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PAPER

An Ontology and SWRL-Based Framework for Healthy Food Recommendation in Middle Childhood

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ABSTRACT

Food recommender systems have garnered attention in various research domains. Despite extensive research, the development of healthy food recommender systems specifically targeting middle childhood age children remains scarce. This age group is susceptible to critical transitions, and mismanagement can lead to rapid weight gain, type 2 diabetes, and cardiovascular diseases. To address this gap, we propose a framework for developing a healthy food conversational recommender system tailored to middle childhood age. Our framework comprises ontology and semantic web rule language (SWRL) rules, facilitating knowledge representation and reasoning within the system. We built it by referring to the Nutritional Adequacy Rate from the Indonesian Ministry of Health and typical Indonesian cuisine. The system suggests nutritious options for breakfast, lunch, dinner, and snacks. The adaptability of this framework extends beyond Indonesia, making it suitable for constructing recommender systems tailored to various countries. By adjusting the ontology's data to accommodate each country's culinary landscape, the system becomes versatile enough to cater to diverse cultural dietary preferences, offering personalized recommendations irrespective of geographical boundaries. The evaluation is focused on validating the proposed framework. The results of accuracy testing show that the knowledge design has an accuracy rate of 83.33%.

KEYWORDS

recommender system, conversational recommender system, middle childhood, ontology, semantic web rule language (SWRL)

1 INTRODUCTION

Middle childhood, lasting from six to 12 years, is an important period in the development of eating behaviour and the emergence of unhealthy eating patterns. This period is a transitional period from infancy to early childhood adolescence. Children at this age experience several transitions which include body growth, brain growth, motor and perception skills, cognitive skills, motivation and social, psychopathology, social context, and behavioural genetics [1]. These processes begin

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to become apparent in this period, such as rapid weight gain and the emergence of insulin resistance [2], [3]. Day et al. have examined positive genetic correlations between insulin levels, type 2 diabetes, and cardiovascular disease [4]. The World Health Organization (WHO) states that non-communicable diseases such as cardiovascular disease, cancer, chronic respiratory diseases, and diabetes are the main causes of around 71% of deaths in the world. WHO further stated that unhealthy eating patterns are one of the main causes of non-communicable diseases [5]. Therefore, it is very important to know the nutritional needs of children. If nutritional intake is not met, malnutrition will occur in children and will disrupt the growth process. Under the nutritional adequacy rate from the Indonesian Ministry of Health, children in middle age need daily nutrition such as protein, fat, carbohydrates, fiber, air, vitamins, and minerals. In general, people will choose food that is quick and easy to obtain, even though this food may not necessarily meet a person's nutritional needs.

Recommender systems have been widely used to assist users in obtaining items that suit their needs or wants. The use of recommenders is very broad, including consumer products [6], movies [7], tourism [8], etc. Recommender systems are also used to recommend healthy foods based on nutritional needs, their preferences [9] or their health problems [10]. One of the challenges in the healthy food domain is recommending recipes that are nutritionally sound and appealing to users. Users of food recommender systems often prefer popular recipes, which tend to be unhealthy [11]. During middle childhood, the presence of loss of control overeating had a more significant impact than reports of the amount of food consumed [12]. This suggests that loss of control of overeating behaviour is a key factor in understanding the development of unhealthy eating patterns during this stage. This issue provides an open challenge and opportunity for developing a food recommender system which is designed for this specific age group and the food recommendation address these considerations whereas promoting growth and avoiding degenerative illness at the early age.

Cold start is one of the main issues in recommender systems [13]. Knowledge-based recommender system is an approach that is able to overcome the user cold start problem, where the user does not have historical data [14]. In the context of our system, this condition applies directly to the target population of children, for whom no prior dietary preference records exist. The combination of ontology and SWRL is widely used to guarantee the accuracy of recommendations. Ontology is used as a knowledge representation [15], [16], a pattern that has been established across recommendation domains beyond food [17], as well as semantic web rule language (SWRL) rules for reasoning. Ontology can store a lot of information that must be considered in choosing a food menu. SWRL can describe ontologies in formal language so that knowledge can be read by machines. Ontology has been widely used to develop recommender systems such as in the domain of consumer products [18] an also food recommender systems [19], [20]. In a food recommender system, SWRL can be used to model the acceptance criteria of seafood quality tests [21], or make inferences in helping menu selection for older adults [22]. Despites the positive result of these existing studies, the recommendation is not designed specifically for the middle childhood whose nutrition need is specific rather than the adults or general people which has been explained previously.

Based on this explanation, there are several research questions rise. The main question is how to develop a model of healthy food recommender system that built based on the combination of ontology and SWRL. Then the secondary question is how accurate this ontology and SWRL combined based healthy food recommender system on producing the recommendation. There are two issues regarding the accuracy assessment. The first issue is regarding the assessment method while the second issue is regarding the level of accuracy.

In this study, we propose a novel framework within the realm of knowledge-based conversational recommender systems consisting of ontology and SWRL, specifically designed for healthy food recommendation system targeting middle childhood age groups. Notably, the formulation of rules within this framework is based on regulatory directives outlined by The Minister of Health of the Republic of Indonesia [23]. Moreover, this framework can be used also for other countries by adapting the information in the ontology to the typical foods of each country.

While machine learning and deep learning approaches have been extensively utilized in the development of food recommender systems [24], [25], these methods require large amount of dataset and effortful pre-processing steps to effectively give robust recommendation results. Moreover, dataset in the field of food recommendation usually has little variations and relatively statics, with some specific and standardized rules developed by experts. Thus, in this study, we choose to develop a knowledge-based framework because to its deterministic nature. Even though knowledge-based systems are deterministic, rigorous accuracy testing remains indispensable due to potential uncertainties inherent in the knowledge base. This testing serves to identify the impact of assumptions or estimations on the system's accuracy, thereby enhancing its reliability. Additionally, it is possible that there are some input circumstances that makes knowledge inappropriate.

In health-sensitive domains, deterministic systems offer a critical advantage: recommendations are auditable against regulatory guidelines, ensuring compliance with dietary standards even in the absence of historical user data [15]. This is particularly important when the target population is children, where safety and nutritional correctness must take precedence over preference optimization.

The arrangement of the remainder of this paper is as follows. The detailed summary and review of the recent studies regarding the food recommender system and the fundamental concept of knowledge-based system is presented in section two. The presentation of the recommender system including the system architecture, ontology design, and SWRL rule is exhibited in section three. The experiment performed in this work, including the scenario and result is presented in section four. Section five presents conclusion and the future work.

