Minced Potatoes, Noodle, Yogurt
Alternative 5	Chickpea Stew, Tavern Rice, Yogurt, Pickle
Alternative 6	Tomato Soup, Chicken Döner, Rice, Ayran
Alternative 7	Moussaka, Bulgur Rice, Cacik Sekerpare Dessert
Alternative 8	Lentil Soup, Stuffed Peppers, Yogurt, Seasonal Fruit
Alternative 9	Haricot Bean, Rice, Yogurt, Turkish Doughnuts
Alternative 10	Forest Kebab, Bulgur Rice, Cacik, Pickle

Table 3. The importance of the criteria weight for TOPSIS and VIKOR

	Decision Maker 1	Decision Maker 2	Decision Maker 3	Decision Maker 4
Criteria	Weights	Weights	Weights	Weights
Calories	0.3	0.4	0.3	0.4
Cholesterol	0.2	0.2	0.1	0.2
Fiber	0.1	0.1	0.1	0.1
Saturated fat	0.2	0.1	0.2	0.1
Sodium	0.1	0.1	0.1	0.1
Sugar	0.1	0.1	0.2	0.1

Linguistic terms are utilized to make it easier for nutritionists to make subjective judgments about the various criteria. Fuzzy numbers are used to approximate these linguistic terms for computational simplicity. Linguistic expressions for criteria are very unsatisfactory (VU), unsatisfactory (US), satisfactory (S), high satisfactory (HS), and very satisfactory (VS). Their values are (1, 1, 3), (1, 3, 5), (3, 5, 7), (5, 7, 9), and (7, 9, 9), respectively (Tom et al., 2015). Linguistic expressions for criteria importance are very unacceptable (VA), unacceptable (UA), just acceptable (JA), acceptable (A), and highly acceptable (HA). Their values are (1, 1, 3), (1, 3, 5), (3, 5, 7), (5, 7, 9), and (7, 9, 9), respectively (Tom et al., 2015). The importance weight of the criteria for fuzzy TOPSIS and fuzzy VIKOR is given in Table 4.

Four MCDM methods, namely TOPSIS, VIKOR, fuzzy VIKOR, and fuzzy TOPSIS, were employed to rank the alternative menus. The distances from the positive ideal and negative ideal are given in Figure 4 for TOPSIS and fuzzy TOPSIS. The maximum desirability (Si) and the lack of desirability (Ri) are given in Figure 5 for VIKOR and Fuzzy VIKOR. VIKOR indices for the VIKOR and fuzzy VIKOR methods and closeness coefficients for TOPSIS and fuzzy TOPSIS are presented in Figure 6 for each alternative. If an alternative's closeness coefficient is closer to 1, it indicates better performance in TOPSIS and fuzzy TOPSIS compared to other alternatives. The alternative with the minimum VIKOR indices score is the best for VIKOR and fuzzy VIKOR. According to the results from VIKOR and TOPSIS, alternative 2 emerges as the best menu when compared to the others. According to the results from fuzzy VIKOR and fuzzy TOPSIS, alternative 3 is the best menu.

The food industry's growing concerns about sustainability have made creative approaches to culinary operations imperative. Designing the menus and recipes from a sustainable perspective is a good way to decrease the environmental impact of restaurants (Coskun, Genç, & Coskun, 2023). Future studies might look at sustainable menu and recipe planning techniques to support sustainable food services in restaurants. To develop novel methods for reducing the environmental effects of food services, more study is required. In addition, big data can make it possible to track the eating and drinking habits of customers and provide them with more individualized menus. Big data analytics may be utilized in future studies to comprehend consumer preferences and tastes.

Table 4. The importance weight of the criteria for fuzzy TOPSIS and fuzzy VIKOR

	Decision Maker 1	Decision Maker 2	Decision Maker 3	Decision Maker 4
Criteria	Weights	Weights	Weights	Weights
Calories	A	A	A	A
Cholesterol	UA	JA	A	UA
Fiber	A	JA	JA	A
Saturated fat	UA	JA	JA	UA
Sodium	UA	A	VA	UA
Sugar	A	A	UA	A

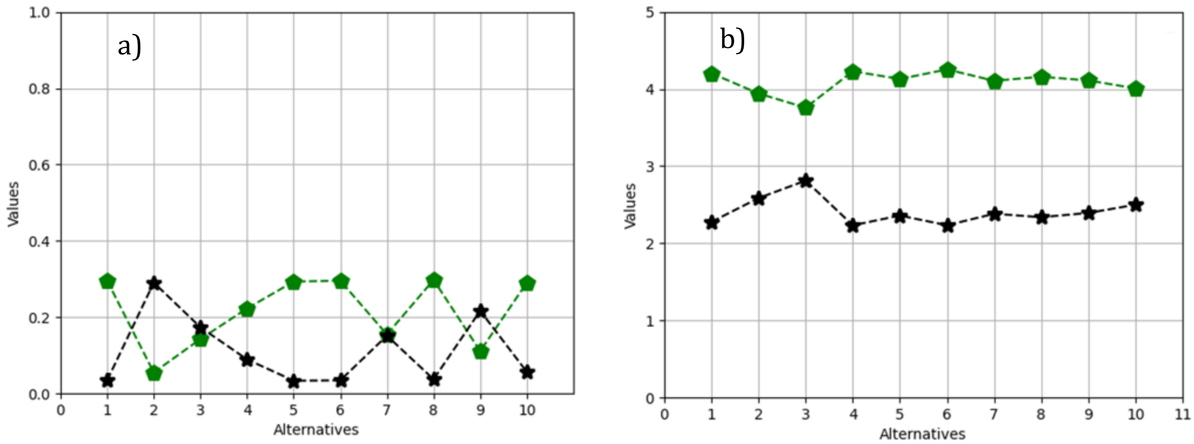

Figure 4. TOPSIS (a) and Fuzzy TOPSIS (b) results (distance from positive ideal solution is green and distance from negative ideal solution is black).

