Cell Phone-based Diabetes Self-Management and Social Networking System 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. Daily diabetes care is primarily handled by the patients and their families, and the effectiveness of diabetes control is largely impacted by self-care strategies and behaviors. Thanks to the quasi-ubiquitous use of cell phones in most AI tribes, in this paper we propose a cell phone- based proactive diabetes self-care system, MobiDiaBTs. It is customized for AI patients using a personalized approach that considers the unique social, cultural, political, and demographic characteristic of AIs. The platform effectively and automatically collects users' physical and social behavior data and offers real-time diabetes health recommendations. It also can help a patient to interact with fellow patients in a trust-worthy and privacy-preserving environment.**

Keywords*— *diabetes; self-management; personalized care; semantics; prediction; American Indian

I. INTRODUCTION

Compared with other racial/ethnic groups in the United States, American Indians (AI) are disproportionally affected by diabetes and diabetic complications. In particular, the likelihood or diabetes diagnosis of AI is more than twice of whites [1]; while the rate of an AI youth being diagnosed with type 2 diabetes is nine times higher than that of their white peers. Diabetes remains a major cause of mortality and morbidity among AIs across the U.S. [2]. According to Zimmet et al. [3], "although diabetes has a genetic component, the incidence and prevalence of the disease have increased dramatically as traditional lifestyles have been changed by westernization, with accompanying increases in body weight and diminished physical activity". Moreover, the economic, social, and physical conditions in the places AIs live and work have a major influence on the health disparities existing between AIs and the general U.S. populations. The roots of health disparities and risk factor burden for the AIs in the Northern Plains are multi-faceted including low incomes, low graduation rates, poor nutrition and cultural factors. In addition to poverty, limited transportation, long distances between housing and clinics, limited access to affordable healthy foods, underfunded and understaffed health services all contribute to an overall lack of access to diabetes care.

To tackle the lingering health disparities among AIs, healthcare professionals, scientists and engineers, policymakers, and communities are all looking for more effective healthcare delivery for this population. Clearly, translational research regarding the underlying causes of AI chronic disease disparities is needed, and identification of improved, evidence-based primary and secondary prevention programs are required to improve the management of diabetes and to eliminate these disparities.

Despite the many existing software tools, web-based services, mobile apps, and social network groups, little effort has been targeted at developing self-management tools tailored for AIs, in which lower rates of health literacy, cultural differences, poverty, and social determinants of health need to be addressed. Existing tools ignore or undervalue the importance of issues such as language barriers (e.g., use of professional/medical terminology), barriers created by levels of education between patients and providers, and most importantly, life experience of AI patients. AI individuals may interpret disease and self-management strategies differently from other cultural groups. Failure to consider their perspectives and experiences of disease will continue to lead to failure in curbing diabetes in these populations.

To address the aforementioned problems in existing works, we propose a personalized diabetes self-care system, MobiDiaBTds, customized for AI patients. The proposed system considers the unique social, cultural, and demographic characteristic of AIs. It transforms AI diabetes care from the traditional reactive and hospital-centered to preventive, proactive, evidence-based, person-centered care. By utilizing the quasi-ubiquitous nature of cell phones in AI population, MobiDiaBTs is built on the cellphone technology, an accessible resource for most AIs. The system enables personalized Diabetes Self-Management based on the abundant daily physical data collected from the cell phones of the individual participants, also the special socio-economic, cultural, ethnic, and geographical status particularly to AI patients. Combined with clinical diabetes recommendation and guidelines, the system can make more appropriate and useful recommendations (e.g., food intake, physical workout, and predicted blood glucose levels). Moreover, we propose a secure social networking platform customized for AI patients. We use a semantics-based approach to help users find appropriate peer patients to build

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friendship and provide peer support based on their health concerns and social behaviors. Moreover, we will provide practical security mechanisms to help users identify the trustworthiness of information sources and protect their privacy.