2 RELATED WORK

The healthy food recommender system has been developed for many years. In general, these studies can be split into two issues: health and commercial. The existing health issue-based food recommendation systems were developed based on the nutrients and other health-related parameters, such as calories, fat, cholesterol, protein [26], sugar, and so on. The common objective of the health issue-based food recommender system is maintaining health conditions through food choice [26]. On the other hand, the existing commercial issue-based food recommender systems were generally developed based on the users' preferences, historical transaction [27], rating [26], etc. The common objective of the commercial issue-based food recommender system is increasing transactions [27].

Many studies regarding the food recommender system were developed by exploiting machine learning or deep learning techniques, such as graph convolutional network [28], recurrent neural network [27], deep learning-based group clustering [29], latent dirichlet allocation (LDA) [30], genetic algorithm [31], hierarchical ensemble method [32], deep image clustering [33], long-short-term memory (LSTM) [34]. Machine learning technique provides flexible system so that it can be upscaled easily without extensive modification. Although this technique is proven effective in many studies, this method highly depends on the massive dataset for the training process. On the other hand, knowledge-based recommender systems provide deterministic recommendations, and do not depend on large datasets for model building. A deterministic approach is needed in the health domain, because it has a big risk if the system makes wrong recommendations.

Meanwhile, the healthy food recommender system that specifically developed for middle childhood age is rare to find. Moreover, the use of SWRL and ontology as framework for developing food recommender system is also rare to find. Within the knowledge-based recommendation approach, two distinct techniques materialize: case-based and constraint-based methodologies. The case-based technique furnishes content-driven product recommendations, drawing upon systematically organized knowledge encapsulated in the form of cases [35]. In contrast, the constraint-based technique operates through rule-based paradigms. These rules meticulously delineate the mapping between user requirements and the inherent features of products [36], [37].

User requirements, product properties, and rules are parameters in a knowledge-based recommender system [18]. When applying a knowledge-based recommendation system to the semantic web, benefits can be obtained from its underlying ontology. Ontology in the semantic web can be used to represent domain knowledge. Ontology support automated reasoning to determine new information that is not explicitly specified in the knowledge base. The representation of knowledge structure and constraints is implemented using the SWRL. SWRL is an extension of the web ontology language (OWL) that adds knowledge-based capabilities to OWL. SWRL can infer new knowledge from existing knowledge. Rules in SWRL consist of antecedents (body) and consequents (head). Antecedents are conditions that must be met for rules to be executed, while consequents represent newly inferred knowledge [38]. In SWRL, it is possible to perform variable operations using built-in modifiers that contain logical operations, such as Boolean operations, mathematical calculations, string operations, time, lists, and URIs.

2.1 Body mass index

Body mass index (BMI) is a widely used indicator for assessing body weight status. It's calculated by dividing an individual's weight in kilograms by the square of their height in meters [39] as follows:

$$BMI = \frac{W}{H^2} \tag{1}$$

This value helps evaluate whether an individual's weight aligns with their height, and the WHO has defined specific BMI catories [40], which are underweight (BMI < 18.5 kg/m^2), normal weight (18.5 ≤ BMI < 25 kg/m^2), overweight (25 ≤ BMI < 30 kg/m^2), and obesity (BMI ≥ 30 kg/m^2).

While BMI serves as a valuable tool for assessing population-level weight status and identifying potential health risks associated with weight, it's important to note its limitations. BMI is a general indicator and doesn't directly measure body fat percentage or distribution, making it less accurate for assessing an individual's overall health [41].

2.2 Percent daily value

Percent daily value (%*DV*) is a term commonly found on nutrition labels, indicating the percentage of a specific nutrient that a serving of food contributes to the recommended daily intake, typically based on a 2,000-calorie daily diet, a general reference for adults. %*DV* helps consumers understand a food item's nutrient content and make informed dietary choices. It's provided for various nutrients such as fat, saturated fat, cholesterol, carbohydrates, fibre, protein, sugars, vitamins, sodium, and minerals. %*DV* are determined based on dietary guidelines established by regulatory authorities such as the U.S. Food and drug administration (FDA) and may vary across regions and countries. However, %*DV* isn't personalized and may not align with individual nutrient requirements, which can depend on factors such as gender, age, activity level, and specific health conditions. For personalized nutrition advice, it's essential to consider individual dietary needs and consult healthcare professionals or registered dietitians.

The %*DV* can be calculated as the percentage ratio of nutrition to the daily value. If %*DV* is ≤ 5%, it's considered low, and if it's ≥ 20%, it's categorized as high.

$$\%DV = \frac{nutrition(g)}{daily\, value(g)} \times 100 \tag{2}$$

3 PROPOSED FRAMEWORK

Our proposed framework consists of two parts: 1) an ontology, 2) SWRL rules. These two parts represent the knowledge design of a knowledge-based recommender system. The ontology is prepared by adapting the types of typical Indonesian food. The rules accommodate calorie needs based on Ministry of Health regulation [22]. We adjust this SWRL based on the middle childhood age category. This conversation-based recommendation system uses the Telegram Bot API to enable chatbot interactions as shown in Figure 1. First, the Extractor processes user profile information (weight, height, age) using Natural Language Understanding (NLU), a core DialogFlow feature that interprets human language and maps text entities into numeric variables. These variables become queries to access the Ontology in the Interface component, which organizes the knowledge. Before the chatbot responds with the final result in the form of a menu list that matches the user profile, the semantic reasoner executes and evaluates decision-making logic based on SWRL rules against the ontology knowledge.

