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METHODOLOGIES AND APPLICATION

Healthy diet assessment mechanism based on fuzzy markup language for Japanese food

Mei-Hui Wang · Kanta Kurozumi · Mikiko Kawaguchi · Chang-Shing Lee · Hiroshi Tsuji · Shusaku Tsumoto

Abstract Owing to the change of our lifestyle, more people suffer from chronic diseases, such as obesity or diabetes. Making improvements in terms of diet and physical activity is helpful for people to reduce the risk of suffering from these chronic diseases. This paper presents a healthy diet assessment mechanism based on fuzzy markup language (FML) for Japanese food. This mechanism is based on the dietary standard, food exchange list (FEL), published by the Japan Diabetes Society, to assess one person's dietary healthy level according to his/her personal profile, his/her daily physical activity, and how balanced he/she consumes food items. We use FML to describe the knowledge base and the rule base of the constructed fuzzy logic system. Additionally, ontology stores the necessary knowledge base and rule base of the adopted fuzzy inference mechanism. The proposed mechanism operates as follows: (i) Dieticians first define the nutrient facts of the collected food items. (ii) The involved subjects record their personal information, eaten food items, and daily physical activity. Through the constructed FML-based personal profile ontology, the estimated energy requirement and the estimated unit requirement for each food group are obtained after inference. (iii) Finally, one-day dietary healthy level is inferred by the proposed fuzzy inference mechanism. From the experimental results, the proposed mechanism is feasible to apply to Japanese dietary assessment. In the future, we will integrate with genetic learning algorithm and collect more subjects' records to further improve the performance.

Keywords Ontology · Fuzzy inference mechanism · Fuzzy markup language · Dietary healthy level assessment · Food exchange list

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1 Introduction

With the development of computerization and automation, most industries have faced the problems with transformation from analog to digital devices. However, transforming expert's skilled experience into the machine-understandable knowledge is a big challenge for the computer. Moreover, the classical digital logic operates on discrete values, either one or zero, which is not suitable to express human's domain knowledge. As a result, Zadeh (1965) proposed fuzzy logic in 1965. The technologies of fuzzy logic have greatly contributed to solve such an uncertain problem to manage the vague or imprecise information in the real world. Nowadays, it has been applied to many fields from control theory to artificial intelligence. For example, derived from artificial intelligent concepts with fuzzy logic values, a flexible and smart

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algorithm was developed to aid in the selection of a learning management system (Cavus 2010). Lee and Wang (2011) proposed a fuzzy expert system for diabetes decision support application. Lacagnina et al. (2014) compared a fuzzy model with a well-known statistical approach for diagnostic decision-making in patients with chronic nasal symptoms. Motlagh et al. (2012) proposed an expert fuzzy cognitive map for reactive navigation of mobile robots.

Ontology consists of a hierarchical description of classes and concepts in a specific domain, and includes a vocabulary of terms together with the specification of their meaning (Noy and McGuinness 2001). Fuzzy ontologies extend classical ontologies to represent imprecise and vague knowledge (Bobillo and Straccia 2013). And, researchers have been developing different tools and languages to construct ontologies. For example, Stoilos et al. (2010) studied fuzzy extensions of the Semantic Web language OWL and presented two further fuzzy extensions of OWL based on fuzzy subsumption and fuzzy nominal. Bobillo and Straccia (2013) integrated fuzzy ontologies and aggregation operators to encode some examples of aggregation operators using the language fuzzy OWL 2. Zhang et al. (2013) proposed a formal approach and an automated tool for constructing fuzzy ontologies from fuzzy XML data resources. Lee et al. (2010b) proposed an ontology-based fuzzy inference system for computer Go applications. Lee et al. (2010a) proposed a type-2 fuzzy ontology and applied to diabetic-diet recommendation.

Owing to the increasing popularity of developing semantic languages to deal with vague information in the real world, fuzzy markup language (FML) was designed and developed by Acampora and Loia (Acampora and Loia 2005a, b; Acampora et al. 2013) to model different components of the fuzzy controller in a taxonomic way and then to provide a flexible and dependable solution to these uncertain problems. Its implementation is based on the employment of semantic tags. It not only can consider modeling the fuzzy controllers, but also can describe the knowledge base and the rule base of the fuzzy logic system independently and effectively (Acampora and Loia 2005a, b; Acampora et al. 2013). Incorporated ontology with FML and a fuzzy logic system, our previous works assessed one-day meal's dietary healthy level for Taiwanese meals (Wang et al. 2010; Lee et al. 2010c, 2012). Wang et al. (2010) proposed an ontology-based multi-agents for intelligent healthcare applications. Lee et al. (2010c) proposed a diet assessment based on type-2 fuzzy ontology and FML. Lee et al. (2012) proposed a novel genetic FML to learn the suitable fuzzy sets and handle the uncertainties in the group decision-making process among dieticians. Thereafter, Wang et al. (2011) and Kurozumi et al. (2013) extended this mechanism to Japanese diet. Apart from diet domain, Acampora et al. (2010, 2012), and Liu et al. (2013) applied FML to express the knowledge base and rule base of the Electrocardiogram (ECG) domain, university assessment, and ambient intelligence, respectively. Acampora and Loia (2005b) applied FML and fuzzy technology to an adaptive ambient intelligence environments.

Kurozumi et al. (2013) adopted food exchange list (FEL) standard to assess the healthy level for Japanese meals and considered that the estimated energy requirement (EER) for each person and the estimated unit requirement (EUR) for each food group are fixed during the experimental period. However, in this paper, each subject's EER is variable each day, and it is decided according to each person basal metabolic rate (BMR) and his/her everyday physical activity. EER and EUR for each food group are obtained from his/her personal information and the uncertain factors such as his/her daily hours of sleeping and exercise. The proposed fuzzy inference mechanism first infers the daily physical activity level via the constructed ontologies, including FML-based personal profile ontology and FML-based Japanese dietary assessment ontology. Then, the proposed mechanism can evaluate how moderate the consumption of the nutrients is and how balanced the intake is based on the inferred physical activity.

This paper is organized as follows: Japanese dietary standard ontology model is introduced in Sect. 2. The ontology model for FML-based Japanese dietary assessment is described in Sect. 3. Healthy diet assessment mechanism applied to Japanese food is introduced in Sect. 4. Experimental results are shown in Sect. 5. Finally, discussions and conclusions are given in Sect. 6.

2 Ontology model for Japanese dietary standard

Sections 2.1 and 2.2 introduce three Japanese dietary standards, namely, (i) Kagawa Nutrition University Diet (KNU-Diet) published by Kagawa Nutrient University (Laboratory of Basic Nutrition, Kagawa Nutrition University 2007), (ii) Japanese Food Guide Spinning Top (JFGST) published by Ministry of Health, Labour and Welfare of Japan, and Ministry of Agriculture, Forestry and Fisheries of Japan (Ministry of Health, Labour and Welfare of Japan 2010; Ministry of Agriculture, Forestry and Fisheries of Japan 2010), and (iii) Food Exchange List (FEL) published by Japan Diabetes Society (The Japan Diabetes Society 2002). Then, the dietary standard ontology is introduced in Sect. 2.3.

2.1 Introduction to Japanese food standard: KNU Diet and Japanese Food Guide Spinning Top

KNU Diet was proposed by Kagawa in 1948 (Laboratory of Basic Nutrition, Kagawa Nutrition University 2007). It is based on calorie to manage personal health and 80 kcal is regarded as one point. This rule gives an understandable and a practical way to estimate the sum of calorie and each nutrient. KNU Diet consists of four food groups, including (i) Group_1: dairy products and eggs, (ii) Group_2: fish, meat, and beans, (iii) $Group_3$: vegetables, potatoes, and fruits, and (iv) $Group_4$: grains, sugar, oils, and others. The estimated energy requirement, EER, is set according to one person's age, gender, and activity level. Assume one person's EER is 1,600 kcal (20 points), which means that this person needs to choose 3-point, 3-point, 3-point, and 11-point food items from Groups 1, 2, 3, and 4, respectively, to maintain one-day physical activity (Laboratory of Basic Nutrition, Kagawa Nutrition University 2007). However, KNU Diet is not suitable to assess the dietary healthy level due to the following three reasons: (i) KNU Diet was proposed for a long time ago and is not utilized nowadays, (ii) nutrients of carbohydrate and protein in $Group_1$ should be separated, and (iii) vegetables and fruits in $Group_3$ should be separated too.

Published by Ministry of Health, Labour and Welfare of Japan (Ministry of Health, Labour and Welfare of Japan 2010), and Ministry of Agriculture, Forestry and Fisheries of Japan (Ministry of Agriculture, Forestry and Fisheries of Japan 2010), Japanese Food Guide Spinning Top (JFGST) allows not only dieticians but also ordinary people to manage healthy eating habit. JFGSP uses one spinning to represent the recommended one-day consumed servings for five food groups. The skewer the spinning, the more unbalanced the diet (Ministry of Agriculture, Forestry and Fisheries of Japan 2010). JFGST consists of five food groups, including (i) grain dishes (main nutrient is carbohydrate) like rice, bread, noodles, and pasta, (ii) vegetable dishes (main nutrient is vitamin and mineral), (iii) fish and meat dishes (main nutrient is protein) like meat, fish, egg, and soybean, (iv) milk and dairy products (main nutrient is calcium), and (v) fruits (main nutrient is vitamin C and potassium) (Ministry of Agriculture, Forestry and Fisheries of Japan 2010).

