Knowledge Engineering

DiaBuddy - A Knowledge Based System for Type 1 Diabetes Management

Project Report by Luisa Ebner, Frederic Chamot and Michelle Sieling

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1 Application Domain: Type 1 Diabetes Management

Type 1 Diabetes Mellitus (T1DM) is a chronic metabolic disorder, characterized by abnormal blood glucose regulation patterns, with which only 5-10% of all diabetes cases are being accounted for [1]. The defining component in T1DM is the immune system related destruction of pancreatic β-cells, responsible for the secretion of insulin [2]. Type 1 diabetes requires lifelong treatment consisting of blood glucose monitoring, exogenous insulin administration, meal planning as well as suffering from disease management related complications and comorbid conditions [1, 2]. Poor glycaemic control is one of the greatest risk factors of diabetes related complications and has been a focal point of an ongoing bulk of research on the disease [1, 3]. Recent advances in continuous glucose monitoring (CGM) have enabled real-time CGM, which aims at improving patient self-care [3]. This technology however still remains limited because of the delays between detection of glucose levels in interstitial fluid compared to venous levels (5-10 min) as well as the delayed onset of action of rapid insulin (10-30 min) [3].
This is why artificial pancreas (closed-loop glycaemic control systems) have only been introduced very recently and are far from being readily available [4]. The majority of T1DM patients are still required to manually monitor and reason about their future glucose levels in order to take adjusting actions. Constantly monitoring one's own food intake, discounting physical activities and assessing stress levels and hormonal balance together to then inject appropriate doses of insulin or ingest the right amount of glucose, make up a very time-consuming duty. In fact, managing T1DM is a very knowledge and time intensive task, that severely restricts the daily life of patients and allows them little spontaneity in terms of food intake and sports. Furthermore, it is extremely difficult, especially for recently diagnosed patients, to assess the combined effects of ingested food and physical activity on their glucose level. Even tailored diabetes programs cannot sufficiently convey the profound, specialized knowledge in a short period of time. However, it takes many years of experience to successfully counteract glucose fluctuations with manual injections. Before that, injecting appropriate amounts of insulin at the right time depicts a delicate task, which in turn represents a major health risk for young or inexperienced patients. After all, this motivates the development of an external, knowledge-based system in the form of a smartphone application that helps patients monitor their blood glucose levels and presents them reasoned, on-time recommendations on adequate amounts of insulin/glucose to inject/ingest. The same could relieve patients of the burden of calculating and assessing suitable insulin doses and at the same time teach them how food, sports and blood glucose concur. Input to the system are the subcutaneous glucose level invasively measured by the patient's CGM, several parameters of physical activity measures by the patient's smartwatch and finally information about food intake, which the patient inserts manually to the proposed smartphone application. The system output should be an accurate recommendation on the amount of insulin to inject at a certain time as well as diagrams or text explaining the occurrence of the recommendation. The system has to communicate with the patient and his (smart) devices as well as apply suited food, diabetes and sports ontologies.

2 Context Models

2.1 Problems & Solutions

Organization Model	**Problems and Opportunities Worksheet OM-1**
PROBLEMS AND OPPORTUNITIES	* In T1DM, blood glucose regulation is abnormal due to a lack of insulin production in the pancreas. Constant monitoring and manual adjustments of the blood glucose level through insulin injections/glucose ingestion are necessary to keep the blood glucose in a target range and thus, avoid disease related complications and comorbid disorders. * The demanding tasks of T1DM disease management disrupt patient's daily life including negative impact on social life, work, exercise and life quality in general. * Especially for newly diagnosed patients, T1DM disease management can be challenging. Skills and knowledge, such as estimating nutritional values and taking into account the effects of physical exercise only develop slowly over time. It is however important that blood glucose values are managed appropriately also in the early stages of the disease following its diagnosis.
ORGANIZATIONAL CONTEXT	**Mission**: * Allow for optimal blood glucose control in T1DM patients, prevent extreme fluctuations and thereby keep the patient healthy and free of secondary disease * Enable the patient to gain insights into the dynamic interplay of factors that influence the blood glucose levels * Help recently diagnosed patients develop an intuitive understanding of those factors in order to make accurate assessments in daily life glucose management **External Factors**: * Local Healthcare regulations * Cooperation with doctors * Availability of technology (i.e. CGM systems, smartwatches, smartphone) **Strategy**: * Provide accurate intervention recommendations to the patients (e.g. amount of insulin to inject/ glucose to ingest) * Provide reasoning for blood glucose fluctuations to increase awareness of bodily reactions to certain activities/foods.
SOLUTIONS	* Develop a knowledge based system for T1DM disease management, e.g. a smartphone application that continuously monitors blood glucose levels, predicts future blood glucose concentrations and, whenever required, sends an intervention notification to the user with recommended actions to take. * Organize training sessions for recently diagnosed T1DM patients to teach them estimate their blood glucose dynamics and let them gain insight into the interacting factors contributing to blood glucose level variation.

Table 1: Worksheet OM-1: Problems, organizational context, and possible solutions.

2.2 Process & People involved

Organization Model	Variant Aspects Worksheet OM-2
STRUCTURE	see Figure 1
PROCESS	see Figure 2
PEOPLE	disease managing patient
RESOURCES	1. constant glucose monitoring system e.g. dexcom G6, freestyle libre 2. insulin/glucose 3. smartwatch data 4. self reported food intake
KNOWLEDGE	1. practical knowledge and experience with the disease (reaction of body to food, exercise etc) in order to know when to intervene 2. knowledge about macro-nutrient composition of different foods 3. blood glucose concentration reaction to food or insulin

Table 2: Worksheet OM-2: Variant aspects, people, resources and knowledge involved in T1DM management.

