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Food Recommendation for Mental Health by Using Knowledge Graph Approach

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Abstract. There are many social factors have led to the crises of human mental health. Series of mental disorders, such as the depression, anxiety, and autistic disorder, have seriously affect human life. However, healthy diet can be a recommended way for improving mental health. The gut-brain axis, which is a bi-directional pathway that promotes diets work and regulates mental health in the body. As recent nutritional researches, food can be transformed into nutrients for feeding the gut microbiota. Furthermore, the nutrients can be metabolized as activators for mental health through the gut-brain axis. In this case, integrating these complex associations is necessary for exploring the function of food on mental health. Although there is a large scale of researches about food, gut microbiota and mental disorders that have been published but seldom been further reorganized. In this paper, we curate heterogeneous data sets from multiple sources and propose a framework about food recommendation for mental health by using knowledge graph approach. There are two available case studies, which are designed for demonstrating the application about food recommendations based on SPARQL query. The results have shown that our system have integrated useful knowledge and can be used to design proper diet patterns for patients with mental disorders. It's worth mentioning that our knowledge graph can also be extended to general human health and provide more convincing results for food researches and disease interventions.

Keywords: Knowledge graph · Diet · Gut microbiota · Mental health

1 Introduction

With the increasing of mental disorders in the world, that brings serious burden on the human health and social life [1]. Taking the depression disorder as an example, as the World Health Organization[1] (WHO) recorded, there are around

[1] https://www.who.int/health-topics/depression.

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5% of adults worldwide suffered from depression. The traditional intervention of mental disorder is hardly implemented widely due to its high cost in most countries [2]. As a result, healthy dietary patterns are being encouraged more often on the intervention of various mental disorders [3]. Many mental diseases, such as depression disorder [4], anxiety [5] and Parkinson syndrome have been verified to be associated with diet pattern [6]. For example, the Mediterranean diet, has been confirmed as a recommendation diet pattern for depressive patients [7]. Thus, the researches about biological function of food could have significant promotion for the prevention and therapy of mental disorders [8].

The effect of food on mental health are bi-directional, which be explained by the its biological characteristics. Although human mood can temporarily affect the choices of food, the diet and nutrition are long-term contributors to mental health [9]. There are different types of components about food, which can be divided into vitamins, minerals, lipid, proteins, sugars, etc. Due to its diversity of components, food can have multiple biological functions [10]. The digestion of food in human gut transform the nutrition compounds into the functional activators in gut microbiota. Furthermore the gut brain axis also promotes an effective transportation of metabolic nutrients between gut and brain community [11]. For example, the food with polyunsaturated fatty acids (e.g. omega-3 fatty acids), such as fish oil [12], have increased the proportion of beneficial bacteria (e.g. Bifidobacteria [13]) in gut community. Through the gut-brain axis, the bacterial metabolisms have been confirmed to promote the consumption of the pro-inflammatory factors in the brain and relief the depressive symptom [14]. In this case, our work is dedicated to integrating existing knowledge and designing applications around the food recommendation on mental health.

There are strong relations between mental diseases, gut microbes, and dietary nutrients according to biomedical experiments. There also have deep learning methods applied on mental health researches [15]. As huge numbers of related literatures have been published, it is necessary to integrate existing knowledge for further research [16]. There already have related works, such as a database named VMH [17], which is a metabolic database developed based on human metabolism associations with Mendelian diseases. Another database called MENDA [18], which also focus on the associations between metabolism and depression. These database are constructed based on text mining in biomedical literature manually, which is hard for further updating. In recent researches, knowledge graph has been introduced for representation learning on the intricate associations. For example, Ting Liu et al. [19] proposed a knowledge graph based on gut microbes and neurotransmitters about depression. Fu et al. [20] also used knowledge graph approach for mining relationships between depression and its complications. And Haussmann et al. [21] constructed a knowledge graph based on food recipes and properties, which can provide recipe proposals through on semantic queries. However, there is still a lack of research about using knowledge graph for food recommendation on mental health.

