User-friendly health-conscious recipe adaptation system using fuzzy linguistic variables

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Abstract. While food significantly impacts our daily lives, the health implications of dietary choices are equally crucial. Recipe adaptation systems emerge here as a helpful practice for automatically modifying food to recipes. They offer users diverse options to substitute ingredients while fulfilling specific needs. However, users may lack expertise in nutrition, making health-conscious decisions more challenging. In this study, we propose to use fuzzy linguistic variables to offer easily understandable nutritional information for final users. We show the process of incorporating fuzzy nutritional labels into the final interface of a food system, demonstrating the practical implementation of our approach. This user-friendly interface empowers individuals with understandable dietary information to make informed choices, thus improving the nutritional quality of their food selections.

Keywords: Natural language processing · Fuzzy modelling · Linguistic variables · Food computing

1 Introduction

Food and nutrition are essential for humans. Unhealthy diets and poor nutrition are among the top risk factors for various diseases globally. This is the case of cardiovascular diseases (e.g., heart attacks and stroke), certain cancers, and diabetes[3]. As an illustrative example of this, cardiovascular diseases are the leading cause of death globally, taking an estimated 17.9 million lives each year[4]. In addition, WHO estimates that the actual global world prevalence of being overweight among adults of both sexes with BMIs$\geq$25 is 38.9% [26]. These facts motivate the urgency of tackling nutrition standards and advice in food recommendation and dietary assessment computational systems.

Here arises the recipe adaptation task. It consists of modifying a food recipe automatically by substituting its ingredients with others that meet specific restrictions [14]. Therefore, recipe adaptation systems facilitate a selection of the

[3] https://www.who.int/news-room/fact-sheets/detail/malnutrition
[4] https://www.who.int/health-topics/hypertension/cardiovascular-diseases

most suitable food substitutions from among which the user can choose for their purposes. One example could be reducing the sugar intake in a particular recipe by considering other suitable low-sugar options.

In previous work, we have addressed recipe adaptation by providing, for each ingredient, a variety of options that fulfil their restrictions [15]. However, including nutritional information about the ingredients can significantly enhance our previous approach by providing dietary guidelines to improve the recipe's health features. It would have relevant outcomes for society in incentivising and promoting healthy habits and nutritional knowledge among the population.

The general recommendations for a healthy and balanced diet may not be familiar to individuals with no expertise in nutrition, even though they may have information about the nutrient amounts they consume in their meals. Therefore, there is a need to design user-friendly and educational interfaces to present nutritional information in an easily understandable format. In this way, we provide users with a supportive environment for making healthy-aware decisions for modifying recipes of their choice.

In this study, we propose to include fuzzy linguistic variables to model the health attributes of foods. To achieve this, we part from the nutrition facts from the foods and align with the health standards recommended by international healthcare associations such as the WHO. Specifically, we utilise three fuzzy variables —low, medium, and high— to represent the presence of specific nutrients and propose a comprehensible and user-friendly format to display this information in a recipe adaptation system. The key contributions are as follows:

1. This study introduces the integration of fuzzy variables as a key element in modelling health attributes of foods. These variables are based on globally accepted and recognised nutritional and health standards.
2. Using fuzzy linguistic variables serves as a user-friendly approach, enabling the representation of nutritional knowledge in a comprehensive manner that is accessible to the non-expert population. This approach aims to bridge the gap in understanding nutritional information for individuals who may not have expertise in the field.
3. The study presents health-aware recipe adaptation by including nutrition-aware variables in user interfaces for the recipe adaptation task. To the best of our knowledge, this is the first attempt to incorporate health-aware nuances into the recipe adaptation process. Furthermore, the proposed approach is designed to be extensible to other food computing systems, proving its potential relevancy beyond the recipe adaptation context.

2 Related work

The analysis of food data has led to significant advances and widely used applications among the population, thus highlighting the importance of processing and exploiting food data knowledge for the common good. These advances fall under the term food computing, which first appeared in 2015 to position computational systems in the intersection with agriculture studies [9]. Subsequently, [13] revived the term to reference technological applications related to food. Recipe data plays a main role in these systems, especially in natural language processing approaches, due to the substantial presence of textual data.