The rest of the paper is organized as follows. Section II surveys the related work. Section III describes the details of the proposed system and its enabling technologies. Section IV presents the implementation and evaluation of the proposed mechanisms. Concluding remarks are provided in Sections V.

II. Related Work

An abundance of information regarding Diabetes Self-Management (DSM) has been compiled and made available to the general public by federal government agencies such as *Medicare*, *National Institutes of Health*, and *Centers for Disease Control and Prevention*, as well as numerous hospitals and healthcare organizations. Many of the DSM tools are packaged into comprehensive reading materials, while others are in the form of simple pamphlets or flyers. A number of software applications exist for DSM and education (e.g. http://www.mendosa.com/software.htm), including log sheets, web-based software, insulin dose calculators, and other standalone windows software products. Results from a study of over 70 randomized controlled trials of DSM supports its effectiveness in type 2 diabetes, particularly in the short term [24]. Positive outcomes of DSM were reported on knowledge of the disease, frequency and accuracy of self-monitoring of blood sugar, self-reported dietary behaviors, and blood sugar control.

Creative and innovative uses of technology are much needed to transform healthcare in this population from reactive and facility-based to a preventive, proactive approach that is person-centered and utilizes appropriate technologies. Many mobile medical or health applications have been developed for the purpose of DSM. Example mobile DSM applications include BG Monitor Diabetes [4], BlueLoop [5], Calorie Counter PRO [6], Diabetes in Check [7], Diabetes Tracker [8], and OnTrackDiabetes [9], These applications normally include functionalities such as: tracking and recording patients' data (e.g., food, blood sugar levels, exercise, blood pressure, weight, medications, and moods), maintaining history of patients records, visualizing data, setting reminders, planning meals, providing recipes and food guide.

In addition, social network sites and Blogs (e.g., Diabetes Mine [10], Tudiabetes [11], DiabetesTeam [12]) have started to drive the paradigm shift in diabetes patient confidence. They are increasingly taking the words of recommendations from peers and the opinions from online sources as compared with the traditional communication channels. At these sites, patients of diabetes and their families are sharing all kind of information including medical news, research results, treatment tips, menu ideas, and tools for daily management. The topics of the shared information range from the basic diabetes definition to diabetes treatments, daily personal management, pregnancy complicated by diabetes and more. On Facebook, there are many active diabetes groups such as "Diabetes Self-Management" and "Young People with Diabetes – South and Central America", that share personal experiences and promote professional exchanges and actions.

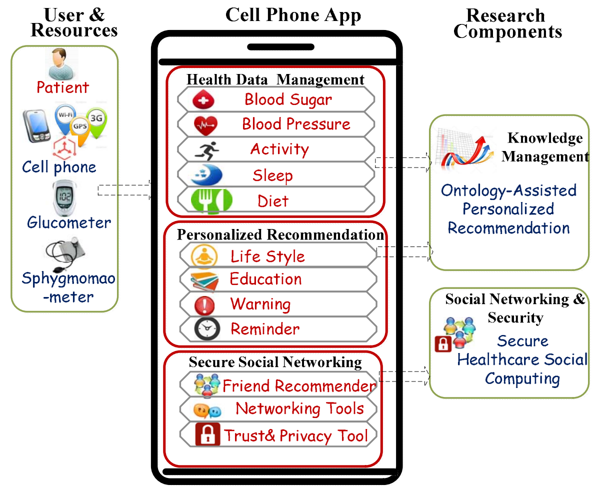

Fig. 1. The proposed framework

Despite the many existing work, little effort has been targeted at developing self-management tools tailored for AIs, in which lower rates of health literacy, cultural differences, poverty, and social determinants of health need to be addressed. The goal of this paper is to address this issue.

III. System Design

We propose the following general framework (shown in Fig. 1) of DSM for AIs. Using a cellphone as the platform, the major component is the development of integrated solution based on knowledge management, machine learning, and secure social networking. This solution is able to monitor and display self-management information, provide reminder and warning messages, generate recommendations based on the information collected. Moreover, this solution enables a patients to interact with fellow patients, make personal connections, obtain and give support, in a trust-worthy and privacy-preserving environment.