Thus, we propose a more generic knowledge graph around food, gut microbes, and mental health. The work in this paper are mainly focus on two aspects. (i)

The integration and transformation of heterogeneous data sets into structured knowledge, which is about food, gut microbiota and mental disorders. (ii) There are case studies designed based on knowledge graph provide the applications for food recommendations on human disorders. Finally, we also draw conclusions about our work and discuss future possibilities in food and human health.

2 Knowledge Enrichment

This paper works on the knowledge about the effect of food on human mental health, which is based on the hypothesis proposed in recent researches. That is the food consists of nutrients can promote gut microbial metabolism, which also have further effect on mental health through the gut brain axis.

2.1 Data Source

The data sets consist of the interactions and ontology, which has been shown in Table 1 as the detailed sources and descriptions. It will demonstrate the multi-sources data about knowledge graph from three areas: food, gut microbiota and mental disorders. We will also introduce the detailed statistics of the integration.

Table 1. Statistics of integrated data sets in knowledge graph.

Source	Relation	Entity	Triples	Description
FoodData Center	9	1,220,480	2,332,603	Food and components
FoodOn	56	56,079	79,769	Food ontology
Chinese products	7	160,802	215,863	Food ontology
KEGG	5	23,212	74,286	Microbial metabolites
NCBI taxonomy	5	984,031	1,306,152	Microbial ontology
MENDA	5	2,367	2,633	Depression and metabolic
MiKG	3	1,138	1,234	Mental diseases and microbes
SNOMED CT	63	2,064,178	4,291,226	Disease ontology
MESH	3	483,663	261,556	Disease ontology
Total	140	1,637,915	13,346,991	Total statements (4,741,023 inferred)

- ***FoodData Central (FDC).***[2] The FDC dataset provides a large amount of description on general and experimental food. We have integrated a total of 34,250 specific food, in which each item has its unique identifier and a standard weight of 100g. More specifically, the food comes from various brands and has particular components, which can be used to classified into various food categories.
- ***FoodOn.***[3] FoodOn is a food-centered ontology, which is contributed by the curators within academia and the OBO Foundry consortium. And we take use of the FoodOn for entity linking.

[2] https://fdc.nal.usda.gov/download-datasets.html.
[3] https://github.com/FoodOntology/foodon.

– ***Chinese Product.***[4] Chinese Product is a general list around food that is released by the China National Bureau of Statistics. We also use this for mapping our food samples to food ontology manually.
– ***KEGG.***[5] KEGG is a database consists of the whole metabolic pathway maps both in human and microorganisms. We have mapped around 230 nutrients components into gut metabolites and got related bacterial metabolism pathways.
– ***NCBI taxonomy.***[6] NCBI taxonomy focus on classification of microorganisms. We have integrated the phylogenetic trees of 322,917 bacteria from the NCBI taxonomy as gut microbial ontology.
– ***MENDA.*** There are 5,675 metabolite associations with depression from MENDA that have been compiled in our knowledge graph. We also integrate 157 gut microbes that have association with mental disorders from the database.
– ***MiKG.*** MiKG is also a knowledge graph around mental health, in which we integrate 1,234 gut microbes associated with mental diseases.
– ***MeSH.***[7] MeSH provides comprehensive disease terminology, which can be used for disease entity linking in our knowledge graph.
– ***SNOMED CT.***[8] It is a global common language standards for clinical terms contributed by the domain experts, and we also use their unique identifiers for disease items.

In conclusion, there are ontology and associations around foods, gut microbes, and diseases in our knowledge graph, which can be well represented through the knowledge graph structure.

2.2 Data Preprocessing

There are a huge number of heterogeneous knowledge in our knowledge graph after data integration. During data processing, entities from different knowledge bases may have various descriptions, which need to be linked to standard unique identifiers. In our knowledge graph, we use the Uniform Resource Identifier (URI) to represent each entity, and retain their description and attributes from the different knowledge bases.