One serving of grain dishes, vegetable dishes, fish and meat dishes, milk and dairy products, and fruits is defined as inclusion of 40 g of carbohydrate, approximated amount of 70 g, inclusion of 6 g of protein, inclusion of 100 mg of calcium, and approximated amount of 100 g, respectively. JFGST recommends that one person consumes about 5–7, 5–6, 3–5, 2, and 2 servings of grains dishes, vegetable dishes, fish and meat dishes, milk, and fruits, respectively, to maintain daily physical activity. Additionally, JFGST also recommends exercising, drinking water or teas, and enjoying snacks, confection, and beverages moderately for Japanese (Ministry of Health, Labour and Welfare of Japan 2010; Ministry of Agriculture, Forestry and Fisheries of Japan 2010).

JFGST sets "serving" as a standard to express a certain nutrient value (Ministry of Agriculture, Forestry and Fisheries of Japan 2010). The definition of one serving is appropriate for an easy estimation; however, it is not appropriate for assessing the dietary healthy level because JFGST does not consider the difference among the nutrition from different food groups. Let us use "one serving of rice" and "one serving of bread" as examples to make explanations. According to the food database published by Ministry of Education, Culture, Sports, Science and Technology of Japan (Ministry of Education, Culture Sports Science and Technology of Japan 2013), one serving of rice contains 181 kcal, 2.7 g of protein, and 0.3 g of fat; however, one serving of bread contains 226 kcal, 8.0 g of protein, and 3.8 g of fat. Hence, JFGST does not consider the above-mentioned feature of food. For this reason, using JFGST to assess dietary healthy level has a possibility of biasing the evaluation.

2.2 Introduction to Japanese food standard: food exchange list

Because both KNU Diet and JFGST have some problems with assessing the dietary healthy level, this paper adopts Food Exchange List (FEL) as a standard to estimate the dietary healthy level. FEL was published in 1965 by the Japan Diabetes Society as a dietary therapy for diabetics to achieve the goal of (i) appropriate calorie, (ii) limiting the quantity of carbohydrate, (iii) balance of carbohydrate, protein, and fat, and (iv) appropriate supply of vitamins and the mineral. It has been used not only by diabetics but also by healthy people to keep a balanced eating habit (The Japan Diabetes Society 2002).

Because of FEL, we are able to estimate not only the amount of calorie by units (one unit is 80 kcal), but also the provided calories from three main nutrients, namely carbohydrate, protein, and fat. Additionally, EUR for each food group is defined based on EER so that FEL can estimate the balance among different food groups. As a result, this paper evaluates the dietary healthy level based on FEL. The recommended diets in the FEL are in good agreement with the composition of the daily diet of the average Japanese people, and are referred to as healthy food (Kajinuma 2001). Table 1 shows FEL's food groups, including $List_1$, $List_2$, $List_3$, $List_4$, $List_5$, $List_6$, $Group_{Seasoning}$, and $Group_{Others}$. $List_1$ and $List_2$ belong to $Group_I$ that mainly consists of carbohydrate. $List_3$ and $List_4$ are $Group_{II}$ and it mainly contains protein. $List_5$ is $Group_{III}$ and its main nutrient is fat. For $List_6$ ($Group_{IV}$), its main nutrient is vitamins and minerals. According to FEL, in the case of 20 units per day (1,600 kcal), the recommended values of one-day EUR for $List_1$, $List_2$, $List_3$, $List_4$, $List_5$, $List_6$, and $Group_{Seasoning}$ are 11, 1, 4, 1.5, 1, 1, and 0.5 units, respectively. Generally speaking, $Group_{Others}$ contains some food items like liquor, juice, sweets, or jam which are unhealthy for people to consume too much. Therefore, the less units for $Group_{Others}$ that one person consumes, the healthier he/she will be.

2.3 Japanese dietary standard ontology

Figure 1 shows the four-layer Japanese dietary standard ontology, namely domain, category, concept, and instance

Table 1 FEL's food groups, food items of each group, and the gram of contained nutrient per unit (The Japan Diabetes Society 2002; Kajinuma 2001)

Group	List	Food type	Food items	Gram of contained nutrient per unit (g)		
				Carbohydrate	Protein	Fat
I	$List_1$	Grains, potatoes, beans, vegetable rich in carbohydrate, beans, and peas (excluding soybeans)	Rice, taro, sweet potato, breads, noodles, flour, corn, pumpkin	18	2	0
	$List_2$	Fruits	Apple, orange, peach, strawberry, banana	20	0	0
II	$List_3$	Seafood, fishes, meats, eggs, cheese, soybeans, and soy products	Salmon, Pacific saury, octopus, shrimp, oyster, satsuma, beef, pork, chicken, sausage, ham, egg, cheese, soybean, natto, tofu	0	9	5
	$List_4$	Milks, dairy products (excluding cheese)	Milk, yogurt	6	4	5
III	$List_5$	Oils, fats	Vegetable oil, peanuts, butter, dressing, mayonnaise	0	0	9
IV	$List_6$	Vegetables (excluding some vegetables rich in carbohydrate), seaweed, mushrooms, konnyaku	Tomato, carrot, cabbage, eggplant, laver, shiitake mushroom, konnyaku	13	5	1
Seasoning		Seasoning	Miso, sugar, sweet cake	None	None	None
Others		Others	Liquor, juice, sweets, jam	None	None	None

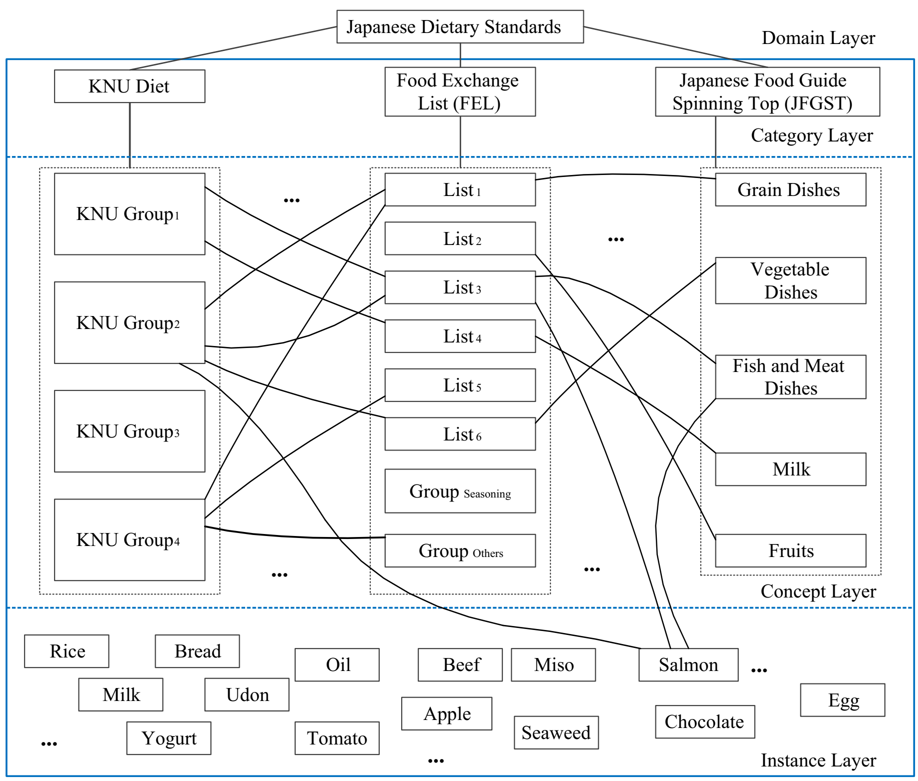
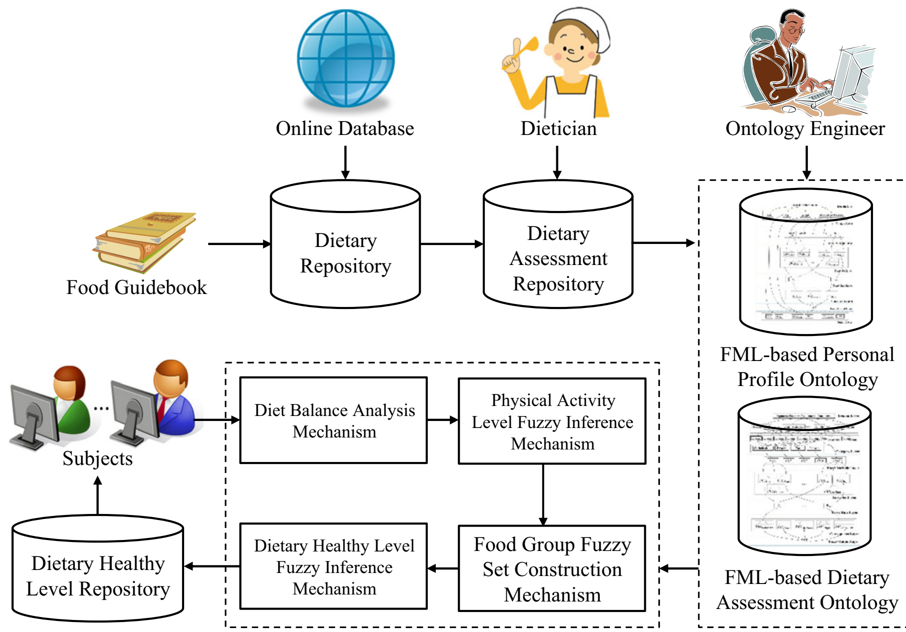


Fig. 1 Structure of Japanese dietary standard ontology

Table 2 Brief descriptions about the Japanese dietary standard ontology

Domain layer: this layer represents the domain name of the ontology
Category layer: this layer is composed of KNU Diet, FEL, and JFGST to describe three Japanese dietary standards
Concept layer: there are several concepts in this layer. For example, KNU Diet has concepts KNU $Group_1$, $Group_2$, $Group_3$, and $Group_4$. JFGST has concepts grain dishes, vegetable dishes, fish and meat dishes, milk, and fruits. FEL has concepts $List_1$, $List_2$, $List_3$, $List_4$, $List_5$, $List_6$, $Group_{Seasoning}$, and $Group_{Others}$. There is a relation between one concept and another concept, for example, KNU $Group_2$ (meat, fish and beans) has a relation with FEL $List_1$ (grains, potatoes, beans, and vegetable rich in carbohydrate) because both groups are with beans
Instance layer: this layer consists of various instances for each concept in the concept layer. For example, salmon is an instance of $List_3$ of FEL, $Group_2$ of KNU Diet, and fish and meat dishes of JFGST

Fig. 2 Structure of healthy diet assessment mechanism (Kurozumi et al. 2013)



layers, to describe the concepts and the relations among three food standards in Japan. The brief descriptions are listed in Table 2.