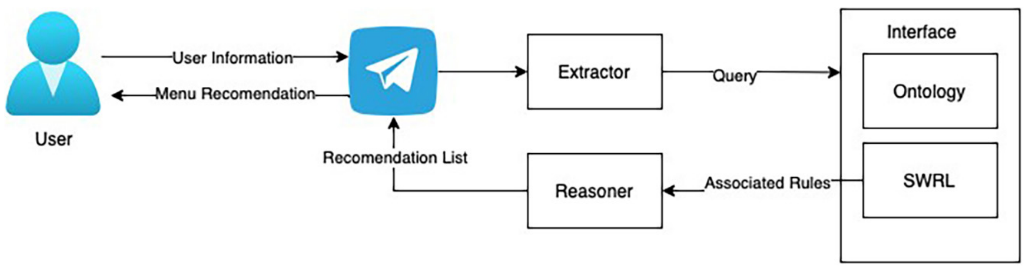

Fig. 1. The system architecture

3.1 Ontology design

The developed ontology structure consists of five main classes, semantically interconnected as shown in Figure 2. The Menu and Nutrient classes are linked through the level nutrients property to represent the specific nutrient content of each food item. The nutrient content of each food item is represented by the level nutrients property. Food classification is identified from the Type class which is linked to the Menu class through the is not contains relationship. Unlike other classes, the Person class is designed to store the user profile, while the BMI_level class provides a taxonomy of nutritional status (such as Normal or Overweight) as a basis for inference rules. This structure allows the system to map the user's nutritional needs to the menu options in the knowledge base.

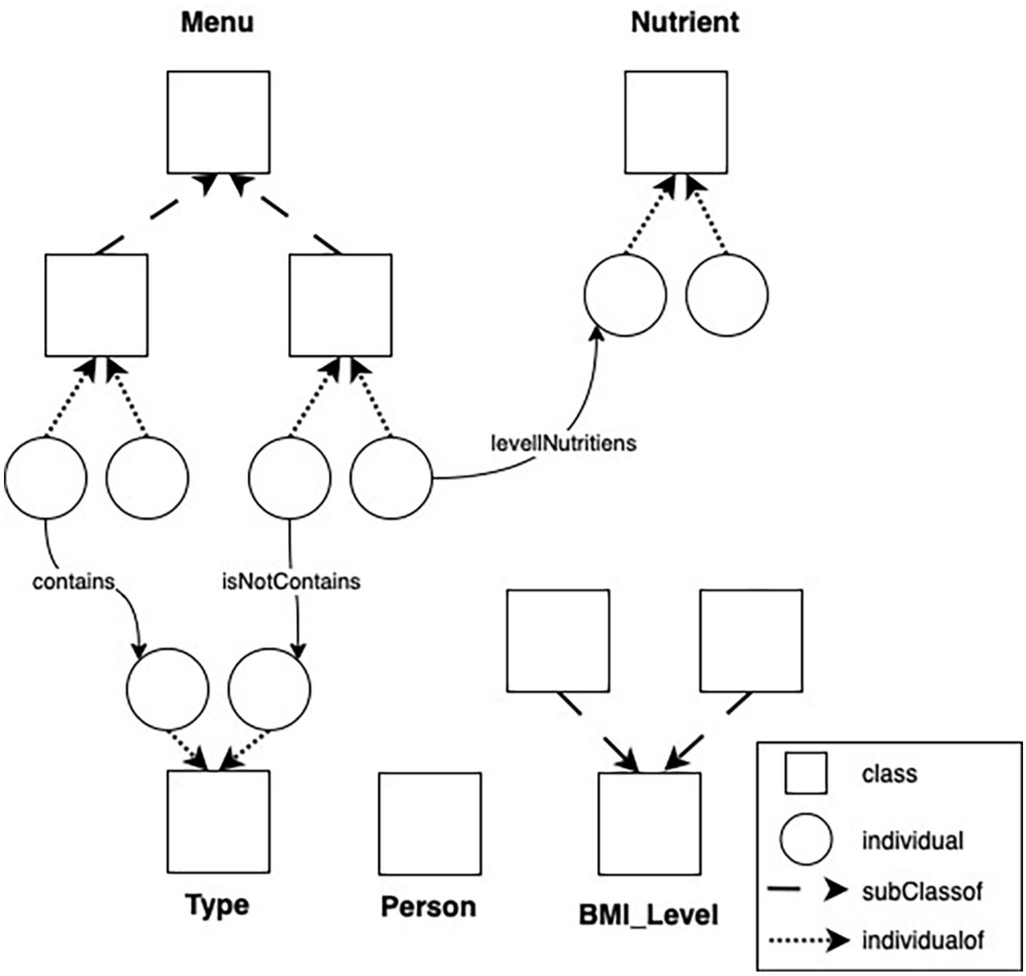

Fig. 2. The structure of ontology

The hierarchy of typical Indonesian food is shown in Figure 3. The Menu class is divided into three subclasses, i.e., Beverages, food group, and snack. Food group are divided into several subclasses based on their nutritional content: Vegetables, Fruits, Carbohydrates, and Protein. Snack are divided into two subclasses: Cracker and Cake. The name of the food item is represented as an individual at the bottom of the hierarchy. For example, the name of the food item "Tumis Buncis" is included in the vegetable subclass class. We present all individuals in Indonesian, to represent the names of typical Indonesian foods. Based on the Menu class taxonomy, the inference engine can automatically classify the menu according to the nutritional category that best matches the user profile.

