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# Ontology-based Food Menu Recommender System for Pregnant Women Using SWRL Rules

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**Abstract:** Pregnancy is a crucial period in a woman's life because her body must prepare and support the growth and development of the fetus. During pregnancy nutritional needs will increase. Lack of nutritional intake during pregnancy can cause serious health problems, one of which is anemia. However, excess nutrition during pregnancy also has a negative impact on pregnant women. Therefore, a recommender system is required to provide food menu recommendations according to the daily nutritional needs of pregnant women. Currently, there has been a lot of research on ontology-based food recommender systems that can provide food recommendations to users, but there is no research that specifically provides food menu recommendations tailored to the requirements of pregnant women. Therefore, this study proposes an ontology-based food menu recommender system using SWRL (Semantic Web Rule Language) rules for pregnant women. In this study, ontology is used to represent food knowledge and its nutritional content, and SWRL rules are used to reason logical rules in the ontology to determine the appropriate food menu for pregnant women. This recommender system also considers diseases and allergies that pregnant women have so that it can provide food menu recommendations that are more suitable for users. From 15 data samples from pregnant women, the system provides 75 food menu recommendations for pregnant women. Based on the validation results that have been carried out, the precision value is 0.986, the recall is 1, and the F1-score is 0.992.

**Keywords:** Food Recommender System; Ontology; Pregnant Woman; Recommender System; SWRL

## INTRODUCTION

Pregnancy is a crucial period in a woman's life where good nutritional intake is an important factor in influencing the health of the mother and fetus. During pregnancy, the body's nutritional requirements will increase. This is because the fetus grows by taking in the nutrients from the mother's body. Therefore, pregnant women need to pay attention to their nutritional intake with a complete and balanced menu. Healthy and balanced nutritional intake during pregnancy has a good impact on the mother's health and the development of the fetus (Kementerian Kesehatan RI, 2014).

Lack of nutritional intake during pregnancy can cause serious health problems that endanger the mother and the development of the fetus. One of the effects of nutritional deficiencies during pregnancy is anemia. Anemia in pregnant women can cause bleeding, shock, low birth weight, miscarriage, prolonged labor, uterine atony, and premature birth (Ernawati, 2017). Apart from that, excessive nutritional intake during pregnancy also has negative impacts, such as weight gain. Excessive weight

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gain during pregnancy can increase gestational diabetes, preeclampsia, high birth weight, cesarean section, postpartum weight retention, and increased risk of preterm birth (de Seymour et al., 2019).

Considering this issue, we need a food menu recommender system that can help recommend daily menus that suit the needs of pregnant women. One common recommendation technique is an ontology-based recommender system. Ontology-based recommendation is a knowledge-based recommender system that utilizes ontology to represent knowledge (Yang, 2010). Ontology-based recommender systems have similarities with expert systems, both utilize domain knowledge for inference and decision-making. They also rely on rules and logic to provide relevant results. The difference is that ontology-based recommender systems provide item recommendations based on user preferences, while expert systems mimic the decision-making abilities of specialists in a specific domain to provide solutions or answers to specific problems (Mekruksavanich, 2016).

In previous research regarding ontology-based food recommender systems, Ali et al developed an ontology-based health service recommendation system to monitor patients' bodies and recommend certain foods and medicines with an average accuracy value of 83% (Ali et al., 2018). Sambola et al developed an ontology-based nutritional recommender system using SWRL rules that can identify levels of excess weight in users and offer appropriate dietary plans with an average accuracy of 87% (Mckensy-Sambola et al., 2021). Adila et al developed a food menu recommender system for individuals with coronary heart sufferers, utilizing ontology and SWRL. This study uses a Telegram bot to assist users in determining suitable food and water requirements for coronary heart sufferers with an F1-score accuracy of 93% (Adila & Baizal, 2023). Ontologies play an important role in the development of recommender systems. Previous research has shown that incorporating ontology knowledge into the recommendation process can increase the accuracy and help to overcome limitations in the recommender system, like cold-start /ramp-up and data sparsity problems (Tarus et al., 2018).

The previously mentioned research was able to develop an ontology-based recommender system that can recommend food menus to users, but there has been no research that specifically considers the needs of pregnant women. Because the nutritional needs of pregnant women are different from those of non-pregnant women. Therefore, in this research, we developed an ontology-based food menu recommender system for pregnant women using SWRL rules. This recommender system uses a Telegram chatbot to help pregnant women choose a food menu that suits their needs. This recommender system also provides menu recommendations by considering user allergies and diseases such as anemia and gestational diabetes, so that it can provide food menu recommendations that are more suitable for users. In this study, ontology is used to represent knowledge of food and its nutritional content, and SWRL rules are used to carry out reasoning on the ontology to determine the appropriate food menu for pregnant women.