Recipe adaptation refers to the modification of the content of a recipe to meet a given constraint. This constraint can arise from various reasons, such as restrictive diets because of medical indications, allergies, ideology, or even geographical considerations [14]. This task is tackled in the literature through three main avenues: creating pseudo-recipes [4], automatic text generation [3], and ingredient substitution. This study explores the latter.

By substituting ingredients, recipe adaptation focuses more on modifying ingredients based on external and specialised knowledge. The most common approaches in the literature are primarily based on studying food item co-occurrence to identify interchangeable ingredients and additions to existing recipes. In [28], the authors proposed an algorithm to discover alternative ingredients in existing recipes. More recent approaches leverage the inference process in graph networks to identify potential substitutions [21]. This concept is also addressed in [11], where the authors introduce an ontology-based approach to leverage the recipe context, the qualities of the food, and resources from existing ontologies. A different approach is proposed in [17], where the authors use a siamese network to predict novel ingredient pairings by learning existing food item combinations in recipe data. The approach employed in this study takes advantage of the textual information within recipes and contextual language models such as BERT [5] to identify food alternatives based on semantic information [15]. Another text-based approach is FoodBERT [18], a BERT-based food substitution model that uses an approach based on ground truth dataset and human evaluation. The authors have also proposed a multimodal version to enhance the quality of alternatives in dietary use cases.

Including dietary and health-related data has become an essential component within food systems, particularly in the context of recommendation [23, 24]. These guidelines can be integrated at the diet level (those that refer to daily consumption), recipe level (regarding the overall nutritional information of a recipe), and ingredient level. The latter corresponds to the approach that follows this study and relates to the nutritional information of food items.

FoodRecNet [8] is a food recommendation system with health features centred on daily-oriented recommendations.Market2Dish [25] aids recipe retrieval with health-conscious options. In a prior study, we proposed employing linguistic variables to include health nuances at the recipe level, aiming to enhance health recipe recommendation [16]. This involved integrating a health categorisation of recipes with recipe and user data within a graph neural network. However, the goals of the mentioned methods differ from our own since the guidelines they integrate are at the diet level. In [4], the authors developed a WHO score for recipes to generate new recipes meeting healthy standards. Regarding food level guidelines, HTFRS [20] utilises the macro-nutrient amounts to assess the health factor of a given food for a health-aware recommendation. FoodKG [10] is a graph-based recipe recommendation method incorporating health guidelines linked to the recipe content.

In the era of Artificial Intelligence, where society demands models that are explainable and easily understandable, it is essential for the user's communication with the systems to be in terms that they can easily understand and comprehend. Fuzzy logic techniques have been demonstrated to improve data understandability in several domain-specific applications [6, 7], offering improved visualisations and understanding to end-users. They allow for expressing complex problems in a comprehensible format, for example, in the healthcare domain. [27], Therefore, fuzzy techniques can enable us to propose new frameworks offering comprehensive data for final users [1].

To the best of our knowledge, this study marks the first attempt to integrate linguistic health knowledge into the recipe adaptation task. We propose to incorporate health-related information in the user interface of a recipe adaptation system using fuzzy linguistic variables. This interactive process provides users without nutrition expertise with health-related details regarding the ingredients, facilitating the health-conscious decision-making of adapted recipes.

3 Method

In this section, we outline the workflow for building a health-conscious recipe adaptation system with fuzzy modelling of health linguistic variables. First, we provide a brief overview of the recipe adaptation method we previously proposed on [15]. Next, we detail the integration of fuzzy modelling into the system, aiming to enhance its usability and health-conscious capabilities.

Our methodology parts from three primary resources, as illustrated in Fig 1: recipes (and consequently, their ingredients), food databases (used to acquire nutritional data for the recipe ingredients) and nutrition guidelines (such as those from WHO or FSA). We use the recipe data and the food databases for the adaptation of recipes. We use the nutrition guidelines in order to provide health-related information within the recipe adaptation system.

