University restaurants menu planning using mathematical modelling

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Summary

This research aimed to develop a mathematical model for university restaurants menu planning, seeking to formulate nutritionally adequate meals that meet students' dietary preferences at the lowest cost. The study was divided into three steps: at the first stage, a survey was conducted with 329 college students, in order to identify their preferences regarding 69 foods from the Brazilian cuisine; at the second stage, an integer linear programming (ILP) model for menu generation was developed; and at the third stage, an algorithm was developed to design the foods using a linear programming model. With the application of the model, meals were elaborated meeting the imposed nutritional needs related to 13 of the 14 nutritional elements considered. Additionally, the proposal also made possible elaboration of diversified meals throughout the approached period consistent with the students' food preferences, which was the differential contribution of this study. It is concluded that the mathematical model is able to assist nutrition professionals in the development of menus for university restaurants, and it can be adapted for use by another audience taking into account adequacy of nutritional requirements.

Keywords

diet planning; food selection; integer linear programming; mathematical modelling; nutrition requirements

Following the global trend towards a higher energy density diet, it is clear that representative changes have been occurring in the population's eating habits. A portion of this population is characterized by college students, who undergo changes in their routine such as long hours of study, increased level of cognitive demand, limitations in social skills, increased anxiety, besides behavioural and environmental changes [1, 2]. The economic constraint that some university students have may compromise the consumption of health-compatible foods since this type of food is usually more expensive than the easily prepared and/or processed foods [3]. These factors affect students' eating habits, placing them in situations of restricted nutritional choice [4].

Students start eating in places that usually provide high energy foods [5] and eating easily prepared or processed foods high in fat, sugar, simple carbohydrates and low in nutrients that contribute to health maintenance [6]. Food choices have low priority over other commitments, making it easier to buy fast, cheap and foods incompatible with health [7]. Lack of time due to high demands and overload of university activities makes students eat fewer meals throughout the day or eat them at irregular times [8].

College students have a high cognitive requirement that can be affected by nutritional restriction [9]. When nutrient intake is inadequate, the student will not be able to compensate the nutritional loss caused by nutritionally deficient meals [8]. Inadequate consumption of certain nutrients may result in dysfunctions that may not be recovered immediately after supplementation [10]. Poor nutritional status can expose individuals to changes in physical, cognitive and/or behavioural functions, as well as accelerate brain aging, affecting

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students' learning ability [11, 12]. Proper nutrition, meeting all nutritional requirements, provides an improvement in students' cognitive and behavioural performance [13].

A significant number of students eat at university restaurants. One way to meet part of students' minimum nutritional needs is by providing balanced meals in these establishments. University restaurants should provide health-promoting meals in accordance with nutritional recommendations, contamination-free, present diverse menus, and provide foods of common acceptance among users at a price consistent with student budgets [2, 8]. To enable deployment of practical solutions for the current nutritional situation at the university and to elaborate balanced meals that meet the set of nutritional requirements imposed for the college population, mathematical modelling can be used, since it is a useful tool for creating dietary models aiming to adapt meals to profiles and nutritional requirements [14]. Over time, mathematical modelling techniques have been applied in the area of nutrition and dietetics.

The most common approach is Linear Programming (LP), which has been used to develop food mixtures for supplementing at-risk children in rural Mozambique [15] and to formulate meals to address acute malnutrition of children in Ethiopia [16]. LP has been employed for formulating supplemental diets with therapeutic foods for malnourished children in East Africa, meeting the lowest cost requirements for nutritional use and palatability of foods [17]. Linear and non-linear programming were used to develop experimental diets based on local foods that meet the nutrition standards for pre-school children in rural Malawi [18]. LP was used to design snack recipes for Filipino secondary students, meeting nutritional requirements and food palatability [19]. LP has been also used to develop nutritionally adequate diets with lowest cost, according the recommendations, for French adults [20, 21]. It has been used also to develop diets meeting nutritional requirements, using the typical foods of Japanese cuisine [22]. Integer goal programming, an optimization technique with integer variables to solve problems with multiple objectives in which the decision maker define satisfying levels of value of each objective (goals), was used to design menus that meet nutritional requirements while reducing the carbon footprint, for school children in Spain [23]. A multiobjective optimization model, an optimization technique with binary variables to solve problems with conflictant multiple objectives, was used to plan menus complying with nutritional and health issues, eating habits and with low greenhouse gas emissions for an Italian nursing home [24]. In addition, reviews were published on the various applications of mathematical modelling applied to diet problems including nutritional aspects, costs, food acceptability and sustainability [25, 26].