## LITERATURE REVIEW

A recommender system is a system that uses input data to predict the likes or interests of its users (Lü et al., 2012). Recommender systems have been classified according to several categories based on the type of information managed. Some of the commonly used classifications are collaborative filtering, demographic filtering, content-based filtering, constraint-based recommendations, knowledge-based recommendations (Toledo et al., 2019), and ontology-based recommendations (Bagherifard et al., 2017).

In computer science, ontology is a tool for formally modeling the structure of a system. This model includes entities and relations between entities that are used to achieve certain goals, such as understanding the system, designing applications, or analyzing data (Guarino et al., 2009). Ontology-based recommender systems are similar to knowledge-based recommender systems. This recommender system avoids some of the problems that exist in classic recommender systems, such as ranking sparsity, cold-start problems, and overspecialization. This occurs because ontologies focus more on the domain of knowledge rather than ranking. Ontology-based recommender systems generally use ontologies to represent knowledge about a particular domain, including entities, properties, and relationships between those entities (Tarus et al., 2018). Ontologies have become a common choice for use in developing recommender systems, such as for recommending tourist destinations in a conversational mechanism (Baizal et al., 2021), assisting users in recommending appropriate and relevant digital learning (Tarus

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et al., 2018), and providing music recommendations based on user preferences (Rodríguez-García et al., 2015).

Ontologies have also been used to develop food recommender systems. Mckensy-Sambola et al developed a nutritional recommendation system by utilizing ontology and SWRL rules that can identify levels of overweight and obesity in users. Subsequently, the system will provide the most suitable diet recommendations based on the user's preferences and offer meal recipes with nutrients that meet the user's caloric needs (Mckensy-Sambola et al., 2021).

Spoladore et al developed an ontology-based telehealthcare system named HeNuALs, which is intended to recommend nutritional and healthy lifestyles for elderly people with chronic diseases. This system uses semantic technology to consider user data such as medical records, food intake, and physical activity to produce appropriate recommendations (Spoladore et al., 2021).

Ali et al developed an IoT-based health service recommender system using Type-2 Fuzzy Ontology. This research utilizes Web Ontology Language (OWL) to provide knowledge of information about patients such as medical conditions history, food consumed, and drug prescriptions. Afterward, this research uses SWRL and fuzzy logic to optimize the recommendation process and uses Description Logic (DL) and SPARQL to evaluate the ontology (Ali et al., 2018).

## METHOD

In this work, we propose an ontology-based recommender system to provide food menu recommendations for pregnant women. We use the Protégé ontology editor (Musen, 2015) to create and edit the ontology, such as defining classes, individuals, properties, and SWRL rules.

### Calculating the Daily Calorie Needs of Pregnant Women

The daily calorie needs of pregnant women refer to the amount of energy or calories required by pregnant women during pregnancy. We use Broca's method which has been modified by Katsura to calculate ideal body weight based on a person's height (Arfianto, 2019). Equation (1) is used to calculate the ideal body weight if the body height is above 160 cm.

$$BBI = (height - 110) \quad (1)$$

Equation (2) is used to calculate the ideal body weight if the body height is below 160 cm.

$$BBI = (height - 105) \quad (2)$$

Equation (3) is used to calculate the ideal body weight for pregnant women.

$$BBIH = BBI + (GA \times 0.35) \quad (3)$$

Note:
BBI = Ideal body weight
BBIH = Ideal body weight for pregnant women
GA = Gestational age (weeks)

After getting the results of calculating the ideal body weight of pregnant women, the next step is to calculate the calorie requirements of pregnant women. This study utilizes the Harris-Benedict method to calculate the daily calorie requirements of pregnant women (Harris & Benedict, 1918). Equation (4) is used to calculate Basal Energy Expenditure (BEE).

$$BEE = 655 + (9.6 \times BBIH) + (1.8 \times height) - (4.7 \times age) \quad (4)$$

Equation (5) is used to calculate Total Energy Expenditure (TEE) based on physical activity and additional calories for pregnant women.

$$TEE = BEE \times Activity\ Factor + Additional\ Calories \quad (5)$$

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Activity factor and additional calories are shown in Table 1 (Sensussiana, 2018) and Table 2 (Kementerian Kesehatan RI, 2019).

