

Ontology-Based Recommender System for Personalized Physical Exercise in Obesity Management

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Abstract: In Indonesia, obesity is a serious health issue, and rates have risen recently because of sedentary lifestyles and poor eating practices. We suggest a proactive self-care suggestion system specifically created for Indonesians who are dealing with obesity to address this problem. Our recommender system attempts to give customers individualized suggestions for healthy lifestyle modifications that will make it easier for them to manage their weight. Because social media is so widely used in Indonesia, we created our system as a Telegram Chatbot. Our system may provide personalized suggestions based on a particular gender, activity level, fat mass, and difficulty of exercise that are relevant to Indonesians by fusing the user's ontological profile with generic clinical guidelines and standards for the management of obesity. Ontologies with Semantic Web Rule Language were used in the development of our system since SWRL ontologies are thought to perform better. Evaluations carried out using case studies and expert verification illustrate the usefulness of our suggested method, and the validated result of 88.8 percent demonstrates that our system can deliver good suggestion results for the user.

Keywords: Chatbot; Obesity; Ontology; Recommender System; Semantic Web Rule Language

INTRODUCTION

People of all ages are affected by the obesity problem, which is mostly brought on by technological improvements and lifestyle changes (Zhang et al., 2018). Worldwide, the frequency of obesity and being overweight has been rising quickly, necessitating urgent attention. With obesity levels reaching 28.7% (Body Mass Index ≥ 25), In Southeast Asia, Children under five who are obese or overweight are more prone to live in Indonesia. (Rachmi, Li, & Alison Baur, 2017). Due to inactivity, 10.8% of children aged 5 to 12 are obese, which lowers their energy levels and raises their risk of obesity ("FactSheet Obesitas-Kit Informasi Obesitas. - Direktorat P2PTM," 2018). Additionally, severe obesity can limit a person's mobility and lower their quality of life, which can worsen socioeconomic disadvantages and the unemployment rate (Sakinah et al., 2022). To enhance the populace's overall health and wellbeing, combating the obesity problem in Indonesia calls for a comprehensive strategy that encourages healthy lifestyles, increases awareness of proper nutrition, and promotes regular physical activity (Prasetyo & Istiono, 2021; Susilo et al., 2022).

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Numerous variables that differ from nation to nation are responsible for obesity. In industrialized nations, factors like dietary habits, physical activity, way of life, environmental characteristics, and heredity are researched (Dewi, Tanziha, Solechah, & Bohari, 2020). In developing nations, urbanization, lifestyle modifications, socioeconomic position, and food security are crucial (Casari et al., 2022). According to UNICEF's conceptual framework, obesity is mostly brought on by healthy behaviors including dietary choices, physical activity levels, and heredity. The framework cites access to health care, job habits, parenting, household food security, and environmental factors as the main contributors to obesity. At a deeper level, the issue is rooted in the nation's political, economic, and educational conditions (UNICEF, 2021).

Since everyday obesity care is generally managed by individuals and their families, self-care strategies and habits have the biggest impact on weight control. Numerous health and wellness-related programs, websites, smartphone software, and social media platforms have evolved to help individuals manage their weight on their own. For instance, the applications MadMuscles (Uniwel, n.d.) and Freeletics ("Intensive Workouts & Individual Training Plans | FREELETICS," n.d.) provide customers customized workout plans depending on their tastes. Depending on their fitness objectives, they assist customers in customizing their routines.

Research on recommender systems has been done to guide people on their health and welfare. Utilizing a sample of user data to generate food suggestions based on customer preferences that produced 170 suggested food menus, the Food Recommender System (FRS) (Aditya, Baizal, & Dharayani, 2023) stores knowledge in an ontology and processes it using the Semantic Web Rule Language (SWRL). To provide systematic recommendations for exercise and nutrition, Yunyoung Nam (Nam & Kim, 2015) suggested using multi-mode sensors such as a wrist-mounted sensor, three-axis accelerometer, pressure sensor, and laser in an activity recommendation system to treat obesity.