A. *Ontology-enhanced Personalized Self-management Recommendation*

It is very important to provide diabetes patients with real-time guidelines and recommendations based on their current health status. As mentioned, using ambient sensors and users' cellphones, we can monitor user's physical status and lifestyle, which will be used as evidence for life-style recommendation. There are a number of evidence-based clinical guidelines available for diabetes screening, diagnosis, and management. The major guidelines include those from the American Diabetes Association (ADA), the American Association of Clinical Endocrinologists (AACE), the Indian Health Service (IHS), and the Center for Medicaid and Medicare Services (CMS), Department Veterans Affairs and Department of Defense (VA/DoD), World Health Organization (WHO), International Diabetes Federation (IDF), Institute for Clinical Systems Improvement (ICSI).

Regardless of the existence of these guidelines and recommendation, most of them are made for general patients. If we directly apply these recommendations to AI patients without

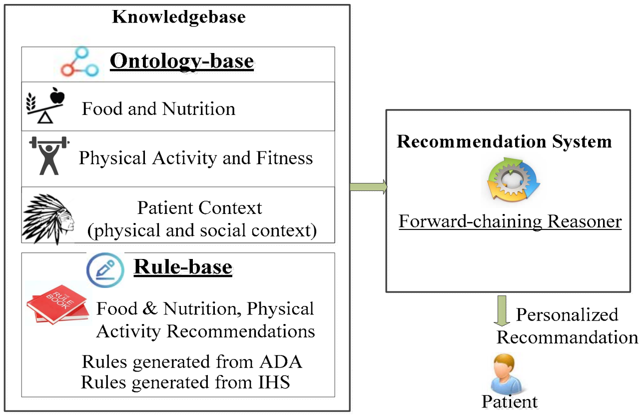

Fig. 2. Architecture of ontology-enhanced recommendation system

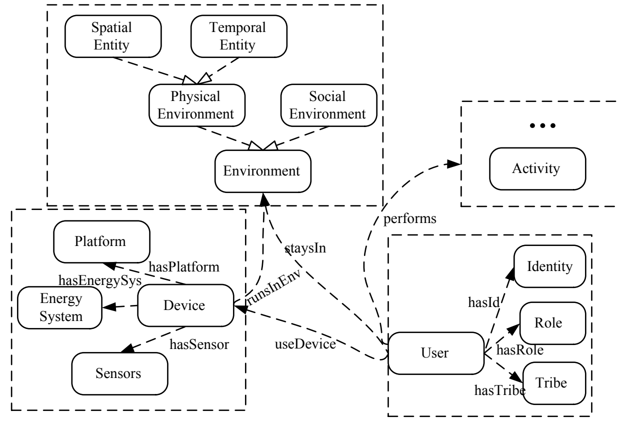

Fig. 3. A snippet of high-level patient context ontology

considering their special socio-economic, cultural, ethnic, and geographical status, the usefulness of the recommendation will be jeopardized. For example, a proper diet recommendation is crucial for diabetes patients. We can find such general recommendation from existing guild lines. However, each person has his/her unique diet preferences. Also, as many AI tribes are located in "food desert", in which too many foods (such as seafood) are either too expensive or unavailable for the AI patients. If recommended with unavailable or unaffordable food, AI patients cannot get the benefits at all. Therefore, making personalized recommendation is especially important for them.

We propose an ontology-enhanced recommendation system (Fig. 2) to provide real-time personalized recommendation for AI diabetes patients. The domain we consider in this project is the well-being and lifestyle of AI diabetes patients. This domain includes several different types of knowledge, such as knowledge about patients' context including physical and social context, knowledge about food and nutrition, workout, medication, etc. In order to provide a common understanding of this domain and reconcile heterogeneous knowledge sources, we utilize an ontological approach. This approach can provide common terminology of different concepts. Moreover, it can model different interactions and relations between different types of knowledge. For example, the ontology can model how nutrition and workout affect the health of a patient, and how nutrition and workout should change depending on the conditions of a patient.

