Recipe Recommendation for Health Care Using Food Functionality Knowledge Graph and Probabilistic Logic Programming

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ABSTRACT

Daily dietary choices play an indispensable role in mitigating lifestyle-related diseases. Functional components found within foods may offer potential benefits in this regard. We constructed a knowledge graph that links these functional components of food to recipes and further developed a recommendation system to suggest dishes that may contribute to the alleviation of lifestyle-related diseases. Since dietary requirements can vary significantly depending on the specific disease and individual conditions, combining these requirements forms a vast probabilistic distribution. Our proposed system makes recommendations based on the dietary requirements specific to the disease by employing probabilistic logical programming, which utilizes a knowledge graph about food and information about the user's condition. Meanwhile, nodes in the knowledge graph, such as food functionalities or recipes, are characterized by their relationships with other surrounding nodes, such as food ingredients. To handle and solve these characteristics, we employ the deep learning probabilistic logical program. And the result of the experimentation, we have constructed a system that recommends recipes effective for lifestyle-related diseases based on functional ingredients.

KEYWORDS

Knowledge Graph, Probabilistic Logic Programming, Health Care

ACM Reference Format:
Akio Kobayashi, Akira Hashimoto, Tetsuo Katsuragi, and Takahiro Kawamura. 2018. Recipe Recommendation for Health Care Using Food Functionality Knowledge Graph and Probabilistic Logic Programming. In *Proceedings of he 12th International Joint Conference on Knowledge Graphs (IJCKG '23).* ACM, New York, NY, USA, 8 pages. https://doi.org/XXXXXXX.XXXXXXX

IJCKG '23, December 08–09, 2023, Tokyo, Japan

ACM ISBN 978-1-4503-XXXX-X/18/06…$15.00
https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

Today, lifestyle-related diseases have become a significant public health issue globally. According to statistics published by the World Health Organization (WHO) in 2022[15], there is an increasing trend in deaths caused by non-communicable diseases. Notably, deaths due to diabetes have surged by 70% between 2000 and 2019, emphasizing the urgent need for measures against lifestyle-related diseases worldwide. A primary cause of these diseases is found to be closely linked to daily dietary habits. In 2020, the WHO released five guidelines for preventing lifestyle-related diseases, emphasizing the importance of revisiting dietary ingredient balance and avoiding excessive intake of salt, fat, and carbohydrates. Given this backdrop, there has been a recent surge in the provision of daily food-logging tools and health-improving recipe recommendation systems[2, 11, 14]. Most of these systems determine recipe recommendations based on the essential nutritional content of meals and user metrics like BMI. On the other hand, specific foods possess functional properties that can promote health, including mitigating lifestyle-related diseases. However, databases organizing this functional information or systems utilizing it have yet to be proposed, and it remains underutilized in recipe recommendations. In this study, we collate and aggregate various functional component databases, linking items in food and recipe databases to construct a knowledge graph, thereby systematizing information on food functionality. In addition to storing this knowledge graph in our NARO-linked databases [10], we also propose a method of using this knowledge graph to recommend recipes that are effective in improving lifestyle-related diseases. Recognizing that the necessary functionalities, nutrients, physical and mental conditions differ depending on the type of lifestyle disease and individual users, our approach implements a probabilistic logical inference. This method is considered apt as it probabilistically represents whether to apply specific conditions based on user and meal characteristics. This research establishes recommendation rules targeting obesity, a lifestyle-related disease, and implements these recommendations using the constructed knowledge graph and inference system.

And as a result of the experimentation, we have constructed a system that recommends recipes effective for lifestyle-related diseases based on functional ingredients.

2 RELATED WORK

Numerous systems for recipe recommendation that utilize databases, knowledge graphs, and ontologies related to food have been proposed. Many of these aim to recommend recipes tailored to users' profiles. While not all of these systems explicitly aim to improve lifestyle-related diseases, most take into consideration the balance of food and indirectly aim to recommend recipes that could improve lifestyle-related diseases.