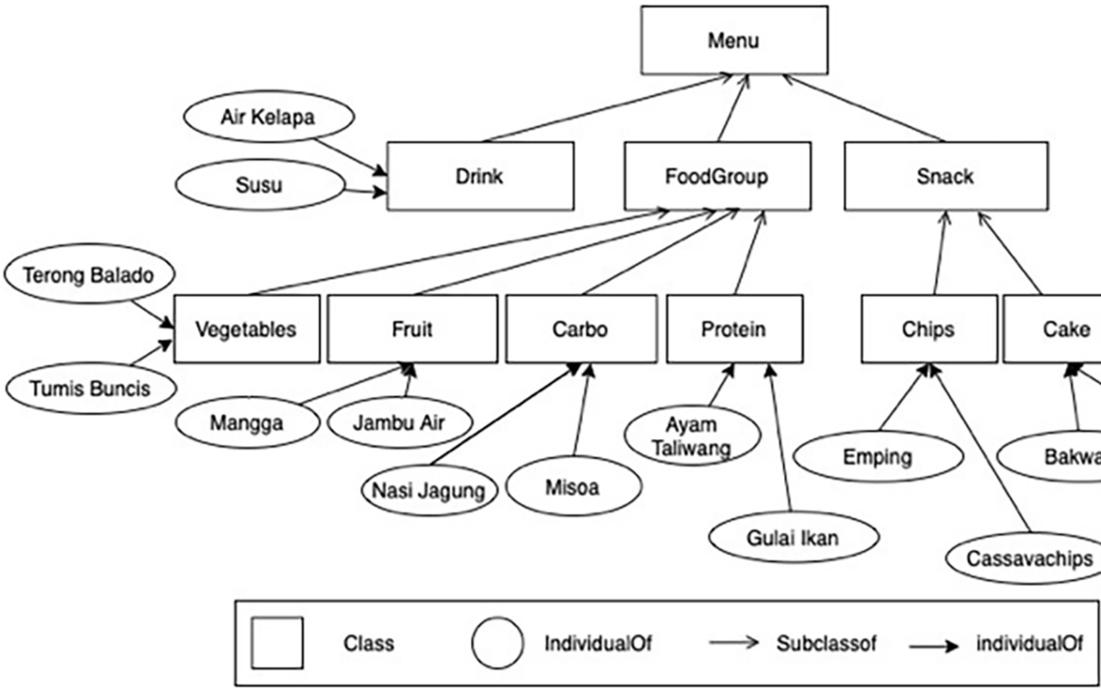

Fig. 3. The hierarchy of class Menu

Figure 4 depicts the hierarchy of classes BMI Level, Nutrient and Type. The class BMI Level serves as a categorization framework for users based on their BMI value, a derived metric from the user's weight and height. Meanwhile, class Nutrient represents the categorization of nutrient. Users are stratified into BMI Level subclasses, i.e., Overweight, Underweight, Obesity, and Normal. Meanwhile the Allergic predispositions, such as allergies to Milk, Seafood, TreeNuts, Peanuts, Eggs, Chicken, and Wheat, are encoded within the class Type for subsequent deployment in food selection processes sensitive to allergenic considerations. User-specific characteristics are represented by the class Person, with some data properties such as hasActivity, hasAge, hasBMI, hasAllergy, hasGender, hasHeight, hasName, and hasWeight.

The class User has some data properties, such as hasGender, hasAge, hasBodyWeight, hasHeight, hasAllergies, or hasDislikedFoodItems, hasBMIValue, hasCaloricContent, and hasActivityLevel. Within the class Menu, data properties include hasServingSize, hasNutrientCal, hasNutrientCarbo, hasNutrientFat, hasNutrientProtein. The hasNutrientCal, hasNutrientCarbo, hasNutrientFat, hasNutrientProtein data property signifies the classification of nutritional attributes as either low or high for each menu item. The constraint property within the class Menu operates in a disjoint manner with the object property IsNotContains, both of which are object properties that encapsulate Type individuals. These properties serve as the representational framework for the inclusion or exclusion of specific food constituents corresponding to allergenic considerations within each menu item.

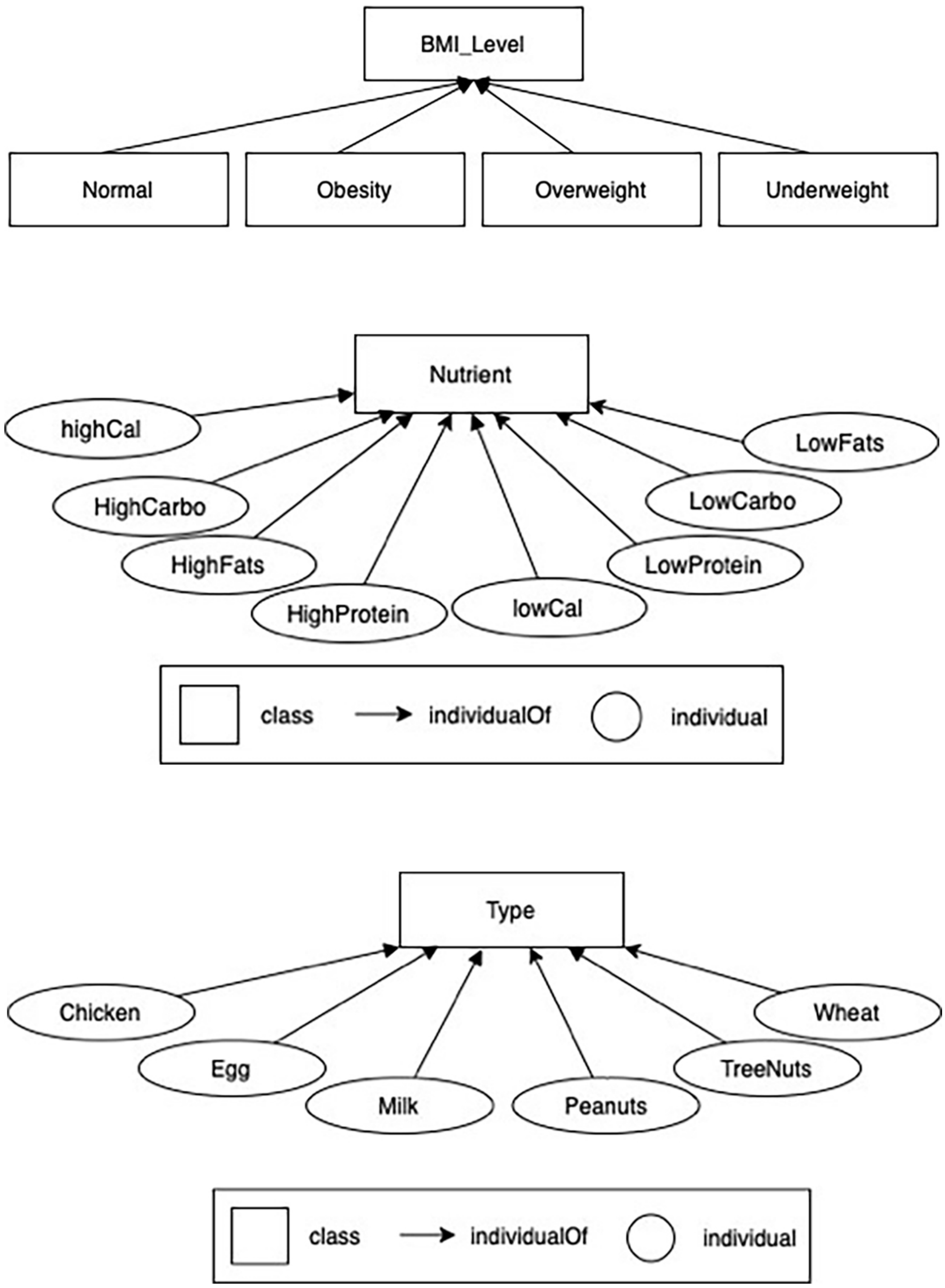

Fig. 4. The hierarchy of classes BMI level, nutrient and type

3.2 Semantic web rule language rules

The SWRL rules are employed to infer recommendations based on the established ontology. Several rules are in place to derive food recommendations that align with user characteristics, i.e., the person assessment rule (PAR), nutrient identification rule (NIR), calorie requirement rule (CRR), and menu recommendation rule (MRR). CRR is divided into 3 groups of rules, each to determine the calorie needs, calorie consumption required, and meal portion distribution. All these rules will be explained in later Subsections. The correlation schematic of these rules can be seen in Figure 5.