Despite the massive amount of research and application behind existing self-care and exercise advice for obesity, most of them are universal. They don't consider unique characteristics like user activity level. Existing systems downplay the significance of users' fat mass and exercise level.

We propose an ontology-based physical exercise recommender system employing a Telegram chatbot and SWRL to help control obesity and help people lose weight to address the constraint. The recommender system will employ unique characteristics like gender, relative fat mass, activity level, and the muscle area that the user wants to train to create relevant wellness and exercise recommendations that are more suitable for the users.

LITERATURE REVIEW

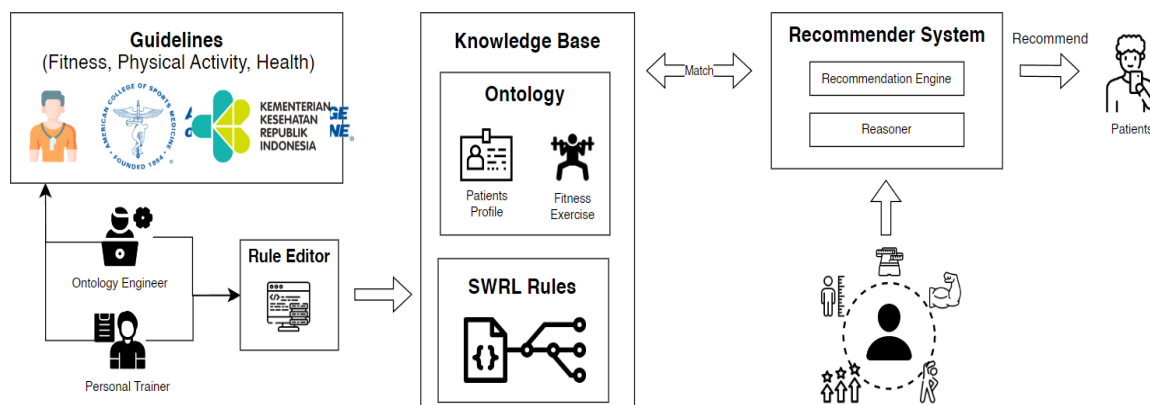
These days, recommendation systems provide users with beneficial wellness advice based on their current state of health, information from their past, and suggestions from other users. Ontology-based techniques have been used to produce recommendations utilizing domain knowledge and rules (Chatterjee & Prinz, 2022; Chatterjee, Prinz, Gerdes, & Martinez, 2021; Tacyildiz & Ertugrul, 2020). Compared to other methods, like those based on collaborative filtering, the rule-based methodology used in this study has several benefits. Rule-based approaches take the issue of data scarcity into consideration, and the knowledge format is standardized, in contrast to the other two strategies, which can occasionally be inconsistent and inaccurate (Alian, Li, & Pandey, 2018). However, ontology-based recommendation systems need rigorous guidelines that might not always be available.

For instance, Basnayake et al (Basnayake, Peiris, Wickramaratna, & Jayathunga, 2021) created an ontology-based software that uses a person's measures of the body, preferred forms of exercise, age, food, and medical history to help reduce physical activity in obese and overweight persons. To retrieve the recommendation, they used SPARQL (Simple Protocol and Resource Description Framework Query Language) queries. Addressing the competency questions and the inspections of the domain experts serve to verify accuracy and correctness.

An ontology model for managing obesity was created by Kim et al (Kim, Park, Min, & Jeon, 2013) which permits impulsive engagement and ongoing weight monitoring using mobile devices. The study covers implementation, evaluation, inferred data, and success or failure in behavior change. A formal definition of knowledge as ideas and their interactions within a domain can be found in an ontology. To

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customize health status evaluations, Sojic et al. (Sojic, Terkaj, Contini, & Sacco, 2016) used Ontology Web Language (OWL) to construct a particular ontology in the subject of obesity. The classification of personal files and automatic inference of one's health state made possible by the ontology are important for assessing and preventing obesity. The ontology rules were written utilizing SWRL. OWL and SWRL were utilized by Chi et al. (Chi, Chen, & Tsai, 2015) to develop a dietary consultation recommender system. The patient's sickness stage, physical state, level of activity, amount of food consumed, and significant dietary restrictions were all used to develop the knowledge base.

