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Personalized Advice and Feedback for Diabetes Patients

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Abstract

Diabetes is a widely spread, major epidemic. Proper treatment minimizes the risk of secondary diseases, but particularly elderly patients and those who have just been diagnosed experience difficulties in doing so. The GlycoRec system aims to support patients in making decisions that are related to the treatment by modeling their behavior and their physiology. In this paper, we describe the aims and first steps towards the development of GlycoRec and provide preliminary results on our analysis of variations in recipes, which will be used for providing personalized nutritional advice.

1 Introduction

Diabetes mellitus is a widely spread chronic disease that affects about 8.3% of the world adult population (Shi & Hu, 2014). Even though there is no known cure for diabetes, it can be managed through a combination of diet, exercise and medication. This implies that patients have to take several important decisions on a daily basis, such as: can I eat this, what is my blood sugar level, how much insulin should I take right now? To avoid secondary conditions, such as cardiovascular diseases, it is of high importance that patients are able to manage their diabetes treatment on their own, aiming at near normal glucose levels (American Diabetes Association, 2014).

Most patients who treat their diabetes with insulin go through the same routine several times each day: they monitor their current blood glucose level using a glucometer; they estimate their carbohydrate intake; they calculate the required insulin doses and inject an appropriate amount. Different types of insulin that vary in onset and duration of action may be used.

One of the challenges in managing diabetes is the necessity for patients to learn how their body reacts to food intake, activity and insulin application. Mobile apps currently available for calculating insulin dose without reference to individual needs show systemic issues such as missing validity checks of input data affecting the safety of patients (Huckvale, Adomaviciute, Prieto, Leow, & Car, 2015). Telemedicine and the improved acceptance of smart phones and tablet computers among patients and physicians may contribute to improved patient guidance and self-empowerment (Schildt & Mertens, 2012).

2 The GlycoRec Project

The GlycoRec project[1] aims to develop a system that provides diabetes patients with personalized support and advices for improving their everyday lives and managing their disease. GlycoRec will provide patients with information and advice regarding their nutrition, physical activities, and the use of medicine. This empowers patients to better communicate their needs with their doctors and advisors, and to better implement advices and stated goals in their everyday lives.

The GlycoRec system supports decisions and gives individualized recommendations based on the patient's behavior, physiology and treatment history. Individualized advice may include:

- estimation of nutritional characteristics such as carbohydrate content and glycemic index of meals
- recommendations on insulin application based on glucose level, activity and food intake
- warnings if blood glucose levels are at risk of leaving the target range

Complex adaptive interactive systems such as GlycoRec require systematic elicitation and documentation of requirements (Gena & Weibelzahl, 2007).

Based on an extensive review of the literature, we designed a survey for patients to explore both the patients' situation as well as the main barriers they encounter. Questions on the patients' current situation referred to their strategies for managing their disease as well as the technologies available to them. The exploration of barriers encountered will help to tailor functionality to patients and prioritize features. Moreover, semi-structured interviews with diabetes nurses will be conducted in order to validate the survey results and to elicit expert knowledge on diabetes management strategies (Dix, Finlay, Abowd, & Beale, 1998; Weibelzahl, Jedlitschka, & Ayari, 2006).

[1] https://www.pfh.de/hochschule/forschung/forschungsprojekt-glycorec.html

3 System Architecture

The GlycoRec architecture follows the high level pattern of interactive adaptive systems in accordance with (Jameson 2008) comprising inference, modeling and adaptation decision. Figure 1 depicts an outline of the high-level system architecture. A variety of sensor data are collected including actual glucose level as measured by a glucometer, level of activity, and insulin application. Data are gathered through smart phone, smart watch and networked glucometer and insulin pen, stored in a central database and analyzed in order to model current glucose level.

Patients interact with the system via smart TV, tablet, or smart watch. While the smart watch interface is designed for interaction during the day where both the patient and the system can initiate interaction, the smart TV interface supports review and reflection on historical data and facilitates identification of patterns over time. Patients can also share their records with their physician or their diabetes nurse for discussion of their diabetes management.