Table 1 Value of activity factors

| Activity Level | Activity Factor |
|---|---|
| Bed rest | 1.2 |
| Light | 1.3 |
| Moderate | 1.4 |
| High | 1.5 |

Table 2 Additional calories for pregnant women

| Trimesters | Additional Calories |
|---|---|
| 1st trimester | + 180 |
| 2nd trimester | + 300 |
| 3rd trimester | + 300 |

**Recommender System Flow**

Figure 1 explains the flow of an ontology-based food menu recommender system for pregnant women. This recommender system uses Telegram as a chatbot platform. First, the system will take information from the user such as age, height, weight, gestational age, activity level, allergies, and diseases. All this information is processed by the handler. Afterward, all this information will be transmitted to the ontology using owlready2 and processed using SWRL rules. After that, the system performs reasoning to make new conclusions based on logical rules and information contained in the ontology. Finally, the system will generate food menu recommendations, which will subsequently be delivered to the user.

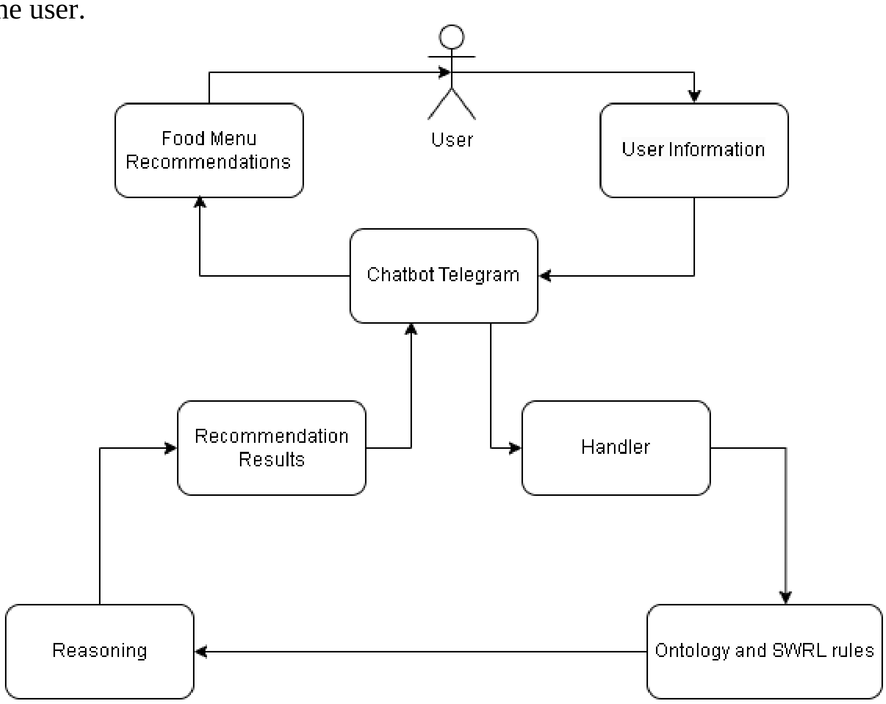


Fig. 1 Recommender System Flow

**Ontology Design**

Figure 2 illustrates the design of an ontology for a food menu recommender system for pregnant women. The ontology design comprises five main classes: Menu, Person, Trimester, Allergy, and NutrientLevel.