METHOD

Numerous studies have employed ontologies based on OWL to overcome issues with knowledge representation and data interchange. However, the eHealth sector requires further assistance in integrating semantic rules, sensor data, semantic annotations, preference settings, clinical advice, health risk prediction, and specially curated suggestion generation of an individual's health and wellness.

To deliver real-time individualized suggestions for obese patients, we suggest an ontology-based recommendation system. In Fig. 1, the system framework is depicted. Semantic rule sets and an ontology-based knowledge base form the foundation of the suggested system. The ontology knowledge base stores patient profiles, activity levels, fat mass, the muscle regions they want to train, and their desired exercise difficulty.

Evidence for personalisation in the context of obesity is provided by this kind of information. The ontology also has wellness and preference categories and linkages, such as muscle group, activity level, and fitness exercise, which are pertinent to the management of obesity. In conclusion, obesity-related system facts are included in the ontologies. To develop the semantic rule set, we merged guidance from the medical literature on obesity with insights from a fitness expert. (Piercy et al., 2018). The knowledge we gather will be turned into logical rules that computers can understand. Our reasoning engine utilizes information from our knowledge base and semantic rules to offer helpful advice for individual users. Below, we will provide an overview of the key study topics that were considered during the development of our system.

Ontology Knowledge

The exercise plan ontology is a paradigm that we have created for exercise regimens. To give consumers individualized and pertinent workout information, our model considers their unique characteristics and interests. It considers crucial elements including activity level, muscles targeted, and workout difficulty based on the user's health. We employ ontologies to arrange patient profile data effectively and clearly. This knowledge base aids in the customization of self-management strategies for obese people.

We use RFM (Relative Fat Mass) in place of BMI (Body Mass Index). The RFM index is an easy-to-use instrument that calculates body fat mass using the waist measurements and height ratio. This

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method is more accurate than the BMI and more precise than other methods for calculating body fat percentage. RFM has been validated, and the original authors' most recent research has established gender-specific obesity cut-off values. It's crucial to remember that the RFM equation has a gender component (Woolcott & Bergman, 2019).

$$\text{Male RFM} = 64 - 20 \times \left(\frac{\text{height[cm]}}{\text{waist [cm]}} \right) \quad \square \square \square$$

$$\text{Female RFM} = 76 - 20 \times \left(\frac{\text{height[cm]}}{\text{waist [cm]}} \right) \quad \square 2 \square$$

Use a tape measure that is looped around the body and placed at the top of the hip for the best results, determine height and waist size. Make sure that the measures are in the same unit system whether using the English or the metric system. To diagnose obesity and a higher mortality risk, 30% for men and 40% for women are indicated as RFM cut-offs (Woolcott & Bergman, 2020). The American Council on Exercise's (Table 1) cut-offs might be used to interpret the relative fat mass result.

Table 1 RFM Classification

Classification	Females (%fat)	Males (%fat)
Essential Fat	10% - 13%	2% - 5%
Athletes	14% - 20%	6% - 13%
Fitness	21% - 24%	14% - 17%
Average	25%-31%	18% - 24%
Obese	32% and higher	25% and higher