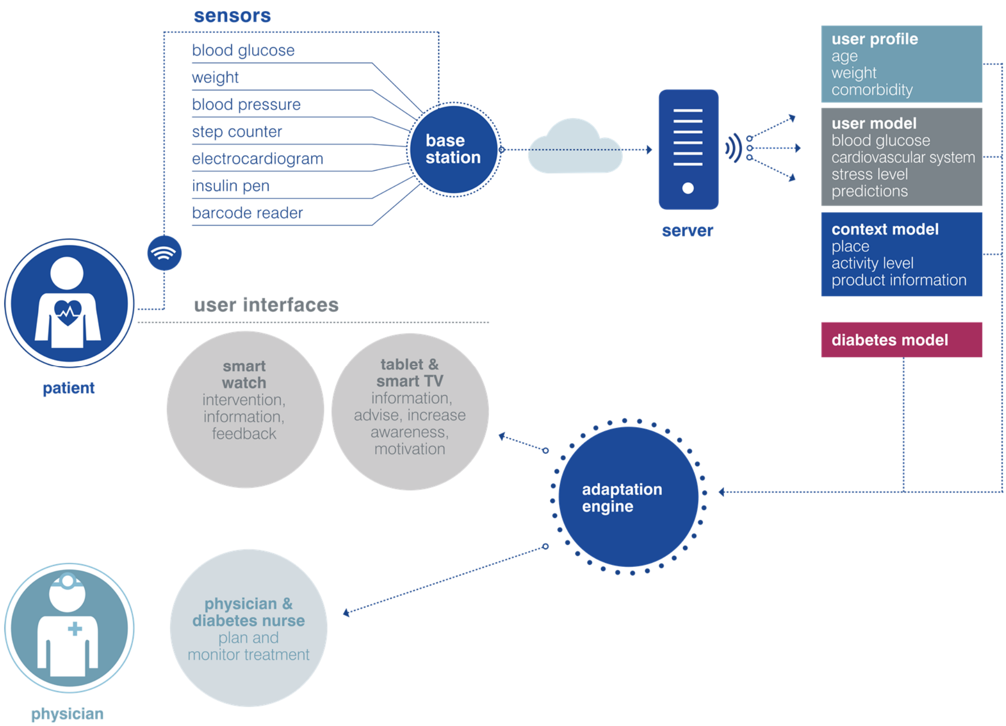


Figure 1: Overview of the architecture of the GlycoRec system

4 User Modeling and Adaptation

From a user modeling perspective, GlycoRec tackles a number of challenges, including but not limited to:

Firstly, physical reactions to insulin, food intake, and activity in diabetes are idiosyncratic. While the general patterns are known, individual patients seem to respond differently in similar situations, depending on factors such as age, weight, general heath, medication, comorbidities, to name but a few. Individual response patterns need to be observed and learned.

Secondly, this will involve combining a variety of sensor data. We have selected a number of candidates, but it will be necessary to narrow down the list for both modeling and practical reasons.

Thirdly, the available data vary greatly in granularity and quality. While for instance activity level can be assessed on a continuous basis, most patients measure their glucose level three to seven times a day, with some patients measuring only once a day. So while validation and readjustment of glucose level measures are sparse, the (predicted) glucose level need to be assessed at any time in order to be able to issue warnings. Accordingly, models will differ in certainty at different points in time.

Fourthly, the development process is subject to a number of regulations, as any device involved in the treatment of patients is considered a medical device that needs to be compliant with ISO 13485 (International Standards Organization, 2003). User testing and iterative development is less flexible under these conditions.

Lastly, designing the adaptive user experience for patients is challenging as the disease has huge impact on the patients' lives anyway. Any additional effort and new processes in managing their disease will only be accepted if the benefits are obvious and the required input is minimal, i.e., data collection and modeling need to happen with minimal or no user interaction in the background, but if and only if intervention is required the system needs to take initiative and make reliable recommendations.

5 Nutritional Advice

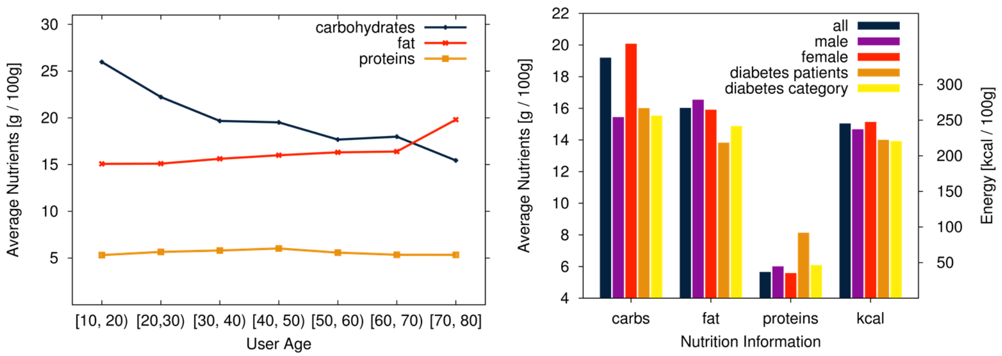
How can patients be enabled to estimate nutritional characteristics of their meals more accurately and to plan balanced meals in the first place? Here we explore the potential of online recipe recommenders for generating healthy meal plans. Recommending healthy meals is tricky. The used ingredients are the single most important reason for liking or disliking a meal. Nevertheless, there are health-conscious users who also take nutritional information into account (Harvey, Ludwig, & Elsweiler, 2012). In a feasibility study on recipe recommendation, Freyne and Berkovsky found that both content-based (e.g. ingredients) and collaborative approaches (taste, context) should be taken into account (Freyne & Berkovsky, 2010).

Despite the availability of online nutritional information[2], these databases only provide information on single ingredients and/or standardized products such as ready-made meals. Our goal is to provide diabetes patients with recommendations and feedback in everyday situations, including:

- How many carbohydrates can I expect the Thai curry on the menu to contain?
- Which recipe variation best matches both my dietary restrictions and my taste?

