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A Personalized Recommendation System to Support Diabetes Self-Management for American Indians

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ABSTRACT The epidemic of diabetes in American Indian (AI) communities is a serious public health challenge. The incidence and prevalence of diabetes have increased dramatically with accompanying increases in body weight and diminished physical activity. In this paper, we propose a proactive diabetes self-care recommendation system specifically for AI patients. It recommends healthy life style to users to fight for their diabetes. Thanks to the quasi-ubiquitous use of cellphones in most AI tribes, we choose cellphones as the platform to provide smart personal care for AI patients. By integrating the AI users' ontological profile with general clinical diabetes recommendation and guidelines, the system can make personalized recommendations (e.g., food intake and physical workout) based on the special socioeconomic, cultural, and geographical status particularly to AI patients. The proposed system was implemented as mobile applications. Evaluations performed by use case studies and human expert verification demonstrate the effectiveness of the system.

INDEX TERMS American Indian, diabetes, ontology, reasoning, logic, self-management, recommendation, personalization.

I. INTRODUCTION

With more than 16% of the population have been diagnosed, American Indians (AI) and Alaska Natives (AN) have the highest age-adjusted prevalence of diabetes among all U.S. racial and ethnic groups [1]. Moreover, up to 30% of AI/AN have prediabetes, or higher-than-normal blood sugar levels associated with increased risk of type 2 diabetes [2]. The prevalence of diabetes in AI/AN has caused a great deal of pain and suffering in this community. According to Indian Health Service (HIS), AI/AN have a higher incidence of long-term complications of diabetes and a higher probability of developing serious diabetes-related complications. Among AI/AN adults, diabetes is a major cause of morbidity (blindness, kidney failure, lower-extremity amputation, and cardiovascular disease), disability, decreased quality of life, and premature mortality [3].

Although different genetic constructions of AI/AN can be a reason for this disparity, the more recent dramatic increase of the incidence and prevalence of this disease may be caused by giving up traditional lifestyles in favor of westernization, with accompanying increases in body weight and diminished physical activity [4]. In addition, besides the genetic predisposition and changing of traditional life style, the economic, social, and cultural conditions may also play a major influence on the health disparities that exist between AI/AN and the general U.S. populations. In U.S., most AI/AN have lower incomes, lower graduation rates, higher rates of tobacco use, and poorer nutrition. Furthermore, limited transportation and limited access to healthcare services all lead to poor diabetes care.

As daily diabetes care is primarily handled by patients and their families, the effectiveness of diabetes control is largely impacted by self-care strategies and behaviors. There have appeared many health and wellness-related applications, including software, websites, mobile applications, and social media to assist people in self-managing their diabetes. For example, *CalorieKing* [5] and *GoMeals* [6] are two apps that provide their users with knowledge about food. They can give detailed nutritional information for many foods and restaurant menu items. They help users to adjust the food portion size and provide an actual food label. *Glucosio*[7] is another app for diabetic patients. It tracks important metrics like A1C, body weight, ketones, cholesterol, blood pressure, and more. It also helps users to set targets and reminders to keep their program on point.

Research on recommendation systems have been carried out aiming at providing users with health and wellness guidance. For example, Food Recommendation System (FRS) [8] uses food clustering analysis for diabetic patients. It recommends the proper substituted foods in the context of nutrition and food characteristics. Clustering is used to group similar food based on the similarity of eight significant nutrients for diabetic patient. Suksom *et al.* [9] proposed a personalized food recommender that can help users select their diet based on nutrition guidelines. The recommender utilizes a food and nutrition database and knowledgebase. Rule-based knowledge can provide food recommendations to users based on their nutrition requirements. Very similarly, Tumnark *et al.* [10] propose an ontology-based personalized dietary recommendation for weightlifting to assist athletes meet their requirements. They also use a food and nutrition ontology working with a rule-based knowledge framework to provide specific menus for the athlete's diary nutritional needs and personal preferences.

Despite the tremendous research efforts and existing apps of diabetes selfcare and recommendation, most of them are general for all population. They do not consider the special property of AI/AN patients, who experience poverty, lower rates of health literacy, special tribal culture, and limited access to healthcare services. Existing systems ignore or undervalue barriers created by language gaps, education gaps between AI/AN patients and health providers. If we directly apply these recommendations to AI/AN patients, the usefulness of the recommendation will be jeopardized: AI/AN patients may not understand the recommendation represented using professional medical terminology. Moreover, the recommended food or lifestyle may be unavailable in the AI/AN tribe location that is in a food desert; the recommended items can be unaffordable; or the recommendation may be culturally or religiously inappropriate. Failure to consider AI/AN patients' perspectives and experiences will lead to failure in curbing diabetes in this population.

To address the limitations in existing works, we propose a personalized diabetes recommendation system customized for AI/AN patients. The recommendation system will respect the special socio-economic, cultural, ethnic, and geographical status particularly to AI patients. By integrating the AI users' profile with general clinical diabetes guidelines, the system can make useful wellness and lifestyle recommendations which are more appropriate to AI users.

The rest of the paper is organized as follows. Section II surveys the related work. Section III details the system design, and Section IV explains the implementation and evaluation of the proposed system. Concluding remarks are provided in Section V.