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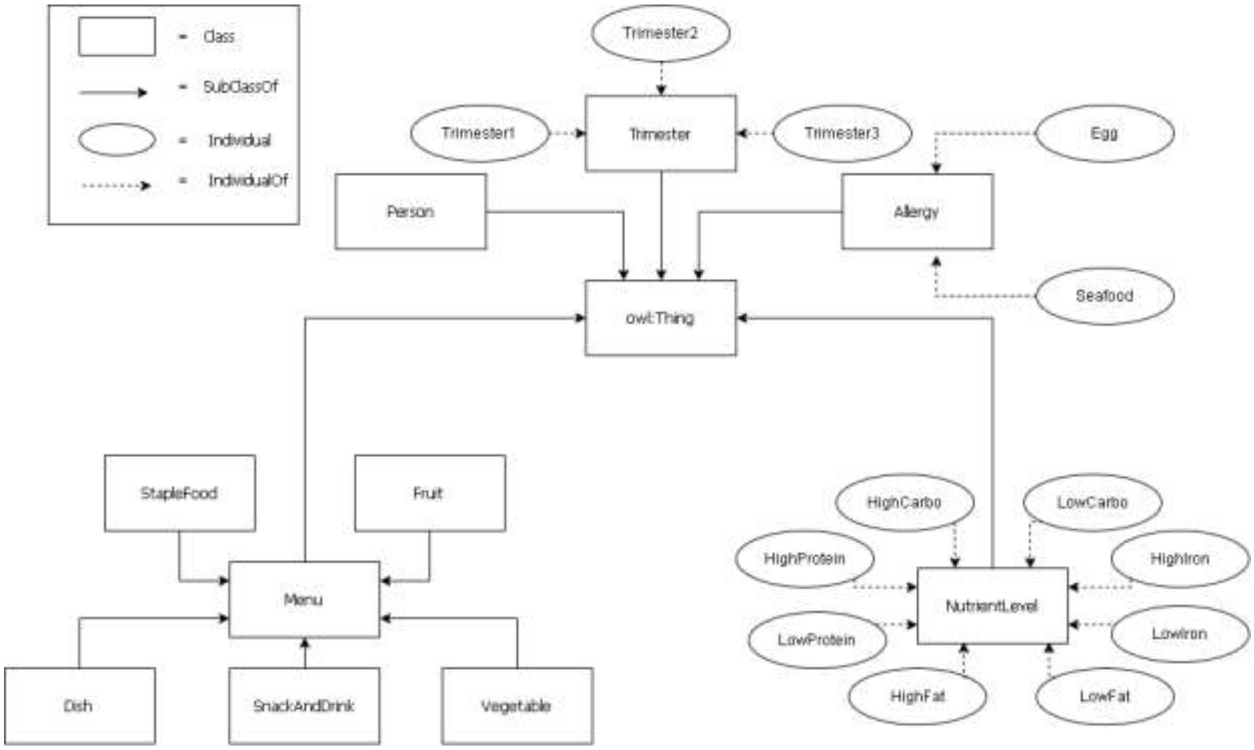


Fig. 2 Ontology Design

Menu class stores information related to food such as food name, nutritional content, etc. This data is taken from the Indonesian food composition table 2017 (Kementerian Kesehatan RI, 2018). Menu class is classified into several subclasses based on food type such as staple foods, side dishes, vegetables, snacks or drinks, and fruits. Person class stores characteristic information about users such as age, height, weight, gestational age, allergies, diseases, etc. Trimester class is used to classify the trimester of a pregnant woman's womb. Allergy class stores various types of allergies in pregnant women. NutrientLevel class is used to classify foods based on their nutritional content, such as high protein, low protein, high fat, low fat, high carbohydrate, etc.

Each of these classes contains individuals. Individuals represent specific instances of the classes. For example, the Fruit class has individual names of fruits such as apples, avocados, papayas, bananas, etc. Each individual in this ontology has data properties and object properties. Data properties are used to associate a class or individual with data values, an example of data properties can be seen in Figure 3. Object properties are used to connect two entities or classes in ontology. For example, hasNutrientLevel is used to connect the Menu class with individuals in NutrientLevel class. The data properties and object properties utilized in this ontology can be seen in Table 3.

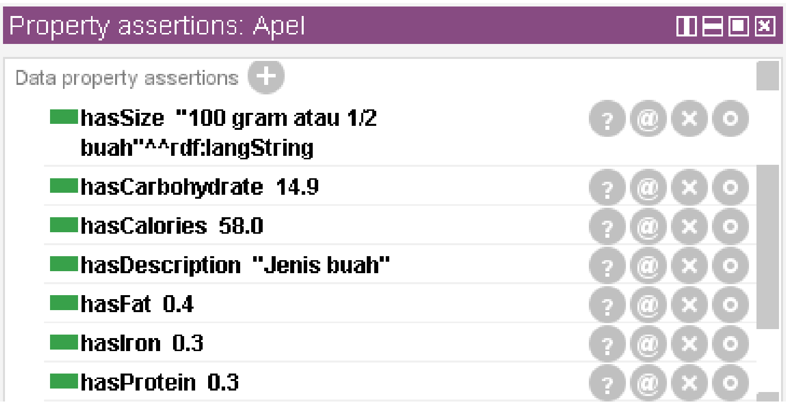


Fig. 3 Example data properties for the individual apple

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Table 3 Data Properties and Object Properties