To the best of our knowledge, there are no recommendation systems that focus on the functionality of foods. However, there are recipe recommendation systems that reference knowledge graphs, such as those that analyze texts about recipes and users' health conditions[11, 14], and those that optimize various necessary parameters for recommendation based on a knowledge base through machine learning[1, 2, 21].

Furthermore, when considering health in recipe recommendations, multiple systems [3, 7, 17, 20] have been proposed that primarily standardize rules based on intake limits of essential nutrients set by each country's responsible ministries. These systems also consider users' preferences when making recommendations.

In particular, Chen et al. [3] proposes a multi-task learning method that combines a knowledge base, users' eating history, and intake limits of essential nutrients. This method simultaneously learns the recipes that a user can intake and the preferences derived from their eating history.

Other relevant to this study are systems like the one in the HEALs project[1] that considers the user's health condition and allergies[11], and systems that identify user profiling through food preferences to recommend recipes[1].

In this study, we aim to encourage a revision of dietary habits as a preventive measure when individuals exhibit physical measurements that suggest a potential risk for lifestyle-related diseases. To realize this, it is essential to be able to set conditions to be considered in dietary habits for each corresponding lifestyle-related disease. Moreover, the importance of these conditions varies depending on individual characteristics such as constitution; thus, they should be applied probabilistically. Therefore, to adopt recommendation rules suitable for each lifestyle-related disease, we employed an approach based on probabilistic logical inference grounded in rule-based systems.

The knowledge bases used in these studies often include large-scale food ontologies like FoodOn[5], FoodKG[11], large-scale recipe data like Recipe1M+[13], and extensive databases of food compounds like FlavorDB[8], FooDB[2]. None of these databases focus on food functionality. We believe that combining these with databases on functional food components, such as the proprietary database from the National Agriculture and Food Research Organization[3], or the Consumer Affairs Agency's functional food notification information search service[4], would enable the recommendation of more effective recipes for lifestyle-related diseases.

[1]https://idea.rpi.edu/research/projects/heals
[2]www.foodb.ca
[3]https://nousanbutsu-kinou.rad.naro.go.jp/
[4]https://www.fld.caa.go.jp/caaks/cssc01/

3 SYSTEM OVERVIEW

The overview of our system construction approach is illustrated in Figure 1. Initially, we constructed a knowledge graph by integrating a dataset related to functional components that we gathered online with existing datasets on recipes and foods. For the existing recipe dataset, we utilize a structured dataset from Recipe1M+, a large-scale recipe dataset that contains recipes, ingredients, respective nutritional components, their quantities, and cooking steps. The rationale for selecting this dataset is the same as other existing recommendation systems: nutritional balance is the primary focus for improving lifestyle-related diseases. Therefore, it is essential to choose a dataset where the amount of each nutrient is explicitly specified. For the data on functional components, we used data collected from the food functionality database published by the National Agriculture and Food Research Organization[5] and the search service for functional notification products provided by the Consumer Affairs Agency[6]. While many of these functional component data are linked to compounds, the search service of functional notification products is not always linked to specific foods. As a result, we first constructed a temporary knowledge graph by associating these data with foods and compounds in FlavorDB, a comprehensive database on food compounds. Subsequently, by linking this knowledge graph with the structured data from Recipe1M+, we built a knowledge graph embedded with information on food functionality and nutritional components.