1) Ontological model

We adopt and revise existing ontologies in food, nutrition [13, 14] and physical activity [15] to model important concepts and relationships in diabetic recommendation. We add more concepts/properties to fit for the AI population. For example, for food ontology, we add "availability" and "price" property, so that recommendation rules can be customized based on these properties. Moreover, we also adopt and revise our previously defined context ontology [16] to include AI-community specific biocultural concepts, which can model the socio-economic, cultural, ethnical, and geographical aspects of AI, so that each AI tribe can instantiate their own case. Fig. 3 shows part of the high-level context ontology used in MobiDiaBTs. In this figure, classes are depicted as rectangles and properties as arrow lines (with *subsumption* relation as hollow arrows and other relation as solid arrows). Besides general classes defined in the upper ontology, a number of sub-classes are defined to model more specific context.

2) Ontology-based inference

With the ontology and the rule-based knowledgebase constructed, reasoning can be performed on top of it. Inferences performed on the knowledge are the building blocks used to generate personalized advice. We employ rule-based knowledgebase together with the predefined ontology, which is description logic in nature, to make personalized recommendation to AI patients. In particular, we model existing recommendations/guidelines regarding diabetes with first-order logic on the basis of the pre-defined ontology. Then we make use of ontological logic to infer appropriate recommendations for AI patients, taking into account their physical condition and socio-economic, cultural, ethnic, and geographical status.

We implement an ontology-based inference engine to fulfil the functionality of a recommendation system. We use forward chaining as the implementation strategy, as it is one of the most important methods of reasoning. Forward chaining can be described logically as repeated application of modus ponens. Rules in our knowledgebase are formatted as First Order Logic (FOL), which can be further modeled by the "IF-THEN" clauses that follows the IF (antecedent) THEN (consequent) format. The inference engine then uses forward chaining to search the inference rules until it finds one where the antecedent (IF clause) is known to be true. When such a rule is found, the engine can conclude, or infer, the consequent (Then clause), resulting in the addition of new information to its data.

Let us consider a scenario for the use of rules to recommend food and nutrition for AI diabetes patients. A recommendation can be translated to rules like this:

IF *(Patient.Sensors.Hypertension==High)* ***THEN***

Patient.RecommendedNutriton=(Low-Fat AND No-Sodium) ***AND***
Patient.RecommendedFoodFlavor=Low-Salty

IF *Patient.RecommendedIngredientNutriton==(Low-Fat AND No-Sodium)* ***AND*** *(Patient.Location==NorthDakota)****THEN***
Patient.RecommendedIngredient=

(Cabbage Or Broccoli Or Caulifower Or BrusselsSprouts)

As shown in this example, based on the general rule and user's context (blood pressure and geographical location), appropriate food ingredients are recommended to the patients.

B. Semantics-based Secure Social Networking

Nobody understands what it is like to have diabetes better than someone with diabetes. Social networking offers diabetes patients an opportunity to know more about their illness and get peer support from others with similar experiences. This is especially important for AI individuals living in rural areas with limited peers to contact with. Despite the benefits offered, there are many risks that accompanied with online healthcare social networking. Personal health information belongs to the most sensitive information of an individuals. The disclosure of personal health information to untrusted parties can result in serious consequences, ranging from social embarrassment and dissolution of relationships to the termination of insurance and employment contracts. It could be more dangerous to place trust on false information. "There is nothing that can destroy the value of a peer to peer support group faster than harmful information, exploitive behavior, and disrespectful interactions" [17]. Harmful information can either be inaccurate medical information or inappropriate therapy recommendations. "Because of the prevalence of motivated reasoning and emotional information processing in these domains, information cascades can develop frequently and spread rapidly if they are not actively contravened" [17]. Therefore, privacy and trust are two very important issues.