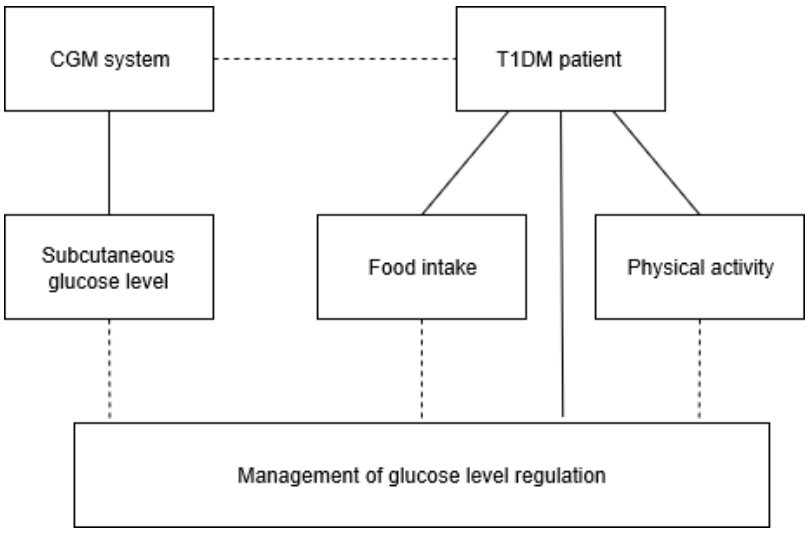

Figure 1: Structure and people in the current situation

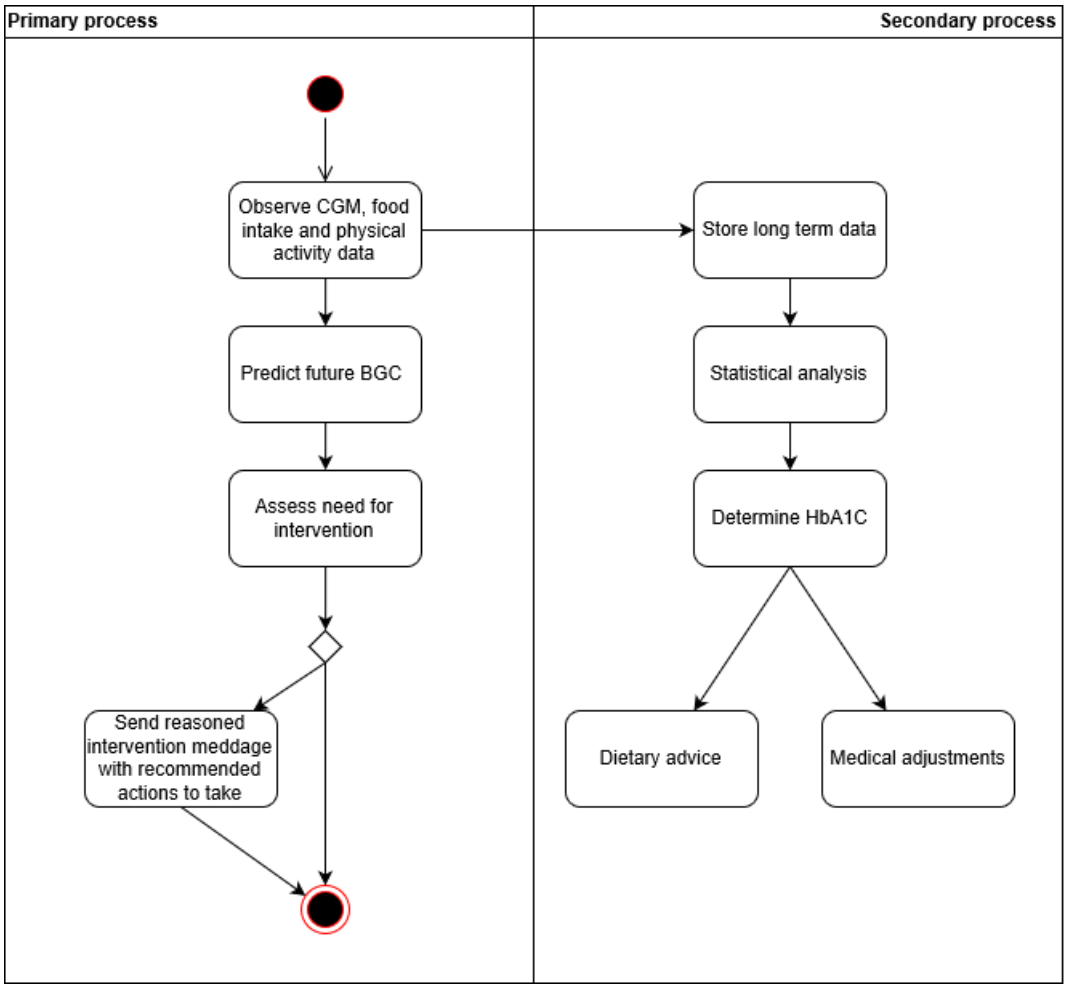

Figure 2: Primary and secondary diabetes management processes in the current situation depicted as an UML activity diagram.