As a first step towards personalized nutritional advice, we analyzed an extensive dataset from the German recipe website Kochbar.de[3], provided by Kusmierczyk et al. (Kusmierczyk, Trattner, & Nørvåg, 2015).

5.1 Age, Gender, Condition and User Preferences



a) Age *b) Other characteristics*

Figure 3: Average nutritional facts of recipes for a) different user ages as given by recipe authors and b) different user groups and recipe category "diabetes".

We identified *differences in eating patterns* with respect to gender, age group, and dietary restrictions such as diabetes. Figure 2a shows average nutritional values of recipes created by different age groups: carbohydrates significantly decrease with age ($F = 152$, $p < 0.01$). Figure 2b shows the average nutritional values of the recipes provided by different user groups. Most notably, recipes provided by female users are, on average, richer in carbohydrates than recipes provided by male users ($t = 52.108$, $p < 0.01$). This is in line with our previous observation, as male users are on average older (50.9 years) than female users (43.8 years) in our dataset ($t=86.529$, $p < 0.01$). Recipes of self-reported diabetes patients (65 users; higher fraction of male recipe authors) are lower in fat ($t=-2.991$, $p < 0.01$) and contain clearly more protein than

2 e.g. http://www.mri.bund.de/de/service/datenbanken/bundeslebensmittelschluessel.html

3 https://www.kochbar.de

recipes from other users (t = 5.629, p < 0.01) - which is in line with recommendations from diabetes information centers.

5.2 Canonical Meals and Their Variations

We clustered popular meal names into "*canonical meals*" and analyzed to what extent these meals *vary in terms of ingredients and nutritional value*. We selected the 200 most frequently used recipe titles as "canonical meals", to which we assigned all recipes of which the title contained the title of the canonical meal. The top-10 canonical meals contained between 1,085 and 1,812 variations. These insights provide directions for strategies to find the best recipe or for adapting recipes to user needs and preferences.

To find out to what extent canonical meals vary in nutritional value, we selected three different, representative meals (obtained from the most frequently used recipe titles) and calculated the means and standard deviations - see Table 1. We also analyzed which ingredients are associated with recipes that are high and low in carbohydrates, fat, proteins, and energy.

Potato salad is low in protein, but the standard deviations are relatively high. Ingredients associated with high protein are meat and fish, low-protein recipes contain vegetables instead, such as pickles, radish, olives and asparagus. The same pattern can be found for lasagna. Low-fat cheese cake is associated with low-fat milk products and high-fat with chocolate and cream cheese.

Meal	**No. of Recipes**	**Carbohydrates [g]**		**Fat [g]**		**Proteins [g]**		**Energy [kcal]**	
		Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev
Potato Salad	1,863	10.26	8.025	13.09	17.64	3.27	3.60	171.25	151.17
Cheese Cake	1,681	29.93	15.68	11.97	9.29	7.32	2.97	256.29	95.96
Lasagna	1,187	8.44	10.81	13.23	11.00	8.06	6.18	185.43	137.25

Table 1. Nutritional facts per 100g for three popular canonical meals.

These findings confirm our expectation that it is possible to estimate the nutritional value of certain dishes from the recipes associated with these dishes and that one can identify ingredients associated with high or low levels of food value. This provides a good base for developing food recommender systems that suggest "better recipes" and alternative ingredients for particular recipes.

5.3 Discussion

The results of this first analysis confirm that anticipated differences between user groups are reflected in the data of the Kochbar.de dataset. In addition, we were able to identify popular "canonical" meals and many recipes and variations for these meals. As reported in more detail in (Rokicki, Herder, & Demidova, 2015), this allows us to find ingredients that are commonly associated with high or low levels of carbohydrates, protein, fat and energy. Using these insights, we aim to develop methods for recommending recipes that fit both the desired meal and the user's dietary needs.

Moreover, we aim to explore ways to interactively estimate the ingredients and the associated nutritional value of restaurant meals, take-away or otherwise ready-made food. There is a growing number of people who do not cook for themselves or have insufficient knowledge on nutrition. There is great uncertainty among diabetes patients when trying new restaurant meals, especially when on vacation in foreign countries. Personalized food recommendation has the potential to address these issues.

6 Future Perspectives

This three-year project commenced in January 2015 and is in its early stages. Requirements have been gathered. Significant involvement of patients in the development process and the application of further user centered design methods (Norman, 1988) is planned for the next phase. A user evaluation including validation against physiological parameters of treatment quality such as the HbA1c value (Larsen, Hørder, & Mogensen, 1990) will demonstrate the effects of the system.

As part of the adaptive advice and feedback, the system aims to provide patients with advice and information on the nutritional value of a meal, and to recommend them alternative meals or ingredients. This paper provides some first insights and confirms the feasibility of the approach. A particular challenge for the food recommender will be to provide detailed feedback on the precision of its estimations and the resulting recommendations. Particularly for "canonical meals" with many variations, estimations may need to be refined with additional user input and feedback.

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