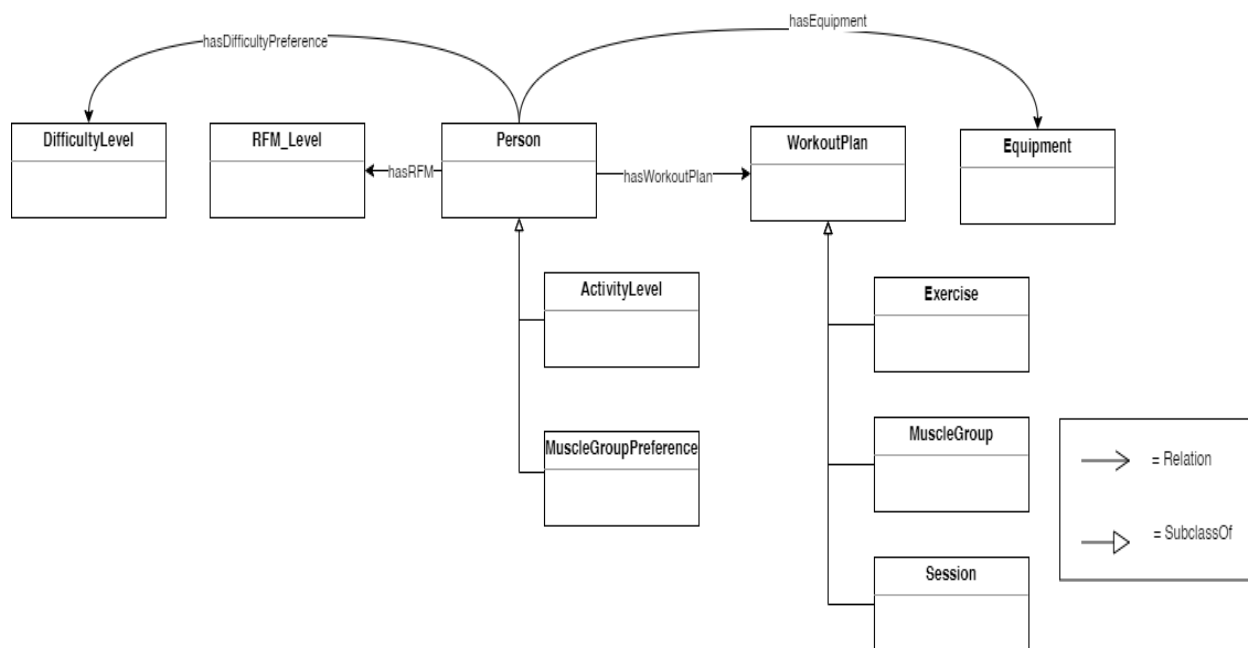
The 2008 Advisory Committee claims, Even if they do not meet the recommended target range, those who are not physically active can improve their health by raising their activity level (as shown in Table 2) (Petridou, Siopi, & Mougios, 2019). More recent information also supports the idea that reducing inactivity can have significant health benefits, regardless of age, even if individuals do not meet the recommended target range.

Table 2 Activity Level

Category	Daily Activity
Inactive	Not engage in any physical activity other than light to moderate movement.
Active	Adults that exercise for 150 to 300 minutes of moderate exercise each week.
VeryActive	Exercise more frequently than the equivalent of moderate exercise for 300 minutes each week.

Fig. 2 displays some of the key ideas and connections in the ontology design. Fig. 2 illustrates the four main classes. The main class is *Person*, *RFM_Level*, *WorkoutPlan*, and *Equipment*. *Person* class store of a user properties and preferences of the workout plan. The subclasses of the *Person* class are *activitylevel*, *DifficultyPreference*, and *MuscleGroupPreference*. *RFM_Level* class based on calculated

values from user input height and waist circumference. *WorkoutPlan* class stores the properties of the workout plan that will recommend to the user. The subclasses of the *WorkoutPlan* class are *Exercise*, *MuscleGroup*, *Session*. *Equipment* class stores equipment for the exercise if the exercise needs equipment to do.



Creating Rule Sets

To address obesity, it is important to have a comprehensive understanding of the available treatment and management options. In addition to consulting with specialists from the kekartargetfitness with specific expertise in obesity, our team has done considerable research on wellness-based recommendations. We have also gathered information from credible public documents and websites. However, for the average user, sifting through all this information and determining what applies to their specific situation can be challenging due to time and intellectual constraints. Therefore, we have developed general recommendations based on our research to address obesity. SWRL is W3C standard for production rules based on ontologies. We used SWRL to display the created rules. SWRL is a powerful OWL-based rule language (Jean-Baptiste, 2021).