Although several studies presented the use of mathematical modelling for planning diets, many of them were only conceptual, either restricted to a short time of meal scheduling, considered the portion size of dishes by using a continuous approach rather than an integer approach (discrete pre-defined portions of meals), did not consider the specific parameters of each group of individuals, or even presented impractical meals given the palatable aspect such as taste and texture of meals. One of the biggest difficulties in using mathematical models for elaboration of diets lies in the inclusion of palatability in the models [27].

In this context, the present study aimed to develop a mathematical model for menu planning of university restaurants, using an integer linear programming (ILP) and a food selection algorithm, addressing menu definitions that meet nutritional needs and preferences of students at minimum cost.

MATERIALS AND METHODS

The study was structured into three stages:

1. Data collection in order to identify the dietary preferences of college students.
2. Development of a linear programming model for meal preparation.
3. Elaboration of a food selection algorithm and feedback of the mathematical model.

Food preferences search

A cross-sectional study was conducted at a Federal University located in Paraná state, South Brazil, in order to identify students' level of preference regarding pre-selected foods. Data were collected through a questionnaire. A number of 128 foods were selected including vegetables, tubers, cereals and derivatives, meat and derivatives, which are traditionally consumed and normally offered at any time of the year in the study region.

In order to facilitate the assimilation of responders over the questionnaire questions, some foods were classified and grouped according to their similarity characteristics [28, 29] and only one food item for each group was available in the questionnaire (for example, the 14 different types of beef available became the beef item).

The food grouping criterion was based on conceptual similarity, the ability of the respondent to make distinctions between foods, and the similarity of nutrients in the same portion size [30]. After grouping, a total of 69 food items formed the questionnaire. To determine the food preference of students, we used a nine-point hedonic scale, where: 1 = dislikes a lot and 9 = likes a lot [31]. The questionnaire was sent to student e-mail addresses via Google Drive platform (Google, Mountain View, California, USA).

This information gathered was used in the mathematical model algorithm, to stipulate the weights (degree of importance) of the most preferred foods, by altering the input data of the entire linear programming model, aiming to generate meals consistent with the preferences of the university public.

Mathematical modelling

The mathematical model consisted of two modules:

- Module 1 – mathematical modelling of optimization through ILP,
- Module 2 – algorithm for long-term distinct meal generation.

Integer linear programming for meal composition

The model for menu planning of university restaurants was based on mathematical dietary models [32, 33]. The model was developed via mathematical optimization modelling through ILP. For its elaboration, four types of information were considered:

- types of foods and their nutritional characteristics,
- portion size of food,
- recommended nutritional values for age group,
- food costs.

For diet formulation, a total of 133 foods were considered. The nutritional information of the foods was obtained from the Brazilian Table of Food Composition [28]. The foods were classified into seven groups:

- rice,
- beans,
- cereals and derivatives,
- vegetables, tubers,
- salads,
- meat and derivatives,
- desserts.

This classification aimed to generate meals with a greater variety of foods, considering that at least one food from each group should be included in the meal. Rice and beans were classified in isolated groups because they are considered part of all meals, being the basis of the Brazilian diet. Unit portion sizes of each food were defined according to the recommendations for consumption [29] and taking into account the nutritional needs for the age group of the students.

The model comprised the nutritional data from the dietary reference intakes (DRI) [34–38] considering consumption recommendations for 12 nutrients and minerals: protein, carbohydrate, dietary fibre, magnesium, manganese, phosphorus, iron, potassium, copper, zinc, thiamine and vitamin C. To identify the nutritional needs according to the DRI recommendations by age group, information was obtained from the Federal University regarding the ages of college students participating at the full-time courses. Among the 1935 students, 640 (33.1 %) were female and 1295 (66.9 %) were male. The average age was 22 years for both men and women, validating the use of the DRI nutritional recommendations for individuals from 19 to 30 years old.