We use the unique identifier from the FDC as the representation of each item of food, which can be mapped to other data sources through the label. The label of food from FDC may be a food name or a paragraph of food description. Firstly, we take use of the exact matching to map some simple names of food. And for the complex food descriptions, they will be split by the comma into strings, and we will use the first word in the string as the food label. The others are mostly unnecessary and will be retained as description labels or removed

[4] http://www.stats.gov.cn/tjsj/tjbz/tjypflml/.
[5] https://www.genome.jp/kegg/compound/.
[6] https://www.ncbi.nlm.nih.gov/taxonomy.
[7] https://www.nlm.nih.gov/mesh/meshhome.html.
[8] https://www.snomed.org/snomed-ct/.

directly. For example, the food description in FDC is "Chocolate milk, ready to drink, low fat", in which only "Chocolate milk" is what we need, and can be used to map in the FoodOn and Chinese Product knowledge bases with the unique representation. We also define some rules for mapping the food categories. For example, we sort the description of class with "drinks" (i.e. Soft drinks, Diet soft drinks) into a sub-class of "Beverages". However, due to the complexity and variety of category descriptions, we also make some manual efforts. For example, "Cakes and pies" and "Rolls and buns" are both the sub-classes of "Baked products". In general, we take use of a semi-automatic method and integrate food knowledge of 128 food categories and 34,250 food labels.

Similarly, the nutrient of food can be linked to the metabolites with the unique identifier in KEGG, in which their semantic relationships can be represented as "owl: sameAs" through the rules in OWL. Finally, we have mapped 123 nutrients to gut metabolites. We also link diseases to the ontology from MeSH or SNOMED CT through their labels. In this case, the description with "'s" that will be removed to ensure the exact matching. Such as the "Alzheimer's Disease" will be mapped to the Alzheimer Disease. Similar way with mapping compounds, the matching process also ignores the effects of case, singular and plural, and the sequence of the words. In a word, we have integrated the 277 diseases with their ontology.

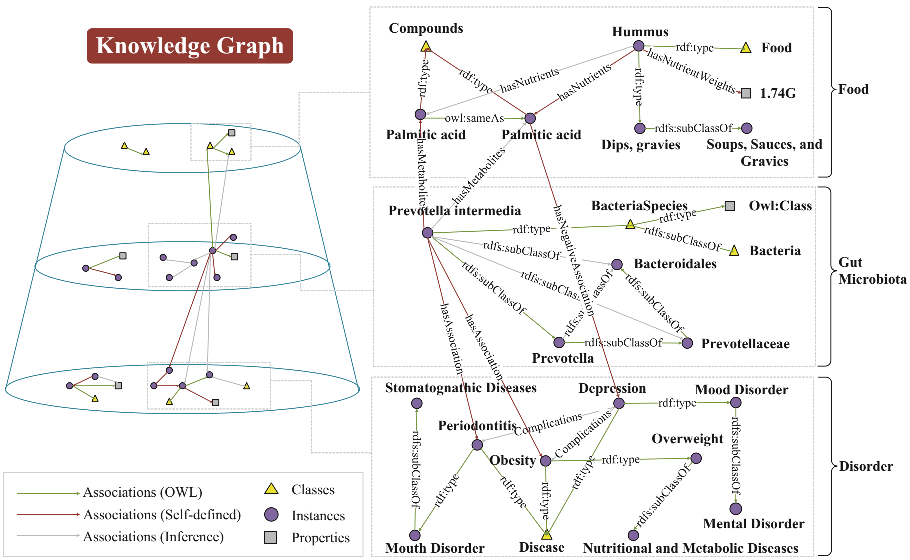

Fig. 1. An example of the graph structure in knowledge graph. The ontologies are mainly food, gut microbiota, and disorder. Associations are mainly from OWL (well-defined general relations), self-defined relations, and inference (relations that inferred from knowledge reasoning). And Knowledge graph also includes multiple entities as classes, instances, and properties. This figure has shown an example of the food could affects complicated disorders through the gut microbial metabolisms, which has been represented as a graph structure comprehensively.