II. RELATED WORK

Nowadays there have been many recommendation systems appeared to give users beneficial wellness recommendations for performing a specific activity that will improve their health, based on their given health condition and set of knowledge derived from the history of the users and other users similar to them. Based on the algorithms used in the recommendation systems, we classify them into three categories, namely machine learning-based, collaborative filtering-based, and rule-based systems.

A. MACHINE LEARNING-BASED PERSONALIZED HEALTH RECOMMENDATION SYSTEM

Machine learning is one of the fastest growing technology being applied to healthcare domain. It provides superior benefits in improved disease diagnoses, analyses and prevention. Many machine learning-based systems have been designed to provide personalized lifestyle recommendation / intervention. For example, Fadhil [11] proposed a supervised machine learning algorithm to classify users and help caregivers to personalize their intervention feedback. The system was trained through the participants' profiles, activity performance, and feedback from the caregivers. A prototype system, *CoachMe*, was presented, aiming to promote healthy lifestyle and activities and reduce risk of chronic diseases.

Preuveneers and Berbers [12] developed a mobile application that assisted the Type 1 insulin dependent diabetic patients to keep track of food intake, physical activities, blood glucose levels and insulin dosage. The proposed system utilized hidden Markov model to monitor users' location and then recognize past behavior, and eventually inferring their activities for the purpose of assisting users in decision making on daily drug dosage.

Archenaa and Anita [13] investigated analyzing big data for developing effective health recommendation engine. The proposed approach applied a Bayesian network on multi-structured healthcare data on life style, physical health factors, mental health factors and their social network activities. Lifestyle recommendations could be made based on the classification results.

Many commercial mobile applications such as RapidCalc Diabetes Manager [14] mySugr [15] and Diabetes:M [16] recorded users' food intake, physical activities and blood glucose level. Based on the information, these systems can adjust the insulin dosage using machine learning-based approaches.

B. COLLABORATIVE FILTERING-BASED PERSONALIZED HEALTH RECOMMENDATION SYSTEM

Collaborative filtering (CF) [17] has been widely used to make recommendations of a person's preferences based on other similar persons' preferences. The rationale behind this technique is that people often get the best recommendations from someone with tastes similar to themselves. Collaborative filtering encompasses techniques for matching people with similar interests and making recommendations on this basis. Systems can compare a user's health conditions to his/her previous conditions or other users with similar medical conditions. If there is evidence in a user's history, that the execution of a certain activity has improved the user's health conditions, it can be concluded that the activity can help him/her or other users with similar health issues and improve their health conditions [18].

The *Cohesy* system [18] uses collaborative filtering techniques on large amount of users' health data and generates different recommendations, notifications and suggestions to the users. The system can monitor and detect potential emergencies. Moreover, it can help users find others with similar conditions, so that they can exchange their experience. Similarly, Kulev *et al.* [19] designed a physical exercise recommendation system that uses collaborative filtering to identify similar users and learn their physical activity patterns that may improve their health condition and use that knowledge to make recommendations.

Hors-Fraile *et al.* [20] designed two collaborative filtering-based recommendation systems to assist people quit smoking. The hybrid recommender integrates content-based, utility-based, and demographic filtering to tailor health recommendation messages. Kim *et al.* [21] proposed a context-aware collaborative model using the context information to fill the missing values in a collaborative filtering process. The proposed system can provide menu services in the u-healthcare services.

C. RULE-BASED PERSONALIZED HEALTH RECOMMENDATION SYSTEM

Rule-based approaches (such as [9], [10], and [22]–[25]) have been applied to implement recommendation systems as well. They make use of domain knowledge and rules to generate recommendations. Our proposed approach in this paper belongs to the rule-based approaches. According to [22], rule-based reasoning approaches have several key advantages over other approaches such as collaborative filtering-based approaches for recommendation. The first advantage is that it overcomes the data scarcity (or "cold start") obstacles which machine learning and collaborative filtering-based approaches suffer. Another advantage of rule-based approaches is its uniformity of the knowledge format. While the other two techniques can be inconsistent and unreliable when the accuracy of historical data cannot be guaranteed. On the other hand, rule-based recommendation approaches require the predefined rules which may not be available.

As some examples of rule-based recommendation systems: Skillen *et al.* [22] proposes a profile-based ontology with rule-based system to help people with dementia to accomplish their everyday tasks, such as shopping etc. Sivilai *et al.* [23] proposed another rule-based recommendation system for elderly Thai people to make plans for their food and nutrition. Lee *et al.* [24] proposed an intelligent ontological system for diabetic food recommendation, based on a fuzzy algorithm that generates fuzzy numbers for all types of food to be combined with the personal food ontology for Taiwanese. Very similarly, Al-Nazer *et al.* [25], Suksom *et al.* [9], and Tumnark *et al.* [10] proposed food and nutrition recommendation using rule-based approaches.

III. SYSTEM DESIGN

Evidence-based clinical guidelines and recommendations have been used for diabetes screening, diagnosis, and management [26]. However, these recommendations are usually general and abstract in nature and do not consider the special property of AI patients. If we directly apply these recommendations to AI patients without considering their special socio-economic, cultural, ethnic, and geographical status, the usefulness of the recommendation will be jeopardized. For instance, a proper diet recommendation is crucial for diabetes patients. We can find such general recommendation from existing guidelines. However, the language used in these guidelines may be so abstract and professional, that the AI patients may not be able to understand. As an example, a food recommendation with description of "low-sodium low-trans fat" may be hard to understand for AI patients with low-medical literacy. Moreover, AI patients may have their unique diet preferences. A recommendation should respect these preferences. Furthermore, as many AI tribes are in "food desert", in which too many foods (such as seafood) are either too expensive or unavailable. Therefore, making personalized recommendation is especially important for them.