System Implementation

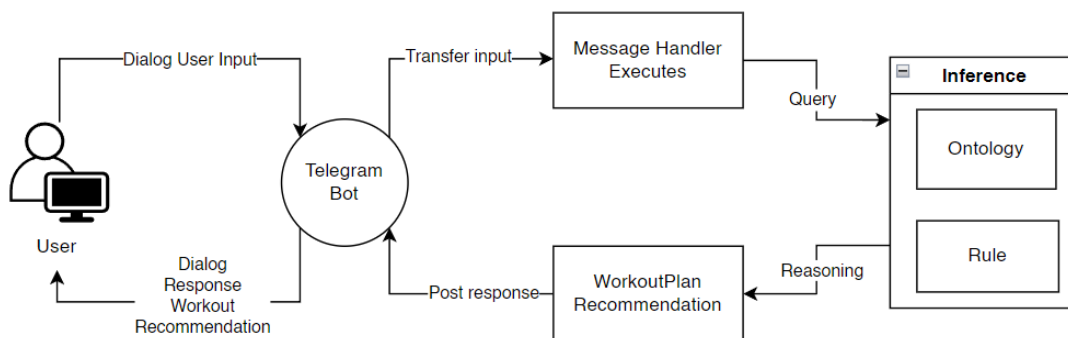
We have implemented the proposed ontology, SWRL, and recommendations system into a Telegram Chatbot. By integrating the bot into a Python chatbot for Telegram, we have examined the suggestions functionalities.

a. System Flow

Our research involved creating a chatbot on the Telegram platform that can be accessed from various devices like laptops, mobile phones, and computers. Users can input their personal information such as gender, height, waist circumference, activity level, difficulty preference, and muscle group preference which the system then sends to the handler as a query. Based on the user's inquiry, the system generates recommendations using SWRL and ontology. These recommendations are then sent back to the user through the chatbot interface. You can refer to Fig. 3 for a visual representation of the process.

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b. Implementation of ontology and SWRL

We utilize Protégé version 5.6.1 to create the ontology and employ the top-down (tree) approach, which involves establishing classes, sub-classes, and instances, as depicted in Fig.

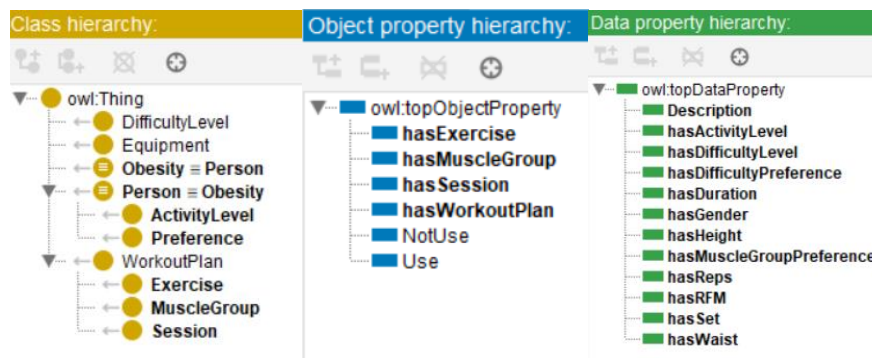


Fig. 4 Class hierarchy, Object properties, and Data Properties

4's class hierarchy.

Every class in ontology is equipped with a data property that provides additional information about the class. Object properties are also defined to establish semantic relations between instances of each class. Fig. 5 also displays the data and object properties that are employed to create hierarchies and conceptual relationships between instances.