Existing trust and privacy mechanisms cannot be used directly in the AI diabetes social networks due to the special property of this network: users of MobiDiaBTs, namely, the AI participants, may have limited knowledge and experiences of Information Technology to understand and set the privacy and trust rules. Moreover, unlike traditional social networks in which social communities are pre-built from real-world relationships, users in MobiDiaBTs are grouped by their medical problems. In addition, users normally hide their real identities. Therefore trust and "closeness" values between users cannot be easily obtained; privacy or trust based on these criteria cannot be applied.

To address the aforementioned issues, we propose a secure social networking platform customized for AI patients. We use a semantics-based approach to help users automatically find appropriate peer patients to build friendship and provide peer support based on their health concerns and social behaviors. Moreover, we provide practical security mechanisms to help users identify the trustworthiness of information sources and protect their privacy.

1) Semantics-based friend discovery

To connect users for friendship in MobiDiaBTs raises the challenge of discovering users with similar health concerns/interests. For AIs, location should also be considered in that they are more likely to communicate with people from the same tribe or location [18]. We utilize ontology to represent user profiles and context to automatically infer similarity and relationships between users. Ontology standards support inference mechanisms that can be used to enhance semantic matchmaking. We compare users' profiles by their ontology similarity. Profile matching is implemented by calculating the similarity between profiles to be matched. The profile similarity calculation involves following four steps:

a) Extracting user's profile: The profile of a user is extracted from the user's self-description and his/her social networking history. It can be represented by a vector containing an AI patient's basic information, such as disease, symptoms, conditions, tribe location.

b) Computing concept semantic distance: Next, the semantic distance between two concepts has been calculated based on our predefined common ontology. We adopt our previously proposed distance-based approaches [19] to measure the semantic similarity between ontology concepts. The basic idea is to identify the shortest path between two concepts in terms of the number of edges and then translate that distance into semantic distance. Our approach improves the accuracy by integrating factors, such as the depth of a node in the hierarchy and the type of links.

c) Computing concept semantic similarity: The similarity between two concepts is defined as the complementary of their semantic distance.

d) Computing social profile similarity: For two patients represented by two profile vectors, the similarity between their profiles is defined as the normalized maximum of the pairwise concept similarity.

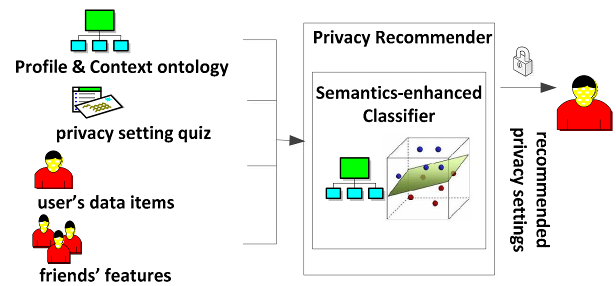

Fig. 4. Architecture of the privacy recommender

2) Intelligent privacy recommender

To help AI users without professional background to effectively protect their privacy, we propose a semantics-assisted privacy configuration mechanism that applies machine learning techniques on users' context and their privacy configuration history to automatically generate a set of privacy configuration rules. Before using MobiDiaBTs, users are required to take a simple and short quiz on their privacy preferences. The quiz result is called privacy configuration history, which describes how the users conceive their privacy preferences under different contexts. This privacy configuration history is leveraged to predict users' privacy settings in the future. Based on our previously proposed privacy setting tool SPAC [20], our privacy recommender learns users' privacy configuration patterns by learning on users' profiles and privacy setting history. Based on the patterns, MobiDiaBTs can recommend future privacy configuration settings.

The privacy recommender is implemented as a classifier, which classifies user's decision on whether or not to permit the access of a certain private data item to a particular user (or friend). Finally, each personal data item would be classified as either "permit" or "deny" for each of the user's friends. MobiDiaBTs predicts access settings by using the existing settings. Fig. 4 depicts the architecture of the proposed recommender.