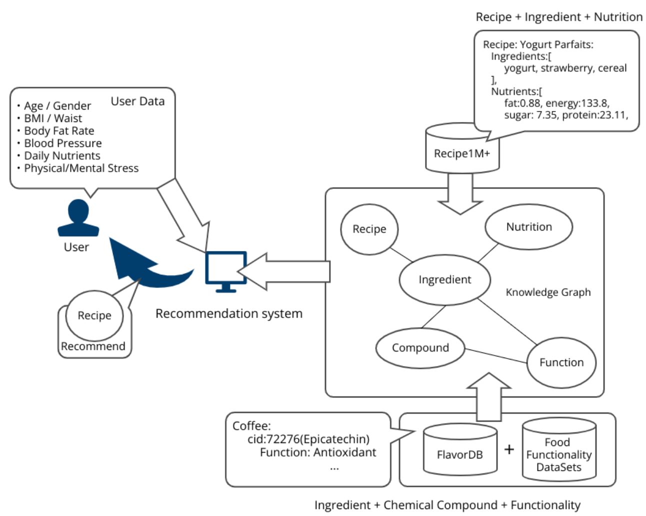

Figure 1: System Overview.

To utilize this knowledge graph, we constructed separate user data for 1,000 individuals to perform recipe recommendations. This dataset includes information on the user's height, weight, body fat percentage, blood and urine test results, and approximate data on the nutritional components they consume daily. This dataset allows us to gauge whether a user tends to have lifestyle-related diseases and if there is an excess or deficiency of specific nutrients,

[5]https://nousanbutsu-kinou.rad.naro.go.jp/
[6]https://www.fld.caa.go.jp/caaks/cssc01/

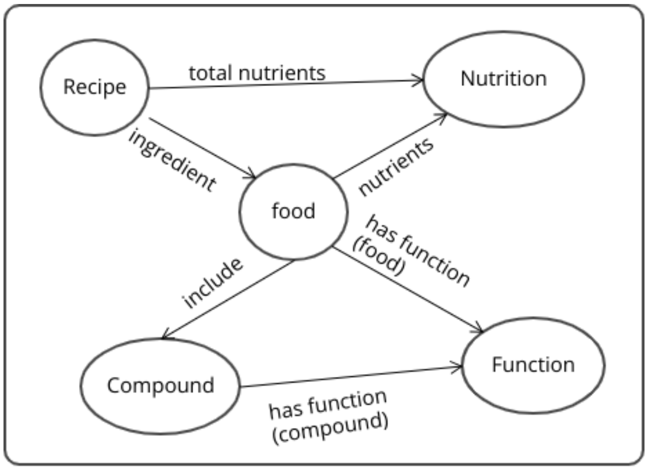

Figure 2: Proposed ontology for recipes, foods and its functionalities.

Table 1: Knowledge graph instances.

Instance type	amount
Recipe	51,235
Food (Ingredient)	357
Nutrient	6
Compound	60,493
Function	61
Edge (Recipe to Food)	311,435
Edge (Recipe to Nutrient)	307,410
Edge (Food to Nutrient)	2,142
Edge (Food to Compound)	1,868,610
Edge (Food to Function)	73
Edge (Compound to Function)	61

encompassing most of the information necessary for recipe recommendations. By referencing this data alongside the data on the knowledge graph using a probabilistic logical reasoning program, we can achieve recommendations for recipes effective in improving lifestyle-related diseases and express the importance of conditions to consider during recipe selection regarding probability values. It is anticipated that this approach can be utilized in applications like alternative recipe recommendations or the development of other recipes.

4 KNOWLEDGE GRAPH CONSTRUCTION

The knowledge graph proposed in this study is defined by an ontology consisting of classes of recipes, ingredients, nutritional components, compounds contained in ingredients, functional, and edges indicating their respective relationships. This ontology is illustrated in Figure 2. Additionally, the number of instances for each class and edge is presented in Table 1.

Each edge is directed, and while edges representing inverse relationships are also included, they are omitted in Table 1 and in the ontology representation in Figure 2 for simplicity. Furthermore, matching from Compound to Function was challenging with FlavorDB, and only one-to-one correspondences could be obtained. As a result, the number of nodes in the function class and the number of edges from the compound class are the same.