We propose an ontology-enhanced recommendation system to provide real-time personalized recommendation for AI diabetes patients. The system framework is illustrated in Fig. 1. The proposed system is based on an ontology-based knowledgebase and a set of semantic rule sets. The ontology knowledgebase contains patients' profiles including health, preference, culture, social-economic status, and context information of the environment where the patient stays.

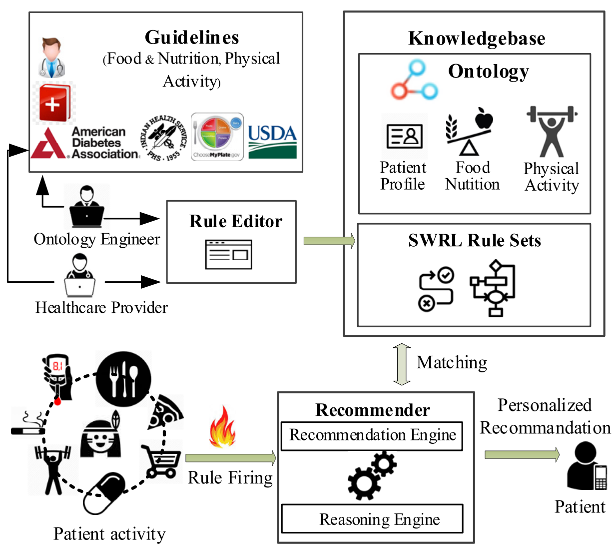

FIGURE 1. The framework of the personalized recommendation system.

This type of information provides evidence for personalization. The ontology also includes concepts and relations about wellness and lifestyle such as food, nutrition, and physical activity. In summary, the ontologies include facts of the system. A sematic rule set is generated based on the professional diabetes healthcare guidelines from medical literature (such as [27]–[29]) and professional knowledge of physicians. The collected knowledge will be converted to logic-based rules which computers can understand. Based on the facts from the ontology knowledgebase and the semantic rules from the rule set, a reasoning engine can make inferences and give personalized recommendations to a particular user. In the rest of this section, we present each of the major research components to construct the system.

A. CREATING ONTOLOGY KNOWLEDGEBASE

To provide AI users with relevant and adapted information for their special need and preferences, the system must consider the different social-economic and cultural characteristics of the patients and all contextual situations that influence patients' lifestyle choices. For this purpose, we propose a biocultural user profile ontology that models valuable biological, cultural, socioeconomic, and environmental factors affecting users' well-being. We use ontologies to capture patient profile and biomedical knowledge in a formal but simple, powerful and incremental manner. It works as a knowledgebase for the personalization of AI patients' conditions and self-management plans.

We use a multi-phased iterative and incremental ontology design and development methodology. In particular, the ontology development process includes six work phases which are used by ontology engineers and developers to prepare, design, implement, test, and deliver ontology. Among the six phases including (1) scope definition, (2) knowledge acquisition, (3) specification, (4) conceptualization, (5) implementation, and (6) evaluation, each phase is cyclically and incrementally repeated. At each new cycle the ontology will be further detailed and extended. Different personnel (domain experts, ontology engineers, and final users) may get involved in different phases.

Fig. 2 shows some of the major concepts and relationships of the high-level ontology. As shown in the figure, the most important part of the ontology is the definition of the user's profile, which includes basic user information, physiological profile, capability profile, health profile, preference profile, and social profile. We also reused and revised some existing ontologies [30]–[33] about food, nutrition, and workout, to make them fit for the AI wellness recommendation system. For example, for the food concept, we added traditional food, food availability, locally preferred food, etc.

B. CREATING RULE SETS

1) KNOWLEDGE ACQUISITION

A diabetes management system must depend on a comprehensive knowledgebase of diabetes treatment and management. We have systematically explored wellness-based guidelines from four different dimensions, namely diabetes management general guidelines, food and nutrition guidelines, physical workout guidelines, and AI-related healthcare guidelines.

To get general recommendations of diabetes, we adopt the guidelines from multiple resources including American Diabetes Association (ADA) [27], the British Dietetic Association (BDA) [28], Association of Clinical Endocrinologists