We utilize the aforementioned ontology to improve the accuracy of the recommender. Introducing ontology into the recommender provides additional clues about the underlying reasons for which a user may or may not allow access for particular items. Therefore, integrating ontology knowledge hidden in the heterogeneous data provides more realistic similarity calculation for the classification.

3) *Fuzzy trust managemeng*

We implement a personalized self-managed trust tool to establish trust relationships among participating AI diabetes social network users. Again, we utilize ontology to identify the semantic relationship and proximity between entities in the social network. We apply fuzzy logic to represent and evaluate trust. Fuzzy logic is a good candidate for evaluating trust in social networks as it takes into account the uncertainties of trust, which has a certain degree of vagueness and involves truth degrees that one requires to present and reason about [22]. Fuzzy inference can tolerate vague inputs and allow reasoning using imprecise linguistic terms, such as "very trustworthy" or "untrustworthy". More importantly, as pointed out by Leite and Ricarte, fuzzy-based modeling performs better in combining contradictory information [21].

Previously we proposed a fuzzy model to evaluate trust values in healthcare social networks [22]. We apply the same model in MobiDiaBTs to evaluate trust. In particular, we incorporate several most important trust factors in this model. The first factor is similarity. In a health-related social network, the most significant benefit is the sharing of common experience among participants. Studies have suggested that perceived similarity is associated with increased levels of affect and trust [23]. People with similar health issues may find it easier to connect with each other, and be more comfortable in sharing factual information and emotional feelings [22]. Another factor is the role of the users. In MobiDiaBTs users take different roles. For instance, patients are users who seek to manage and improve their health, while physicians, nurses and occupational therapists are registered and trained healthcare professionals. People normally give different trust levels, and consequently reveal different personal information to different users with different roles in a healthcare social network. Reputation is another important factor affecting user's trust to others. This is especially true for healthcare community, in which people tend to trust information sources with good reputation.

IV. IMPLEMENTATIN AND EVLUATION

A prototype of MobiDiaBTs is implemented and deployed on a set of iPhone and Android phones. The prototype implements most of the aforementioned core features. These features include: (semi)automatic and manual data input/collection, semantics-based healthy life-style recommendation, reminders, and warning. We also implemented the secure social networking services which include profile management, friend matchmaking, privacy and

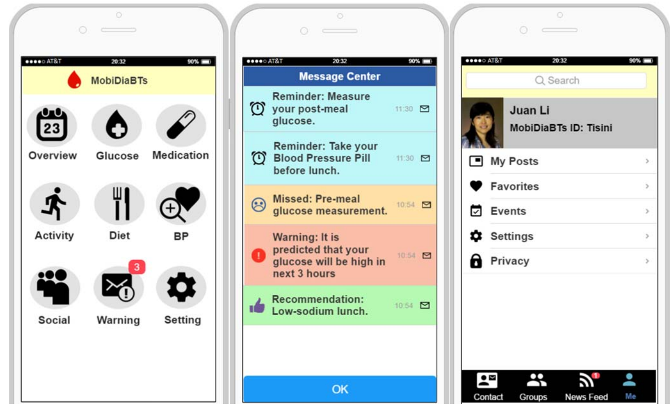

Fig. 5. Screenshot of the prototype system MobiDiaBTs

trust recommendation. Fig. 5 shows the screenshot of the mobile application running on iPhone 6 plus. The backend server is running on Microsoft Azure cloud.

We also performed experiments to evaluate the performance of the proposed system. In the first part of the experiment, we try to evaluate the appropriateness of the personalized recommendation mechanism. Ideally, we should invite a significant number of AI participants to use and evaluate it. However, currently we cannot find enough AI users for our prototype. As an alternative solution, we create a food ingredient recommendation scenario and define a usefulness score, the usefulness score is defined as follow:

$$usefullnessScore(R) = correctness(R) \times [\alpha \times LocaltionAppropriateness(R) + \beta \times PriceAppropriateness(R) + \gamma \times SeasonAppropriateness(R) + \delta \times CultrueApprropriateness(R)]$$

$$correctness(R) = \begin{cases} 1, & if\ R\ is\ logically\ correct \\ 0, & otherwise \end{cases}$$