3 Ontology model for FML-based Japanese dietary assessment

In this Section, we give an overview about the proposed dietary assessment system in Sect. 3.1. Then, we propose two FML-based ontologies, namely, a personal profile ontology in Sect. 3.2 and a dietary assessment ontology in Sect. 3.3.

3.1 Structure overview

Figure 2 shows the structure of the healthy diet assessment mechanism applied to Japanese food and its operations are shown in Table 3.

3.2 FML-based personal profile ontology

Figure 3 shows the eight-layer FML-based personal profile ontology. Its descriptions are as follows:

- Domain layer: This layer represents the domain name of the ontology and the domain name is personal profile ontology.
- Category layer: There are some categories, including gender, age, weight, and physical activity level. According to Ministry of Health, Labour and Welfare of Japan (2010), estimated energy requirement (EER) has a relation with daily basal metabolic rate (BMR) and physical activity level (PAL). Besides, BMR and PAL are related to one person's gender, age, and weight. BMR is calculated by Eq. (1) according to Ministry of Health, Labour and Welfare of Japan (2010). Take an 18 to 29-year-old and 63 kg-weight man for an example. His daily basal metabolism standard is about 24 kcal/kg so his daily BMR is about 1,510 kcal. Therefore, EER is calculated by Eq. (2) according to Ministry of Health, Labour and Welfare of Japan (2010).

$$\mathrm{BMR}(\mathrm{kcal/day}) = \text{Basal metabolism standard } (\mathrm{kcal/kg/day}) \times \mathrm{weight}(\mathrm{kg}) \quad (1)$$

$$\mathrm{EER} = \mathrm{BMR} \times \mathrm{PAL} \quad (2)$$

Table 3 Operations of the FML-based Japanese dietary assessment system

Gather nutrition facts of each food item and the information of the involved subjects' standard EER from the food guidebook (Kagawa 2012) and the online database (Ministry of Education, Culture Sports Science and Technology of Japan 2013). Then, they are stored into the dietary repository
The involved dieticians verify and define the detailed nutrient facts for each collected food item and they are stored into the dietary assessment repository
The ontology engineer constructs the FML-based personal profile ontology and FML-based dietary assessment ontology. The knowledge base and the rule base of the fuzzy inference mechanism for PAL and DHL are also incorporated with the constructed ontology after discussing with the involved dieticians
The involved subjects record and input the personal information like their gender, age, weight, hours of sleeping, hours of taking-up stable activity, hours of doing light/medium/heavy exercise, and daily consumed food items
The diet balance analysis mechanism analyzes the values of PCC, PCP, and PCF according to the collected one-day consumed food items and the constructed ontology
The physical activity level fuzzy inference mechanism infers each involved subject's one-day physical activity level according to the constructed ontology
Based on the inferred PAL, each involved subject's one-day EER, one-day EUR for each food group, and the value of PCR are required. Then, the food group fuzzy set construction mechanism constructs the fuzzy sets EUR_1, EUR_2, EUR_3, EUR_4, EUR_5, EUR_6, $EUR_{Seasoning}$, and EUR_{Others} according to the acquired EER, and each group food EUR
After that, dietary healthy level is inferred by executing the dietary healthy level fuzzy inference mechanism according to the built ontologies. The inferred DHL is stored into the dietary healthy level repository
Finally, the involved subjects get the results via the provided interface

Fig. 3 FML-based personal profile ontology

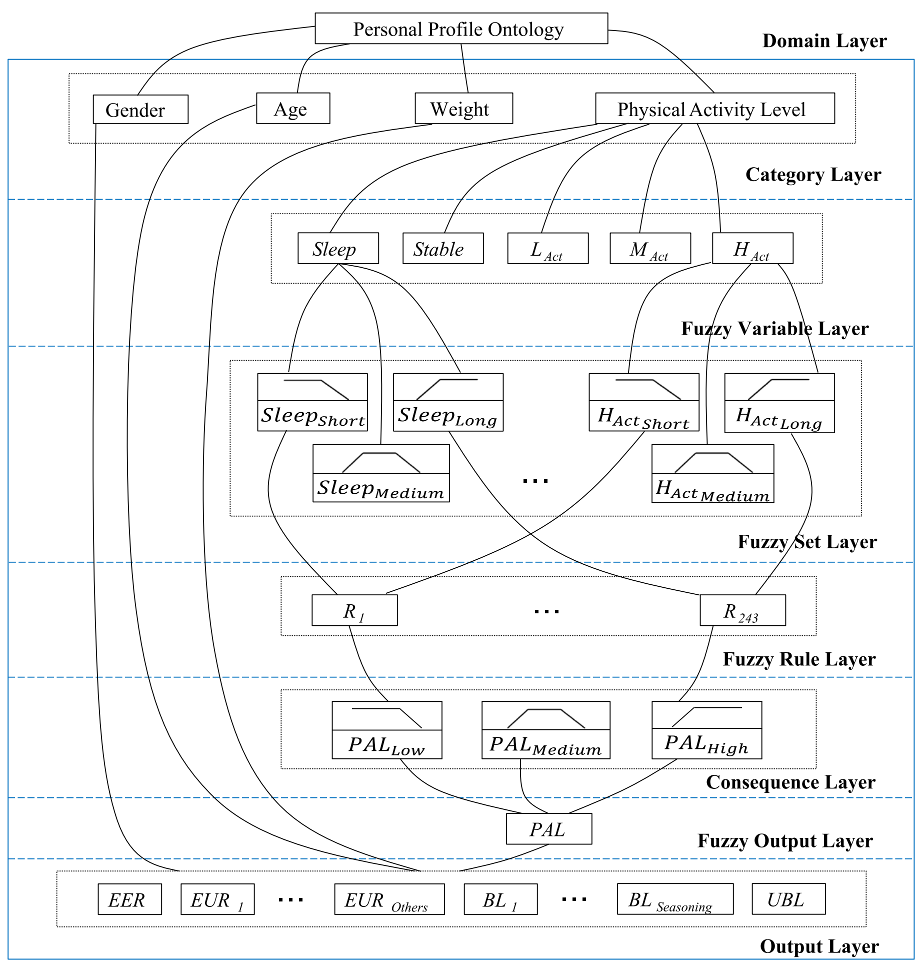


Table 4 Relationship between physical activity level and the number of hours of taking-up activities (Ministry of Health, Labour and Welfare of Japan 2010)

Fuzzy variable	Descriptions of the taking-up activities	Examples of taking-up activities	PAL based on taking-up-activity number of hours		
			PAL_{Low}	PAL_{Medium}	PAL_{High}
Sleep	Sleeping	Sleep	7–8	7–8	7
Stable	Stable activity	Watching TV, conversation, eating, desk working, bathing, or sitting	12–13	11–12	10
L_{Act}	Light exercise	Walking slowly, cooking, stretching, or playing music when sitting	3–4	4	4–5
M_{Act}	Medium exercise	Walking moderately, riding a bicycle, playing with child, playing music when standing, or playing valleyball/badminton	0–1	1	1–2
H_{Act}	Heavy exercise	Running, moving furniture, going up the stairs, climbing mountains, playing soccer/tennis/skiing, or swimming	0	0	0–1

Ranges of low-level, medium-level, and high-level physical activity, that is, PAL_{Low}, PAL_{Medium}, and PAL_{High}, are 1.40–1.60, 1.60–1.9, and 1.9–2.20, respectively

- Fuzzy variable layer: According to Ministry of Health, Labour and Welfare of Japan (2010), PAL is classified into three levels: low, medium, and high. If PAL is low, medium, or high, it means that the value of PAL is about 1.40–1.60, 1.60–1.9, or 1.9–2.20, respectively (Ministry of Health, Labour and Welfare of Japan 2010). Additionally, different activities, like sleeping, watching TV, or making light/medium/heavy exercise, have a different effect on the physical activity level. Table 4 shows the relationship between the physical activity level and the number of hours of taking-up activities. Take sleeping as an example. Table 4 shows PAL becomes lower when hours of sleeping are increased. This is because the longer you sleep, the less calories you need. On the contrary, the longer you do an exercise, the more calories you need. That is, your physical activity level becomes higher. Based on the above discussions, five fuzzy variables, namely, Sleep, Stable, L_{Act}, M_{Act}, and H_{Act}, are set in this layer to express the number of hours that one person takes up some activities like sleeping, doing stable activity, making light/medium/heavy exercise.
- Fuzzy set layer: The layer is composed of some fuzzy sets. For example, fuzzy variable Sleep has three fuzzy sets, namely "$Sleep_{Short}$, $Sleep_{Medium}$, and $Sleep_{Long}$", to present the linguistics of sleeping for a short, medium, and long number of hours, respectively. Fuzzy sets "$Stable_{Short}$, $Stable_{Medium}$, $Stable_{Long}$", "$L_{ActShort}$, $L_{ActMedium}$, $L_{ActLong}$", "$M_{ActShort}$, $M_{ActMedium}$, $M_{ActLong}$", and "$H_{ActShort}$, $H_{ActMedium}$, $H_{ActLong}$" are defined for fuzzy variables Stable, L_{Act}, M_{Act}, and H_{Act}, respectively.
- Fuzzy rule layer: There are 243 rules composed to express relationship between the fuzzy set layer and the consequence layer.
- Consequence layer: Fuzzy variable physical activity level (PAL) has three fuzzy sets, namely, PAL_{Low}, PAL_{Medium}, and PAL_{High}. According to the stored knowledge in the constructed ontology, the inferred output PAL is obtained in the fuzzy output layer.
- Output layer: From the information of gender, age, and weight in the category layer and PAL in the fuzzy output layer, EER is obtained in the output layer based on the inferred PAL. EUR of each group is defined based on the obtained EER. For example, EURs of $List_1$, $List_2$, $List_3$, $List_4$, $List_5$, $List_6$, $Group_{Seasoning}$, and $Group_{Others}$ are EUR_1, EUR_2, EUR_3, EUR_4, EUR_5, EUR_6, $EUR_{Seasoning}$, and EUR_{Others}, respectively. Herein, BL_1, BL_2, BL_3, BL_4, BL_5, BL_6, and $BL_{Seasoning}$ represent the balanced level for $List_1$, $List_2$, $List_3$, $List_4$, $List_5$, $List_6$, and $Group_{Seasoning}$, respectively, whereas UBL represents the unbalanced level for $Group_{Others}$. This is because the less number of units for $Group_{Others}$ the involved subject consumes, the healthier he/she becomes.