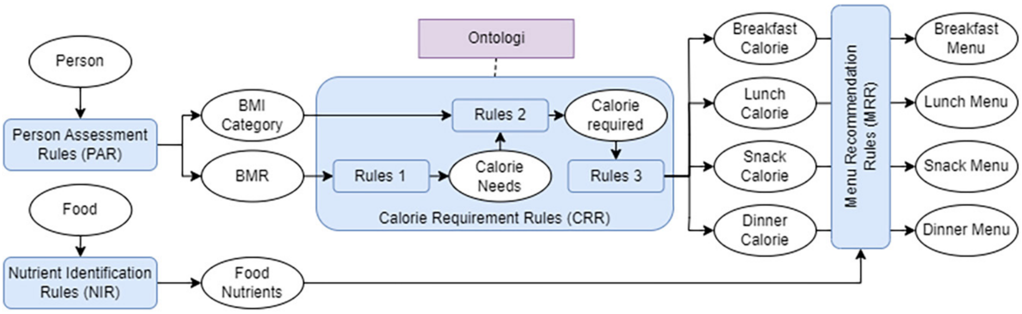

Fig. 5. Systematic map of the proposed SWRL rules

Person assessment rules. PAR is a collection of rules that assess a person in terms of BMI and BMR measurement. It will also classify the person within 4 weight condition categories, i.e., underweight, normal, overweight, and obesity. These rules will give some object properties to the user as an individual of class person.

Nutrient identification rules. Each entity of class Menu has level nutrient as one of its object properties. There are three different nutrients, i.e., carbohydrate, protein, and fat, which are classified into low and high categories, thus giving a total of 6 rules. Two examples of the rules within this category are low protein and high protein identification. The rules for other nutrients, carbohydrates, and fats, are similar with only difference in the object property component involved (substitute to hasNutrientProtein property in the example).

Calorie requirement rules. We use 4 meal categories, i.e., breakfast, snack, lunch, and dinner. The daily caloric requirements of users are split based on the percentage agreed upon by nutritionists, with 25% of the daily caloric needs allocated to breakfast, 25% to lunch, 20% to dinner, and 30% to snacks. Users classified as obese and overweight according to their BMI levels are not recommended to have an afternoon snack. The calories intended for the afternoon snack will be incorporated into breakfast, resulting in a larger percentage of food allocation for breakfast, which becomes 35%.

Table 1. Some examples of menu recommendation rules

Case	Rule
Daily calorie requirement for overweight	person(?p) & overweight(?p) & hasCalorieNeed(?p, ?a) & subtract(?s,?a,300) –> hasCalorie(?p,?s)
Daily water needs	person(?p) & hasweight(?p,?w) & multiply(?wt,?w,30) & divide(?water,?wt,1000) –> hasWater(?p,?water)
Snack recommendation for underweight person	person(?p) & underweight(?p) & Snack(?f) & Fruit(?f1) & subtract(?bba,?pcf,?pcf1) & hasNutrientCal(?f,?sc) & roundHalfToEven(?s,?tc) & divide(?pcf,?c,3) & multiply(?pcf1,?pcf,0.005) & roundHalfToEven(?pf1,?bba) & hasNutrientCal(?f1,?sc1) & SnackCal(?p,?c) & add(?tc,?sc,?sc1) & add(?ba, ?pcf1,?pcf) & greaterThanOrEqual(?s,?pf1) & roundHalfToEven(?pf,?ba) & greaterThanOrEqual(?pf,?s) –> hasSnackA(?p,?f) & hasSnackA(?f, ?f1)
Breakfast menu recommendation for normal person	person(?p) & normal(?p), Karbo(?f), hasNutrientCal(?f,?nc) & add(?tc,?nc,?nc1) & subtract(?bba,?c,?pcf1) & Vegetables(?f2) & roundHalfToEven(?pf1,?bba) & greaterThan(?tcf,?pf1) & greaterThan(?pf,?tcf) & hasNutrientCal(?f1,?nc1) & hasNutrientCal(?f2,?nc2) & add(?tc1,?tc,?nc2) & BFCalorie(?p,?c) & roundHalfToEven(?tcf,?tc1) & multiply(?pcf1,?c,0.005) & Protein(?f1) & add(?ba,?pcf1,?c) & roundHalfToEven(?pf,?ba) –> hasBreakfastMenu(?p,?f) & hasBreakfastMenu(?f,?f1) & hasBreakfastMenu(?f1,?f2)

(Continued)

Table 1. Some examples of menu recommendation rules *(Continued)*

Case	Rule
Lunch menu recommendation for overweight person	person(?p) & normal(?p), Karbo(?f), hasNutrientCal(?f,?nc) & add(?tc,?nc,?nc1) & subtract(?bba,?c,?pcf1) & Vegetables(?f2) & roundHalfToEven(?pf1,?bba) & greaterThan(?tcf,?pf1) & greaterThan(?pf,?tcf) & hasNutrientCal(?f1,?nc1) & hasNutrientCal(?f2,?nc2) & add(?tc1,?tc,?nc2) & BFCalorie(?p,?c) & roundHalfToEven(?tcf,?tc1) & multiply(?pcf1,?c,0.005) & Protein(?f1) & add(?ba,?pcf1,?c) & roundHalfToEven(?pf,?ba) –> hasBreakfastMenu(?p,?f) & hasBreakfastMenu(?f,?f1) & hasBreakfastMenu(?f1,?f2)
…….	…..

The first group has eight rules, correspond to four categories of activity for man and woman. The second and the third group has four rules, correspond to 4 BMI categories. We also put an additional rule in this category to determine daily water needs of an individual. Thus, CRR has in total of 25 rules.