Regarding cholesterol intake levels, data from the Dietary Guidelines for Americans was used as reference [39]. Energy needs were obtained based on the median of young adults (19–24 years) of both sexes with moderate activity [40]. Thus, within an established range of 9205 kJ (women) and 12133 kJ (men), a reference value of 10878 kJ per day was considered for the population studied (representing average needs for men and women).

For the formulation of meals to meet men's and women's necessities, minimum and maximum nutrient requirements were stipulated. To stipulate the minimum need, the highest values of minimum nutritional needs of both sexes were considered. For the maximum amount of nutrients, the lowest values of maximum nutrient consumption of both sexes were considered. These data were adjusted to satisfy the requirements for a lunch meal, equivalent to 35 % of daily nutritional needs [41].

Food costs were defined through a market survey that identified product prices at two major merchants and wholesalers in the study region. Based on the prices collected from the different merchants for each food, the lowest cost for each food was considered.

The model considered the following information:

- daily (minimum and maximum) nutritional needs for young people or college adults,
- portion size of each food in its category,
- total amount of food consumed in the meal,
- costs associated with the meal.

The mathematical model for determination of the composition of meals is represented by Eq. 1:

$$Z = \sum_{j=1}^{J} c_j\, x_j \tag{1}$$

where Z is cost function, j is food indexer, c_j is cost of food j per serving, x_j is number of food portions j.

Subject to:

$$\sum_{j=1}^{J} e_j\, x_j \geq E_{\min} \tag{2}$$

where e_j is total energy of food j per serving and $E_{\min}$ is minimum energy to be consumed in the meal.

$$\sum_{j=1}^{J} a_{ij}\, x_j \geq D_i \quad \text{for } i = 1, \dots, I \tag{3}$$

where i is nutrient indexer, a_{ij} is nutrient amount i in a serving of food j, D_i is minimum amount of nutrient i in meal.

$$\sum_{j=1}^{J} a_{ij}\, x_j \leq D_i^* \quad \text{for } i = 1, \dots, I \tag{4}$$

where D_i^* is maximum amount of nutrient i in meal.

$$\sum_{j \in N_k}^{J} x_j \,\substack{\leq \\ \geq}\, H_k \qquad \text{for } k = 1, \dots, K \tag{5}$$

$$x_j \in Z^+ \qquad \text{for } j = 1, \dots, J \tag{6}$$

where k is food groups indexer, H_k is number of portions allowed for food N_k of category k and Z^+ is set of non-negative integers.

The objective function (Eq. 1) minimized the total cost of the meal. Constraint (Eq. 2) defined that each meal should provide a minimum of $E_{\min}$ 3807 kJ for lunch. The constraint set (Eq. 3) and (Eq. 4) determined the minimum and maximum amounts of nutrients allowed in the meal. Constraint group (Eq. 5) refered to the number of food portions of each group N_k, to k = 1, ..., 7. Constraint data (Eq. 5) are presented in Tab. 1. Food portions were established according to local consumption habits. Restrictions (Eq. 6) stated that the number of food portions must be integer and a positive number. The model was solved using Lingo 13.0 optimizer (LINDO Systems, Chicago, Illinois, USA) with data implemented through a spreadsheet.

Tab. 1. Number of portions per food group.

Group	Category	Number of portions	
		Min.	Max.
1	Rice	1	1
2	Beans	1	1
3	Side dish (cereals and derivatives)	1	1
4	Side dish (vegetables and tubers)	1	2
5	Salads (salad greens, raw salads and cooked salads)	1	3
6	Meat and derivatives	1	1
7	Dessert	1	1

Menu generating algorithm

The menu was elaborated with the aim to obtain different minimum cost meals with varied foods. For this propose, a non-repetitive food selection algorithm was used to generate a meal for day t over a period of n days (t = 2, ..., n). The objective of the algorithm was to change the input food data for the ILP model, so that the foods already used were not included in subsequent meals, avoiding repeated foods in meals.