2.3 Technical and Business feasibility

Organization Model	**Checklist for Feasibility Decision Document: Worksheet OM-5**
BUSINESS FEASIBILITY	1. *What are the expected benefits for the patient from the considered solution?* The major benefit is the patient's increased ability to maintain blood glucose concentration constant, leading to a larger proportion of time levels are kept in the desired goal range. This reduces daily negative side effects of extreme glucose concentrations and lowers the risk of developing comorbid diseases on the long term. For recently diagnosed patients, the application can function as a tutor that helps learn the necessary skills and knowledge to manage the disease quickly. The system intervention recommendations will surpass the judgements of novice T1DM patients and will thus increase the glucose regulation accuracy. 2. *How large is this expected added value?* Continuous Glucose Monitoring (CGM) systems are already widely used as their positive effects are well known, especially for patients that have difficulty anticipating and reacting to fluctuating glucose levels. By reducing the risk to develop secondary conditions known to occur in T1DM (e.g. impaired vision, kidney problems), the life expectancy and quality can even be increased using this system, also lowering medical costs later in the patients life. Added value furthermore arises from less doctor visits and use of medicines. 3. *What are the expected costs for the considered solution?* Expected costs mainly concern the development of a capable smartphone application that can communicate with CGM systems and smartwatches. It also needs to be able to employ food, diabetes and sport ontologies and may process user input. As such, it is a rather sophisticated application, that will demand for profound programming and design expertise. Once implemented, we do not expect the system to need much maintenance. Prerequisites are a CGM system, a smartwatch and smartphone. 4. *How does this compare to possible alternative solutions?* An alternative solution to this would be a closed-loop system that uses a similar form of future glucose concentration prediction (e.g. auto-regressive models, recurrent neural networks, ...). The same is connected to an insulin/glucose pump that takes the human out of the loop and manages the glucose levels by continuously administering the correct amount of insulin in order to avoid large fluctuations in blood sugar levels. Setting up and maintaining those systems is more time consuming and by far more expensive. Eventually, most implementations are not yet publicly available. 5. *To what extent are health risks and uncertainties involved regarding the considered solution direction?* Generally the risks are not much higher compared to traditional T1DM disease management. It is important that the user is informed about the capabilities and limitations of the system and is aware that every recommendation of the system merely is a suggestion and should not blindly be trusted or replace the users own (educated) judgement.

Organization Model	**Checklist for Feasibility Decision Document: Worksheet OM-5**
TECHNICAL FEASIBILITY	1. *How complex, in terms of knowledge stored and reasoning processes to be carried out, is the task to be performed by the considered knowledge-system solution?* Not necessarily extremely complex, however it requires knowledge from multiple domains, i.e. nutritional composition of foods, effects of macro-nutrient combinations on blood glucose levels, time frame of the effects of slow and fast insulin, and knowledge about the interplay between blood glucose levels and physical exercise. 2. *Is it clear what the success measures are and how to test for validity, quality, and satisfactory performance?* During development of the application the performance of the system needs to be tested by comparing the outputs and intervention moments to the judgement of the expert in order to correctly assess the quality of the system before deployment. Also, pilot studies could be conducted using a within subjects design where a group of T1DM patients uses the system for a certain period, and the time of glucose levels in range is compared to the baseline condition (without the system). 4. *How complex is the required interaction with end users (user interfaces)?* While designing the application a priority should be to make the interface simple, intuitive and unambiguous. The end user should not have to learn first about how the application works, everything should be designed in a way that there only is a small, or preferably no learning curve. 5. *How complex is the interaction with other information systems and possible other resources (interoperablity, systems integration)?* The application will need access to both the data from the CGM system and live data from the smartwatch. It is likely that in both cases different brands or models require slightly different integration and working on a generic implementation design will be crucial to ensure compatibility with the majority of currently available devices. 6. *Are there further technological risks and uncertainties?* It is of course possible that functionality is compromised if smartphone, smartwatch or CGM operating systems are updated. Catching those errors when they occur is very important to avoid malfunctioning of the application leading to suboptimal recommendations or even wrong predictions and adverse health consequences.

Organization Model	**Checklist for Feasibility Decision Document: Worksheet OM-5**
PROJECT FEASIBILITY	The application domain builds on various forms of domain expertise, primarily including medical facts, nutritional knowledge and T1DM knowledge in general. Skills needed on the project team are: 1. experience in treating T1DM (diabetes expert) 2. knowledge about the co-active effects of nutritional intake, physical activity and current blood glucose concentration 3. knowledge of experienced patients with regard to glucose level intervention necessity 4. access to food/exercise/T1DM ontology's 5. app development skills
KNOWLEDGE & PROPOSED ACTIONS	1. *Focus:* What is the recommended focus in the identified problem-opportunity areas? Enable better glucose regulation understanding in recently diagnosed T1DM patients by providing reasoned intervention recommendations. 2. What are the expected *results, costs, and benefits*? Better glucose level control, less extreme values, less secondary disease occurrence, less need for medical professional advice, lowered medical costs and more accurate disease management quantification. 3. What *project actions* are required to get there? Set up a project team and schedule for system development. Conduct patient/expert interviews to develop and quantify rules for knowledge base/interventions. Implement existing macro-nutrition ontology into system. Develop smartphone application with user interface. Validate the method using the experts.