Recipe adaptation. We part from recipe data to extract the ingredients. Some recipe resources already contain the ingredients in a structured format, so we can directly obtain them. Other previous studies apply a NER to extract the ingredients used in a recipe [2]. Then, we align the recipe ingredients to the food dataset to expand their information to include nutritional facts. Once we have aligned both data sources, we have the recipe ingredients linked to their nutritional information obtained from an external resource.

We have employed a Sentence-BERT [19] model re-trained on recipe preparation texts to learn food and cooking knowledge, e.g., information regarding common ingredient combinations or cooking methods. The details on the model training are detailed in [15]. This model allows us to learn the semantics needed for finding potential substitutes for the recipe ingredients in the external food database based on their nutritional features. As a result, the method provides the top-k best potential substitutions for each ingredient in the recipe.

Fuzzy modelling for health-conscious recipe adaptation. We use the food's nutritional data and the guidelines for fuzzy modelling the healthy profile of each of the ingredients. This modelling allows us to obtain the fuzzy health labels. Fig. 1 illustrates the workflow and the role of fuzzy modelling in building a user-friendly and healthy-aware recipe adaptation interface. When the user chooses a recipe, the system recommends the best food options for substituting an ingredient. Throughout this process, alongside the ingredients, the system displays the fuzzy variables representing the nutritional quality of the foods. This informative display qualifies the user to make informed choices, facilitating the generation of an adapted recipe based on their preferences.

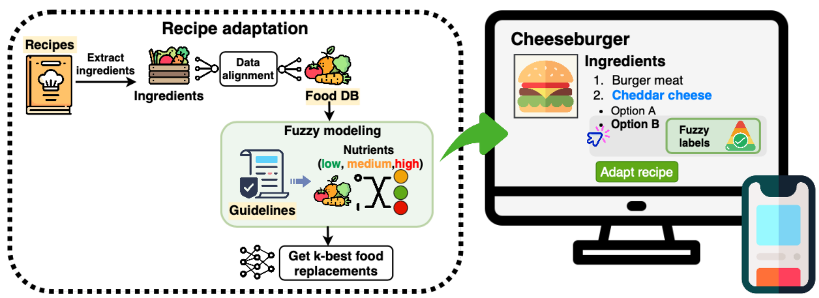

Fig. 1: Workflow of the proposed approach.

4 Fuzzy linguistic modelling

A linguistic variable is a variable with values expressed in words or sentences in a natural or artificial language [29]. This concept offers an approximate representation of ideas that can be described using quantitative terms, leading to the field known as fuzzy logic.

Table 1 illustrates the guidelines proposed by the WHO and other European associations[5] regarding recommended intake of specific nutrients. They specify criteria for classifying the presence of specific nutrients as low, medium, and high per 100g of food. We have modelled the fuzzy variables for four nutrients: fat, saturated fats, sugars, and salt. In the context of these nutrients, a low presence is desirable, while high amounts should be avoided. Consequently, our approach comprises 12 linguistic variables, with three labels for each of the four nutrients. The last column, i.e., "Max per day", refers to the daily recommended amounts by the WHO, indicating thresholds that the population should not exceed. These recommendations are based on estimations for an individual of healthy body weight consuming approximately 2000 calories daily.

[5] `https://www.heartuk.org.uk/low-cholesterol-foods/saturated-fat`

Table 1: Health standards provided by the WHO and European associations. It states recommended quantities of specific nutrients per each 100g of food.

100g per food	**Low**	**Medium**	**High**	**Max. per day**
Fat	3g or less	3-17.5g	17.5g or more	66g
Saturates	1.5g or less	1.5-5g	5g or more	22g
Sugars	5g or less	5-22.5g	22.5g or more	50g
Salt	0.3g or less	0.3-1.5g	1.5g or more	5g

4.1 Fuzzy linguistic variables

We have designed three fuzzy linguistic variables for each nutrient —low, medium, and high— following the guidelines outlined in Table 1. These variables are within the interval $I :\rightarrow [0, 100]$. This decision relies on the nutritional data of foods and the criteria in Table 1, both designed for a 100-gram portion.