| Data Properties | Object Properties |
|---|---|
| hasActivity | hasVegetableRecommendation |
| hasAge | hasStapleFoodRecommendation |
| hasAnemia | hasSnackAndDrinkRecommendation |
| hasBBI | hasFruitRecommendation |
| hasBBIH | hasDishRecommendation |
| hasBEE | hasNutrientLevel |
| hasBfCal | hasTrimester |
| hasCalories | isNotContains |
| hasCarbohydrate | |
| hasDescription | |
| hasGestationalDiabetes | |
| hasDinnerCal | |
| hasEggAllergy | |
| hasFat | |
| hasGestationalAge | |
| hasHeight | |
| hasIron | |
| hasLunchCal | |
| hasName | |
| hasProtein | |
| hasSeafoodAllergy | |
| hasSize | |
| hasSnackCal | |
| hasTEE | |
| hasWeight | |

**Create SWRL Rules**

SWRL rules are used to conclude food recommendations that suit the needs of pregnant women according to the design principles of SWRL (Lan, 2004). There are several rules to get food recommendations that suit the needs of pregnant women, such as calculating BEE, calculating TEE, nutritional classification, distribution of calories, etc. The following are several SWRL rules used in this recommender system.

a. Gestational age classification
   The following are some rules to classify gestational age based on trimester.
   *Person(?p) ^ hasGestationalAge(?p, ?ga) ^ swrlb:lessThanOrEqual(?ga, 13)*
   *-> hasTrimester(?p, Trimester1)*
   *Person(?p) ^ hasGestationalAge(?p, ?ga) ^ swrlb:greaterThanOrEqual(?ga, 14) ^ swrlb:lessThanOrEqual(?ga, 26) -> hasTrimester(?p, Trimester2)*
   *Person(?p) ^ hasGestationalAge(?p, ?ga) ^ swrlb:greaterThanOrEqual(?ga, 27) ^ swrlb:lessThanOrEqual(?ga, 40) -> hasTrimester(?p, Trimester3)*
b. Calculating Basal Energy Expenditure
   The following are the SWRL rules for calculating the BEE using the Harris-Benedict method.
   *Person(?p) ^ hasBBIH(?p, ?weight) ^ hasHeight(?p, ?height) ^ hasAge(?p, ?age) ^ swrlb:multiply(?mr1, ?weight, 9.6) ^ swrlb:multiply(?mr2, ?height, 1.8) ^ swrlb:multiply(?mr3, ?age, 4.7) ^ swrlb:add(?ar1, ?mr1, 655) ^ swrlb:add(?ar2, ?ar1, ?mr2) ^ swrlb:subtract(?bee, ?ar2, ?mr3)*
   *-> hasBEE(?p, ?bee)*

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c. Calculating Total Energy Expenditure

These SWRL rules are used to calculate TEE by considering several factors such as BEE, gestational age, and activity. Below are examples of the SWRL rules for calculating TEE based on bedrest activity, light activity, moderate activity, and high activity in the first trimester.

*Person(?p) ^ hasBEE(?p, ?bee) ^ hasTrimester(?p, Trimester1) ^ hasActivity(?p, "bedrest"^^rdf:PlainLiteral) ^ swrlb:multiply(?mr1, ?bee, 1.2) ^ swrlb:add(?mr2, ?mr1, 180) -> hasTEE(?p, ?mr2)*

*Person(?p) ^ hasBEE(?p, ?bee) ^ hasTrimester(?p, Trimester1) ^ hasActivity(?p, "ringan"^^rdf:PlainLiteral) ^ swrlb:multiply(?mr1, ?bee, 1.3) ^ swrlb:add(?mr2, ?mr1, 180) -> hasTEE(?p, ?mr2)*

*Person(?p) ^ hasBEE(?p, ?bee) ^ hasTrimester(?p, Trimester1) ^ hasActivity(?p, "sedang"^^rdf:PlainLiteral) ^ swrlb:multiply(?mr1, ?bee, 1.4) ^ swrlb:add(?mr2, ?mr1, 180) -> hasTEE(?p, ?mr2)*

*Person(?p) ^ hasBEE(?p, ?bee) ^ hasTrimester(?p, Trimester1) ^ hasActivity(?p, "tinggi"^^rdf:PlainLiteral) ^ swrlb:multiply(?mr1, ?bee, 1.5) ^ swrlb:add(?mr2, ?mr1, 180) -> hasTEE(?p, ?mr2)*

d. Classification of food nutrient

Below are some SWRL rules for grouping foods based on the level of nutrient content in the food.