3.3 FML-based Japanese dietary assessment ontology

According to the concepts of the FEL, Fig. 4 shows the seven-layer structure of the constructed FML-based dietary assessment ontology. Its descriptions are as follows:

- Domain layer: This layer represents the domain name of the ontology.
- Category layer: Some food items only belong to one food group whereas some others belong to more than one food group. For example, French toast belongs to $List_1$, $List_3$, $List_4$, $List_5$, and $Group_{Seasoning}$ and it contains nutrients carbohydrate, protein, and fat. Additionally, $List_1$, $List_2$, $List_4$, and $List_6$ contain carbohydrate. $List_1$, $List_3$, $List_4$, and $List_6$ contain protein. There exits fat in $List_3$, $List_4$, $List_5$, and $List_6$. After consuming one food item, we can

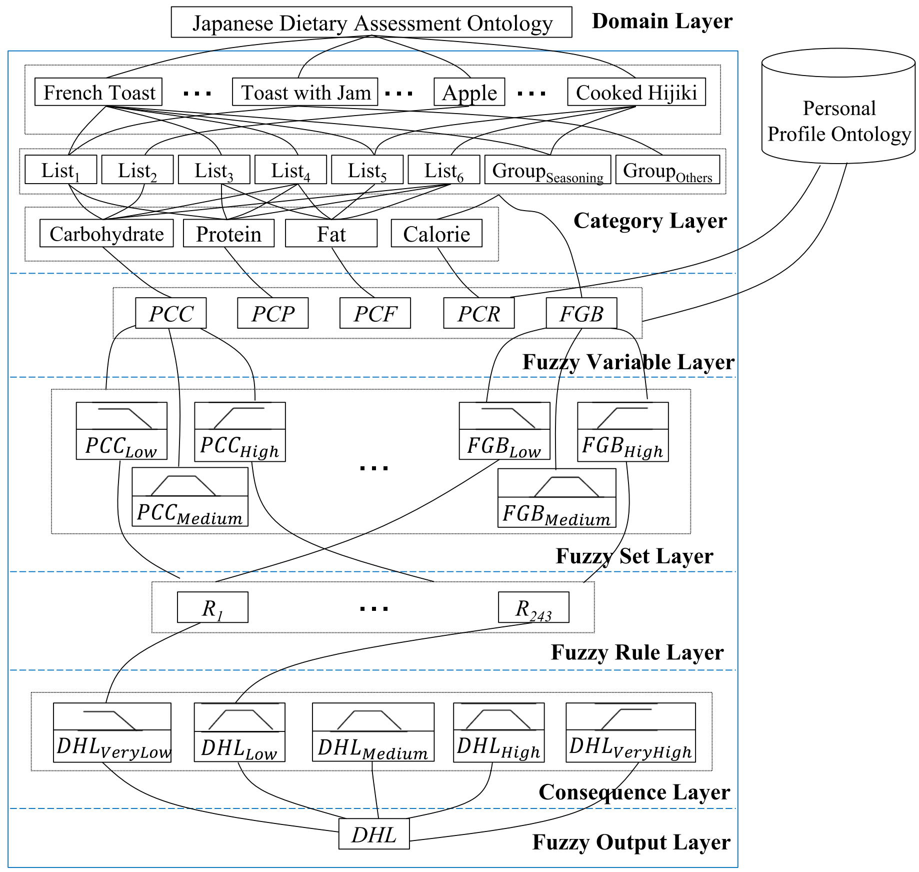


Fig. 4 FML-based dietary assessment ontology

acquire the necessary energies from the calories this food item contains.

- Fuzzy variable layer: There are fuzzy sets, namely, percentage of calories from carbohydrate (PCC), percentage of calories from protein (PCP), percentage of calories from fat (PCF), and percentage of caloric ratio (PCR) in this layer to evaluate the consuming level of each nutrient and calorie. The Food Group Balance (FGB) is also set to evaluate how balanced the person's eaten food items. PAL is inferred according to the constructed personal profile ontology. PCR and FGB have a relationship with PAL.
- Fuzzy set layer: The fuzzy sets, namely, "PCC_{Low}, PCC_{Medium}, PCC_{High}", "PCP_{Low}, PCP_{Medium}, PCP_{High}", "PCF_{Low}, PCF_{Medium}, PCF_{High}", "PCR_{Low}, PCR_{Medium}, PCR_{High}", and "FGB_{Low}, FGB_{Medium}, FGB_{High}" are defined in this layer to describe the linguistic terms of the fuzzy variables PCC, PCP, PCF, PCR, and FGB.
- Fuzzy rule layer: There are 243 fuzzy rules, R_1, R_2, …, and R_{243}, defined in this layer.
- Consequence layer: This layer represents the linguistic meanings of Dietary Healthy Level (DHL), including $DHL_{VeryLow}$, DHL_{Low}, DHL_{Medium}, DHL_{High}, and $DHL_{VeryHigh}$.
- Output layer: Based on the constructed ontology, the inferred output DHL is obtained in this layer.

4 Healthy diet assessment mechanism applied to Japanese food

In this section, the diet-balanced analysis mechanism is first introduced in Sect. 4.1. Next, the physical activity level fuzzy inference mechanism and food group fuzzy set construction mechanism are described in Sects. 4.2 and 4.3, respectively. Finally, the dietary healthy level fuzzy inference mechanism is described in Sect. 4.4.

4.1 Diet-balanced analysis mechanism

The acquired calories are obtained from the fact how many units consumed in each food group. For this reason, PCC, PCP, and PCF are set to represent the percentage of calories from carbohydrate, protein, and fat, respectively. The values of PCC, PCP, PCF are acquired from the collected meal records and the pre-defined dietary assessment ontology. The calories that carbohydrate, protein, and fat per gram contain are 4, 4, and 9 kcal, respectively. Based on Table 1, PCC, PCP, and PCF are calculated by Eqs. (3), (4), and (5), respectively. The actual consuming calories are calculated by Eq. (6) because one unit is 80 kcal in FEL. Hence, daily EER is acquired according to the involved subject's BMR

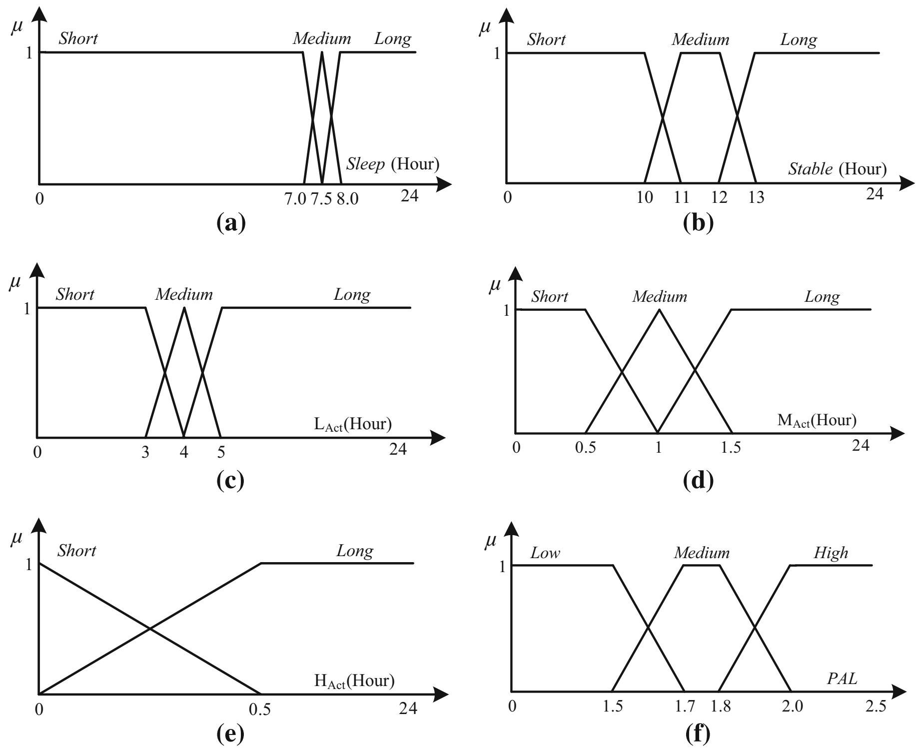


Fig. 5 Fuzzy sets for fuzzy variables **a** Sleep, **b** Stable, **c** L_{Act}, **d** M_{Act}, **e** H_{Act}, and **f** PAL

and daily inferred PAL so PCR is calculated by (7).