- **Low.** We use a trapezoidal membership function. The four-element vector controlling shape is (0, 0,`low_amount`, `max_amount`).
- **Medium.** We use a triangular membership function. The three-element vector controlling shape is (0, `medium_amount`, `max_amount`).
- **High.** We use a trapezoidal membership function. The four-element vector controlling shape is (`low_amount`, `max_amount`,100,100).

The fuzzy variables follow the same pattern for the four nutrients. We detail them below. Here, `low_amount` signifies the maximum nutrient amount considered low, while `high_amount` represents the threshold beyond which a nutrient is considered high. `Medium_amount` corresponds to the midpoint between `low_amount` and `high_amount`, and `max_amount` indicates the maximum nutrient amount recommended for daily consumption.

The system takes four numeric values as input, i.e., the amounts in grams of sugar, fat, saturated fats and salt of a specific ingredient. We use these amounts to obtain the membership degree for the 12 fuzzy linguistic variables (representing low, medium, and high levels for the four nutrients). These degrees are obtained using the membership functions for low, medium, and high described above. The output variable is modelled by categorising it into low, medium, and high, as illustrated in Fig. 2. It represents how healthy the recommendation is based on the four input nutrient values. The higher the output, the healthier the combination of the input values.

For the inference of the fuzzy system, we have designed a set of fuzzy rules to incorporate the general recommendations provided by the WHO. These rules are formulated on the premise that high amounts of the nutrients described in Table 1 should be avoided, while low amounts are preferred. Our control system is defined by using the following premises:

- If the nutrient amount is high, the output value is low.
- If the nutrient amount is medium, the output value is medium.

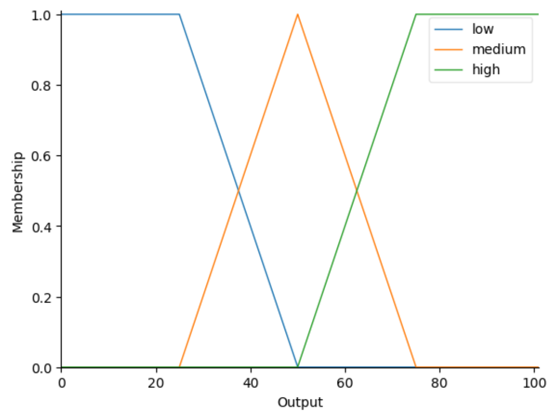

Fig. 2: Modelling of the output variable.

– If the nutrient is high, the output value is low.
– If the amounts of two nutrients are simultaneously low, we implement this rule to be more strict in assigning a higher output.

Based on these premises, we have defined the rules to consider all possible combinations, resulting in a total of 14 fuzzy rules.

5 Experiments and results

5.1 Data

Recipe dataset. We have used Recipe1M+ [12], one of the most comprehensive datasets on the topic. It comprises 1,029,720 recipes gathered from online cooking platforms such as Food.com or AllRecipes.com.
Nutritional dataset of foods. We have used the CoFID dataset[6]. It is maintained by the Public Health Agency (PHE) of the Department of Health and Social Care in England. We have used the *Proximates* table to obtain information regarding fats, saturates and sugar. Additionally, we have used the *Inorganics* table to obtain the salt amounts of the foods. This table provides sodium values, but as detailed in CoFID database documentation, we have multiplied these values by 2.5 to get the corresponding salt amount.

5.2 User-friendly visualisation

Fig. 3 shows the user-friendly interface we have designed for recipe adaptation, incorporating fuzzy variables. This screenshot represents the system view while

[6] https://www.gov.uk/government/publications/composition-of-foods-integrated-dataset-cofid

adapting a recipe named "Amazing and Easy Chicken Wings". The ingredients and instructions are not displayed to save space in the figure. The recipe adaptation system offers alternatives for the original ingredients, such as "Mustard, prepared, yellow", shown in Fig. 3. For this ingredient, the system presents various options. We have selected "Mustard, powder" to show the system behaviour with the fuzzy variables. This behaviour applies to the rest of the ingredients.