Table 3: Worksheet OM-5: Feasibility of the solution of creating a knowledge based smartphone application to support T1DM understanding and management

2.4 Selected Knowledge Intensive Task

Task Model	Task Analysis Worksheet TM-1
TASK	Glucose Level Assessment
ORGANIZATION	Primary process carried out internally by the knowledge based system.
GOAL AND VALUE	The goal of the assessment task is to classify the difference between the predicted and the optimal blood glucose level (input to the assessment subtask) into one of three possible glucose level categories defined by value ranges. The category indicates whether the predicted blood glucose levels is 1. within, 2. above or 3. below a fixed normal range. The assessment task leads to a decision about the category that characterizes the patient's blood glucose level. This is of value as every category is associated with a certain intervention type. As such, the assessment step indicates the type of intervention recommendation as a major step towards the intended, precise value recommendation.
DEPENDENCY AND FLOW	*Input tasks*: Monitoring task including 1. data entry, 2. parameter selection, 3. blood glucose prediction (see Figure 5) *Output tasks*: Diagnosis task including 1. hypotheses creation 2. hypothesis selection 3. observation of evidence 4. verification of the result (see Figure 6)
OBJECTS HANDLED	*Input objects*: Medical and nutritional knowledge stored in diabetes and food ontologies/knowledge bases glucose level delay rules as expert knowledge personal activity and food intake data from smart watch- and phone subcutaneous blood glucose level data from CGM system *Output objects*: A decision category / Information string *Internal objects:* norm and intervention rules as expert knowledge
TIMING AND CONTROL	Carried out every time, patient data is received as part of the monitoring task. Each time, data is received and a current blood glucose level is predicted, the assessment task is carried out. (i) *preconditions* the assessment task can only be carried out when a real-valued difference between the predicted and the optimal blood glucose level has been calculated. This requires a raw data entry, the selection of relevant parameters for blood glucose prediction, knowledge about the optimal value as well as the prediction and difference calculation itself. (ii) *postconditions* The system has to be available and functioning to continue with the diagnosis task.
AGENTS	The knowledge based system
KNOWLEDGE AND COMPETENCE	norm and intervention rules as assessment criteria
RESOURCES	minor computing power within the smartphone application system
QUALITY AND PERFORMANCE	The task is not time-critical, but it is expected that the right category can be assessed quickly (in less than a second).

Table 4: Worksheet TM-1: First analysis of the smartphone application's assessment task.

Task Model	**Knowledge Item Worksheet TM-2**	
NAME POSSESSED BY USED IN DOMAIN	Glucose Level Assessment Criteria Knowledge Based System Glucose Level Assessment Type 1 Diabetes Mellitus Disease Management	
Nature of the knowledge		**Bottleneck / to be improved?**
Formal, rigorous	X	
Empirical, quantitative	X	
Heuristic, rules of thumb		
Highly specialized, domain-specific	X	
Experience-based		
Action-based		
Incomplete		
Uncertain, may be incorrect		
Quickly changing		
Hard to verify	X	X
Tacit, hard to transfer		
Form of the knowledge		
Mind		
Paper	X	
Electronic	X	
Action skill		
Other		
Availability of knowledge		
Limitations in time		
Limitations in space		
Limitations in access		
Limitations in quality	X	X
Limitations in form		

Table 5: Worksheet TM-2: Knowledge asset characterization plus identication of bottlenecks.

2.5 Knowledge used in selected Task

2.6 Expected Capabilities of Human User

Agent Model	**Agent Worksheet AM-1**
NAME	*Type 1 Diabetes Patient*
ORGANIZATION	The knowledge based system is solely developed for the patient's use. The patient is in the centre of the primary process, acts as the only user of the system and actively communicates with the latter via app usage.
INVOLVED IN	Data entry task
COMMUNICATES WITH	The knowledge based system integrated to a smartphone application
KNOWLEDGE	1. knowledge on nutritional value of food, on the glycaemic effect of physical activity, stress and hormonal balance. 2. skill to measure and inject insulin (cf. TM-2)
OTHER COMPETENCES	Smartphone application usage
RESPONSIBILITIES AND CONSTRAINTS	Maximum possible accuracy of the dimensions/amount and ingredients of meals taken are limited. Constraints may be imposed on the patient when eating meals that were not prepared by the patient himself, e.g. in a restaurant. This limits the agents ability to enter precise food intake information.

Table 6: Worksheet AM-1: The T1DM patient.

3 Knowledge Acquisition

Multiple different domains of knowledge flow into the modelling process of the system. T1DM is a well studied disease and as such it is covered well with regard to medical textbook knowledge on the disease dynamics and management process. Other textbook knowledge areas relevant to this systems are both the decomposition of food into its macro-nutritional elements as well as the metabolic process associated with the uptake of those elements. The initial aim of this project was to embed a food ontology into the system which would have allowed for a straightforward and potentially also educative food reporting structure where macro-nutrition composition could be inferred based on the input of a global food category. Then, after entering e.g. "[user ate] {150gr} of banana", the system were able deduct the exact nutritional values of that meal and not only internally process this in order to predict its effects on the blood glucose but also to output a message to the user to inform him about the nutritional content and its potential effects on glucose levels. Unfortunately, as will be discussed later, the granularity of decomposition of the currently available food ontologies do not satisfy the requirements of T1DM management in that they do not decompose the sub-types of carbohydrates.
With regard to the practical knowledge, we were able to get in contact with two T1DM patients, who both had more than 15 years of experience in managing the disease as well as a nurse specialized in the treatment of T1DM at a local hospital near Amsterdam. The process of knowledge acquisition that led to the development of the final knowledge model can be described in the three stages covered in three sections as *Knowledge Identification*, *Knowledge Specification* and *Knowledge Refinement*.