We created two main sets of SWRL rules for this project: one for computation/definition and the other for wellness advice. Compounds based on rules use formulas like arithmetic operations to gather already-known information and derive implicit knowledge. Specific words and limits define these rules. For example, the following SWRL rule is used to compute the RFM for a person:

Person(?p), hasGender(?p, "Male"), hasHeight(?p, ?h), hasWaist(?p, ?w), divide(?diverresult, ?h, ?w), multiply(?multipliedResult, 20, ?diverresult), subtract(?rfm, 64, ?multipliedResult) -> hasRFM(?p, ?rfm)

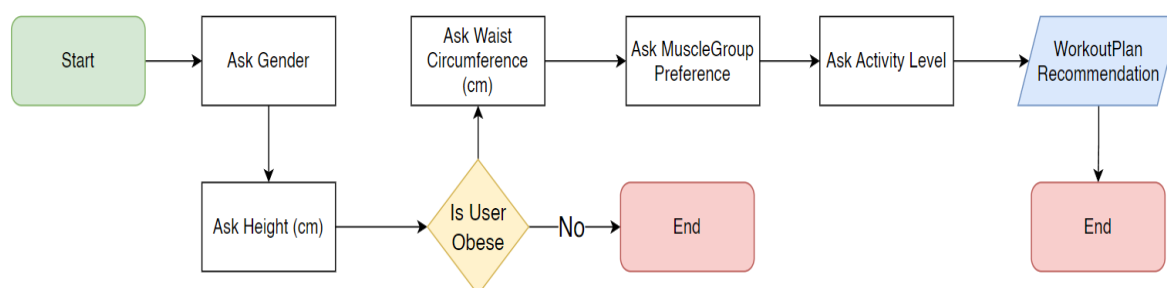
Exercise recommendations are generated using recommendation-based rules that utilize causal logic. For example, these SWRL rule consider the user's preferences to suggest suitable workouts:

Person(?p) ^ hasActivityLevel(?p, "inactive") ^ hasDifficultyPreference(?p, "beginner") ^ hasMuscleGroupPreference(?p, "UpperBody") ^ WorkoutPlan(?wp) -> hasWorkoutPlan(?p, ?wp) ^ hasWorkoutPlan(?p, InactiveBeginnerUpperBodyWorkoutPlan)

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Our system generates personalized workout plans based on the information provided by the user. We developed our chatbot using Python language and connected it to Telegram API. User information such as gender, height, waist circumference, activity level, difficulty preference, and muscle group preference recommend a workout plan that includes specific sessions, exercises, sets, and repetitions. For a better understanding of the conversation flow, please refer to Fig. 5.



RESULT

Through case studies and expert analysis, we evaluated the personalized recommendation system's efficacy.

Use Case Study

The case study that follows demonstrated the usefulness of the suggested approach and put our customized proof-of-concept solution for obese individuals to the test. Assume Soni Andika stands 173 centimeters tall and has a 95-centimeter belly circumference. Soni decides to work out his entire body at the beginning despite having a low level of activity. RFM can be computed or inferred concurrently. Based on Soni's unique data, the system may present a Workout Plan menu that is specifically suited to Soni to regulate Soni's weight and exercise level, for instance, the system can offer basic advice. Fig 6 displays a screenshot of Tim's chatbot interaction. Soni receives these Workout Plan choices depending on her preference information.

Expert Verification

Additionally, the workout plan recommendations list created by the system in Spreadsheet has been confirmed by fitness professionals on our research team. To determine genuine positive, false positive, and false negative values, expert validation results are used. Calculations for the F-Score, precision, and recall can be done based on these data to determine how accurate the suggested outcomes are.

Sample user data for the validation process were obtained from obese people who filled out a Google form with a minimum age limit of 20 years. The number of sample user data obtained is 30 samples. It produced 510 samples of exercise recommendations. Of the 408 exercise samples approved by three fitness experts, 102 were inappropriate.