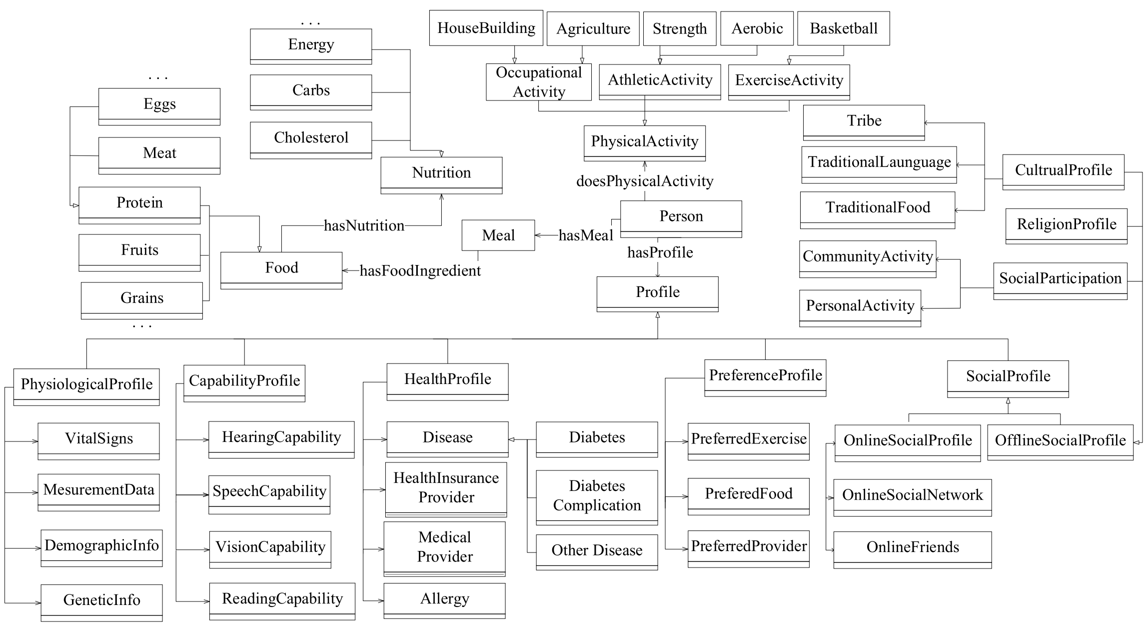

FIGURE 2. Part of the high-level ontology.

and American College of Endocrinology (AACE/ACE) [29], Nutritional Recommendations for Individuals with Diabetes [34] and the prevention and control of the type-2 diabetes by changing lifestyle [35]. These websites and documents aim to assist diabetic patients and their healthcare providers to manage this disease. To further refine the knowledge in food, nutrition and diet, we also extracted knowledge from the Dietary Guidelines for Americans (USDA) [36], Dietary Reference Intake [37]–[39] and many other websites such as [40] and [41]. To get detailed knowledge on life style and physical exercise, we refer information sources like American Diabetes Association (ADA) [27], Eat Heathy – Be Active Community Workshops (EHBA) [42] and American Heart Association [43]. Finally, to get healthcare guidelines specifically to AI patients, we refer sites such as Indian Health Services (IHS) [44], American Indian and Alaska Health [45] and National Indian Health Board [46].

As an example, the following statement from ADA [27] provides a guideline about *Fat*: "The ideal amount of dietary fat for individuals with diabetes is controversial. The Institute of Medicine has defined an acceptable macronutrient distribution for total fat for all adults to be 20–35% of energy. The type of fats consumed is more important than total amount of fat when looking at metabolic goals. People with diabetes should be advised to follow the guidelines for the general population for the recommended intakes of saturated fat, dietary cholesterol, and trans-fat. In general, trans fats should be avoided."

In summary, all the guidelines used in this system are extracted from authoritative public documents and websites. However, for normal users to go through these resources and connect what applies to their conditions would be nearly impossible given the time and intellectual limitations.

2) RULE GENERATION

After we have collected the professional guidelines from the knowledge sources, we then convert them to rules that computers can "understand", so that recommendation can be automatically provided to patients based on reasoning over their specific user profile, context and the rules. Based on the practical problem-solving experiences, we adopted the most popular *"premise→conclusion"* logic form to describe the medical rules. Each rule is made up of a body (known as an antecedent) and a head (the consequent). Rules in this format can be understood as the "IF-THEN" clauses which follows the IF (antecedent) THEN (consequent) format. The premise of this logic form can be defined by the logical conjunction of set of logical expressions. Each expression is constructed based on logical operators to connect concepts/variables representing user profiles (such as health status, allergy condition, body type) and users' real time context (such as vital signs, time and locations). These concepts are connected by the properties they belong to and are chained to other facts by the properties in a step-by-step manner. In the case that a patient activity event is fired or a service request is initiated, the conditions expressed within these logical expressions will be evaluated to be true or false. If all pre-conditions are evaluated to be true, it will then lead to a conclusion. The conclusion could be anything pertaining to the recommendations, e.g. if a specific food item is good for diner, or the amount of time for exercise, etc.

3) RULE PRESENTATION

We choose to use the Semantic Web Rule Language (SWRL), an expressive OWL-based rule language to present the generated rules, as SWRL is the W3C standard for production rules based on ontology. It is a combination of the OWL DL and OWL Lite with the Unary/Binary Datalog RuleML sublanguages of the Rule Markup Language [47]. It combines the OWL knowledgebase and inference rule to perform reasoning about OWL ontology instances and infer new knowledge about them.