3.1 Knowledge Identification

In order to get an overview over all of the elements that could be relevant to our knowledge model, we initially conducted unstructured interviews with our diabetes patients. The main goal of these interviews was to map the structural elements that frame the daily disease management of T1DM and to understand which specific knowledge items would play a central role in the knowledge model. It became clear rapidly that the core concepts of the disease management relevant to the model would be rule type instances that associated a certain external influence to its effect on the glucose levels, e.g. a certain amount of macro-nutrients (sugars, simple carbohydrates, complex carbohydrates, fat, protein), specific levels of physical activity, or the injection of insulin. The most part of those initial interviews was thus used to conceptualize what specific rule types would be needed and how they would look like on a qualitative level. As a short example, the different types of carbohydrates each required a specific, yet closely related rule type, i.e. x amount of sugar increases the glucose levels y amounts, starting after a delay of z minutes and spanning a certain duration. The rule types for simple and complex carbohydrates would take the same structure, but with different values. Fat and protein again followed another rule type structure, again closely related to each other but different on a quantitative level. After this stage of the knowledge acquisition process, we had derived the qualitative structure of those rule types, as well as rule types regarding physical activity, and the conceptual relations between the different types of blood glucose measurements, such as subcutaneous, current blood glucose and future blood glucose.

3.2 Knowledge Specification

In the next stage of the acquisition process we decided to conduct a series of structured interviews with the diabetes patients in order to quantify the rule types in a way that was both intuitive to the patients as well as eligible for the implementation of the system later on. This involved extracting numerical values for the delay of onset for the different macro-nutrients, quantifying the total increase of those nutrients, and specifying the total duration over which this increase would take place. A large part of this expertise, however, proved to be practical, tacit knowledge acquired over many years of managing the disease and both patients struggled to extract raw numbers describing their solutions based on heuristics and intuition. At the end of this series of interviews we were nevertheless able to quantitatively describe all of the conceptually derived relations and rule types from the earlier stage of the knowledge acquisition process.

3.3 Knowledge Refinement

Finally, to confirm our current domain understanding both on a qualitative and quantitative level we conducted another structured interview with the nurse specialized in the treatment of diabetes patients. She was able to confirm the structure of our rule types as well as the numerical formulas we derived during the earlier interviews. She however stressed that those numerical values are very likely to vary to an unknown extent between patients. This is something that we were not able to include further in the building of our knowledge model but needs to be kept in mind both when evaluating the applicability of a system as proposed in this project as well as possibility for improvement in further research on this topic. After the last interview we thus had derived both the conceptual and numerical relationships of the elements influencing the blood glucose levels and were we able to confirm those relations independently by a trained specialist.

4 Knowledge Model

Knowledge is a complex form of information, often referred to as information about information. In any case, analyzing and modelling knowledge requires specialized tools. [5] In the following chapter, the knowledge model is presented, which specifies the knowledge and reasoning requirements of the prospective T1DM support system. Put differently, the knowledge model helps clarify the structure of the underlying knowledge intensive domain of diabetes and manual blood glucose control as well as the information-processing monitoring task at the core of the proposed system.

4.1 Task Knowledge

An important aspect of knowledge refers to the question of what we want to do with it. [5] In our case, this is the development of a diabetes management software application that helps patients minimize the risk of dangerous glucose fluctuations and relieve the duties of constant self-monitoring. As to that, the section *Task Knowledge* describes the goals to be achieved by applying knowledge in the proposed application domain of type 1 diabetes support. It states the intentions, the software application pursues and how these goals can be realized through a decomposition into subtasks and inferences.

4.1.1 Task Specification

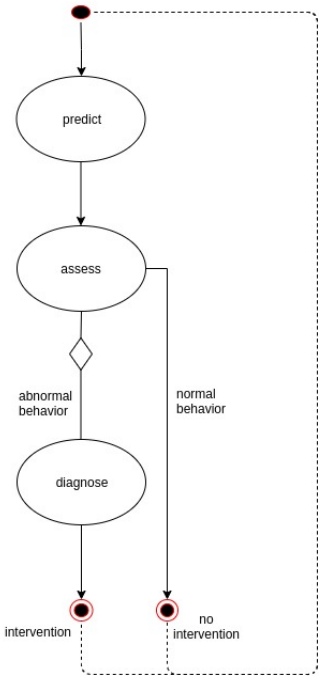

Figure 3: Prototypical diagram of the task layer.