3 Knowledge Graph Construction

Based on the hypothesis that food could affect mental disorders through gut microbial metabolisms, we design the general architecture of our knowledge graph. An example of network in our knowledge graph is shown in Fig. 1.

After the integration of heterogeneous data, there is a large number of binary associations originally, which need to be further transformed into triples. The triples are represented by the format of Resource Description Framework (RDF), which consists of subject, predicate, and object. Specifically, both subject and object are the factual concepts or property descriptions, the predicates are associations. And our knowledge graph could be well understood through the structured representations as triples.

There are also some ontological associations can be acquired from the original data sets. For example, apple products are the subclass of the general fruits, which can be represented in knowledge graph as (apple products, rdfs: subclassOf, fruits). That relation represents an inclusion relationship between classes, such as fruit is a general class that includes apple, banana products, etc. Besides, the apple juice is an instance of the apple products, and their association can be represented as the "rdf: type". After the binary relations are transformed into the format of RDF, the heterogeneous data are given more semantic representations based on the graph structure. Except for well representing our original knowledge, our knowledge graph could also inference more implicit relations based on the knowledge reasoning. Those applications of food recommendation can be completed automatically by the inference rules of the knowledge graph.

4 Cases Studies

We have designed two case studies based on the knowledge retrieval and knowledge reasoning in the knowledge graph. The query cases mainly focus on the food characteristics and the effects of food on mental health through gut microbial activities. And for each case study, we will design a SPARQL query to obtain the associations as the table, and also drawn picture for description. In the cases, we just use part of food and mental health as examples, that both cases can be easily extended to generic applications.

4.1 The Properties of Food on Human Gut

The first case is about the properties of food, which include the categories of food, the weight of nutrient and the associations between nutrients and gut metabolites. Taking the question for example: how much Vitamin B can be absorbed from the mixed meal as the milk with the egg products. Based on the natural language question, we have designed the SPARQL query:

SPARQL case 1: How much Vitamin B can be absorbed from the mixed meal as the milk with the egg products.

```
select distinct ?Eggname?Milkname?Nutrientname((?eggweight + ?milkweight) AS ?Weight) where
{ {?egg pq:hasNutrients ?nutrient;
pq:hasNutrientWeights ?eggunit;
rdf:type ?eggclass;
rdfs:label ?eggname.}
{?milk pq:hasNutrients ?nutrient;
rdfs:label ?milkname.}
?eggclass rdfs:label ?eggclassname.
{?nutrient rdfs:label ?nutrientname;
pq:hasNutrientWeights ?eggunit;
pq:hasNutrientWeights ?milkunit.}
?eggunit rdf:value ?eggweight.
?milkunit rdf:value ?milkweight.
filter regex(?nutrientname,“Vitamin B”,“i”)
filter regex(?eggname,“Egg”,“i”)
filter regex(?milkname,“Milk”,“i”) }
```

Table 2. The properties of food on human gut.

No	Egg products	Milk products	Gut metabolites	Weight (mg/200 g)
0	Potato salad with egg	MILK, 1%	Vitamin B-12	0.082
1	Egg omelet or scrambled egg	Milk, skim	Vitamin B-12	0.071
2	Roll, egg bread	Soy milk, light	Vitamin B-12	0.082
3	Egg, whole, fried with butter	Milk, whole	Vitamin B-6	6.591
4	Shrimp-egg patty	Chocolate milk	Vitamin B-6	6.766
5	Egg, whole, boiled or poached	Yogurt, coconut milk	Vitamin B-6	6.602

Through the SPARQL query, we have obtained 254 egg products and 402 milk products. As part of results have been shown in Fig. 2, the milk and egg products are various in different brands or characteristics, which is random paired in the results. Totally, we have acquired around 80,000 results in this case. We assume that the weight of each food instance is 100 g. And the results is the sum of the vitamin B (taking Vitamin B6 and Vitamin B12 as examples) in mixed diet. The unit of vitamin B is milligram in 200 g diet (100 g milk and 100 g egg products). The detailed results shown in Table 2, the sum of the Vitamin B12 in the mixed meal is about 0.08 mg (in the mixed diet of egg salad and 1% milk), varying slightly from food pairs. It is worth mentioning that according to the WHO [22] reported, the recommended intake of Vitamin B12 for adults is 2.4 g per day. And it can demonstrate this mixed diet is suitable for the intake of Vitamin

