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Intelligent Support Systems for Lifestyle Change: Integrating Dialogue, Information Extraction, and Reasoning

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Abstract. Behavior change support systems need to take into account individual needs and preferences to provide appropriate support. In this demonstration, we illustrate how this might be achieved through the explicit modeling of user characteristics within knowledge graphs (KG), captured in a dialogue between the system and the user. We demonstrate how up-to-date information enables reasoning for providing personalized support.

Keywords. Dialogue, Knowledge graphs, Reasoning, Behavior support system

1. Introduction

For behavior change support systems to offer adequate support, they should be able to adapt to the diverse and evolving nature of the users in unforeseen circumstances [1]. One way to adapt a system is by implicitly learning users' preferences in different circumstances from behavior data. However, behavioral data reflects people's past behavior rather than their future desired behavior. Capturing the latter is particularly important for systems intended to support a user in changing their behaviors. In this demo, we propose a complementary approach that accurately and explicitly represents important domain-specific information (**domain KG**) and user-specific information such as context and its influences on norms and values (**user KG**). Besides the ability to store dynamic and static knowledge, KGs offer transparency and explainability, as the system's reasoning process becomes explicit [2]. This user model must be updated at run-time to capture, for example, the changes in context [3, cf.] through direct **dialogue**. This dialogue be-

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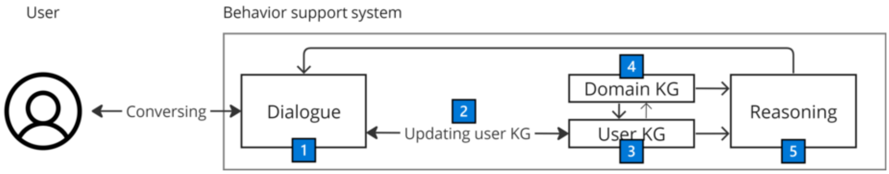

Figure 1. System Architecture.

tween the system and users allows for the exploration of evolving contextual nuances [4], enabling the user model updates and consequently adapting to changes in users' context and needs. The insights gathered are then **extracted** using RDF triples and named graphs [5] to update the user model. With the information in the KG-based user model, the system can **reason** about the next steps, whether to provide support, request further information, or resolve any inconsistencies, ensuring the support remains personalized and relevant.

This demo presents a system aimed at supporting individuals, particularly those managing Type 2 Diabetes (T2D), in adopting healthier lifestyles. The primary purpose is to showcase the integration of various research domains—namely, dialogue, information extraction, knowledge representations, and reasoning—into a unified pipeline that addresses the complex challenge of behavior support.

2. Demo Overview

The system integrates five key components, as shown in Figure 1. Below we elaborate on the technical aspects of each component and illustrate their roles in creating a comprehensive support system that adapts to individual user needs and contexts.

1 Dialogue A dialogue component engages users in "Alignment Dialogue" [6], designed to gather information crucial to ensuring the support provided is in alignment with the users. Given the complexity inherent in such dialogues, a rule-based approach is employed in this demonstration to manage and guide the interactions effectively.

2 Information Extraction This component transforms text (e.g., "I love walking") into a subject-predicate-object structure (e.g., Pedro-like-walking). We use RDF triples and named graphs to recursively combine knowledge units into complex structures capable of expressing the content, form, and context of a dialogue [5].

3 User KG The User KG organizes RDF triples from the Information Extraction Component. The User KG uses an OWL-based Ontology that includes concepts to represent user contexts, preferences, values, and others. The User KG contains the user's health data such as blood sugar and weight, as well as the user's values, preferences, and other important factors. This information is used to make personalized recommendations.

4 Domain KG The Domain KG contains medical knowledge about Diabetes and treatment options, e.g. which treatment types work best for which kind of user.

5 Reasoning Engine This component determines the required intervention type, based on the user's health data from the User KG and medical information from the Domain

KG. The system then uses the user's preferences, values, and context from the User KG to select the most suitable action within this intervention type.

An interactive prototype[2] of the support system will be available at the conference. Attendees will be able to converse with the system, see in real time how it updates its knowledge graphs, and examine the reasoning outcomes that inform the user dialogue. This prototype aims to showcase the system's potential for supporting personalized lifestyle changes.

3. Future Work

We plan to test our systems' personalization capabilities against a wide array of different user profiles by interacting with LLM-based simulated users[7], and to personalize the recommendations using reinforcement learning [8].

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[2] Demo video available at: https://youtu.be/slFpI9uBdq4