The colour of the labels corresponds to the linguistic variables: green indicates low (or healthier), orange signifies medium, and red denotes high (or less nutritious). The first label corresponds to the output variable, labelled as "Moderate consumption", falling under the "medium" linguistic variable. Additionally, the system provides detailed information on the four nutrients, each colour-coded according to their respective linguistic labels.

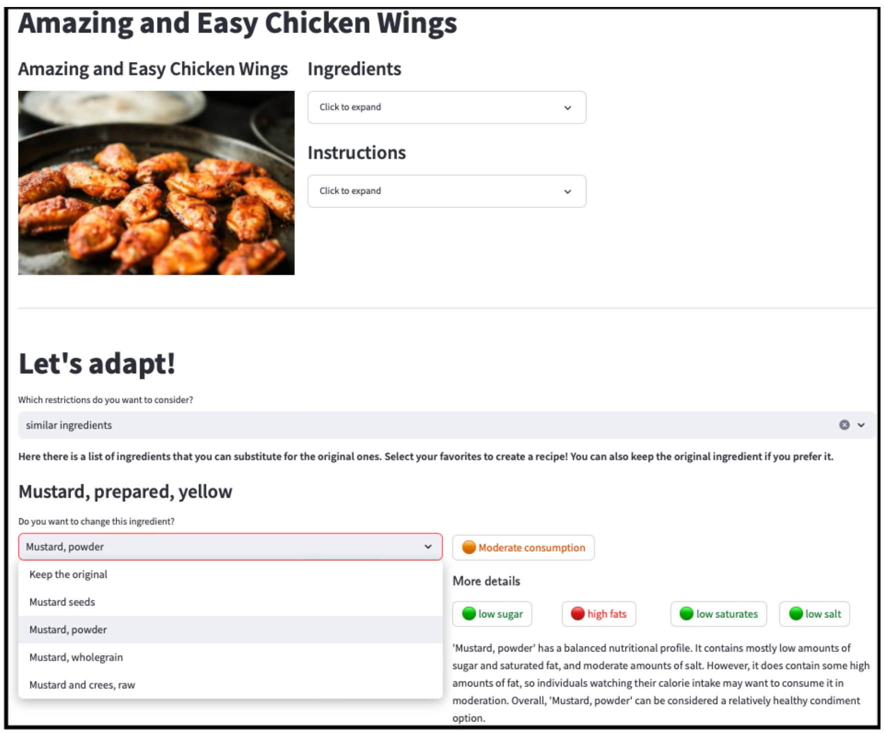

Fig. 3: User-friendly visualisation with fuzzy variables.

The decision to use fuzzy linguistic variables grants interpretability to the system, as we have access to the membership values of all the linguistic variables considered in the modelling. Fig. 4 illustrates the behaviour of the variables influencing the output result. This result corresponds to a waffle visualisation of the membership values of each linguistic variable for the food "Mustard, powder", also illustrated in Fig. 3. From left to right, it shows the membership values for the output value (first column) and the four ingredients (second to sixth columns). The colour references low, medium, and high variables. The low, medium, and high fuzzy variables of the output (i.e., second column) are determined by the rules and membership functions described in Sec. 4.

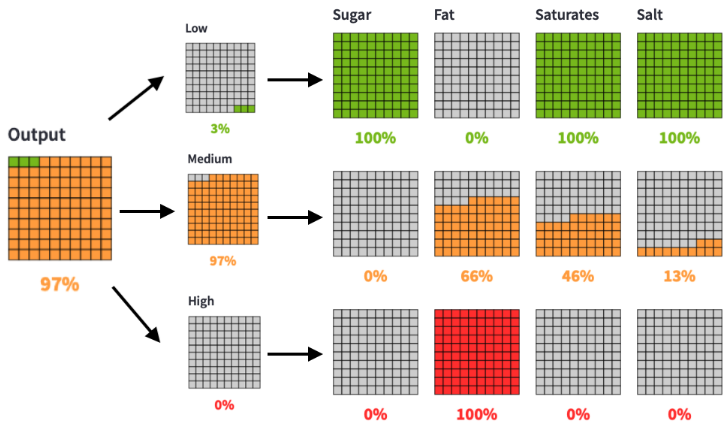

Fig. 4: Interpretability of the output variable.