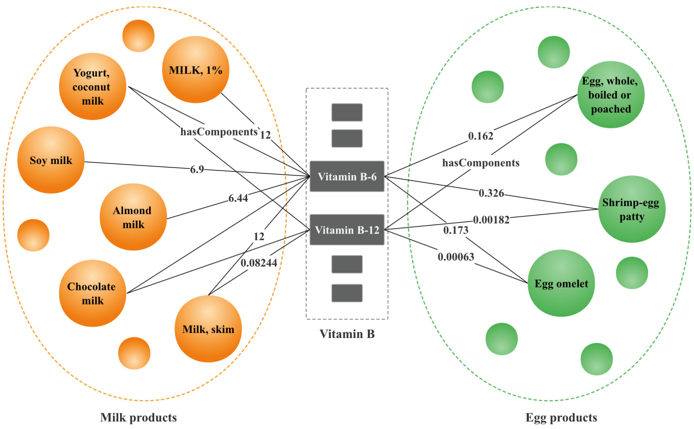

Fig. 2. The properties of food on human gut. In both circles are food with same category, as milk products and egg products. And in the square box are components of the food, as vitamin B. Their links are the weight of compounds in food.

B12 to an adult per day. We can use this conclusion as a reference for further nutritional experiments.

4.2 The Effects of Food on Mental Disorder

This case is about the effects of food on mental disorder through gut microbiota. Based on the hypothesis, there are nutrients from food that have positive effects on mental health, which could also participate in the gut microbial metabolism in human body. Taking the depression disorder as an example, this case is about which gut metabolism pathway could have effect on food and depression. Based on the natural language description, the SPARQL query is as follows.

SPARQL case 2: Which gut metabolism pathway could have effect on food and depression.

```
select distinct ?foodname?fcategory?comname?weight?bacname where
{ ?depression npq:hasNegativeAssociation ?compound;
rdfs:label ?depressionname.
?compound rdfs:label ?comname.
?nutrition owl:sameAs ?compound;
pq:hasNutrientWeights ?unit.
{?food pq:hasNutrients ?nutrient;
pq:hasNutrientWeights ?unit;
rdfs:label ?foodname.}
?unit rdf:value ?weight.
?food rdf:type ?foodclass.
```

```
?foodclass rdfs:label ?fcategory.
?depression npq:hasPositiveAssociation ?bacteria.
?bacteria npq:hasMetabolites ?compound.
?bacteria rdfs:label ?bacname.
filter regex(?depressionname,"depression | depressive | depressed","i") }
```

Table 3. The effects of food on depression based on the gut microbiota.

No	Food name	Food category	Compound	Weight (mg/100 g)	Bacteria	Mental disorder
0	FLOUR, SOY	Legumes and legume products	Glutamic acid (+)	8,870	Enterococcus faecalis	Depression
1	Broccoli, raw	Vegetables and vegetable products	Glycine (+)	89	Enterococcus faecalis	Depression
2	Grape juice	Fruits and fruit juices	Citric acid (+)	216.7	Adlercreutzia equolifaciens	Depression
3	Kiwi	Fruits and fruit juices	Ascorbic acid (+)	84	Bifidobacterium longum	Depression
4	Lettuce, Romaine	Vegetables and vegetable products	Ascorbic acid (+)	7.5	Bifidobacterium longum	Depression
5	BEEF SAUSAGE	Sausages and luncheon meats	L-Threonine (−)	500	Bacteroides ovatus	Depression
6	BEEF SAUSAGE	Sausages and luncheon meats	L-Threonine (−)	500	Bacteroides vulgatus	Depression
7	Whole wheat bread	Baked products	Choline (−)	27.2	Bifidobacterium longum	Depression