The algorithm used as input the list of foods and their respective values of food preferences, and the solution obtained by ILP for t = 1 (lowest cost meal). To change the ILP input data for other meals, the algorithm performed (n – 1) loop with the following operations:

– Generated an S_t list with all foods except those selected in the previous ILP solution.
– Foods excluded in the preceding step were placed on a tabu list F_t that disallowed the food i during a specified tenure period p_i. When a tabu move completed its tenure, the food i was removed from the tabu list F_t and included in S_t list.
– For each food in S_t, a weight (degree of importance) was set by multiplying the food preference by a random number f = [0,1]. This procedure acted as a correction factor, seeking to prevent foods with high preference to be frequently selected for input into ILP model.
– In order to obtain meals closer to students' preferences, foods with weight (degree of im-

Tab. 2. Inclusion of meat in weekly menu.

Tenure period p (days)	Meat in menu on day					
	1st	2nd	3rd	4th	5th	6th
1	+	–	+	–	+	–
2	+	–	–	+	–	–
5	+	–	–	–	–	–

(+) – selection enabled, (–) – selection disabled.

portance) below 20 percentile (in relation to all foods) were eliminated from S_t.
- The food data (S_t list) were loaded to the ILP model and the model generated the meal with the lowest cost for day t (t = 2, ..., n) with the enabled foods.
- The loop ran until $t = n$.

This scheme was not applied to rice, beans and leafy salads, due to the reduced number of food items in these groups, and to desserts that were not included in the food preference survey (five foods belonged to this group: banana, orange, watermelon, tangerine and jelly pudding), making the algorithm use unfeasible. Tab. 2 shows the meat availability according to tenure period p. For the repetition of meat types (beef, pork, chicken and fish) based on a weekly menu (6 meals), it was established that the most preferred meat can be selected up to three times (i.e. p = 1), the meat with the second highest preference may be selected up to two times (p = 2), and meats with the two lowest preferences may be selected up to one time within the established period (p = 5). This rule was applied due to the low variety of foods available in this group.

Tab. 3. Food preference indexes.

Foods	Mean	SD
Rice	7.55	1.64
Beans		
"Carioca" bean	7.04	2.15
Black bean	6.65	2.30
"Feijoada" Brazilian beans	6.21	2.68
White bean	6.00	2.52
Side dish (cereals and derivatives)		
Gnocchi	7.55	1.97
Pasta	7.04	1.82
Pasta Bolognese	6.91	2.24
Pasta with vegetables	6.86	2.53
Rice balls	6.52	2,35
"Carreteiro" rice	6.32	2.42
"Farofa" spiced	6.30	2.15
"Farofa" toasted cassava	5.75	2.11
Sweetcorn	5.56	2.52
Cooked cornmeal	5.32	2.49
"Farofa" Toasted cornmeal	5.20	2.09
Side dish (vegetables and tubers)		
French fries	7.88	1.89
Fried cassava	7.62	1.97
Chips potato	7.48	1.88
"Baroa" potato	7.42	2.74
Boiled potato	7.42	1.85
Boiled cassava	6.85	2.30
Sweet potato	6.16	2.73
Steamed vegetables	5.83	2.82
Boiled kale	5.82	2.79
Pumpkin "Cabotian"	5.32	2.62
Boiled cabbage	5.03	2.82
Spinach	4.97	2.81
Lentils	4.82	2.73
Braised zucchini	4.70	2.87
Chard	4.40	2.60
Pea	4.07	2.61
Okra	3.75	2.81
Eggplant	3.74	2.63

Foods	Mean	SD
Salads (salad greens, raw salads and cooked salads)		
Iceberg lettuce	7.18	2.17
Tomato	7.05	2.35
Lettuce	6.85	2.30
Boiled broccoli	6.62	2.73
Cauliflower	6.21	2.74
Boiled carrot	6.03	2.63
Raw carrot	5.82	2.67
Boiled beet	5.68	2.79
Cucumber	5.61	2.92
Potato salad	5.42	2.82
Raw cabbage	5.18	2.83
Raw kale	5.10	2.78
Raw beet	5.02	2.79
Arugula	4.77	2.90
Green bean	4.71	2.73
Chayote	4.37	2.84
Cress	4.35	2.67
Chicory	4.32	2.63
Bell pepper	4.24	2.81
Canned mixed vegetables*	3.84	2.57
Turnip	3.75	2.53
Chicken	7.73	1.83
Meat and derivatives		
Beef	7.34	2.18
Chicken Stroganoff	7.19	2.32
Fried meat balls	6.76	2.43
Omelette	6.54	2.32
Croquette meat	6.52	2.36
Beef Stroganoff	6.20	2.63
Pork	5.43	2.61
Egg	5.62	2.19
Fish	5.30	2.90
Sausage	5.87	2.53
Meatballs	5.39	2.69
"Barreado" meat	4.54	2.66
"Dobradinha" meat	3.68	2.74

* – mixture of vegetables like carrots, maize or green peas. SD – standard deviation.