In this project, we have created two main groups of SWRL rules, namely the computation/definition -based rules and the wellness recommendation-based rules. The computation-based rule uses formulas such as arithmetic operations to collect available known facts to infer implicit knowledge such as defined terms and parameters. For example, the rule below calculates the EER (Estimated Energy Requirement) for a not very active adult male.

```
Person(?user)                              ^
Weight(?user,?w)                           ^
Height(?user, ?h)                          ^
Age(?user, ?age)                           ^
hasBMI(?user,?bmi)                         ^
Gender(?user,Male)                         ^
lessThan(?bmi,VeryActive)                  ^
swrlb:greaterThanEqual(?age,19)            ^
swrlb:multiply(?t1,15.91,?w)               ^
swrlb:multiply(?t2,?age,9.53)              ^
swrlb:multiply(?t3,?h,539.6)               ^
swrlb:add(?tmp,?t1,?t3,662)                ^
swrlb:subtract(?eer,?tmp,?t2)              ->
EER(?user, ?eer)
```

The recommendation-based rule uses the cause-effect logic to provide wellness recommendations. For example, this rule identifies whether a person's meal exceeds the fat limit.

```
Person(?user)                              ^
hasMeal(?user,?meal)                       ^
hasFat(?meal,?fat)                         ^
hasFatMaxLimit(?meal,?limit)               ^
swrlb:greaterThan(?fat,?limit)             ->
isRecommended(?meal, false)
```

C. RULE-ENABLED PERSONALIZED RECOMMENDATION

Rules can help us to establish the cause-effect relationships in the recommendation system. A reasoning engine is required to determine if the cause (premise or pre-conditions) of a rule is met, thus leading to an effect (consequence or conclusion). Iteratively, the reasoning engine should determine if the consequence of a previously fired rule may cause other rules to be fired. As our rules are represented in horn clause-like format, both forward chaining and backward chaining can be applied for the reasoning.

Forward chaining reasoning repeatedly apply modus ponens rule to infer new facts. It starts with known facts and then looks for inference rules to apply to such facts to generate new consequences/facts. Then the generated consequences can be used as new facts to activate other rules and this process continues until the goal is reached or no rules can be fired. Conversely, backward chaining begins with a list of goals (or a hypothesis) and works backwards to the antecedents to see if they are available. The reasoning engine would search the inference rules until it finds one which has a consequent that matches a desired goal. If the antecedent of that rule is not known to be true, then it is added to the list of goals [48].

Our personalized recommender is based on forward chaining reasoning. As presented in Fig. 1, the reasoner takes the rules from the Rule Base and facts from user profiles and other contextual information from the user profile ontology, and other facts about food, nutrition, physical exercises etc. from other sub-ontologies in the knowledgebase. When an event is triggered (e.g., a wearable sensor detects a user vital sign change, or a specific predefined calendar time comes) or when a user explicitly makes a request through their cell-phone mobile application, the event/request is passed onto the personalized recommendation engine. Then the event/request and the input are used as a variable and facts in the logical operation of the antecedent of rules. At this stage, the reasoning engine will determine if the antecedent of any rule in the rule base is available, and if so it will fire the appropriate rules. The consequence of the fired rule is then used for firing other rules. In this way, the forward chaining-based reasoner can consider user's profile (including health, preference, capability, socioeconomic status), and other context information/event to provide appropriate personalized recommendation.

IV. SYSTEM IMPLEMENTATION AND EVALUATION

We have implemented the proposed recommendation system as a mobile application. We have evaluated the recommendation functionalities by deploying the application onto a set of iPhones and Android phones.

A. IMPLEMENTATION

As shown in Fig. 3, the prototype system, MobiDiaBTs, is built with a modular design for scalability and reliability. The client application can run on both IOS and Android platforms. The recommendation services are deployed on a centralized cloud server. Representational State Transfer (REST) is used to provide the standard interface between mobile clients and the cloud services. The REST-compliant services in cloud side allow mobile clients to access and manipulate system resources by using a uniform and predefined set of stateless operations. The REST API module is implemented using Spark framework [49].

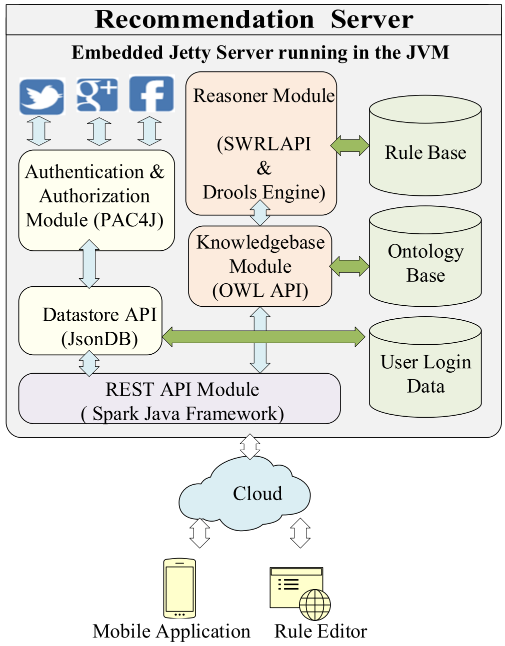

FIGURE 3. The implementation framework of the proposed system.

The recommender server consists of several modules including an authentication & authorization module, a knowledgebase module, and a reasoning module. The authentication & authorization module allows users with different roles (e.g., healthcare provider, patient) to sign up and login to the system and access different interfaces. The module is implemented with OAuth (Open Authorization) standard [50], so that users can use their social network accounts such as Facebook, Twitter and Google. PAC4J framework [51] was chosen as an implementation for the Authentication and Authorization module. The knowledgebase module enables all CRUD (create, read, update and delete) operations on asserted knowledge. It is implemented using OWL API, a Standard Application Programming Interface [52]. The reasoner module implements a reasoning engine that can communicate with the knowledgebase module to extract the asserted facts, and inference rules to infer logical consequences. This module fully supports OWL API to communicate with the knowledgebase module by implementing a reasoner based on one of OWL 2 language profiles – OWL 2 RL profile. OWL 2 RL is chosen because it is designed to implementable using a rule-based reasoner and reasoning is polynomial with respect to the size of the ontology [53]. The reasoner module provides an implementation to manage and support SWRL rules through SWRLAPI [54].