$$\text{PCC} = \frac{4 \times (18m_1 + 20m_2 + 6m_4 + 13m_6)}{\text{Actual consuming calories}} \times 100\,\% \qquad (3)$$

$$\text{PCP} = \frac{4 \times (2m_1 + 9m_3 + 4m_4 + 5m_6)}{\text{Actual consuming calories}} \times 100\,\% \qquad (4)$$

$$\text{PCF} = \frac{9 \times (5m_3 + 5m_4 + 9m_5 + m_6)}{\text{Actual consuming calories}} \times 100\,\% \qquad (5)$$

$$\text{Actual consuming calories (kcal)} = \left(\sum_{i=1}^{8} m_i\right) \times 80\,\text{kcal} \qquad (6)$$

where (i) m_1, m_2, m_3, m_4, m_5, m_6, m_7, and m_8 represent the number of units from List_1, List_2, List_3, List_4, List_5, List_6, $\text{Group}_{\text{Seasoning}}$, and $\text{Group}_{\text{Others}}$, respectively.

$$\text{PCR} = \frac{\text{Actual consuming calories}}{\text{EER}} \times 100\,\% \qquad (7)$$

4.2 Physical activity level fuzzy inference mechanism

The value of the basal metabolism standard (kcal/kg/day) varies with each person's gender, age, and weight. On the other hand, the value of PAL is decided by the metabolic equivalent (MET). MET is a physiological measure to express the energy cost of physical activities and is defined as the ratio of metabolic rate during a specific physical activity to a reference metabolic rate (Ainsworth et al. 2000). Moreover, different humans have different exercise, eating, and dietary habits so that PAL is changeable every day even for the same person (Cabinet Office, Government of Japan 2012). According to (Ministry of Health, Labour and Welfare of Japan 2010), EER per day is calculated by Eqs. (1) and (2) according to daily physical activity level. For these reasons, the fuzzy variables, namely, Sleep, Stable, L_{Act}, M_{Act}, and H_{Act} are defined in this section by referring to Table 4. Figure 5a–f shows the fuzzy sets for fuzzy variables Sleep, Stable, L_{Act}, M_{Act}, H_{Act}, and PAL, respectively.

Table 5 Fuzzy relation weight and fuzzy term weight for fuzzy variables Sleep, Stable, L_{Act}, M_{Act}, and H_{Act}

No.	Fuzzy variable	Fuzzy relation weight	Fuzzy linguistic term (Fuzzy term weight)		
1	Sleep	1	Short (2)	Medium (1)	Long (0)
2	Stable	1	Short (2)	Medium (1)	Long(0)
3	L_{Act}	1	Short (0)	Medium (1)	Long (2)
4	M_{Act}	1	Short (0)	Medium (1)	Long (2)
5	H_{Act}	1	Short (0)	None	Long (2)

The rule base with 243 fuzzy rules is designed by referring the proposed approach in (Lee et al. 2012) and domain experts' opinions. However, different domain experts have different opinions. The 5-point scale and 0–1–2-point scale are considered for the fuzzy relation weight and the fuzzy term weight, respectively. Table 5 shows the fuzzy relation

Table 6 Score_N range of the output fuzzy variable PAL

Fuzzy term	Low	Medium	High
S_N range	[0, 0.33]	(0.33, 0.67]	(0.67, 1]

weight of each input fuzzy variable and its related fuzzy term weight. Take one fuzzy rule for an example. Assume there is one fuzzy rule, and its if-part is "IF Sleep is Short AND Stable is Short AND L_{Act} is Short AND M_{Act} is Short AND H_{Act} is Short". Computed by Eq. (8), this fuzzy rule's score (Score) can be obtained according to Table 5. After the normalization, the normalized rule score (Score_N) is acquired by Eq. (9), where $\text{Score}_{\text{min}}$ and $\text{Score}_{\text{max}}$ are the minimum and maximum rule scores, respectively. Based on the normalized rule score, the then-part of the fuzzy rule could be determined according to the value of Score_N that lies in the interval [0, 1]. Table 6 shows the range of PAL when we divide PAL into three groups. Finally, the completed fuzzy rule is represented as "IF Sleep is Short AND Stable is Short AND L_{Act} is Short AND M_{Act} is Short AND H_{Act} is Short THEN PAL is Medium". The PAL is then inferred by carrying out the proposed method to indicate how much level of physical activity.

$$\text{Score} = \frac{\sum \text{Fuzzy relation weight} \times \text{Fuzzy term weight}}{\sum \text{Fuzzy relation weight}} \tag{8}$$

$$\text{Score}_N = \frac{\text{Score} - \text{Score}_{\text{min}}}{\text{Score}_{\text{max}} - \text{Score}_{\text{min}}} \tag{9}$$

4.3 Food group fuzzy set construction mechanism

In this section, we consider the food group balance. The more a variety of foods that one person consumes, the more balanced the meal is. The balance level is an important factor to indicate how wide a variety of the eaten food items involve. This is because lack of some nutrients beneficial for our bodies like fiber cannot be known when we only consider the balance of carbohydrate, protein, and fat. Therefore, the involved dieticians also plan one-day unique consuming units of each food group for each person. Assume one-day EER is 2,240 kcal so that EURs for List_1, List_2, List_3, List_4, List_5, List_6, $\text{Group}_{\text{Seasoning}}$ (EUR_1, EUR_2, EUR_3, EUR_4, EUR_5, EUR_6, $\text{EUR}_{\text{Seasoning}}$), are 15, 1.5, 5, 3, 1.5, 1, and 1 unit, respectively. Under such an assumption, the fuzzy sets for fuzzy variables EUR_1, EUR_2, EUR_3, EUR_4, EUR_5, EUR_6, and $\text{EUR}_{\text{Seasoning}}$ are constructed and shown in Fig. 6a–g, respectively. Moreover, the consumed units of $\text{Group}_{\text{Others}}$ also affect the balance of the intake food. Owing to the present life style, most people purchase some unhealthy foods such as liquor, juice, and sweets as their meals at the store. However, such kind of foods usually contain more sugar than the natural food, and it is harmful for our bodies if people consume too much sugar. The recommended units of $\text{Group}_{\text{Others}}$ are less than 3 units per day. Figure 6h shows the fuzzy set for fuzzy variable $\text{EUR}_{\text{Others}}$. As above-mentioned discussions, daily EER varies with the inferred PAL. Therefore, the parameters of begin support (BS), begin core (BC), end core (EC), and end support (ES) for fuzzy sets EUR_1, EUR_2, EUR_3, EUR_4, EUR_5, EUR_6, and $\text{EUR}_{\text{Seasoning}}$ will be changed accordingly. For example, if one-day EER becomes 2,016 kcal, then parameters of BS, BC, EC, and ES of fuzzy set EUR_1 are changed from [8, 12, 18, 21] to [7.2, 10.8, 16.2, 18.9]. FGB is calculated by Eq. (10).

$$\begin{aligned} \text{FGB} = {} & \text{BL}_1 + \text{BL}_2 + \text{BL}_3 + \text{BL}_4 + \text{BL}_5 \\ & + \text{BL}_6 + \text{BL}_{\text{Seasoning}} - \text{UBL} \end{aligned} \tag{10}$$

where (i) BL_1, BL_2, BL_3, BL_4, BL_5, BL_6, and $\text{BL}_{\text{Seasoning}}$ represent the balanced level for List_1, List_2, List_3, List_4, List_5, List_6, and $\text{Group}_{\text{Seasoning}}$, respectively, and each value is bounded in the interval of [0, 1]. In other words, BL_1, BL_2, BL_3, BL_4, BL_5, BL_6, and $\text{BL}_{\text{Seasoning}}$ represent the membership degree of fuzzy sets EUR_1, EUR_2, EUR_3, EUR_4, EUR_5, EUR_6, and $\text{EUR}_{\text{Seasoning}}$, respectively. The higher the value, the healthier the meal. (ii) UBL denotes the unbalanced level for $\text{Group}_{\text{Others}}$, that is, the membership degree of fuzzy set $\text{EUR}_{\text{Others}}$. The value is also bounded in the interval of [0, 1]. The lower the value, the healthier the meal.

4.4 Dietary healthy level fuzzy inference mechanism

Based on the dietary assessment ontology and the inferred PAL, DHL is inferred by the dietary healthy level fuzzy inference mechanism. Generally speaking, the recommended PCC, PCP, and PCF are 55–65, 15–18, and 20–24 %, respectively. Besides, the daily actual consuming calories for common people recommend that the range should be between 95 and 105 % of EER, and FGB is bounded in the interval of $[-1, 7]$.