Tab. 4. Menu generated by the mathematical model.

Day	Foods	Weight [g]	Total weight [g]	Cost [BRL]
1st	Rice	150	900	3.15
	Black bean	100		
	Rice balls	100		
	Boiled cabbage	100		
	Steamed vegetables	100		
	Tomato	50		
	Raw beet	50		
	Raw carrot	50		
	Fried chicken leg	100		
	Jelly pudding	100		
2nd	Rice	150	900	3.24
	"Carioca" bean	100		
	Cooked cornmeal	100		
	Braised spinach	100		
	Pea	100		
	Arugula	50		
	Lettuce	50		
	Turnip	50		
	Muscle beef stew	100		
	Banana	100		
3rd	Rice	150	900	3.28
	Black bean	100		
	Pasta	100		
	Boiled cassava	100		
	Boiled kale	100		
	Cress	50		
	Chard	50		
	Lettuce	50		
	Chicken breast	100		
	Tangerine	100		
4th	Rice	150	800	3.28
	"Carioca" bean	100		
	French fries	100		
	Lentils	100		
	Boiled broccoli	50		
	Lettuce	50		
	Raw kale	50		
	Grilled sausage	100		
	Banana	100		
5th	Rice	150	900	3.31
	Black bean	100		
	Gnocchi	100		
	Braised zucchini	100		
	Boiled cabbage	100		
	Arugula	50		
	Iceberg lettuce	50		
	Raw cabbage	50		
	Grilled pork chop	100		
	Jelly pudding	100		
6th	Rice	150	900	3.50
	Black bean	100		
	Pasta bolognese	100		
	Boiled "Cabotian" pumpkin	100		
	Boiled kale	100		
	Cress	50		
	Lettuce	50		
	Raw kale	50		
	Baked fish fillet	100		
	Orange	100		

BRL – Brazilian real.

RESULTS

Food preferences

The food preference questionnaire was made available online to 1750 students at the Federal University. Questionnaire responses were returned from 329 students, being 204 (62 %) men and 125 (38 %) women respondents. The responses related to students' food preference, their means and standard deviations are presented in Tab. 3. Foods were organized in a decreasing order of preference in each of the established food groups. This information was used in the mathematical model algorithm to stipulate weights (degree of importance) to food, alternating the input data of the ILP model, aiming to generate meals consistent with the preferences of the university public.

Generating a menu by the mathematical model

As exemplary title, the mathematical model was applied to generate six lunch-related meals for a university restaurant, addressing the nutritional aspects for the target audience, as well as their food preference. The results are presented in Tab. 4.

Considering the parameters established for the model, regarding the minimum and maximum nutritional needs proportional to a lunch meal (35 % daily needs). Tab. 5 presents the percentages of cholesterol in the meals generated in relation to their maximum needs and Tab. 6 presents the percentages of energy present in the meals generated in relation to their stipulated minimum.

Tab. 7 shows the percentages of carbohydrate, protein, dietary fibre, magnesium, manganese, phosphorus, iron, potassium, copper, zinc, thia-

Tab. 5. Cholesterol in meals of weekly menu.

Cholesterol [mg]			Percentage of max. requirement [%]
Requirement		In meal	
Min.	Max.		
–	105	97.90	93.2
		81.70	77.8
		85.10	81.0
		56.15	53.5
		96.05	91.5
		96.76	92.2

(–) – undefined.

Tab. 6. Energy in meals of weekly menu.

Energy [kJ]			Percentage of min. requirement [%]
Requirement		In meal	
Min.	Max.		
3807	–	4418	116.0
		4046	106.3
		4146	108.9
		4054	106.5
		3862	101.4
		5247	137.8

(–) – undefined.

Tab. 7. Nutritional elements in meals of weekly menu.