4.1 Utilized Datasets

4.1.1 Recipe1M+. Recipe1M+ is a large-scale dataset of recipes and images constructed for the task of retrieving recipes from images, and as the name suggests, it contains over 1 million recipes. These recipes were collected from online recipe-sharing sites, and most of the recipe documents are published in a format that simplifies the parsing of HTML. Among them, some data is released in a structured format based on the nutritional components provided by the USDA, including the amount of nutritional components contained and the amount used during cooking. Given that this is likely the largest dataset with structured data on the nutritional content and quantities used in recipes, we have adopted a structure centered on this data in our knowledge graph.

4.1.2 NARO Food Function Database. The National Agriculture and Food Research Organization provides a search service for functional food components based on their unique research[7], which contains data on 200 types of foods and 30 functional ingredients. While results on the content of various functional ingredients are also provided, the data is in text format and does not have a consistent description style. Therefore, in this study, only the relationships between the foods, their functionalities, and the compounds with these functionalities are used.

4.1.3 Functional Labeling Food Notification Information Search Service. This is a web service[8] provided by Japan's Consumer Affairs Agency, where one can search for a list of products for which manufacturers and others have reported their functional labeling. The notification form allows for various details to be entered; hence, the search results output various information, including the functionality of the product. The functionality is described in natural language, and the content is left to the discretion of the notifier, often resulting in content resembling product advertising. Unlike the NARO database, as of 2023, more than 7,000 entries are registered. However, it's challenging to obtain data in a format that correlates specific ingredients with their functionalities. In this study, we only use data where both the functional ingredient, which is a compound, and its functionality can be identified.

4.1.4 FlavorDB. FlavorDB is a vast database concerning food and the compounds contained within them. While there are other databases detailing the relationships between food and compounds, FlavorDB stands out for its extensive scale and its user-friendly provision of these relationships in a JSON format. Because of these advantages, we adopted it in this study to combine ingredients, functionality, and recipes. FlavorDB has a unique background, having been constructed for research and aggregation related to compound flavors. Consequently, many of the compounds recorded in the database are accompanied by word data related to flavors.

[7]https://nousanbutsu-kinou.rad.naro.go.jp/
[8]https://www.fld.caa.go.jp/caaks/cssc01/

4.2 KG Construction Method

Ingredients and nutritional components data are derived from the Recipe1M+ structured dataset, while information concerning compounds contained in ingredients and functionality is sourced from FlavorDB and various functional component databases aggregated from the web. While it's assumed that nutritional components like carbohydrates, fats, proteins, and salt can be constituted by individual compounds found in ingredients, the specific amounts of these compounds are not included in the data retrieved from FlavorDB. Therefore, representing nutritional components with the compound class was deemed challenging, leading us to treat them as separate classes.

Examples for linking data sourced from various datasets is shown in Table 2. In the table, Data source 1 and 2 respectively indicate the datasets from which the instances for matching are obtained, while Instance 1 and 2 provide examples of each instance.

Ingredients to Compounds: Matching is done based on the food name. While Recipe1M+ ingredients may include information about their processing state, investigating differences in individual compound content was deemed challenging. Therefore, we matched with the food labels on FlavorDB.

Compounds to Functionality: Matching is conducted using PubChemID. While compound data in FlavorDB is tagged with PubChem IDs, many of the data on functional components either have IDs from the Japanese Chemical Substances Dictionary or are merely denoted by their compound names. We manually converted these to PubChemIDs. Due to this, even if the functional ingredients are identical to compounds on FlavorDB, there is a possibility they might differ, such as being different isotopes; thus, a perfect match is not guaranteed. In cases that require adjustments, it's necessary to individually review foundational documents, such as systematic reviews.

Ingredients to Functionality: For certain functionalities or compounds that did not match, we matched based on ingredients containing that function. Ingredient data on FlavorDB is linked to the corresponding species' Wikipedia page. Using this, we retrieved the Japanese label for the relevant concept on Wikidata and matched it with the food labels in the functionality dataset. This approach might introduce some mismatches through incorrect pages. After investigating the accuracy of this matching, it was found to be 92.1%.