Figure 7a–f shows fuzzy sets for fuzzy variables PCC, PCP, PCF, PCR, FGB, and DHL, respectively. The rule base with 243 fuzzy rules is composed of five input fuzzy variables, namely, PCC, PCP, PCF, PCR, and FGB, and each fuzzy variable has three linguistic terms, namely, Low, Medium, and High. Table 7 shows the following information, including (i) PCF, PCR, and FGB are equally important, (ii) PCF, PCR, and FGB play a more important role than PCC and PCP, and (iii) PCP has a much bigger effect on assessing the dietary healthy level than PCC does. Table 8 shows Score_N range of the output fuzzy variable DHL. Based on Tables 7 and 8, the completed fuzzy rule is represented as "IF PCC is Medium AND PCP is Medium AND PCF is Medium AND PCR is Medium AND FGB is High THEN DHL is Very-

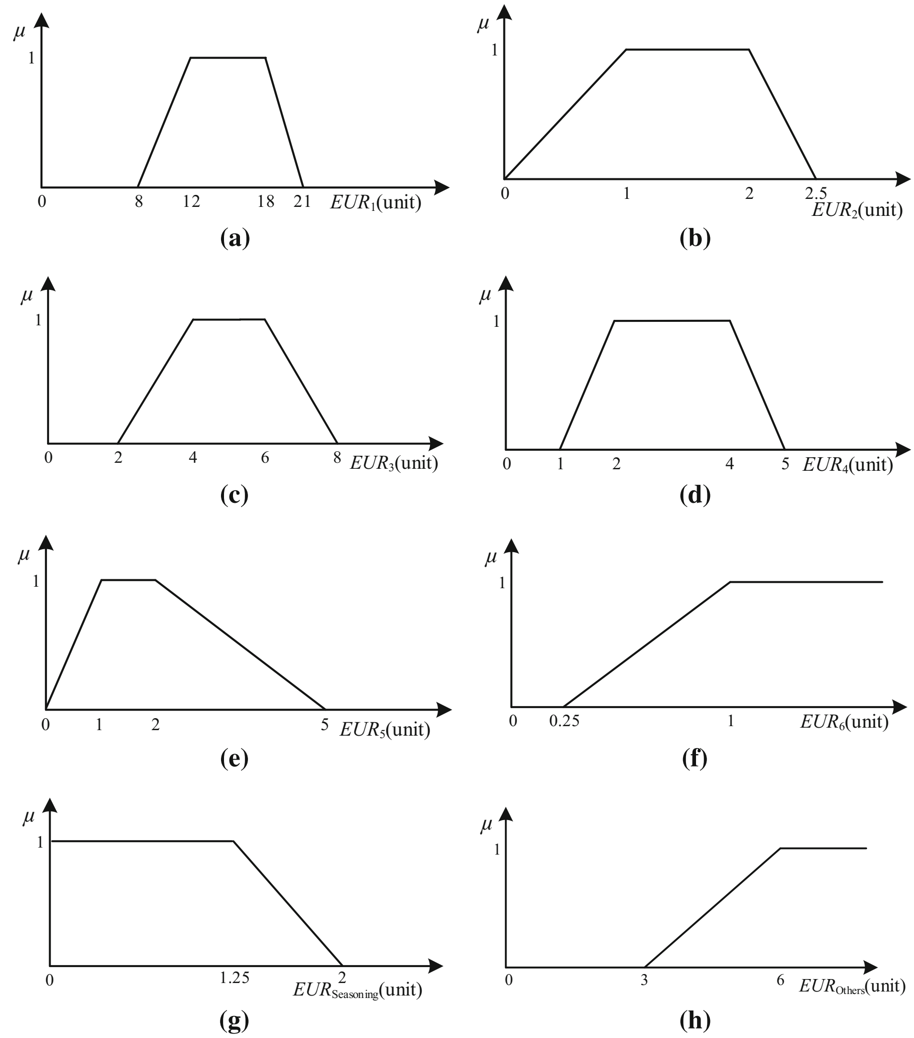


Fig. 6 Fuzzy sets for fuzzy variables **a** EUR_1, **b** EUR_2, **c** EUR_3, **d** EUR_4, **e** EUR_5, **f** EUR_6, **g** $EUR_{Seasoning}$, and **h** EUR_{Others} when one-day EER is 2,240 kcal (Kurozumi et al. 2013)

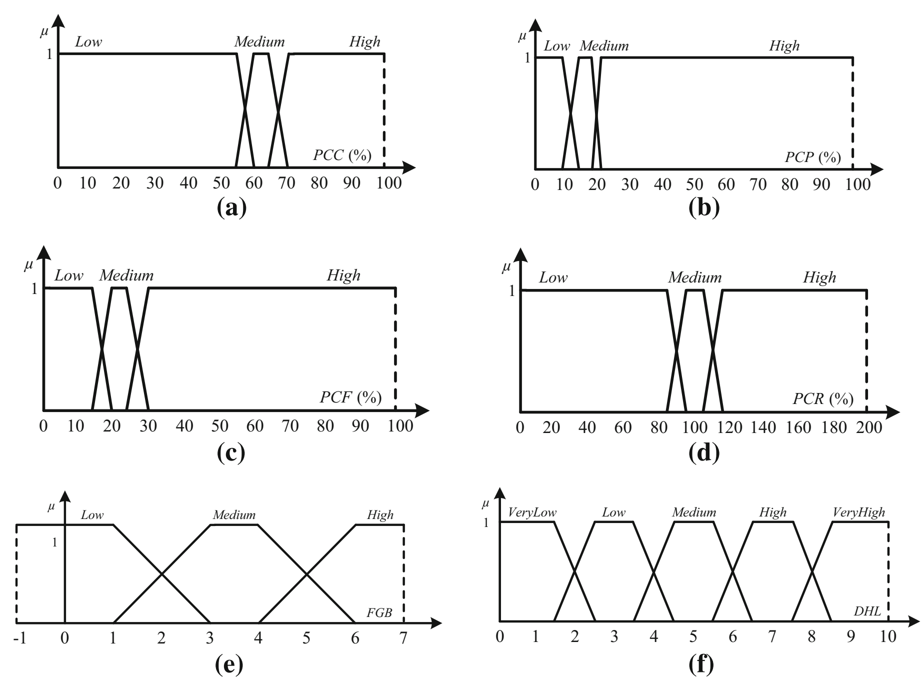


Fig. 7 Fuzzy sets for fuzzy variables **a** PCC, **b** PCP, **c** PCF, **d** PCR, **e** FGB, and **f** DHL (Kurozumi et al. 2013)

Table 7 Fuzzy relation weight and fuzzy term weight for fuzzy variables PCC, PCP, PCF, PCR, and FGB

No.	Fuzzy variable	Fuzzy relation weight	Fuzzy linguistic term (Fuzzy term weight)		
1	PCC	1	Low (1)	Medium (2)	High (1)
2	PCP	2	Low (0)	Medium (2)	High (0)
3	PCF	3	Low (1)	Medium (2)	High (0)
4	PCR	3	Low (0)	Medium (2)	High (1)
5	FGB	3	Low (0)	Medium (1)	High (2)

Table 8 Score$_N$ range of the output fuzzy variable DHL (Lee et al. 2012)

Fuzzy term	Very Low	Low	Medium	High	Very High
S_N Range	[0, 0.2]	(0.2, 0.4]	(0.4, 0.6]	(0.6, 0.8]	(0.8,1.0]

High" after implementing Eqs. (8) and (9). Table 9 shows partial knowledge base and rule base of the dietary healthy level fuzzy inference mechanism.

5 Experimental results

This section shows the experimental results. The basic profile of the involved subject and collected records for 60 days are described in Sect. 5.1. Next, we give some analysis and curves to explain the performance of the proposed mechanism in Sect. 5.2.

5.1 Basic profile and collected records

The involved subject is one 24-year-old and 64 kg-weight Japanese male. According to Ministry of Education, Culture Sports Science and Technology of Japan (2013), his daily basal metabolism standard is 23 kcal/kg. Therefore, BMR is 1,495 kcal/day based on Eq. (2). Table 10 shows the related information if we assume this involved subject's EER is 2,240 kcal (28 units). We can observe that EUR values for List$_1$, List$_2$, List$_3$, List$_4$, List$_5$, List$_6$, and Group$_{\text{Seasoning}}$, i.e. EUR$_1$, EUR$_2$, EUR$_3$, EUR$_4$, EUR$_5$, EUR$_6$ and EUR$_{\text{Seasoning}}$, are 15, 1.5, 5, 3, 1.5, 1, and 1 unit, respectively. As a result, the contained grams of carbohydrate, protein, and fat are 331, 92, and 54.5 g, respectively, according to Table 1.

Table 11 shows this involved subject partial daily meals, including Day 1, Day 2, and Day 60. Then, the involved dietician converts the nutrient facts of each food item into how many units each food group should contain based on FEL standard. Table 12 shows the values of units that each food group contains for each food item, where "–" denotes this food item does not include the nutrient that the corresponding food group provides.

5.2 Descriptions of the performance

In our previous work (Kurozumi et al. 2013), the values of PAL and EER are fixed during the experimental period. However, they are variable each day in this paper. The values of PCR and FGB are changed according to daily physical activity. Table 13 shows partial data of Sleep, Stable, L$_{\text{Act}}$, M$_{\text{Act}}$, H$_{\text{Act}}$, inferred PAL, and acquired EER for 60 days. Table 14 shows the partial input data ofPCC, PCP, PCF, PCR, FGB, and partial inferred DHL for 60 days, where DHL$_{\text{DO}}$ denotes the desired output given by the involved dietician. Additionally, to evaluate the performance of the proposed mechanism, we do two different experiments to infer DHL. Experiment 1 considers the fuzzy relation and fuzzy term weights (see Table 7) to construct the fuzzy rules. Experiment 2 establishes the fuzzy rules without taking the fuzzy relation and fuzzy term weights into consideration. DHL$_{\text{FML}}$ and DHL$_{\text{FIX}}$ are the experimental results after doing Experiments 1 and 2, respectively. Figure 8 shows the curves of DHL$_{\text{DO}}$, DHL$_{\text{FML}}$, and DHL$_{\text{FIX}}$ for 60-day meals. Figure 9 show the curves of absolute values $|\text{DHL}_{\text{DO}} - \text{DHL}_{\text{FML}}|$ and $|\text{DHL}_{\text{DO}} - \text{DHL}_{\text{FIX}}|$. The lower the difference, the closer DHL$_{\text{DO}}$. Mean squared error (MSE) values, calculated by Eq. (11), for Experiment 1 and Experiment 2 are 1.73 and 1.87, respectively. This means we can get a much better performance when we consider the fuzzy weights to construct the fuzzy rules.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{11}$$

where, Y_i represents the inferred result via the proposed approach, $\check{Y}_i$ denotes the desired output recommended by the domain expert, and n is the number of the meal records.