The mobile application client is implemented using Ionic framework [55]. It is platform-independent, which means that it can run on different platforms using the same codebase. A Rule Editor is implemented to allow technical users (system administrators and developers) and non-technical users (medical experts and medical doctors) to manage the rules. The Rule Editor provides smooth and easy user experience for all types of users.

B. EVALUATION

We have evaluated the functionality of the personalized recommendation system by use case studies and human-expert evaluation.

1) USE CASE STUDIES

The two case studies discussed below were used to highlight the utility of the proposed system and to test our proof of concept personalized recommendation system for AI/AN diabetic patient.

In the first case, assume Tim Anderson is a 35-year-old Native American Indian male living in Lower Sioux Indian Community in the state of Minnesota. Tim suffers Type 2 diabetes, high-blood pressure, and is overweighed. The system requires a user to provide some basic information such as age, height and weight. While some other information (such as CPM (Choices Per Meal), EER (Estimated Energy Requirement), BMI (Body Mass Index), blood pressure level (normal, elevated, hypertension I, hypertension II, hypertension crisis)) can be inferred or computed. Based on his profile information and dynamic context information, the system can provide various health recommendations and medical guidelines specific to him. For example, the system can provide general recommendations to help Tim control his diet and stay healthy. Fig. 4. Shows the screenshot of general lifestyle guidelines to Tim. These guidelines are provided to Tim based on Tim's health profile data.

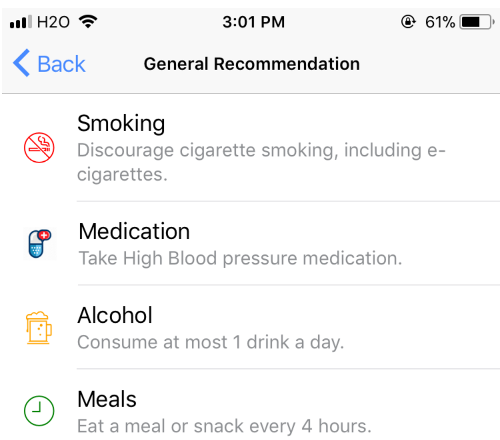

FIGURE 4. Screenshot of general health recommendation.

Our system can provide various types of recommendations for patients at different scenarios. For example, in a particular day at lunch time, Tim sits at MacDonald's for his lunch. Before ordering a Big Mac meal (including one Big Mac sandwich, one small Coke and one medium fries), he asks for suggestions of the system. Our system includes menus of popular local restaurants of Lower Sioux Tribe (Tim's local tribe). The system will calculate the nutrition of the meal as listed in Fig. 5 and pass the nutrition information to the knowledgebase to examine if the meal violates any medical guidelines related to Tim's health conditions.

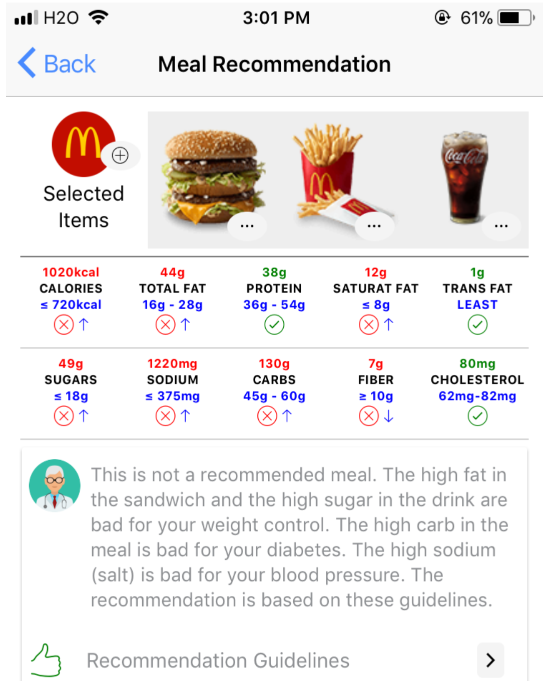

FIGURE 5. Screenshot of a meal recommendation.

Through reasoning applied to user's profile and the medical guideline rules, the system finds that the meal violates nine medical guidelines, namely: too much calories, fat, and sodium, but too little fiber. The nine guidelines are provided below:

1) *Lunch total calories should be 25% of the Person EER. According to the default distribution of caloric intake per meal* [56].
2) *Fiber should be more than 14g/1000 kcals/day, for this meal it should be more than 14g. According to the guidelines of The Institute of Medicine of the National Academies* [38].
3) *Total fat should be in the range of 20-35% of meal energy, according to the guidelines of The Institute of Medicine for obese diabetic patients* [27].
4) *Saturated Fat should be less than 10% of meal energy, according to the Dietary Guidelines for Americans* [36].
5) *Cholesterol should be in the range (250 – 325) mg per dayfor men, for this meal (62-82) mg. According to the guidelines of The Institute of Medicine of the National Academies* [38].
6) *Protein should be in the range (20 - 30) % of meal energy, according to the Diabetes Care guidelines to help successfully manage type 2 diabetes* [27].
7) *Carb Choices per meal should be in the range of 3-4 Choices (45–60) g, according to the medical guidelines from the International Diabetes Center for a male person with diabetes and low activity* [57].
8) *Sugar should be less than 10% of meal energy, for this meal should be < 25g, currently 49g. According to the Dietary Guidelines for Americans* [36].