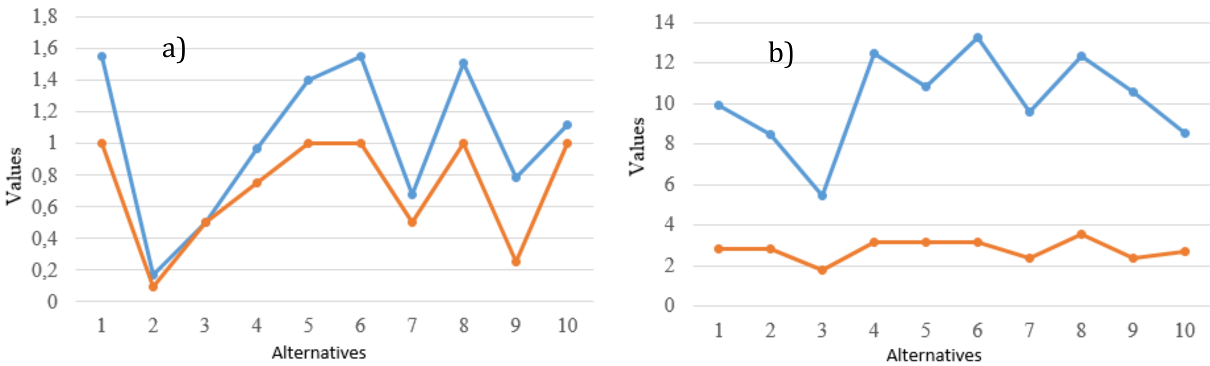

Figure 5. VIKOR (a) and Fuzzy VIKOR (b) results (Si is blue and Ri is orange).

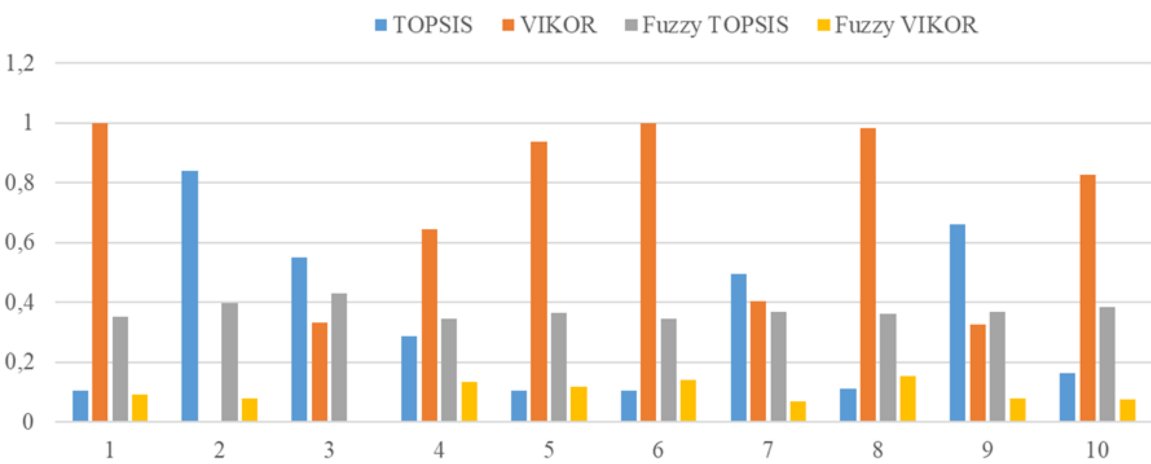

Figure 6. Final results for menu selection

4. Conclusions

Fuzzy MCDM strategies can be employed to address decision-making problems in uncertain environments. One such challenge is menu choice. One such challenge is menu selection, where explicit data determination is difficult. Many people struggle with the problem of deciding on a menu. Several parameters are not clearly defined by numerical values. In such cases, fuzzy numbers can be utilized. This study addresses the menu selection problem through various MCDA approaches, including TOPSIS, VIKOR, fuzzy TOPSIS, and fuzzy VIKOR. According to TOPSIS and VIKOR, Alternative 2 emerges as the best choice, while according to Fuzzy TOPSIS and Fuzzy VIKOR, Alternative 3 proves to be the most favorable option.

The menu plays a vital role in influencing customer behavior. Individuals' aspirations to maintain a healthy weight and cultivate a positive body image can motivate them to opt for healthier menu items. This study may contribute to enhancing the understanding of menu selection among researchers and restaurant owners. Furthermore, it underscores the need for future policies that hold restaurants accountable for offering healthier menu options and ensure that customers are informed about the calories, cholesterol, fiber, saturated fat, sodium, and sugar content of the meals they consume. In future research, this study could be expanded to explore other MCDM methods, and different menus could be evaluated by considering various restaurants.

Author Contributions

The percentage of the author(s) contributions is presented below. All authors reviewed and approved the final version of the manuscript.

	S.L.İ.	D.G.
C	50	50
D	50	50
S	40	60
DCP	60	40
DAI	60	40
L	60	40
W	50	50
SR	50	50

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, SR= submission and revision.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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