Next, we use experimental results about Days 5 and 43, Days 45 and 59, and Day 32 to make discussions as follows:

- Days 5 and 43: Table 14 indicates that the values of PCC, PCP, PCF, and PCR are almost at the same level. For both Days 5 and 43, PCC is Low, PCP is High, PCF is High, and PCR is Low, but FGB is Low for Day 5 and Medium for Day 43. The difference in FGB causes to have a different DHL, that is, DHL is VeryLow for Day 5 but DHL is Low. Hence, FGB is an important factor to decide how much healthy level the eaten food items involve.
- Days 45 and 59: Table 14 indicates that the values of PCC, PCP, PCR, and FGB are almost at the same level. For these 2 days, PCC is Low, PCP is Medium, PCF is High, and FGB is Medium, but PCR is Low for Day 45 and Medium for Day 59. However, the difference in PCR causes to have a different DHL, that is, DHL is Medium for Day 45 but DHL is Low for Day 59. Hence, PCR is also an important

Table 9 Partial FML to infer DHL

```xml
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<FuzzyController ip="localhost" name="">
  <KnowledgeBase>
    <FuzzyVariable domainleft="0" domainright="100" name="PCC" scale="" type="input">
      <FuzzyTerm name="low" hedge="Normal">
        <TrapezoidShape Param1="0" Param2="0" Param3="50" Param4="55" />
      </FuzzyTerm>
      <FuzzyTerm name="medium" hedge="Normal">
        <TrapezoidShape Param1="50" Param2="55" Param3="65" Param4="70" />
      </FuzzyTerm>
      <FuzzyTerm name="high" hedge="Normal">
        <TrapezoidShape Param1="65" Param2="70" Param3="100" Param4="100" />
      </FuzzyTerm>
    </FuzzyVariable>
…
    <FuzzyVariable domainleft="0" domainright="10" name="DHL" scale="" type="output">
      <FuzzyTerm name="verylow" hedge="Normal">
        <TrapezoidShape Param1="0" Param2="0" Param3="1.5" Param4="2.5" />
      </FuzzyTerm>
      <FuzzyTerm name="low" hedge="Normal">
        <TrapezoidShape Param1="1.5" Param2="2.5" Param3="3.5" Param4="4.5" />
      </FuzzyTerm>
      <FuzzyTerm name="medium" hedge="Normal">
        <TrapezoidShape Param1="3.5" Param2="4.5" Param3="5.5" Param4="6.5" />
      </FuzzyTerm>
      <FuzzyTerm name="high" hedge="Normal">
        <TrapezoidShape Param1="5.5" Param2="6.5" Param3="7.5" Param4="8.5" />
      </FuzzyTerm>
      <FuzzyTerm name="veryhigh" hedge="Normal">
        <TrapezoidShape Param1="7.5" Param2="8.5" Param3="10" Param4="10" />
      </FuzzyTerm>
    </FuzzyVariable>
  </KnowledgeBase>
<RuleBase activationMethod="MIN" andMethod="MIN" orMethod="MAX" name="RuleBase1" type="mamdani">
<Rule name="Rule1" connector="and" weight="1" operator="MIN">
      <Antecedent>
        <Clause>
          <Variable>PCC</Variable>
          <Term>low</Term>
        </Clause>
        <Clause>
          <Variable>PCP</Variable>
          <Term>low</Term>
        </Clause>
        <Clause>
          <Variable>PCF</Variable>
          <Term>low</Term>
        </Clause>
        <Clause>
          <Variable>PCR</Variable>
          <Term>low</Term>
        </Clause>
        <Clause>
          <Variable>FGB</Variable>
          <Term>low</Term>
        </Clause>
      </Antecedent>
      <Consequent>
        <Clause>
          <Variable>DHL</Variable>
          <Term>verylow</Term>
        </Clause>
      </Consequent>
    </Rule>
<Rule name="Rule243" connector="and" weight="1" operator="MIN">
      <Antecedent>
        <Clause>
          <Variable>PCC</Variable>
          <Term>high</Term>
        </Clause>
        <Clause>
          <Variable>PCP</Variable>
          <Term>high</Term>
        </Clause>
        <Clause>
          <Variable>PCF</Variable>
          <Term>high</Term>
        </Clause>
        <Clause>
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        </Clause>
      </Antecedent>
      <Consequent>
        <Clause>
          <Variable>DHL</Variable>
          <Term>low</Term>
        </Clause>
      </Consequent>
    </Rule>
…
</RuleBase>
</FuzzyController>
```

Table 10 Related information in case of 28 units per day (EER is 2,240 kcal) (The Japan Diabetes Society 2002)

Contained gram from nutrient (g)			EUR value for different food list and food group (unit)						
Carbohydrate	Protein	Fat	$List_1$ EUR_1	$List_2$ EUR_2	$List_3$ EUR_3	$List_4$ EUR_4	$List_5$ EUR_5	$List_6$ EUR_6	$Group_{Seasoning}$ $EUR_{Seasoning}$
331	92	54.5	15	1.5	5	3	1.5	1	1

Table 11 Partial collected meal records for 60 days

Day	Meal type	Food name	Serving	Standard weight/per serving
1	Breakfast	Bread with butter and jam	1	60 g bread
1	Lunch	Omurice	1	250 g rice
1	Dinner	Kimchi pot	1	200 g pork
1	Dinner	Grain rice	1	69 g
2	Breakfast	None	0	
2	Lunch	Takoyaki	1	8 pieces
2	Lunch	Rice	1	66 g
2	Dinner	Chicken tatsuta with seaweed (box)	1	Include rice, cabbage, dressing
⋮	⋮	⋮	⋮	⋮
60	Breakfast	Rice	1	66 g
60	Breakfast	Miso soup with soymilk	1	85 g
60	Breakfast	Broiled yellowtails	1	90 g
60	Lunch	Nagasaki dish of noodles with various toppings	1	120 g
60	Lunch	Spring roll	1	27 g
60	Lunch	Salad with cheese	1	20 g
60	Dinner	Margherita	1	

Table 12 Fifteen food items' units for different food groups based on FEL

No	Food name	Calorie (kcal)	Unit of different food group							
			$List_1$	$List_2$	$List_3$	$List_4$	$List_5$	$List_6$	$Group_{Seasoning}$	$Group_{Others}$
1	Bread with butter and jam	212	2.0	–	–	–	–	–	–	0.7
2	Omurice	843	4.4	–	2.4	–	2.5	0.3	0.9	–
3	Kimchi pot	442	–	–	5.0	–	–	0.3	0.3	–
4	Grain rice	244	3.1	–	–	–	–	–	–	–
5	Jam toast	212	2	–	–	–	–	–	–	0.7
6	Takoyaki	240	2.5	–	0.4	–	0.1	–	–	–
7	Rice	235	2.9	–	–	–	–	–	–	–
8	Chicken tatsuta with seaweed (box)	680	4.0	–	3.5	–	0.8	0.2	–	–
9	Rice	235	2.9	–	–	–	–	–	–	–
10	Miso soup with soymilk	128	–	–	0.5	–	–	0.6	0.5	–
11	Broiled yellowtails	304	–	–	3.0	–	0.4	0.1	0.3	–
12	Nagasaki dish of noodles with various toppings	552	3.3	–	1.3	–	1.5	0.5	0.3	–
13	Spring roll	368	1.3	–	1.3	–	1.5	0.2	0.3	–
14	Salad with cheese	144	–	–	1.0	–	0.7	0.1	–	–
15	Margherita	432	2.0	–	2.0	–	1.0	0.4	–	–

factor to decide how much healthy level the eaten food items involve.

- Day 32: The results of DHL_{DO} and DHL_{FML} are 4 (between Low and Medium Healthy) and 7.44 (High Healthy), respectively, and the difference between DHL_{DO} and DHL_{FML} is the biggest among 60-day meals. But, input values of PCC, PCF, PCF, PCR, and FGB are 54.4, 17.1, 27.75, 102.5, and 3.92 % so we can know that PCC is Medium, PCP is Medium, PCF is High, PCR is Medium, and FGB is Medium. Under such a situation, the proposed approach regards DHL as High. However, the desired output given by dietician is between Low and Medium

Table 13 Partial data of Sleep, Stable, L_{Act}, M_{Act}, H_{Act}, inferred PAL, and acquired EER for 60 days

Day	Sleep (h)	Stable (h)	L_{Act} (h)	M_{Act} (h)	H_{Act} (h)	PAL	EER (kcal)
1	8.33	10.8	4.20	0.28	0.41	1.67	2,497
2	5.37	14.3	3.55	0.39	0.41	1.65	2,467
3	5.38	13.7	3.81	0.87	0.25	1.64	2,452
4	6.98	14.1	2.29	0.44	0.15	1.45	2,168
5	7.84	11.4	3.60	0.78	0.36	1.58	2,362
6	9.27	8.7	5.12	0.84	0.01	1.76	2,631
7	6.94	11.5	4.29	0.57	0.68	1.87	2,796
8	9.17	10.7	3.08	0.95	0.07	1.45	2,168
9	8.74	11.9	2.41	0.74	0.17	1.49	2,228
10	5.16	14.5	3.35	0.73	0.19	1.52	2,272
				⋮			
32	9.25	10.9	3.07	0.58	0.19	1.41	2,108
				⋮			
43	7.97	11.0	2.72	1.34	0.99	1.75	2,616
				⋮			
45	7.71	12.1	3.06	0.77	0.38	1.57	2,347
				⋮			
51	8.97	10.8	2.41	0.91	0.88	1.67	2,497
52	5.10	16.0	2.01	0.70	0.21	1.50	2,243
53	7.83	12.0	3.37	0.64	0.09	1.47	2,198
54	9.89	10.1	2.90	0.86	0.18	1.62	2,422
55	5.07	12.8	5.24	0.60	0.23	1.86	2,781
56	8.07	11.2	3.18	1.08	0.41	1.68	2,512
57	6.10	13.0	4.08	0.55	0.26	1.80	2,691
58	9.67	10.0	3.58	0.70	0.02	1.57	2,347
59	6.21	13.0	3.81	0.86	0.12	1.66	2,482
60	8.89	10.9	2.40	1.46	0.34	1.71	2,556

Healthy. In the future, we need to improve the constructed fuzzy rules.