9) *Sodium should be less than 1500mg per day, for this meal it should be less than 525mg. According to the Diabetes Care guidelines for people with diabetes and blood pressure* [27].

The SWRL rule corresponding to each guideline is stored in the rule base. For example, related to guideline 9, the corresponding SWRL rule is:

Person(?user) ^
hasMeal(?user,?meal) ^
hasSodium(?meal,?sodium) ^
hasBloodPressure(?user,?bp) ^
moreThan(?bp,NormalBloodPressure) ^
hasEnergy(?meal,?energy) ^
hasEER(?user,?eer) ^
swrlb:divide(?mealPer,?energy,?eer) ^
swrlb:multiply(?limit,?mealPer,1500) ^
swrlb:greaterThan(?sodium,?limit) ->
isRecommended(?meal,false)

From the ontology base, we have the following profile related to Tim:

Tim	*Type*	*Person*
Tim	*hasMeal*	*lunchOption*
Tim	*hasBloodPressure*	*HypertensionII*
Tim	*HasEER*	*2880*
HypertensionII	*moreThan*	*NormalBloodPressure*
lunchOption	*hasSodium*	*1220*
lunchOptionhas	*Energy*	*1020*

Applying Rule 9 on Tim's ontology profile, we can see that Tim's meal has 1220mg of sodium and Tim's blood pressure is the level of Hypertension II. Based on the ratio of calories of this meal and the daily limit for Tim, Tim's lunch sodium exceeds the limitation. Similarly, the rest of the other eight rules can be examined. After processing the meal information and triggering the required rules to check the meal, recommendations for the meal is provided based on user profile and inferred medical information. As can be seen from Fig. 5, Big Mac meal is not recommended. Tim can choose other food items from the menu to get a better meal.

At the end of the day, the system provides Tim with a daily summary of his nutrition's intake as shown in Fig. 6. Based on his food intake, the system warns Tim that his fiber intake is not enough, he should eat more fiber in the future. The system also recommends Tim with food of high fiber.

In another scenario, Ashley is a 27-year-old Native American Indian female living in the Lower Sioux Indian Community in the state of Minnesota. Ashley suffers type 2 diabetes with Sedentary Physical Activity level. Her weight is 150lb and height is 5.3 feet. Based on Ashly's profile, Fig. 7 shows a general physical exercise recommendation (the screenshot only shows the aerobic part of the exercise). Based on the American Diabetes Association's recommendation on exercise [58] and the National Institute of Diabetes and Digestive and Kidney Diseases [59], we recommend four types of exercises including aerobic (such as swimming and hiking), resistant (such as hand weights and elastic bands),

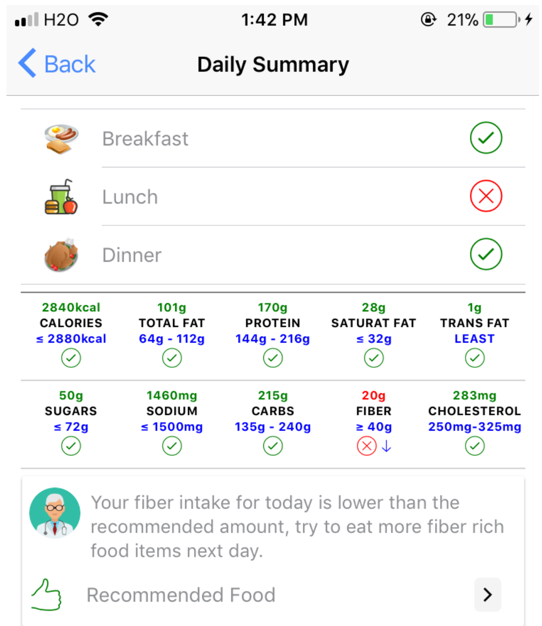

FIGURE 6. Screenshot of daily diet summary.

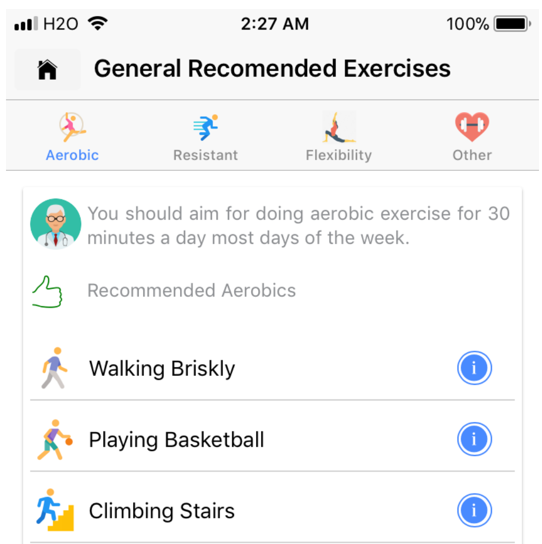

FIGURE 7. Screenshot of general physical activity recommendation.

flexibility (such as yoga and stretching), and other activities such as taking the stairs instead of the elevator and doing chores in the house or garden.