4.1.2 Task Decomposition

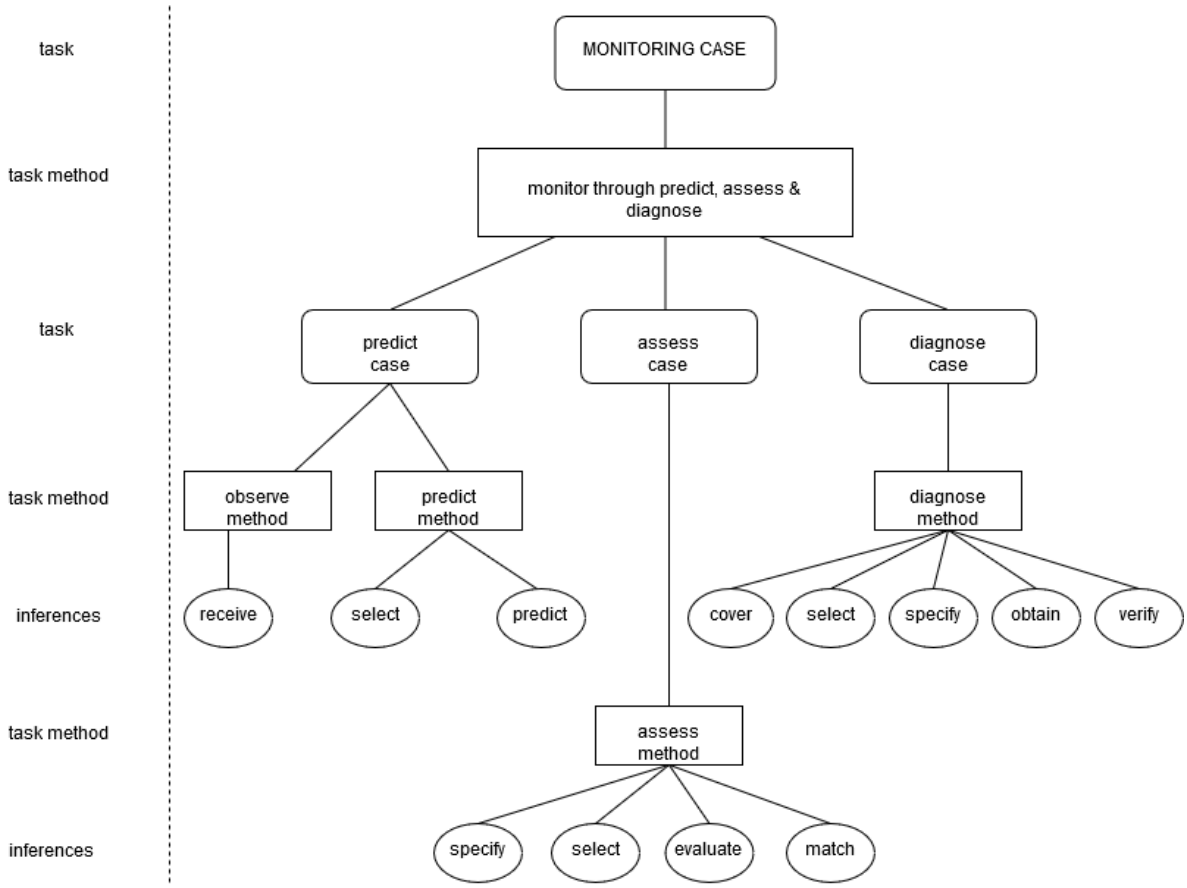

Figure 4: Task decomposition diagram showing the two main task-knowledge types:“task” and “task method”. Two levels of task-decomposition are present with monitoring as the top-level task and diagnosis, assessment and prediction as primitive tasks, which decompose directly into leaf functions.

4.2 Inference Knowledge

Whereas in the chapter on domain knowledge will present the static information and knowledge structures of the T1DM management domain, in the chapter on inference knowledge we describe how static knowledge structures are used to carry out an actual reasoning process. The three main ingredients of inference knowledge are *inferences, knowledge roles* and *transfer functions*. At it, inferences may be understood as the building blocks of the reasoning system, that carry out only one primitive reasoning step. As such, they describe the lowest level of functional decomposition. [5]

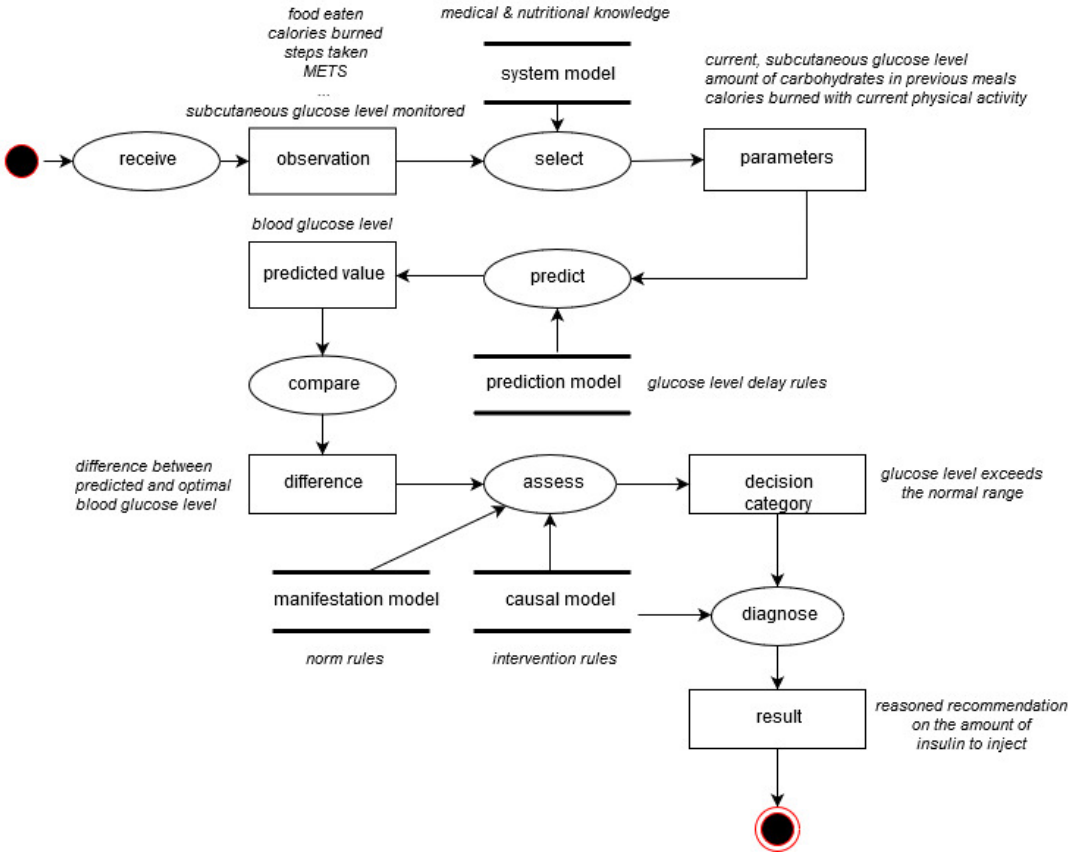

Figure 5: Inference structure in which the roles are annotated with domain-specic examples.