Menu recommendation rules. The food recommendations consist of recommendations for breakfast, lunch, dinner and three snacks (morning, afternoon and evening). To get recommendations for each dinner menu, each recommended menu item is stored in its respective property object. Calories from each menu are added up using SWRL. Some SWRL rules in knowledge are shown in Table 1. If the total number of calories for a person is within the upper limit and lower limit, then the first item is stored in the hasSnackB property of the person object, and the second item is stored in the hasDrinkB property. This process follows the rules of syllogism. The upper and lower limits are increased by 0.005 of calorie requirements.

For users in the overweight and obese BMI level categories, additional rules are applied in the selection of menu items, stating that the items must fall into the low-fat food category. The main meal menu which includes breakfast, lunch and dinner consists of foods categorized as carbohydrates, protein and vegetables. Each menu recommendation has different object properties for storage purposes, with hasSnackA for morning snack, hasSnackB for afternoon snack, hasSnackC for evening snack, hasBreakfastMenu for breakfast menu, hasLunchMenu for the lunch menu, and hasDinnerMenu for the dinner menu.

4 EXPERIMENT AND RESULT

We tested the framework in two stages. In the first stage, we involved 36 respondents to interact with the recommender system. The interactions between respondents and the results of these recommendations are saved. The second stage is validation from experts. In this stage, we involved two experts (nutritionists) to provide an assessment of the accuracy of the system's recommendation results to respondents. The purpose of this knowledge validation process is to ensure that the designed knowledge aligns with the nutritional requirements of an individual. The user interface on the Telegram platform, showing the real-time chatbot interaction flow with chatbot input using Indonesian, is shown in Figure 6. First, the user enters the command "/rekomendasi_makanan" (English: /food_recommendation) and the system responds with several structured questions about age

(6–12 years), weight, and height. The final output displays a very specific breakfast recommendation menu, including calculations of nutritional figures (calories, protein, carbohydrates, fat) and food composition (e.g., 100 grams of "Sayur Bunga Pepaya"). This demonstrates the successful integration of the ontology-based knowledge base with the conversational interface to provide personalized, precise nutritional advice.

Fig. 6. The example of user-system interaction

4.1 Respondent data

In this study, we involved 36 respondents to try our system. Each of these respondents acts as a user of our system. They enter age, height and weight parameters into the chatbot. Users will get recommendations for snacks and breakfast, snacks and lunch, snacks and dinner. The recommendation results from this system will be validated by a nutritionist. Figure 7 shows distinct differences in height and weight. Height is relatively symmetrical, median 129 cm, mean 127.13 cm, with half the population between 119–136 cm. Weight data shows positive skewness: the median is 26 kg, and the mean is 27 kg, an outlier at 63 kg drives this. This may indicate clinical obesity or be a data entry error. Most participants are aged 8–9 (36%), matching growth standards for their age. The outlier must be managed to keep the CRR inference accurate.

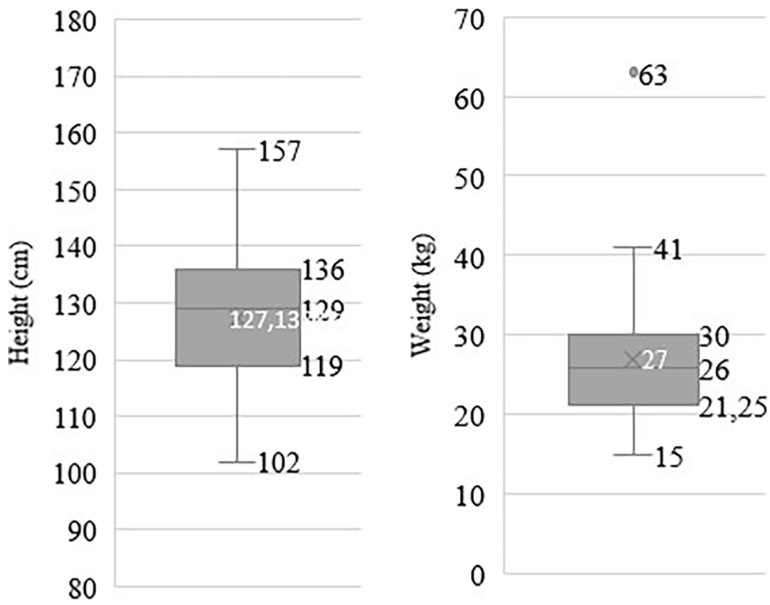

Fig. 7. Box lot of height and weight distribution of respondents

4.2 Ontology validation

We conduct the ontology validation tests using a Pellet reasoner as an OWL-DL testing tool. Pellet reasoner check the consistency of an ontology [42]. Figure 8 shows the result of the Pellet reasoner test, which shows the reasoner process running for 369 ms and performing inferences on the class hierarchy, object property hierarchy, data property hierarchy, class assertion, object property assertion, and individual. The results of the test indicate that the created ontology is logically consistent and can be continued to competency testing.

```
INFO  07:34:18  ------------------------------ Running Reasoner ------------------------------
INFO  07:34:19  Pre-computing inferences:
INFO  07:34:19      - class hierarchy
INFO  07:34:19      - object property hierarchy
INFO  07:34:19      - data property hierarchy
INFO  07:34:19      - class assertions
INFO  07:34:19      - object property assertions
INFO  07:34:19      - same individuals
INFO  07:34:19  Ontologies processed in 369 ms by Pellet
```

Fig. 8. Ontology validation results using pellets

4.3 Context question validation

Context question validation is an evaluation phase of ontology. The validation method uses description logic (DL) queries in Protégé to check whether the ontology can answer nutritional recommendation scenarios. This function is verifying the recommendation food based on allergen rules, food category and nutrient level. DL Queries retrieve inferred classes, based on rules and logical restrictions to check the consistency. Table 2 shows the sample queries and the validation result of query testing, and the results show that all the testing scenarios are valid. The ontology can process all the criteria, including combinations of class.