Nutrient	Amount [mg]			Percentage of min. requirement [%]
	Requirement		In meal	
	Min.	Max.		
Carbohydrate	45500	–	191440	420.7
			128960	283.4
			167830	368.9
			144300	317.1
			130470	286.7
			200910	441.6
Protein	19600	–	55250	281.9
			50410	257.2
			32800	167.3
			54610	278.6
			51380	262.1
			57310	292.4
Fibre	13300	–	23260	174.9
			24160	181.7
			27890	209.7
			30770	231.4
			22850	171.8
			22660	170.4
Phosphorus	245	1400	572.63	233.7
			582.28	237.7
			456.93	186.5
			525.63	214.5
			583.14	238.0
			534.49	218.2
Manganese	0.85	3.85	2.22	261.2
			2.45	288.2
			2.71	318.8
			1.93	227.1
			1.68	197.6
			1.80	211.8
Iron	6.30	15.75	6.49	103.0
			6.32	100.3
			6.36	100.9
			6.41	101.7
			6.31	100.2
			6.31	100.2

Nutrient	Amount [mg]			Percentage of min. requirement [%]
	Requirement		In meal	
	Min.	Max.		
Magnesium	140	–	143.52	102.5
			265.78	189.8
			141.01	100.7
			141.50	101.1
			155.29	110.9
			143.52	102.5
Potassium	1.64	–	1.69	103.0
			1.94	118.3
			1.69	103.0
			1.90	115.9
			1.69	103.0
			1.79	109.1
Copper	0.31	3.50	0.52	166.7
			0.62	200.0
			0.77	248,4
			0.67	216.1
			0.48	154.8
			0.91	293.5
Zinc	3.85	14	4.26	110.6
			7.60	197.4
			3.90	101.3
			9.87	256.4
			4.00	103.9
			5.15	133.8
Thiamin	0.42	–	0.43	102.4
			0.87	207.1
			0.46	109.5
			0.43	102.4
			0.45	107.1
			1.05	250.0
Vitamin C	31.40	700	210.58	670.6
			59.67	190.0
			134.12	427.1
			88.22	280.9
			200.72	639.2
			179.91	572.9

(–) – undefined.

mine, vitamin C present in meals in relation to their minimum needs for the meal.

To verify the operation of the algorithm that considers the criterion of food preference, a simulation of 50 000 meals was employed, in order to identify the probability of each food being enabled for subsequent implementation in the mathematical model. It was verified through the simulation that the algorithm behaved adequately in relation to the proposal, including more frequently the most preferred foods.

DISCUSSION

The mathematical model successfully identified formulations that were feasible and found acceptable, providing to be a functional and reliable method to compose new formulations that meet nutritional recommendations for young adult university students.

Given the parameters established for the model, the meals formulated met the minimum or maximum nutritional needs proposed for a lunch (35 % daily needs) in relation to 13 of the 14 nutritional elements analysed: cholesterol, protein, carbohydrate, dietary fibre, magnesium, manganese, phosphorus, iron, potassium, copper, zinc, thiamine, vitamin C.

Regarding energy, the mathematical model needed to be balanced, as it produced results above 35 % of daily needs (referring to 10 879 kJ). This was because a value equal to or less than 35 % of the required energy requirements did not allow the mathematical model to generate different solutions with the available foods. In some cases, the models show that designing a balanced diet is not possible or that the obtained diet has a high energy level [42]. The mathematical model may fail to produce a feasible diet, in particular when a large number of constraints is set [15]. A reference value can be difficult to reach or even unattainable, either due to an insufficient amount of nutrients in the food supply or incompatibility with another constraint applied in the model [22, 23, 26].

The energy parameter could be reached if the food base was expanded. In order to meet all nutritional constraints, a greater number of foods needed to be incorporated in the diet [27]. A larger database, allowing to consider more candidate ingredients and to assess more ingredient characteristics, was implemented previously [16]. This approach could not be used in our study, as expansion would result in the insertion of more expensive foods into the database, increasing the cost of the meals. This fact would make the proposal and application of the present study unfeasible, as our aim was to generate meals at a low cost for university students. The main function of university restaurants in public universities in Brazil is to provide students with low-cost meals. A similar problem was found where the formulation of the diet via linear programming was affected by the low availability of food, which in turn prevented the fulfilment of some nutritional parameters established for the mathematical model [18]. In a previous study using linear programming, it was found that a nutritious meal that fulfilled nutritional restrictions was too expensive for the analysed case [15]. In another study using linear programming, meals were identified that met all nutritional parameters, but the food database needed to be expanded and the cost increased significantly [21].