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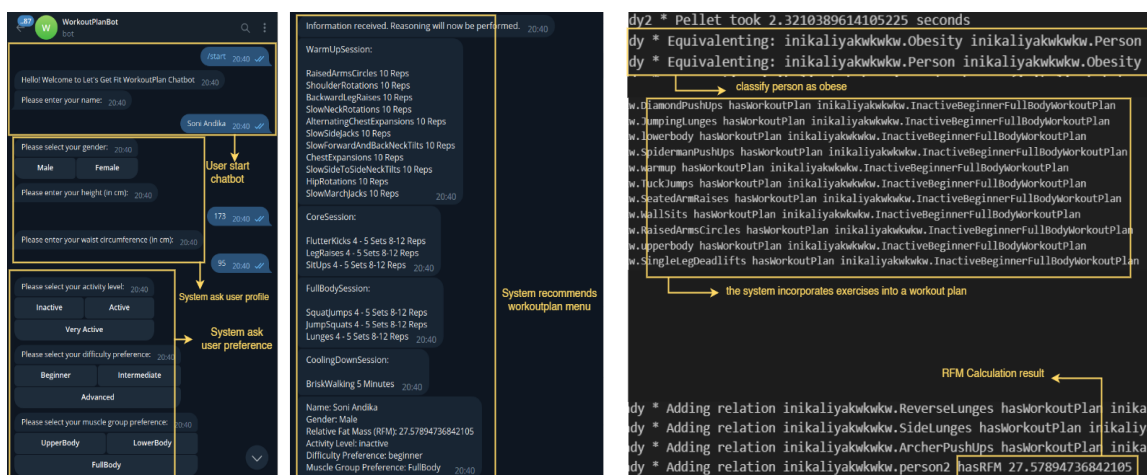


Fig. 6 Interaction between user and the chatbot in telegram

$$Precision = \frac{TP}{TP + FP} = \frac{408}{408+102} = 0.8 \quad \square 3$$

$$Recall = \frac{TP}{TP + FN} = \frac{408}{408+0} = 1 \quad \square 4$$

Recall is the ability of the system to retrieve the appropriate document, while precision is used to measure the effectiveness of a system in finding information. The results are good if the recall and precision values are close to 1.

Information

TP (True Positive)	The results of exercise recommendations that are in accordance with the recommendations of fitness experts
FP (False Positive)	The total results of exercise recommendations that are recommended by the system
FN (False Negative)	The total results of workout suggestions that are not supported by the system or fitness professionals

The F-Score, as well as the average precision and recall value, are obtained using precision and recall. This value can be calculated using the equation below:

$$F - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} = 2 \times \frac{0.8 \times 1}{0.8+1} = 88.8\% \quad \square 5$$

The average precision and recall listed in the F-1 Score are contrasted. The F-1 Score presentation demonstrates the accuracy level, which is very near to 100%.

DISCUSSIONS

In our research, we developed an ontology using various tools and methodologies, such as Protégé version 5.6.1. To enhance our reasoning capabilities, we integrated SWRL rules using Protégé SWRLTab. We used Python to create a chatbot on Telegram. To ensure the chatbot's performance, knowledge representation, reasoning abilities, and usability were up to par, we asked domain experts to test it with predefined queries. The expert validation process provided valuable feedback for improvements, confirming the effectiveness of the ontology, SWRL rules, and chatbot implementation. We successfully created a robust and validated knowledge-based system by combining these tools and expert evaluation.

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CONCLUSION

We discussed our research into individualized fitness plan recommendations in this essay, specifically for obese people. To enable personalization, the recommender is based on the ontology of a person's profile. Recommendations for general exercise for obesity were transformed into rule-based logic that incorporates the recommender's ontology and knowledge base. With the aid of the knowledgebase, a recommendation system based on reasoning can provide consumers with tailored recommendations. The suggested system was tested using test cases and expert verification after being implemented as a prototype. This chatbot has a high accuracy rate of 94.7%, according to the evaluation. It can design individualized fitness schedules and recommend routines for people who are obese to assist them safely lose some weight.

The limitation of this research is the limit of user profiles. Furthermore, researchers have yet to evaluate users' opinions regarding the chatbot's features. It is important to note that this chatbot is exclusively designed for individuals who are not obese and cannot be used in other cases.

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