Functionality to Functionality: All functionalities are represented in Japanese text. We simplified and consolidated their representation based on the National Agriculture and Food Research Organization's functional component database. Functionalities retrieved from the functional product search service were rewritten into a simpler expression. If during this process, the content words perfectly matched those in the functional component database, or if there were similar expressions for the same compound's functionality, they were deemed to be the same functionality.

5 PROBABILISTIC LOGIC PROGRAMMING

Inference was implemented using the 'Learning from interpretations' algorithm in ProbLog, a probabilistic logic programming language. ProbLog is an extended version of a logic programming language that allows assigning probabilities to each logical expression in the source code. Not only can it be described in notation compliant with the Prolog logic programming language, but it also possesses extended functionalities that cater to various inference algorithms. Among the major lifestyle diseases are cancer, heart disease, cerebrovascular disease, diabetes, hypertension, obesity, and fatty liver. For the recommended recipes, we assume the user's dinner and set an upper limit on the nutritional components of the meal to be recommended based on the nutrients the user has consumed throughout the day. In particular, obesity is a significant factor inducing other lifestyle diseases and serves as a barometer indicating issues with one's lifestyle balance. Therefore, using the previously mentioned knowledge graph and the user data discussed later, we devised a method in ProbLog to recommend recipes effective for improving obesity. Criteria for determining obesity are presented in 3. Additionally, physical examination items that may indicate the possibility of obesity, might induce obesity, or may worsen due to obesity are listed in 4.

Furthermore, excessive intake of nutrients, primarily sugars and fats, is cited as the main factor for obesity. Considering these points, the following indicators for recipe recommendation were set, and probabilities for each were determined from the training data:

is_obesity An indicator to determine if a user is obese. It is considered true if the conditions in table 3 are met.

intake_limit An indicator of the upper limit of various nutrients that the user can consume. Assuming dinner, it is determined by the difference between the amount of nutrients the user has consumed until dinner and the daily intake limit.

blood_pressure An indicator to determine if the user has high blood pressure.

urine_protein An indicator of whether protein is present in the user's urine. Protein in urine is more likely to appear due to decreased kidney function, and in cases of obesity, kidney function is more likely to decrease. Hence, it serves as a barometer for the risk of complications due to obesity.

blood_ldl Whether LDL cholesterol exceeds the threshold.

effective_function Whether the recommended recipe contains functional components effective against obesity.

The condition related to stress was removed to reduce computational complexity. A ProbLog snippet that combines these indicators to show recipe recommendations is presented in Figure 3.

As illustrated in the figure, the decision to recommend a recipe is based on the following three criteria: Nutrient Intake Limit Criterion: From the user's dietary history for the day, this criterion checks if the nutritional components of the recipe exceed the permissible intake limits. This criterion is represented in the figure by the 'nutrition_limit' equation. Obesity-Related Criterion: This evaluates whether the user meets any of the criteria indicating obesity or any related measures. This criterion is represented in the figure by the 'obesity_related_problem' equation. Functional Criterion: This checks if the ingredients or compounds in the recipe have functional properties effective against obesity. Represented by the 'has_function' equation in the figure, it retrieves the functional ingredients included in the recipe by exploring the knowledge graph.

Table 2: Data Linking Examples.

Instance Type	Data Sources	Instances	Linking Method
Ingredient	Recipe1M+ FlavorDB	"**yogurt**, greek, plain, nonfat" "**Yogurt**"	Word matching.
Ingredient	FlavorDB Functionality Dataset	"Cabbage" "Cabbage (*in japanese*)"	Match through Wikidata item.
Compound	FlavorDB Functionality Dataset	"Epigallocatechin Gallate" "Epigallocatechin Gallate (*in japanese*)"	Pubchem ID matching.
Functionality	NARO Functionality DB Customer Affairs Agency's DB	"Decrease high blood pressure." "... peptide **decrease high blood pressure** ..."	Manually matching.