In the equation, the appropriateness of each item is determined if the recommended food ingredient is consistent with the context ontology of the AI subject. Fig.6 illustrates the comparison between the usefulness value of our AI personalized recommender and a general recommendation summarized from American Diabetes Association (http://www.diabetes.org/). The values of α, β, γ, and δ are set as 0.25 each. As can be seen from the figure, our personalized recommender is much more useful compared with the general guidelines.

In the next part of the experiment, we evaluated the effectiveness of the semantic-based friend discovery mechanism in terms of recall and precision, which are defined as follows:

$$recall = \frac{|relevantEntries \cap retrievedEntries|}{|relevantEntries|}$$

$$precision = \frac{|relevantEntries \cap retrievedEntries|}{|retrievedEntries|}$$

Fig. 7 and Fig. 8 illustrate the performance of the semantics-based friend discovery of the proposed social networking. Fig. 7 compares of the recall rate of semantics-based friend discover

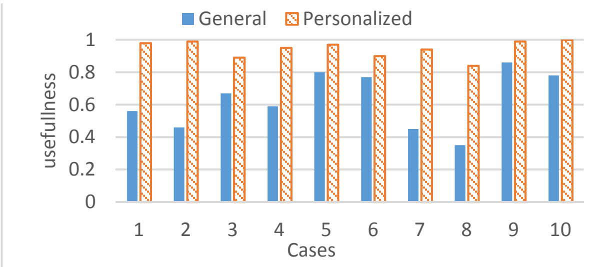

Fig. 6. Comparison of generalized recommendation and personalized recommendation

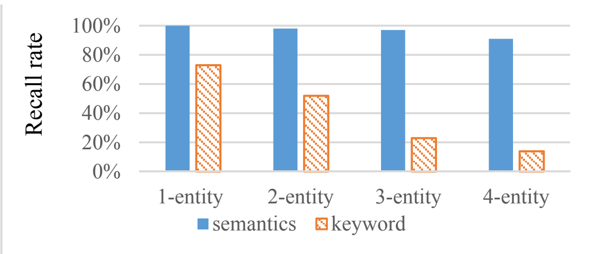

Fig. 7. Comparison of recall rate of semantics-based and exact keyword-based friend discovery

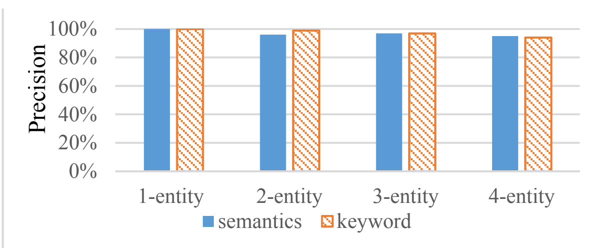

Fig. 8. Comparison of precision rate of semantics-based and exact keyword-based friend discovery

and keyword-based friend discovery. In this experiment, we increase the number of profile properties from 1-entity to 4-entity. It shows that the semantics-based discovery can dramatically improve the recall rates, by finding more friends that are semantically related although literally may be irrelevant. Fig. 8 compares the precision of the two discovery schemes. The semantics-based discovery does not jeopardize the discovery precision. Instead it improves the precision by eliminating the semantic ambiguity problems.

V. CONCLUSTIONS

As little effort has been targeted at developing self-management tools tailored for AIs, in which lower rates of health literacy, cultural differences, poverty, and social determinants of health need to be addressed. In this paper, we propose a cell phone-based diabetes management system to assist AI to better manage their illness and improve live quality. In order to model the unique economic, social, and physical conditions of AI patients and their tribes, we use an ontological model to present the physical and social context specific to AIs. Based on this ontology, personalized recommendation, social networking and trust and privacy management services are provided. The proposed system has been prototyped and evaluated.

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