Table 2. Competency testing for some example questions (queries)

No	Class	Context Testing	DL Query	Validation
1	Menu + Allergy	Menu that does not contain milk	Menu and (IsNotContains value Milk)	Valid
2	Menu + Allergy	Menu that does not contain eggs	Menu and (IsNotContains value Egg)	Valid
3	Menu	Menu containing milk	Menu and (Contains value Milk)	Valid
4	Menu	Menu containing nuts	Menu and (Contains value Peanuts)	Valid
5	Food + Alergi	Foods that do not contain Tree Nuts	Food and (IsNotContains value TreeNuts)	Valid
6	Drink	Drinks containing milk	Drink and (Contains value Milk)	Valid
7	Drink + Alergi	Drinks that do not contain milk	Drink and (IsNotContains value Milk)	Valid
8	Snack	Snacks containing milk	Snack and (Contains value Milk)	Valid
9	Snack	Snacks containing nuts	Snack and (Contains value Peanuts)	Valid
10	Snack + Alergi	Snacks that do not contain nuts	Snack and (IsNotContains value Peanuts)	Valid
11	Snack + Alergi	Snacks that do not contain wheat	Snack and (IsNotContains value Wheat)	Valid

4.4 Validation result and discussion

This study focuses on knowledge design which includes ontology and rules, so we evaluate the accuracy of this knowledge design. For this validation, we involve two nutritionists (domain expert). Validation results from nutritionists are used to calculate the accuracy of recommendations, which also reflects the accuracy of our framework design. We use simple metric as accuracy rather than other metrics because the output of our recommendation is a complete menu with specific calories distribution. The output is not categorical in a strict sense; thus, concept of confusion matrix is not directly applicable. The nutritionists will evaluate whether the recommendation is acceptable or not with some additional notes. In this study, we measure accuracy using the Precision metric, with the formula.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

In the context of recommender systems, this metric can be represented as the proportion of acceptable recommendation by the nutritionist to total recommendation as follows,

$$Precision = \frac{correct\,recommendation}{all\,recommendation} \tag{4}$$

Respondents aged 6 years (14%), 7 years (17%), 8 years (17%), 9 years (19%), 10 years (11%), 11 years (14%), and 12 years (8%). From total 36 recommendations obtained from all respondents' data, the nutritionists evaluate that 30 of them are acceptable, and 6 recommendations are evaluated with some minor notes given, so that we obtained the accuracy of 83.33%. This accuracy value represents the expert acceptability of recommendations. Table 3 shows the result of recommendation validations from 2 nutritionist. Label "Y" and "N" means acceptable and not acceptable recommendation, respectively. Meanwhile Table 4 depicts some suggestions from these experts referring to Table 3.

Table 3. The recommendation validation result

Respondent	Age	Gender	Weight	Height	BMI	Expert 1	Expert 2	NoteID
1	6	P	23	119	16,24	N	Y	Note1
2	6	L	21	106	18,69	Y	N	Note2
3	6	P	17	112	13,55	N	Y	Note3
4	6	P	16	102	15,38	Y	N	Note4
5	6	P	15	103	14,14	Y	Y	
6	7	L	18	109	15,15	N	Y	Note5
7	7	P	20	119	14,12	N	Y	Note6
8	7	P	25	129	15,02	Y	Y	
9	7	L	20	121	13,66	Y	Y	
10	7	P	25	120	17,36	Y	Y	
11	7	L	25	121	17,08	Y	Y	
12	8	P	23	116	17,09	Y	Y	
13	8	L	21	124	13,66	Y	Y	
14	8	P	16	124	10,41	Y	Y	
15	8	P	30	110	24,79	Y	Y	
16	8	P	26	136	14,06	Y	Y	
17	9	L	25	116	18,58	Y	Y	
18	9	L	29	130	17,16	Y	Y	
19	9	L	28	134	15,59	Y	Y	
20	9	L	27	140	13,78	Y	Y	
21	8	P	26	124	16,91	Y	Y	
22	9	L	63	144	30,38	Y	Y	
23	9	P	29	136	15,68	Y	Y	
24	9	L	22	135	12,07	Y	Y	
25	9	L	27	129	16,22	Y	Y	
26	10	P	30	129	18,03	Y	Y	
27	10	P	33	135	18,11	Y	Y	
28	10	L	41	134	22,83	Y	Y	
29	11	L	27	133	15,26	Y	Y	
30	11	L	34	141	17,10	Y	Y	
31	11	L	25	126	15,75	Y	Y	
32	11	L	34	139	17,60	Y	Y	
33	11	L	38	146	17,83	Y	Y	
34	12	L	28	137	14,92	Y	Y	
35	12	L	30	141	15,09	Y	Y	
36	12	L	35	157	14,20	Y	Y	

All six rejected recommendations involved children aged 6–7 years in the underweight BMI category. This pattern is not incidental, constraint-based recommender systems optimize for nutritional targets but lack a preference model, which means recommendations may be nutritionally correct yet unfamiliar or unacceptable to young children [43]. This tension between nutritional compliance and palatability is a known structural limitation of knowledge-based systems when no user preference data is available [44]. The expert notes in Table 4 consistently highlight unfamiliar menu names, inappropriate portion sizes, and insufficient menu variety, all of which point to the absence of a child preference filter rather than errors in the calorie rules themselves. Future work should incorporate a palatability filter as an additional constraint layer, potentially drawing from validated food preference scales for preschool-aged children [45]. Nutritionists emphasize that the food recommendation approach should not rely solely on mathematical calculations but also consider the child's psychological well-being, clear terminology, flexibility in menu changes based on the child's eating habits, cultural familiarity, and biological balance. Therefore, several factors that need to be adjusted include portion sizes, standardized snack nutrition, and increased variety of plant-based proteins and vegetables to ensure the principles of balanced nutrition are met.

Table 4. Some suggestions from nutritionists

Note	Suggestions
Note1	Nutritional information is changed to nutritional needs, such as one 100g serving of vegetables. Is it possible to replace food ingredients by choosing a familiar menu and your child likes using raw, uncooked carrots? Adjust to the child's eating habits and receptiveness so that the child doesn't want to eat.
Note2	Choose a menu that is easy to get or substitute for other ingredients. For snacks, the nutritional value is 150–200 calories and 5 grams of protein
Note3	Unfamiliar menu names need explanation (side dishes or vegetables). Need extra protein. The menu is further clarified, for example wheat bread, fried presto milkfish, carrot cocktail. Providing vegetable choices to children is adjusted to the child's characteristics. The child's tendency to choose food when given food he doesn't like will cause the child not to want to eat. Choosing vegetables can be accepted by children.
Note4	The menu choice is suitable for the morning and is too high in calories (the child won't finish it). Example: Savory rice, dried egg omelet, stir-fried tempe, green beans (Kh protein and fat components included)
Note5	The nutritional value of the snack is 150–250 calories and 5 grams of protein. The protein is still lacking. The type of vegetable menu must be explained so that those reading it understand. You should pay attention to the variety of vegetables, not just one type. Not showing up vegetable protein does not yet represent a balanced diet.
Note6	The calorific value is too high for breakfast. The spaghetti portion is reduced. Menu variations are not suitable. Examples include spaghetti, black pepper meat, vegetables. Menu choices that are familiar to the public, especially school children. A balanced nutritional menu has not yet appeared.