Table 3: Criteria for determining obesity.

Indicator	Criteria
BMI	25
Body Fat Rate	Male:>20%, Female:>30%
Waist Size	Male:>85cm, Female:>90cm

Table 4: Criteria for obesity related diseases.

Indicator	Criteria	Details
Urine Protein	Positive	Possible nephropathy.
High Blood Pressure	> 140/90 mmHg	Causes some deseases.
High LDL Cholesterol	> 140mg/dl	Causes of arteriosclerosis.
High Stress	Stress Check	Causes of overeating.

This criterion is realized by combining the proposed knowledge graph with probabilistic logic inference. By attributing probabilities to each nutritional component in the 'nutrition_limit' equation, it is anticipated that we can identify which nutrients are critical (i.e., typically overlooked by the most of users). Moreover, by assigning probability values to each obesity-related measure in the 'obesity_related_problem' equation, we expect to infer which health issues are more prevalent among the entire user base from these probabilities.

The daily intake limit is determined by the public health authorities of each country. In this study, we adopted the maximum intake level, classified as Body Level III, from the dietary reference intakes data published by Japan's Ministry of Health, Labour and Welfare as the intake limit[6]. As this intake limit varies depending on the user's age and gender, each condition was individually incorporated into the program.

5.1 User Data

In order to carry out the recommendations related to obesity, we created the necessary user data. The user data was constructed to correspond to the obesity-related indicators mentioned above, consisting of general physical measurement data such as height, weight, waist circumference, blood pressure, body fat percentage, and gender. In addition, we also included data from blood tests, urine tests, the presence of physical and mental stress, and the average values of nutrients consumed per day over several days. Regarding the consumed nutrients, since the recommendation is intended for dinner recipes, we used two-thirds of the values for the calculations. We created 1,000 individual user data.

6 RECIPE RECOMMENDATION EXPERIMENT

Using the constructed knowledge graph and user data, we conducted experiments to determine the probabilities of the recommendation formula shown in Figure 3 and various obesity-related indicators. To prepare the training data, we assigned real-number recommendation scores to recipes from Recipe1M+. These scores are automatically assigned based on the permissible nutritional intake and the functionality of the food. If the score is positive, it is recommended, and if it is negative, it is not recommended. The annotated data was created based on this criterion.

These scores are calculated so that recipes containing functional ingredients have a higher score. While it is believed that this method could significantly influence the experiment results, this approach was taken as a preliminary measure, anticipating the future creation of training data on whether each recipe should be recommended to users with the cooperation of registered dietitians.

For the training data, five recipes recommended for each user and five recipes not recommended were randomly extracted from the annotated data, constructing a total of 10,000 sets of recommended and non-recommended data pairs. In selecting these recipes, the selection was narrowed down to 200 recipes in order to facilitate comparisons among users.

The probabilistic values learned for each rule using this training data are presented in Table 5. Training was conducted individually for each user, and the table shows the average ($P(Avg.)$) and standard deviation ($P(Std.)$) of the probabilistic values for each derived fact across users.

Despite the variation in dietary history among users, it is evident that the intake of energy, salt, and protein is on the higher side, suggesting that most users tend to overconsume these nutrients. On the other hand, fats and sugars, which are significantly correlated with obesity, show a relatively low probability, indicating that they are not overconsumed. The results seem to reflect the typical nutritional distribution trends of Japanese cuisine.

