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Personalized and Context-Aware Decision Support System for Diabetes Therapeutics

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Abstract. Personalized recommendations for diabetes therapy can be highly beneficial but complex to make and time-consuming for patients and healthcare professionals. Therefore, we propose a decision support system to help patients and healthcare professionals to make decisions to improve treatments based on the patient's daily life data. The proposed solution allows the collection of patients' data related to their glycemic profile, insulin doses, carbohydrate intake, physical activity, and patient weight. This data provides information for a case-based reasoning system to predict postprandial blood glucose allowing the calculation improvement of bolus insulin. This decision support system aims to reduce patients' hypo and hyperglycemic episodes and improve the patients' time in range.

INTRODUCTION

Patients with diabetes make great efforts to keep their blood glucose (BG) levels within safety limits. Treatment for this chronic disease involves, besides pharmacologic therapy, a set of lifestyle recommendations [1]. Each patient has a characteristic insulin sensitivity as well as different daily routines, diets, mealtimes, and physical activity. Thus, it is essential to personalize the treatment and also adapt and review it over time [2]. Unfortunately, adequate treatment to avoid glycemic excursions is time-consuming for patients and healthcare professionals, requiring several appointments and a multidisciplinary team. In addition, insulin-dependent patients, usually having Type 1 Diabetes Mellitus (T1DM), need to adjust the prandial insulin bolus to the carbohydrates (CHO) of the meal they are going to eat, taking into account the glycemic values at the moment and whether they will exercise in the following hours [3]. Several technologies and systems aim to facilitate the complex management of this disease, trying to provide the most appropriate treatment for each patient. The use of computerized Decision Support Systems (DSS) based on artificial intelligence is not new, however, the evolution of computational power and the ubiquity of smartphones allowed a great improvement of these systems in the healthcare area. Since diabetes is a major public health problem worldwide, some DSSs were developed in this context with different goals. In this work, we propose a DSS to help in the complex task of dosing prandial insulin in a personalized way.

BACKGROUND

The widespread use of personal medical devices such as Continuous Glucose Monitors (CGM), insulin pumps, and wearable Physical Activity Monitors (PAM) allows the collection of a large amount of data, like blood glucose levels, insulin bolus administered, exercise intensity, and heart rate [4]. Also, several mobile applications are available to gather additional data, such as nutritional plans and meals' CHO content. All these technologies provide an essential information basis for the development of Artificial Intelligence (AI) based DSS for diabetes.

A decision can be described as a choice between different options. When taken by humans, decisions can have flaws because they are affected by people's complexity and stress [5]. A DSS provides information to sustain our decisions, judgments, or intuitions, based on data analysis [6]. Regarding diabetes, the DSSs can be designed to be used in a clinical context by healthcare professionals, where the amount of data to analyze can be huge, or in a

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different perspective intended to help patients in their disease-related daily decisions. Both systems have the common goals of facilitating daily management, improving patients' glycemic outcomes, and reducing diabetes complications. There are some examples of AI-based DSS in the literature designed for patients and/or health professionals to assist them in dosing insulin providing therapeutic recommendations. Indeed, different methodologies applying machine learning and deep learning techniques have been used to forecast blood glucose [7, 8, 9] and achieve the optimum insulin bolus [10, 11, 12]. Nevertheless, new systems continue to emerge to predict BG as accurately as possible, allowing the calculation of the optimum prandial bolus, with the ultimate goal of turning safe the technology that could be a life-changer for diabetics, the artificial pancreas. The DreaMed Advisor Pro is a Food and Drug Administration-approved solution focused on bolus insulin optimization for patients with T1DM [13]. This system was designed for patients using insulin pumps and CGM or Self-Monitoring of Blood Glucose (SMBG). This tool provides healthcare professionals with recommendations to correct the basal rate, Insulin to Carbohydrate Ratio (ICR), Insulin Sensitivity Factor (ISF), and other tips related to personal behavior, yet, the impact caused by CHO estimation errors is not considered. The recommendations are shared with the patient only after the experts' approval [14]. Due to this requirement, this system provides therapeutic adjustments a minimum of 14 days apart, not allowing the patient to find the optimal bolus for each meal. The results of the Advisor Pro in the ADVICE4U trial highlight the positive impact that AI-based recommendations can have on the health outcomes of T1DM patients [15].