The cost had a negative influence on food selection and diet quality, mainly through an increase in energy density [43]. Nutritionally adequate diets were found to be often more expensive than healthy-incompatible diets [3, 14, 25, 44]. Higher-income countries enjoy a diverse and nutrient-rich food supply that makes it easier to attain a nutritionally adequate diet than the low-income countries [26]. Diets of high nutritional quality often cost more and have a lower energy density than diets of lower nutritional quality [21]. This illustrates the challenges in formulating nutritious and economically feasible foods. This aspect reinforces the limitations in preparing nutritious meals at low cost in Brazil.

The size (weight) of the meal resulted in a dish averaging 900 g, of which 100 g referred to the dessert portion. This size is considered large but, to meet the nutritional needs, that size was considered. Similar results were obtained in previous studies using linear programming, where optimization invariably increased the total weight of diets [20, 21].

Costs are given for example, as there is a continuous variation in food prices. In the menu generated, the average cost for meals was 3.43 Brazilian real (BRL). However, this cost is equivalent to food only, in practice this value is increased by the operational costs of food preparation. The mathematical model used sought the minimum cost for meals within the restrictions imposed. Mathematical models are useful tools to minimize the cost of meals [17].

Regarding the algorithm proposal to establish distinct meal solutions within a predetermined period, it was found that, in the period stipulated for the generation of six meals, no meal was repeated.

However, based on the parameters determined for the algorithm, some foods were repeated more than once. Forty-one foods were used to formulate six meals, of which 30 foods were present in only one meal, nine other foods were used twice in the period. Rice was present in all meals, black beans in four meals. Beans and rice are the basis of Brazilian cousine and for this reason were kept in all meals. These results are consistent with a previous study [20] that suggested that a repertoire of 35–45 different foods per week, with convenient dietary changes, is necessary and sufficient to reach nutrition recommendations. This is in agreement with a previous study [14], which identified that nutrient adequacy is associated with higher variety of the diet.

It was identified that the algorithm, which considers food preferences, makes meal development more realistic and dynamic, not restricting the model to elaborating meals with a small group of foods (lower cost) or with monotonous solutions (continuous repetition of foods). Some previous studies showed the preference relationship in diet modelling [20, 32, 45, 46], considering as preference the frequency with which the food is consumed. In such cases, the food frequency requirement applies to selecting the basis of foods to be employed for diet formulation through mathematical modelling.

Determining the database for frequently consumed foods becomes a limitation for diet modelling [20]. The frequency of food consumption is generally redundant, resulting in a low variety of foods, which impairs the model's ability to generate meals that meet the imposed nutritional requirements.

In the present study, the food preference was determined through a structured research based on popularly consumed foods available in Brazil. The results of this research comprised the preference indexes, which were used by the algorithm for enabling foods to formulate meals through ILP, enabling various solutions in a pre-determined period.

The model developed in this study translated the nutritional recommendations into low-cost meals for university students with the use of foods of greater preference and realistic food choices. Such information can help nutrition professionals to better take into account the food preference when establishing dietary guidelines, which may improve adherence to them by the general population [20]. The mathematical model can be used to assess whether a nutritionally adequate diet is achievable with locally available foods [18]. Using these models can effectively translate nutrient-based recommendations into realistic food intake patterns for a population [22].

CONCLUSIONS

It is concluded that the mathematical model met the established initial parameters, accepting those related to energy needs, the parameter that had to be balanced so that the mathematical model could provide viable solutions in relation to other considered nutrients. This parameter could be achieved if the food base was expanded, but this possibility was discarded, since the foods used constitute the base of the local food and the inclusion of other foods would make the meal more expensive, disqualifying the initial proposal to develop lowest-cost meals, a limitation presented in this research.

The algorithm developed for inclusion of food in the mathematical model allowed to generate diversified meals over the established period, prioritizing the foods according to the students' preference, which is a differential contribution of this study. The present proposal is an applicable and useful tool for the formulation of meals, which can be adapted to another audience by adjusting the nutritional needs of the target audience.

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