From the average and standard deviation of the 'obesity related problem', it is evident that the variability regarding obesity-related

```
% Recommendation Rule For Obesity Person
t(_)::recommend_food(User,Recipe):-
    obesity_related_problem(User),
    \+ over_nutrition_limit(User,Recipe),
    has_function(Recipe).
    recipe(Recipe),user(User).
% For Obesity Person (No Function But Recommend)
t(_)::recommend_food(User,Recipe):-
    obesity_related_problem(User),
    \+ over_nutrition_limit(User,Recipe),
    \+ has_function(Recipe).
    recipe(Recipe),user(User).
% For Healthy Person
t(_)::recommend_food(User, Recipe):-
    \+ obesity_related_problem(User),
    \+ nutrition_limit(User,Recipe),
    recipe(Recipe),user(User).

t(_)::over_nutrition_limit(User,Recipe):-
    is_over_limit_energy(User,Recipe);
    is_over_limit_salt(User,Recipe);
    is_over_limit_fat(User,Recipe);
    is_over_limit_protein(User,Recipe);
    is_over_limit_sugar(User,Recipe).

t(_)::obesity_related_problem(User):-
    is_obesity_bmi(User); is_obesity_waist(User);
    is_obesity_bfat(User); is_urine_pro(User);
    is_blood_high_cholesterol(User);
    is_high_blood_pressure(User).

has_function(Recipe):-
    has_edge_recipe_ingr(Recipe,Ingredient),(
      has_edge_ingr_func(Ingredient, Function);(
        has_edge_ingr_comp(Ingredient, Compound),
        has_edge_comp_func(Compound, Function),
        compound(Compound))),
    ingredient(Ingredient),function(Function).
```

Figure 3: The ProbLog Snipet of Recipe Recommendation Indicators.

issues is larger compared to other metrics. Moreover, it indicates that nutritional factors are given greater emphasis than whether or not an individual experiences obesity-related concerns when recommending recipes. On the other hand, the proportion of participants exceeding the standard values for obesity is 54%, which is roughly half, and there isn't a significant deviation from the average, suggesting the scoring seems appropriate. Additionally, concerning the obesity standard values, while 54% of the participants exceed the body fat percentage standard, the proportion exceeding the BMI and waist standards are lower (18% and 21%, respectively). This indicates that there are many participants who might have sarcopenic obesity, a condition that has been on the rise in recent years, as referenced in [18].

For the recommendation probabilities, the scores for recipes containing functional ingredients are higher than those without such fact, indicating that recipes with functional components are more likely to be recommended. On the other hand, recommendation formulas targeting non-obese users also scored high, consistent with the observed trend that whether or not a user is obese isn't given significant importance.

Using the results of this learning, we experimented to determine whether it is possible to recommend recipes tailored to individuals. We picked up 25 recipes not used in the training data as test data and selected three obese and three non-obese users to make recommendations. As an evaluation metric, we calculated the rank correlation between the probability value when recommended and the original score. The results are shown in Table 6. In the table, ρ is a rank correlation score. $P(Nut)$ represents the probability value for the fact when excessive intake of any nutrient was observed, $P(Obe)$ represents the probability value assigned for the fact when there is suspicion of obesity, and $FuncPriority$ indicates whether the recommendation probability for recipes containing functional components is higher than for those not containing them. All these are related indicators as to which health improvement metric was effective in recipe recommendation, which is the objective of this study.

From the results, in terms of rank correlation, although the original correct annotation scores and the recommendation rules have a similar philosophy (e.g., scores increase when nutrients are not exceeded or when functional ingredients are included), there was almost no observable correlation. One possible reason for this discrepancy could be that while the recommendation rules determine nutrient excess based solely on threshold values, the score calculation side affects the score based on the degree of exceedance. This could mean that the recommendation system might not have been able to adapt to the changes in ranking due to this influence.

For nutrient excess, the scores generally trended lower, similar to the probability values during training. Particularly, users with low scores (o1, o3, h2) had already exceeded the salt intake limit before the recipe recommendation, suggesting that no matter which recipe was recommended, they would deviate from this condition. As a result, this rule seems to have been less considered.

In practical applications, even if a user has already consumed too much of a nutrient, there is still a need to suggest recipes, so this learning outcome is deemed appropriate. However, as mentioned earlier, there is a lack of metrics to evaluate the degree of nutrient deviation. Therefore, there's a possibility that recipes that are not very appropriate in terms of nutrient balance might be recommended, suggesting a need to refine the rules.