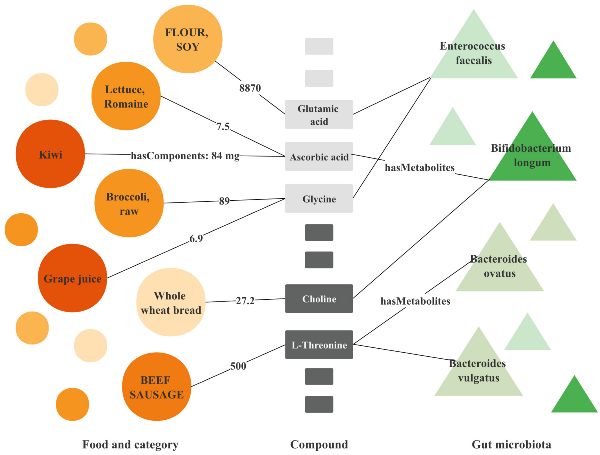

Fig. 3. The effects of food on mental disorder. The triangles are the gut microbiota that could have effects on depression through their metabolites. The various color of the food represent the categories, of gut microbiota represent different genus.

Specifically, we have acquired 9,512 food, which can be divided into 182 food categories, 14 compounds, and 4 microbes that have association with depression. Totally, we obtained around 10,000 results, part of which have been shown in Table 3, Such as the soy flour, which belongs to the legume products, contains around 8.87 g Glutamic acid per 100 g. We have obtained the food instances and categories containing these nutrients, which is based on the premise of the food effect on mental health. And the component in those food may have various effects on depression, which have shown in Fig. 3. Such as the Glutamic acid has been confirmed that has positive effect on depression as reactants in metabolisms of Enterococcus faecalis. The community of gut microbiota is also altered through the metabolites and may affect depression. In this case, we could have more verification results through the multi-pathway effects of food on the mental disorder. These results conducted by our knowledge graph can be further verified through the experimental researches.

5 Conclusion and Discussion

In this paper, we construct the knowledge graph around the effects of food on mental disorders via gut microbes, which provides applications on knowledge retrieval and knowledge reasoning. We make more efforts on the integration and construction of knowledge graph, which can lay foundations on the following applications. According to the effects of food on mental disorders, the factors around gut brain axis are necessary for designing the framework of our knowledge graph. For the validation of the quality of our system, we also design two cases as applications on the knowledge graph. The case studies have shown that our knowledge graph can provides reasonable results that are coincident for our daily food pattern. More importantly, our cases also have shown that the knowledge graph can provide more specific nutrient calculation and microbial evidence in food recommendations.

Our knowledge graph provides more results than existing data sets, which is conducted based on the knowledge inference. And there are huge number of biomedical literature results can be the verification of our inference conclusions. For example, our system give the result that the garlic may have positive effect on Alzheimer disease, which have been verified in published research [23]. And the another evidence about the effect of our result is that the Escherichia coli may have association both with depression and anxiety. This result is inferred from our knowledge graph and have also been reported in the existing research [24]. In conclusion, these convincing results could be use in further researches, as well as being able to provide reliable design directions for future experimental validation.

6 Future Work

We have made some efforts on extracting the effects of food on multiple mental health and construct a framework to build the knowledge graph for obtaining significant query results. In future work, our knowledge graph could have more extensions. It worth mentioning that knowledge graph mainly provides applications, such as the food recommendation and diet designing, which just focus on the mental disorders in this work. Because there are limited structured associations between human diseases (more than mental disorders) and gut microbiota. Furthermore we plan to add more relations between human disease and metabolites, which can promote the designing of food recommendations on general human diseases based on the knowledge inferences. For further experimental validation, more biologists who are still expected to use the results obtained through our knowledge graph as references in their experiments in the future. Knowledge graph will continue being used to work on the effects of food on human health around gut microbiota. We also encourage that our work can provide general knowledge services for human health.

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