In its turn, Castle *et al.* [16], created a mobile application called DailyDose, aimed at adults with T1DM on Multiple Daily Injection (MDI) therapy. DailyDose allows insulin bolus calculation considering the glycemic history, the CHO intake, and physical activity. Although it delivers daily recommendations on CHO intake and exercise needs, it only provides weekly insulin dosage adjustments [17]. This system uses glucose readings to train the K-Nearest Neighbors DSS (KNN-DSS) to detect the causes of hypo and hyperglycemia and suggests corrections to the insulin bolus dosage. Additionally, it uses machine learning forecasting algorithms to predict hypoglycemia events [16]. To analyze the effect of using DailyDose on patients' Time In Range (TIR), Castle *et al.* conducted an eight weeks study with 25 patients, concluding that there were no significant differences in TIR when compared with the two baseline weeks where patients only used the CGM [16]. These results could be related to the fact that the patients only used the DailyDose bolus recommendations 55% of the time. When the recommendations were accepted and followed, DailyDose was associated with TIR improvement.

Brown *et al.* [12] used CBR to obtain a personalized and improved insulin bolus calculation for each meal. They designed a system that incorporates a temporal sequence based on the fact that cases are not isolated, as past events influence current situations. In their system, the solution of the cases is the amount of bolus insulin the patient should take, requiring a great number of cases in the database to find an adequate estimation for a new event. Consequently, it will take considerable time to initialize the system and populate the cases database to obtain more accurate solutions. They store all the cases after reviewing them without any maintenance mechanism. Their results showed that temporal CBR could be an alternative to bolus decision support.

Torrent-Fontbona and López used a similar approach in PepperRec, a Case-Based Reasoning (CBR) bolus recommender for T1DM. PepperRec estimates the Insulin-to-Carbohydrate Ratio (ICR) based on user information, such as meal size, time of day, and physical activity [18]. This way, the authors compensate for the variability in the ICR, adjusting this parameter and the ISF in the bolus calculation, but the error introduced due to CHO estimation is not considered. To validate their tool, they performed an *in silico* study using the virtual population of the UVA/PADOVA simulator, concluding that PepperRec increases the TIR.

The literature review carried out supports the relevance of using AI-based DSS to help specialists and patients to optimize insulin doses and, consequently, improve treatment outcomes. Our proposal has a similar goal to the works mentioned, however, our DSS applies case-based reasoning to predict postprandial BG based on past experiences, compensating the errors introduced due to imprecise CHO estimations, ICR, and ISF variabilities. With the postprandial BG forecast, it is possible to obtain a correction factor to apply to bolus calculation [19]. In this way, the DSS design will suggest, to the user, the optimum bolus for each meal.

PROPOSED DECISION SUPPORT SYSTEM ARCHITECTURE

This section describes the architecture of the DSS developed to help patients with T1DM and healthcare professionals to find the optimal prandial insulin bolus, increasing the TIR and consequently avoiding hypo and hyperglycemia.

The AI technique selected to employ in this DSS was case-based reasoning, a cyclic process that allows solving new problems using previous similar experiences [20]. Among all the AI techniques applied to predict and obtain blood glucose and the optimum insulin bolus, CBR presents several strengths. This technique allows working with heterogeneous and inconsistent data, which is very common in the healthcare area, mainly when data collection relies on patients' commitment. CBR can use quantitative and qualitative information, such as BG values and physical activity intensity, and handle missing values using information from past events, so the system adapts to routine changes easily. Also, the solution obtained is easy to understand because it is presented as a similar case and its solution, which can be relevant to increase user confidence in the recommendations. Diabetes management is weak in theory but huge in experience, so applying an experience management methodology such as CBR in this field becomes natural [21]. According to [22], the optimum bolus can be obtained by Equation 1:

$$B = \frac{CHO}{ICR} + \frac{BG_{\text{preprandial}} - BGT}{ISF} + K - IOB. \quad (1)$$

where B is the required bolus in Units of insulin (U), CHO is the amount of carbohydrates to be consumed in g, ICR is the insulin-to-carb ratio in g/U, $BG_{preprandial}$ is the premeal blood glucose in mg/dL, BGT is the blood glucose target in mg/dL, ISF is the insulin sensitivity factor in mg/dL/U, IOB (Insulin-on-Board) is an estimate of the insulin still active in the body from previous bolus in U, and K is a correction factor used to compensate for the effects of some infection, physical activity or carbohydrates intake. Thus, the authors conclude that K is given by Equation 2:

$$K = \frac{\delta_{BG_{\text{postprandial}}}}{ISF}, \quad (2)$$

where $\delta_{BG_{\text{postprandial}}}$ is the difference between the postprandial and the target BG. More detailed information can be found in [22]. Therefore, this DSS was designed to obtain an accurate prediction of postprandial BG from the CBR similar cases solutions allowing the calculation of K and then applying this correction factor to Equation 1. Figure 1 illustrates the proposed architecture, which encompasses two platforms, a mobile and a web application (app) connected to a central CBR engine. The mobile app, designed to be used by patients, allows the storage of clinical data such as ICR, ISF, target glycemia and limits, and the collection of real-life data from CGM, wearable PAM, or manual input, for example, CHO intake and bolus insulin administered [23]. These data are used to populate the CBR engine with cases. When the patient uses the mobile app bolus calculator, a new case is created in the CBR. Then, the CBR uses the stored cases to find the most suitable solution (i.e., the predicted postprandial BG) for the new case. The predicted postprandial BG is sent to the mobile app to be used to compute the optimal bolus. In turn,

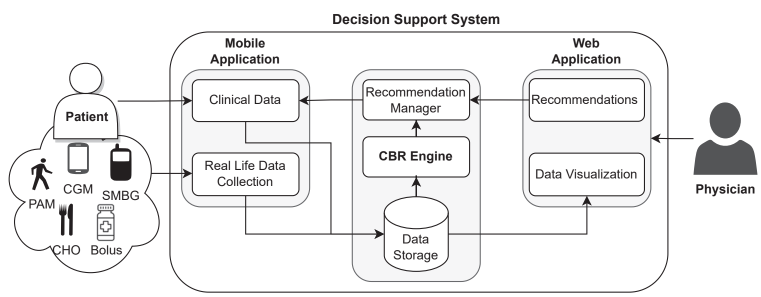

FIGURE 1. Proposed DSS architecture, showing the interaction between the mobile and web platforms and the CBR engine.

the web application was designed to be used in a clinical context by healthcare professionals. Through this platform, it is possible to visualize the data stored by the mobile app and analyze the history of bolus insulin optimization recommendations. Also, the system will assign priority levels to the patients by showing first the patients with a less stable glycemic profile. All the data collected will contribute to improving the CBR database through the addition of new cases.

CONCLUSION

Diabetics treated with MDI need to administer, every meal, an adequate amount of insulin to keep blood glucose within the safe range established by the physician. In standard care, to find the optimal bolus, physicians study patients' characteristics and daily habits. This process implies periodic medical consultations that are exhausting for patients and overload the healthcare systems. DSS has already proven to be an asset in the medical field, so it makes sense to develop this tool that will allow the patient to make insulin bolus adjustments more frequently and easily. The proposed solution allows the collection of day-to-day data from patients and learning through an intelligent case-based reasoning system, generating suggestions for adjustments in the calculation of the insulin bolus. In this way, it is expected to increase the TIR and avoid the life-treating situations of blood glucose excursions.

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