*Menu(?food) ^ hasCarbohydrate(?food, ?carbo) ^ swrlb:greaterThan(?carbo, 33) -> hasNutrientLevel(?food, HighCarbo)*

*Menu(?food) ^ hasCarbohydrate(?food, ?carbo) ^ swrlb:lessThanOrEqual(?carbo, 33) -> hasNutrientLevel(?food, LowCarbo)*

*Menu(?food) ^ hasProtein(?food, ?protein) ^ swrlb:greaterThan(?protein, 5) -> hasNutrientLevel(?food, HighProtein)*

*Menu(?food) ^ hasProtein(?food, ?protein) ^ swrlb:lessThanOrEqual(?protein, 5) -> hasNutrientLevel(?food, LowProtein)*

*Menu(?food) ^ hasIron(?food, ?iron) ^ swrlb:greaterThan(?iron, 2.2) -> hasNutrientLevel(?food, HighIron)*

*Menu(?food) ^ hasIron(?food, ?iron) ^ swrlb:lessThanOrEqual(?iron, 2.2) -> hasNutrientLevel(?food, LowIron)*

e. Daily calorie distribution

According to Almatsier in 2005, the distribution of daily meal portions is 20% breakfast, 30% lunch, 25% dinner, and 2-3 portions for snacks each one 10-15% (Khoirotun et al., 2016). The following are the SWRL rules for distributing daily calories to pregnant women.

*Person(?p) ^ hasTEE(?p, ?tee) ^ swrlb:multiply(?bf, ?tee, 0.2) -> hasBfCal(?p, ?bf)*

*Person(?p) ^ hasTEE(?p, ?tee) ^ swrlb:multiply(?lunch, ?tee, 0.3) -> hasLunchCal(?p, ?lunch)*

*Person(?p) ^ hasTEE(?p, ?tee) ^ swrlb:multiply(?dinner, ?tee, 0.25) -> hasDinnerCal(?p, ?dinner)*

*Person(?p) ^ hasTEE(?p, ?tee) ^ swrlb:multiply(?snack, ?tee, 0.25) -> hasSnackCal(?p, ?snack)*

f. Food recommendations

The system gives food menu suggestions tailored to user allergies and health conditions. If the user has an allergy, it will recommend foods that do not contain the allergy. If the user suffers from diseases such as anemia, it will recommend foods that are high in iron. If the user suffers from gestational diabetes, it will recommend foods that are low in carbohydrates. Below are the SWRL rules for pregnant women who have seafood allergies, anemia, and gestational diabetes.

*Person(?p) ^ hasAnemia(?p, "ya") ^ hasGestationalDiabetes(?p, "ya") ^ hasSeafoodAllergy(?p, "ya") ^ hasEggAllergy(?p, "tidak") ^ StapleFood(?staple) ^ hasNutrientLevel(?staple, LowCarbo) ^ isNotContains(?staple, Seafood) ^ Dish(?dish) ^ isNotContains(?dish, Seafood) ^ hasNutrientLevel(?dish, HighIron) ^ hasNutrientLevel(?dish, LowCarbo) ^ Vegetable(?vegetable) ^ isNotContains(?vegetable, Seafood) ^*

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*hasNutrientLevel(?vegetable, HighIron) ^ hasNutrientLevel(?vegetable, LowCarbo) ^ SnackAndDrink(?snack) ^ isNotContains(?snack, Seafood) ^ hasNutrientLevel(?snack, LowCarbo) -> hasStapleFoodRecommendation(?p, ?staple) ^ hasDishRecommendation(?p, ?dish) ^ hasVegetableRecommendation(?p, ?vegetable) ^ hasSnackAndDrinkRecommendation(?p, ?snack)*

**Chatbot Conversation Mechanism**

Figure 4 shows a conversation mechanism between the user and the chatbot. When the user inputs a command to start a conversation ("/start"), the chatbot responds by introducing itself. After that, the chatbot will ask the user several questions, such as name, age, height, weight, gestational age, activity level, allergies, and diseases. If the user does not answer the question correctly, the system asks the question again. If the question is answered correctly, the chatbot will provide food menu recommendations that suit the nutritional needs of pregnant women. After that the chatbot gives a closing message and the conversation ends. Users also can end a chatbot conversation by entering the command ("/stop").