- Table 14 shows that the partial values of DHL_{DO} and DHL_{FML} whose range is from 1.5 to 7.5 and from 1.02 to 7.75 for 60 meals, respectively. If we classify DHL_{FML} into three ranges, namely, [0, 2], (2, 6], and (6, 10], MSE between DHL_{DO} and DHL_{FML} is 2.08, 1.05, and 4.97, respectively. Our proposed mechanism performs better for medium-healthy meals and it is necessary to improve the performance of high-healthy meals.

6 Discussions and conclusions

In this paper, we present an FML-based mechanism to assess Japanese dietary healthy level based on FEL standard. Additionally, we also build Japanese dietary standard ontology, FML-based personal profile ontology, and FML-based dietary assessment ontology. Some discussions about the difference between the present paper and previous works (Lee et al. 2010a, c, 2012; Kurozumi et al. 2013) are as follows:

- The main difference between the present paper and previous works (Lee et al. 2010a, c, 2012; Kurozumi et al. 2013) is to take physical activity level (PAL) into consideration. According to Ministry of Health, Labour and Welfare of Japan (2010), the estimated energy requirement (EER) is supposed to be changeable depending on each person's daily activities and daily basal metabolic rate (BMR). As a result, in this paper, we consider the involved subject's number of hours of sleeping, taking-up stable activity, and doing light, medium or heavy exercises to infer daily PAL. And, we can acquire daily EER and daily EUR of each food group. Therefore, fuzzy sets EUR_1, EUR_2, EUR_3, EUR_4, EUR_5, EUR_6, $EUR_{Seasoning}$, and EUR_{Others} are constructed according to daily EER and

Table 14 Partial data of PCC, PCP, PCF, PCR, FGB, and DHL for 60 days

Day	PCC (%)	PCP (%)	PCF (%)	PCR (%)	FGB	DHL_{DO}	DHL_{FML}	DHL_{FIX}
1	40.8	20.2	31.0	69.8	3.08	4.0	1.52	1.52
2	59.7	19.0	21.6	46.8	1.83	4.0	5.10	5.10
3	52.4	11.6	21.6	34.3	2.84	6.0	4.70	4.70
4	66.7	10.7	10.5	94.5	1.90	3.5	4.45	4.45
5	35.6	28.1	29.1	62.8	2.00	2.0	1.53	1.53
6	54.9	16.9	23.7	53.4	3.86	4.5	6.98	6.98
7	61.2	11.8	28.0	44.6	2.68	2.5	3.48	4.19
8	73.7	11.0	6.0	86.2	1.53	2.5	2.60	2.60
9	54.8	16.9	17.2	43.2	2.12	2.5	5.02	5.83
10	67.1	15.1	18.0	51.2	2.98	4.0	6.12	6.12
				⋮				
32	54.4	17.1	27.7	102.5	3.92	4.0	7.44	7.44
				⋮				
43	49.9	20.3	27.6	79.8	4.37	3.0	3.05	3.05
				⋮				
45	45.2	17.3	37.0	83.9	3.80	5.0	3.00	3.00
				⋮				
51	50.4	17.6	29.4	91.7	3.92	5.0	4.86	4.85
52	45.6	15.5	32.6	98.2	3.09	5.0	5.00	5.00
53	46.0	14.7	32.7	98.3	3.66	5.0	4.89	4.89
54	51.2	18.4	25.4	80.6	5.54	5.0	5.29	5.29
55	44.6	19.7	30.8	90.1	3.38	2.5	2.96	2.96
56	47.2	15.7	35.0	89.3	4.75	4.1	4.72	4.72
57	47.4	13.2	30.3	88.3	4.35	4.0	3.48	3.48
58	30.7	24.7	43.1	88.8	3.41	2.5	1.81	1.81
59	42.7	17.7	37.8	99.7	3.81	3.5	5.00	5.00
60	59.7	19.0	21.6	84.6	2.28	2.0	1.53	1.53

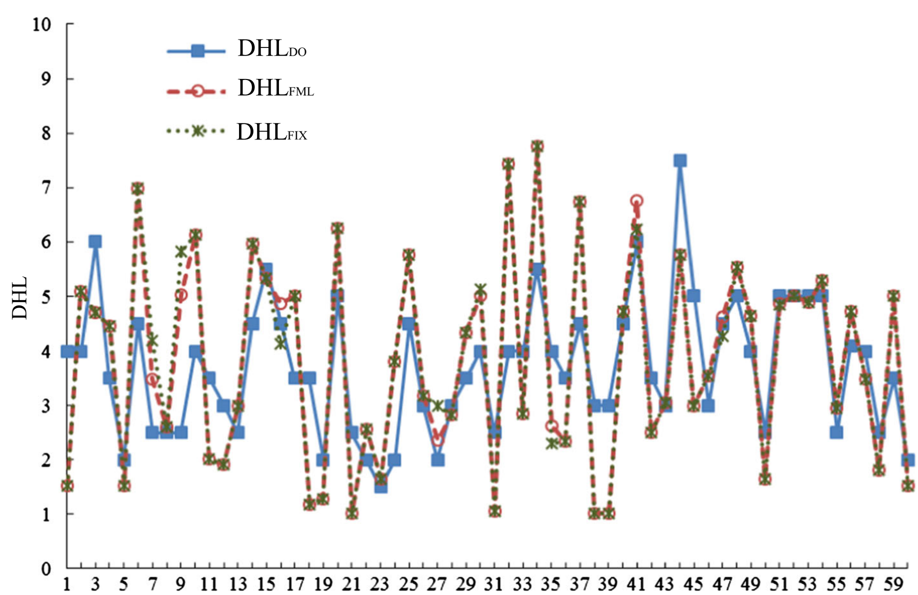

Fig. 8 Curves of DHL_{DO}, DHL_{FML}, and DHL_{FIX} for 60 meals

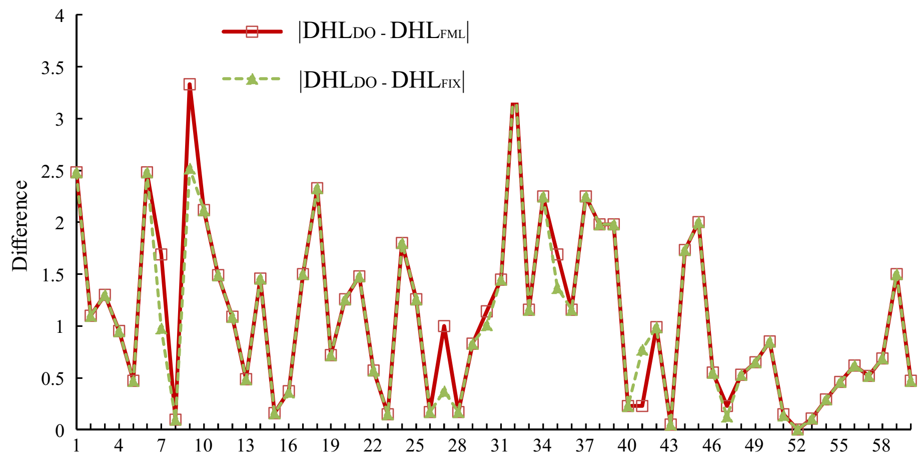

Fig. 9 Curves of absolute values $|\mathrm{DHL_{DO}} - \mathrm{DHL_{FML}}|$ and $|\mathrm{DHL_{DO}} - \mathrm{DHL_{FIX}}|$ for 60 meals

EUR. However, daily fuzzy variables EER and EUR are not defined in our previous works (Lee et al. 2010a, c, 2012; Kurozumi et al. 2013). We only use the planned goal pre-defined by domain experts to construct fuzzy sets for different food groups' balanced level.

- The difference between the present paper and our previous works (Lee et al. 2010a, c, 2012) is that this paper applies the Japanese diet methodology to assess the healthy degree. However, the other published works focus on Taiwanese diet. The challenging problems behind applying the Japanese diet methodology to the Japanese diet are as follows: (i) Japanese dietary standards have been developed for more than 50 years, including KNU Diet, JFGST, and FEL. Each standard has its own features. However, in this paper, the domain expert recommends choosing FEL to estimate the subject's dietary healthy level because FEL is able to both estimate the amount of calorie by units and to provide calories from three nutrients. (ii) Japanese dietary standard is totally different from Taiwanese one. For example, FEL uses one unit to denote 80 calories. However, Taiwanese dietary standard uses one serving to present the amount of the food groups. Hence, it is necessary to adjust our methodology to meet with Japanese dietary standard to compute values of PCC, PCP, PCF, PCR, and FGB. (iii) For man/women from 30 to 50 years old, Japanese requires about 3,000 kcal for one-day activity; however, Taiwanese is about 2,700 kcal. Consequently, knowledge base and rule base are required to adjust to fit the Japanese standard. For example, the recommended balanced percentages of PCC, PCP, and PCF are 55–65, 15–18, and 20–24 %, respectively, for Japanese dietary standard. However, for Taiwanese dietary standard, the balanced ranges of PCC, PCP, and PCF are 55–65, 10–20, and 25–35 %, respectively.

From the experimental results, the proposed mechanism is feasible to apply to Japanese dietary assessment compared with the dietician's evaluation. However, the performance of the proposed mechanism still has some weaknesses that need to be improved in the future. For example, we will consider discussing with the domain experts over the parameters of the fuzzy variables, combining the genetic algorithm to learn the suitable fuzzy sets, and combining type-2 fuzzy sets to handle the uncertainties in the group decision-making process. Additionally, we also consider inviting more subjects and domain experts to involve the research project in the future.

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