The conditions regarding obesity showed a difference in scores between users who are obese and those who aren't, indicating that it is given more importance for users who are obese.

For the rule of functional ingredients, the trend was consistent with the results during training, showing that recipes containing these ingredients were given more importance than those without them.

Table 5: Statics of Learned Probabilities of Formular

formular	$P(Avg.)$	$P(Std.)$
recommend_food(Obesity & Function)	0.711	0.187
recommend_food(Obesity)	0.504	0.235
recommend_food(Healty)	0.717	0.177
nutrition_limit	0.267	0.181
is_over_limit_energy	0.811	0.117
is_over_limit_sugar	0.429	0.160
is_over_limit_salt	0.851	0.155
is_over_limit_protein	0.898	0.122
is_over_limit_fat	0.769	0.128
obesity_related_problem	0.502	0.363

Table 6: Recommendation Result

userID	Obesity	ρ	$P(Nut)$	$P(Obe)$	$FuncPriority$
o1	True	0.025	0.149	0.234	False
o2	True	-0.039	0.497	1.0	True
o3	True	-0.007	0.347	0.714	True
h1	False	-0.004	0.556	$9.13e^{-6}$	True
h2	False	-0.016	0.058	0.009	False
h3	False	0.056	0.300	0.297	True

7 CONCLUSION AND FUTURE WORK

We proposed a system for recommending recipes based on indicators leading to the improvement of lifestyle-related diseases, such as recipes containing functional ingredients. This system combines a knowledge graph that includes data on recipes and functional ingredients with probabilistic logical reasoning. The knowledge graph is composed of the large-scale recipe dataset Recipe1M+, the functional ingredient database provided by the National Agriculture and Food Research Organization, and the functional ingredient labeling food notification database provided by Japan's Consumer Affairs Agency. Such a knowledge graph, which comprehensively records functional ingredients, has not existed before and is considered to be a highly valuable database. On the other hand, it became clear that the data related to functional ingredients could be much better compared to the recipe data obtained from Recipe1M+. Moreover, there needs to be more data related to ingredients, suggesting a need to proceed with data acquisition from external ontologies such as FoodOn. As for functional ingredients, some compound information included in Chebi[9] has features corresponding to food functions, so in the future, we aim to enhance functional information from Chebi. Additionally, as data concerning functionalities and compounds becomes more available, we are considering implementing inferences using probabilistic logical inference programs with deep learning[12, 19, 22], and characterizing each node on the knowledge graph using GraphEmbedding[4], similar to FlavorGraph[16]. Many of FlavorDB's compounds are annotated with flavor information related to the tastiness of food. By adding this information, along with preferences from subject data, we are also exploring recommendations based on taste and food preferences.

For the recipe recommendation system, we defined metrics related to obesity improvement and determined their application probability using the knowledge recorded in this knowledge graph. Additionally, we conducted experiments to determine the probability of recommending recipes based on these probability values. As a result, we could adjust the degree of application of criteria, such as the presence or absence of functional ingredients and the excess or deficiency of nutrients, depending on the user's condition, and train the system to make appropriate recommendations. However, we found that if the user has already exceeded the intake limit for certain nutrients, there's a possibility that a suitable recipe might not be recommended. In the future, we are considering expanding the rules to cover other lifestyle diseases besides obesity and are looking into improvements that allow for more flexible condition settings.

ACKNOWLEDGMENTS

This work was supported by the Cross-ministerial Strategic Innovation Promotion Program (SIP) II- "Technologies for Smart Bio-industry and Agriculture" and III- "Building a sustainable food chain that provides abundant and nutritious food (tentative)" funded by the Bio-oriented Technology Research Advancement Institution.

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Received 18 September 2023; revised 30 October 2023; accepted 21 October 2023