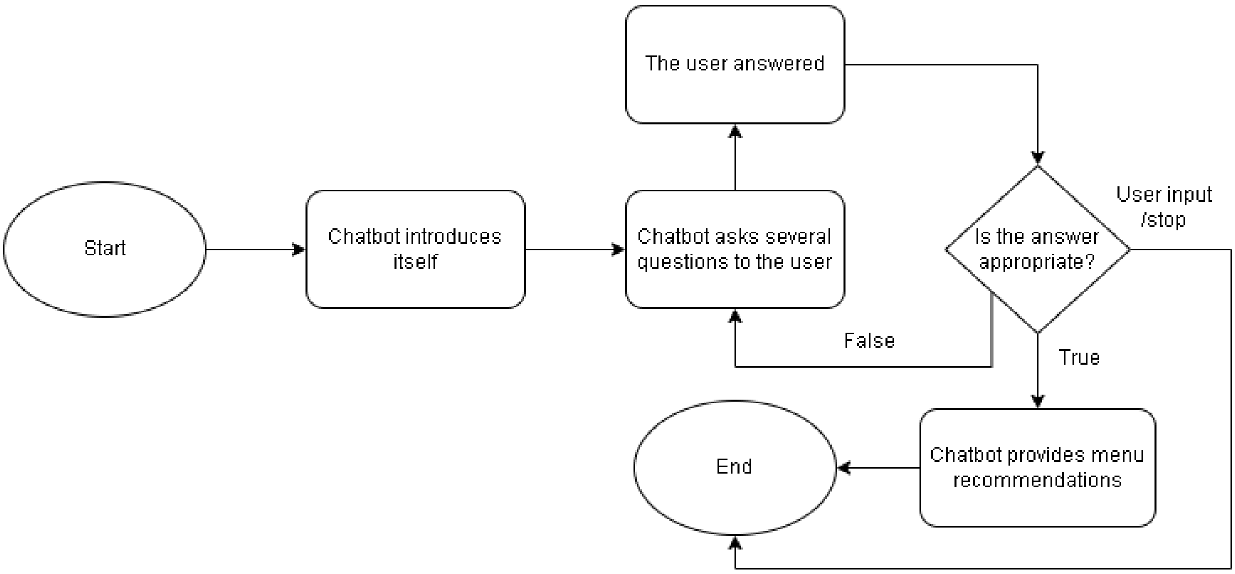


Fig. 4 Chatbot Conversation Mechanism

**Evaluation metrics**

In this work, we use precision, recall, and F1-score metrics. These metrics are used to measure the performance of the food menu recommender system. Equations (6), (7), (8) were used to calculate the metrics.

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

$$F1\_Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

TP (True Positives) refer to the total number of food menu recommendations that align with the nutritionists' suggestions, FP (False Positives) represent the total number of food recommendations proposed by the system but not recommended by nutritionists, and FN (False Negatives) are the food recommendations that neither the system nor the nutritionists suggest.

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## RESULT

The testing was conducted by validating the food menu recommendations with a nutrition expert. Table 4 presents the sample data of pregnant women used for system evaluation. This sample consists of 15 pregnant women including age, height, weight, gestational age, activity level, allergies, and diseases.

Table 4 Sample Data of Pregnant Women

| User | Age | Height | Weight | Gestational age | Activity level | Allergy | Disease |
|---|---|---|---|---|---|---|---|
| user 1 | 26 years | 161 cm | 57 kg | 3 weeks | high | none | none |
| user 2 | 27 years | 156 cm | 60 kg | 14 weeks | light | none | none |
| user 3 | 29 years | 164 cm | 61 kg | 6 weeks | moderate | seafood | none |
| user 4 | 32 years | 155 cm | 70 kg | 33 weeks | bedrest | none | gestational diabetes |
| user 5 | 28 years | 160 cm | 66 kg | 18 weeks | moderate | seafood, egg | none |
| user 6 | 30 years | 159 cm | 55 kg | 6 weeks | high | egg | none |
| user 7 | 31 years | 162 cm | 71 kg | 28 weeks | moderate | none | none |
| user 8 | 29 years | 165 cm | 70 kg | 22 weeks | bedrest | none | none |
| user 9 | 32 years | 159 cm | 72 kg | 30 weeks | light | none | gestational diabetes |
| user 10 | 24 years | 166 cm | 60 kg | 8 weeks | light | egg | anemia |
| user 11 | 30 years | 165 cm | 64 kg | 15 weeks | high | none | none |
| user 12 | 36 years | 170 cm | 69 kg | 16 weeks | moderate | seafood | none |
| user 13 | 25 years | 160 cm | 71 kg | 33 weeks | bedrest | egg | anemia, gestational diabetes |
| user 14 | 28 years | 169 cm | 67 kg | 21 weeks | light | none | none |
| user 15 | 29 years | 165 cm | 62 kg | 25 weeks | moderate | seafood | anemia |

Sample data from pregnant women is then processed into the chatbot to provide food recommendations. These food recommendations include the breakfast menu, morning snacks, lunch menu, afternoon snacks, and dinner menu. Figure 5 and Figure 6 are illustrations of a conversation between the system and the user.