The top level task of the herein proposed knowledge-based system is monitoring. Implemented into a smartphone application, the system is supposed to analyse the dynamic process of blood glucose fluctuations in the human body, constantly affected by processes in and around the human body. By means of monitoring, the system aims to find out, whether a T1DM patient's blood glucose concentration lies within a desired (expected) range or whether there is a discrepancy to the norm in form of too high or too low values.

Our monitoring task is event-driven, meaning that it becomes active every time new data comes in from the patient's CGM system, smartwatch and/or smartphone. This is modelled in the diagram above with the use of the transfer function *receive*. Once a new observation has entered the system, five more inferences are defined for processing the data. Firstly, system parameters are selected that are valuable in view of detecting discrepancies to the normal behavior of the patient's blood glucose concentration. Therefore, the monitoring system deploys a system model consisting of a number of definitions about the normal ranges of each parameter. Among the selected parameters are the subcutaneous blood glucose concentration, current physical activity measures (heart rate, activity type, calories burned) and information about recent food intake. Together, the observed parameter values are then used to predict the patient's unobservable, current blood glucose concentration according to knowledge stored in the prediction model. Next, the predicted value is compared with a fixed norm, resulting in a discrepancy or difference value. The same is then processed further by an assessment step (see Figure 6 and description below), resulting in a decision category, whose manifestations state that the blood glucose concentration is either *above*, *below* or *within* the specified normal range. Finally, this category is input for the diagnosis task, which searches for a reason for the classified (ab-) normal value and derives an adequate intervention recommendation. (see Figure 7 and description below)

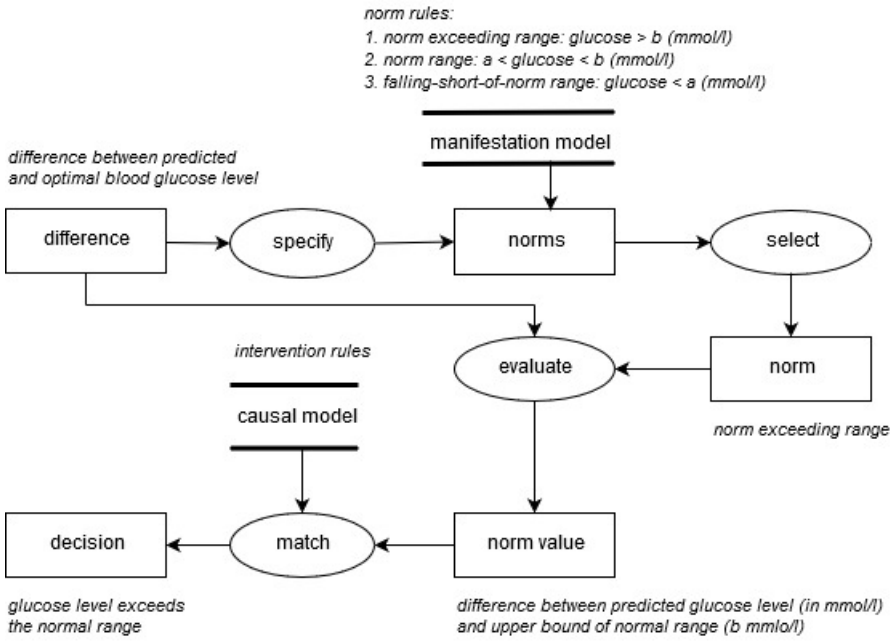

Figure 6: Inference structure of the assessment (sub-)task annotated with domain-specic examples.

The goal of the above stated assessment task is to characterize an abstracted case of the patients input data, namely the difference between the predicted and the (fixed) optimal blood glucose level in terms of a decision class. The underlying knowledge consists of a set of norms and criteria used for assessment. These are stated in the manifestation- as well as the causal model. At the core of the assessment step, the input value is evaluated according to given norms and place the difference value into one of the value ranges within the norm rules. Finally, the output is one of three possible decision classes, which are: 1. patient's blood glucose level exceed the normal range, 2. patient's blood glucose level lies within the normal range, 3. patient's blood glucose level deceeds the normal range". The resulting decision class indicates whether an intervention recommendation should be sent or not. [5]