On a particular day, Ashley consumed extra calories beyond the recommendation. As a remedy, the system provides extra physical activity recommendations to burn the calories. The recommendation is shown in Fig. 8. The recommendation is made based on the extra calories need to be burnt and Ashley's physical parameters. In addition, it will consider Ashley's exercise preferences, local exercise facilities, and the current weather conditions. As the weather is rainy, only indoor activities were recommended. In Lower

Sioux Community, where Ashley lives, there are two workout facilities: Recreation Center and Sioux Falls YMCA. Ashly's favorite exercises include: ice hockey, running, yoga, basketball, weight lifting, body weight squats. The recommendation system would consider all of these factors.

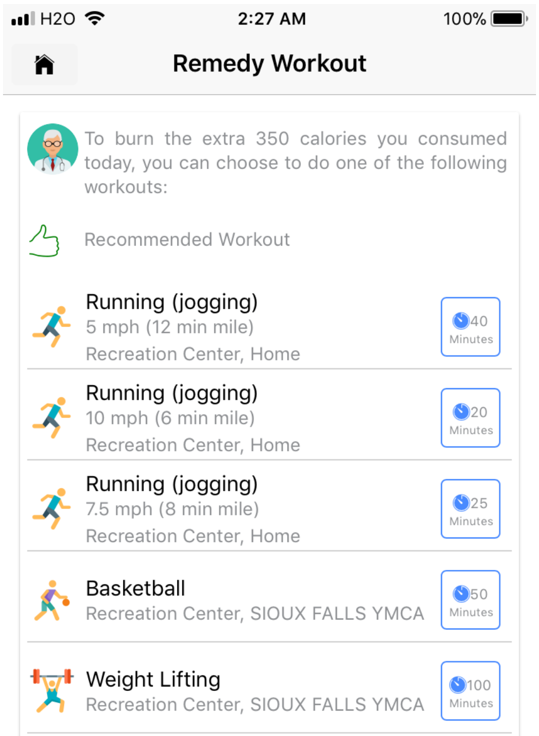

FIGURE 8. Screenshot of extra physical activity recommendation.

While we have described two use case scenarios, our approach is not limited in these two cases and can be applied to multiple scenarios, such as shopping recommendation and social community/event recommendation. These two motivating use case scenarios described above demonstrated the effectiveness of the underneath technology, e.g. user profile modeling, reasoning and rule capabilities. The mobile app shows that the ontology knowledgebase and the reasoning function can work effectively by inferring appropriate recommendations to send back to users based on their specific characteristics.

2) EXPERT VERIFICATION

In addition, medical experts in our research team have verified the recommendations generated by the system. Totally 118 recommendations in seven different scenarios were generated. The scenarios have been designed to cover different situations from all aspects of our recommendations. Experts in our research team including three MDs, one public health graduate student, and one registered dietitian and American Indian diabetes program coordinator have manually verified all of these recommendations. In particular, we provided the experts with user records containing detailed personal profile, scenarios, and corresponding recommendations we provided. In addition, we also listed all the medical literatures we used to make the recommendation. The experts then could use their professional reasoning to identify if our recommendations are correct, relevant, and appropriate.

We measure the recommendation performance in terms of (1) *Accuracy* (or correctness), (2) *Relevancy*, which measures whether or not the system speaks the users' language, with words, phrases and concepts familiar to the users, and (3) *Appropriateness*, which evaluate whether or not the recommendation would produce positive /encouraging outcome. As shown in Table 1, with 100% accuracy, the medical experts have confirmed the correctness of the recommendations. In addition, they agreed that most of the recommendations are relevant or can be understood by the users defined in the scenario. Furthermore, the experts agreed with the appropriateness of the most of the recommendations. For some recommendations about physical exercises, our experts pointed out their concerns: they were afraid that the recommendation may give users lots of pressure and that may discourage the use of the app. They gave us lots of important suggestions on how to provide recommendations in a positive way to encourage users to keep using this app. We are incorporating these comments into our system.

TABLE 1. Expert Evaluation on Use Case Recommendations

Verification Type	# of Cases			
	Total	Accurate	Relevant	Appropriate
General Health Suggestion	7	7	7	6
Meal Recommendation	30	30	29	30
Food Education	16	16	16	16
Grocery Shopping Planning	11	11	11	11
Daily Summary	14	14	13	13
General Exercise Recommendation	20	20	20	18
Remedy Workout Recommendation	20	20	20	15
Satisfaction Rate		100%	98.3%	92.4%

A full-scale evaluation with real AI patients will be conducted in the future. We will evaluate the usability of the system and its performance on improving of patients' health in real life.

V. CONCLUSION

In this paper, we presented our research work on personalized healthcare recommendation specifically for AI diabetic patients. To enable the personalization, the recommender is based on an AI user's biocultural ontology. General clinical diabetes recommendations and guidelines are converted into rule-based logic that integrates with the ontology as the knowledgebase of the recommender. A reasoning-based recommendation system can make personalized recommendation to users with the support of the knowledgebase. The proposed system was implemented as a prototype system and evaluated by use cases and expert verification. Full-scale evaluation with real tribe users will be performed when we have employed enough subjects.

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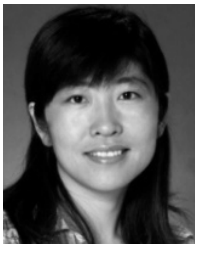

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