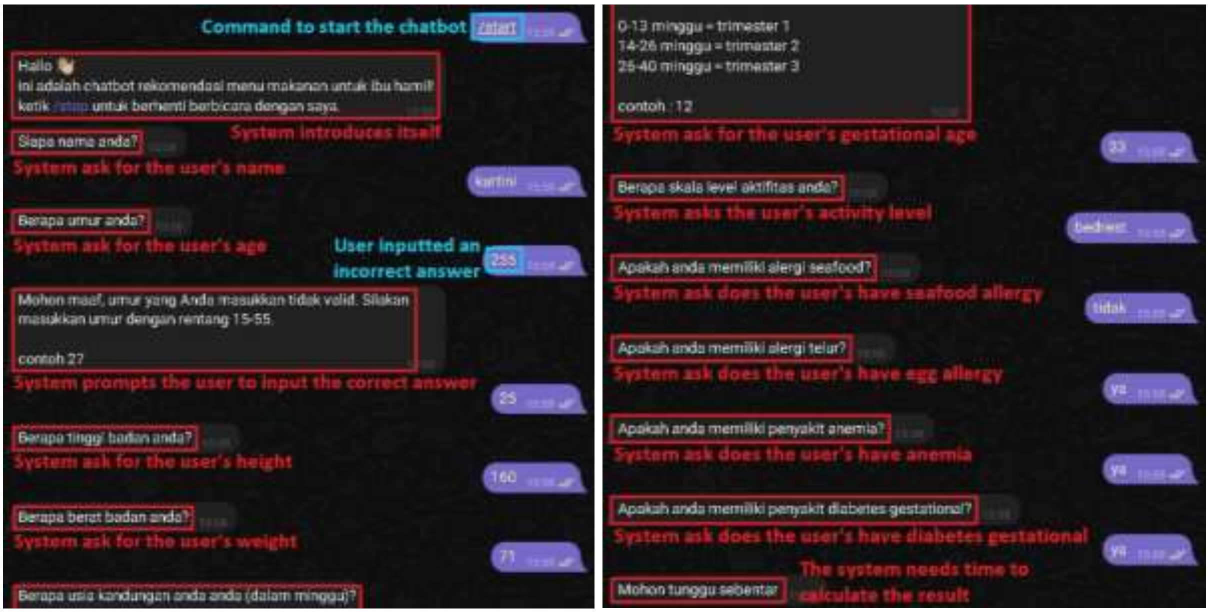


Fig. 5 System asks the user several questions

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Fig. 6 System provides food menu recommendations

From the pregnant women sample data, the system provides 75 food menu recommendations for pregnant women. 74 menus were recommended by nutritionists, and 1 menu was not recommended for pregnant women. From the conducted evaluation, we obtained a precision value of 0.986, a recall of 1, and an F1-score of 0.992.

$$Precision = \frac{74}{74+1} = 0.986$$

$$Recall = \frac{74}{74+0} = 1$$

$$F1\_score = 2 \times \frac{0.986 \times 1}{0.986 + 1} = 0.992$$

## DISCUSSIONS

Based on the results of previous evaluations, we succeeded in creating a food menu recommender system that suits the needs of pregnant women. The limitation of this study is that the system only focuses on the calorie needs of pregnant women and cannot be used for non-pregnant women because the calorie needs of pregnant and non-pregnant women are different. Apart from that, this study also only considered allergies and diseases commonly suffered by pregnant women, such as seafood allergy, egg allergy, anemia, and gestational diabetes.

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## CONCLUSION

In this paper, we present a food menu recommender system using ontology and SWRL rules to provide food menu recommendations for pregnant women by considering allergies, diseases, and calorie needs of pregnant women. This recommender system uses a Telegram chatbot to connect users with the recommender system. The system will ask the user several questions to provide food menu recommendations that suit the user's needs. From the results of the evaluation, the system has successfully given food menu recommendations that meet the needs of pregnant women. The recommender system evaluation results show the precision value is 0.986, the recall is 1, and the F1-score is 0.992. Suggestions for further research, are to add more allergies and diseases that may occur in pregnant women and add more food data so that the system can recommend a more diverse food menu.

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