The procedure we have employed to implement the fuzzy variables is independent of recipe adaptation. These labels are specifically associated with food items used in various tasks. Therefore, our approach is extensible to other food-related systems that require the inclusion of user-friendly health nuances.

Explanations based on fuzzy variables. To favours understandability, the recipe adaptation view also provide an overall explanation of the ingredient health profile based on the fuzzy variables. For generating this explanation, we have utilised a zero-shot prompt engineering procedure for a large language model. We have used the model Llama-2-70b-chat[7], launched by Meta [22]. The 70B parameter version stands out as the one with better performance among the available options, allowing for chat format and dialogue with the model.

Below, we include the prompt used to generate the text explanations. We explicitly have requested that additional information from the model not be included in the response to avoid model hallucinations. Furthermore, we have instructed the model to utilise fuzzy variables and provide explanations of the membership values of the fuzzy variables.

```
I have three fuzzy variables: low, medium and high. I have calculated
a score to represent the membership of the nutrients of a food to these
variables. For {{ingredient}} are:
 - Sugar: low={{low_sugar}}, medium={{medium_sugar}}, high={{high_sugar}}.
```

[7] https://huggingface.co/meta-llama/Llama-2-70b-chat-hf.

```
 – Fat: low={{low_fat}}, medium={{medium_fat}}, high={{high_fat}}.
 – Saturates: low={{low_saturates}}, medium={{medium_saturates}},
   high={{high_saturates}}.
 – Salt: low={{low_salt}}, medium={{medium_salt}}, high={{high_salt}}.
The range is (0,1), meaning the membership percentage to low, medium,
or high nutrient amounts. For example, if low=1, the nutrient amount
is 100% low (highly recommended). If high=1, the nutrient amount is
100% high (hardly recommended). The medium variable mediates between
low and high. I want to tell the user nicely how healthy the
{{ingredient}} is. I want you to:
 – Be brief and avoid numbers.
 – Mention the four nutrients separately.
 –  Only refer to low, high or moderate nutrient amounts.
 – Avoid explanations.
 – Don't complement the answer with external knowledge from this prompt.
```

Implementation details. As previously mentioned, we utilised the recipe adaptation method described in [15], which relies on the Python library Sentence-BERT [19]. We employed the Python library skfuzzy, which offers a framework for implementing fuzzy inference systems, membership functions, defuzzification and other fuzzy logic functionalities. The system's interface has been developed using Streamlit, and the visualisations were created with Altair. For generating the text explanations, we utilised the Hugging Face library Hugchat.

6 Conclusions and future work

In this study, we have introduced the application of fuzzy linguistic labels to enhance a recipe adaptation system's usability and user-friendly interface. Incorporating fuzzy variables enables us to offer users health-related information grounded in the guidelines of international health associations. We also provide final users with a comprehensive explanation of the potential food substitutions, taking into account the fuzzy variables of ingredients and their nutrients. Our approach facilitates informed and health-conscious decision-making when adapting food recipes. Using fuzzy linguistic variables adds understandability to our approach, particularly in determining the overall health label of a recipe. This contributes to the creation of trustworthy and health-aware food systems.

Our modelling is based on estimations for an individual of healthy body weight consuming approximately 2000 calories daily. We plan to extend this work to consider broader individual situations. For this, we will study incorporating insights from nutrition experts for specific use cases, such as individuals with diseases that may require specific dietary indications. We plan to compare the usability and effectiveness of our approach to other techniques in the literature for categorising recipes and food healthiness.

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