In the state-of-the-art food recommender system area, many studies have utilized machine learning approaches, metaheuristic algorithms, or deep learning techniques. A direct comparison is challenging because the nature of data in machine learning-based approaches differs from that in knowledge-based approaches. Machine learning requires large amounts of data, whereas our proposed knowledge-based approach does not. Table 5 presents a comparison of the approaches in the current state-of-the-art literature, based on test results from the references. The metrics used are not identical to ours (Precision), but they all measure accuracy. Approach (1) uses the mean absolute percentage error (MAPE), while approaches (2)–(8) use Precision, indicating a higher level of accuracy. As shown in Table 4, knowledge-based approaches cannot be directly compared with ML-based approaches, as the evaluation datasets, tasks, and metrics differ substantially. The Prec@K values in approaches (2)–(8) are computed on large-scale user interaction datasets, while our precision reflects expert clinical acceptability on 36 pediatric cases. A more defensible argument for our approach is not a higher number, but rather that deterministic knowledge-based systems produce auditable, guideline-compliant recommendations, a property that data-driven methods cannot guarantee regardless of benchmark precision [16].

Table 5. Comparison with other approaches

No	Use Case	Approach	Accuracy	Ref.	Category
1	Food recommendation for Hypertension patients	Genetic Algorithm	MAPE = 0.267	[31]	Data driven-based system (machine learning)
2	Food recommendation common user	Item-KNN	Prec@1 = 0.0124 Prec@5 = 0.0188 Prec@10 = 0.0199	[34]	
3	Food recommendation common user	Meta-Prod2vec collaborative filtering (MPCF)	Prec@1 = 0.0257 Prec@5 = 0.023 Prec@10 = 0.0203		
4	Food recommendation common user	Convolutional Sequence Embedding (Caser)	Prec@1 = 0.0284 Prec@5 = 0.0244 Prec@10 = 0.0209		
5	Food recommendation common user	LSTM	Prec@1 = 0.0281 Prec@5 = 0.0249 Prec@10 = 0.0226		
6	Food recommendation common user	Combination of Deep Learning and Graph Clustering	Prec@10 = 0.0721	[29]	
7	Food recommendation common user	LDA	Prec@10 = 0.0613	[29], [30]	
8	Food recommendation common user	Deep Image Clustering	Prec@10 = 0.0775	[33]	
9	**Food recommendation for middle childhood age**	**Ontology + SWRL**	**Precision = 0.833**	**Proposed approach**	**Knowledge-based system**

4.5 Inter-rater agreement analysis

The system evaluation involved two nutrition experts to assess the relevance of the resulting food recommendations to 36 respondent profiles. The test results showed a rough level of observed agreement of 83.33%, with both experts providing the same assessment in 30 of the 36 cases. To strengthen scientific rigor, an inter-rater agreement analysis was conducted using the Cohen's Kappa metric, based on the contingency table in Table 6. Cohen's Kappa (κ) is obtained through the formula,

$$\kappa = \frac{\rho_0 - \rho_e}{1 - \rho_e} \quad (5)$$

where ρ_0 is the observed agreement, i.e., the proportion of real agreement with the formula,

$$\rho_0 = \frac{agree\,Y - agree\,N}{Total} \quad (6)$$

Meanwhile, ρ_c is the expected agreement, i.e., the proportion of agreement that might occur due to chance, with the formula,

$$\rho_e = P_{yes} + P_{no} \quad (7)$$

where, P_{yes} is the probability that both experts answer "Y" by chance, and P_{no} is the probability that both experts answer "N" by chance. To obtain P_{yes} and P_{no}, we have to multiply the proportion of answers of each expert,

$$P_{yes} = (proportion\ of\ expert\ 1{:}Y) \times (proportion\ of\ expert\ 2{:}Y)$$

$$P_{no} = (proportion\ of\ expert\ 1{:}N) \times (proportion\ of\ expert\ 2{:}N)$$

Table 6. Contingency table of expert evaluations

		Expert 2		Total
		Y	N	
Expert 1	Y	30	2	32
	N	4	0	4
Total		34	2	36

The calculation results show $\rho_0 = 0.8333$, and $\rho_e = 0.8457$, so we get Cohen's Kappa $\kappa = 0.0803$.

Although the Kappa value is in the low category, this does not indicate low quality of agreement between experts. This phenomenon is known as the Prevalence Paradox, where Kappa values tend to be low or negative when one assessment category (in this case, the 'Y' response) significantly dominates the data. Because the system consistently produces relevant recommendations, the probability of coincidental agreement (expected agreement) is very high, exceeding observed agreement. Therefore, the 83.33% agreement rate remains a key indicator that this ontology-based framework has strong functional feasibility in the nutrition domain.

5 CONCLUSION

Our study presents a framework for crafting healthy menus tailored to middle childhood age, comprising an ontology design and SWRL rules. Leveraging this framework, we developed a conversational recommender system integrated with Telegram, chosen for its flexibility in user interaction. While our focus lies on evaluating the knowledge design encompassing ontology and rules, achieving an accuracy rate of 83.33% underscores the effectiveness of our approach. However, we acknowledge room for improvement, particularly in expanding the repertoire of typical foods for specific age groups within middle childhood.

The validation result reveals a discrepancy between system recommendations and children's preferences, especially among 6–7-year-olds, highlighting the need for adjustments, particularly for underweight children in this age range. As our system's knowledge base relies on the Nutritional Adequacy Rate set by the Indonesian Ministry of Health, it may inadvertently suggest unappealing food menus. To address this, future studies should incorporate filters based on general taste preferences to enhance recommendation relevance.

A good conversational recommender system must be able to provide the best user experience. One of the limitations in this study is that we have not involved a complete interaction mechanism, which allows users to provide feedback on the recommendations provided. For future research, we need to develop a system from this framework, which can provide a good user experience, so that we can measure not only accuracy, but also user experience in interacting with the system.

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7 DATA AVAILABILITY STATEMENT

The data used in compiling the proposed model comes from the 2019 Indonesian Food Composition Table (TKPI) and the Nutritional Adequacy Rate from the Indonesian Ministry of Health, that available at https://bit.ly/FoodComposition.

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