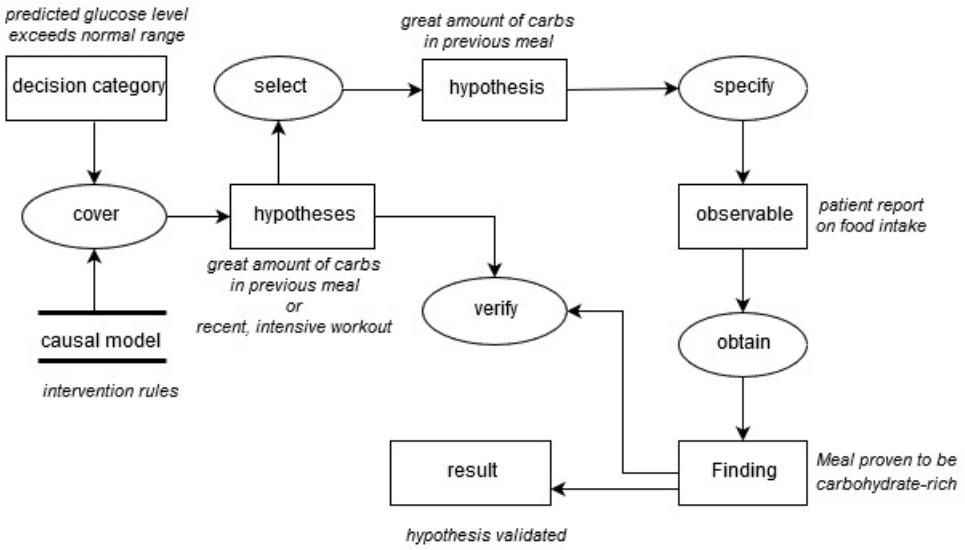

Figure 7: Inference structure of the diagnosis (sub-)task annotated with domain-specic examples.

At the start of the task the inference cover is invoked to generate a candidate solution (the hypothesis) on the basis of the original complaint. In our case the complaint is the decision class resulting from the antecedent assessment task and thus an indication of whether the patient's blood glucose is expected to be too high, too low or in the desired range. Candidate solutions refer to food intake, physical exercise or previous insulin injections.
Subsequently, a candidate solution is selected. In order to see whether it is consistent with the input data, an observable for this hypothesis is specifier and the actual value of the finding obtained. This inference depicts a transfer function, where the app as reasoning agent has previously requested a piece of information, namely a food intake report, from the patient as external agent. Thereby, the app has initiative and the patient holds information. In this case, the candidate hypothesis is a "high carb meal". The observations made by *obtain* is then verified along the set of hypotheses. If the verification step cannot confirm the hypothesis, the *cover* inference is invoked again to generate another hypothesis, and the testing process is repeated. The task method for diagnosis terminates if either the inference verify returns an equal value (in which case the current hypothesis becomes the solution) or the cover inference fails to produce a new hypothesis, in which case the task method fails to find a solution. [5]

4.3 Domain Knowledge

This section poses domain specific knowledge and information types subdivided into the *domain schema* and *knowledge base*. Whereas the domain schema gives schematic descriptions of domain-specific knowledge types and static information, such as *concepts, relations* and *rule types*, the knowledge base contains actual instances of those knowledge types. [5]

4.3.1 Domain Schemas

Concepts

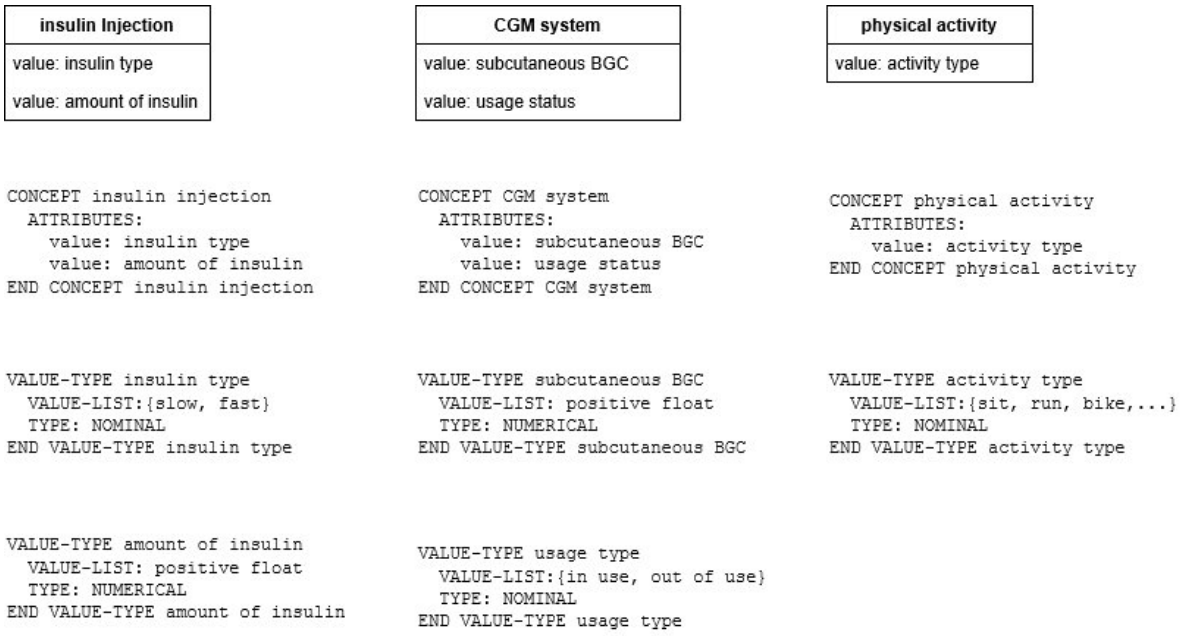

Figure 8: Graphical and textual specification of selected concepts together with their attributes and corresponding value types. Concepts define a set of objects which occur in the T1DM management domain and share similar characteristics and attributes.

Relations

```
CONCEPT carbohydrates
  DESCRIPTION:
  "a biomolecule consisting of carbon,
  hydrogen and oxygen atoms"
  SUB-TYPE-OF food intake
  ATTRIBUTES:
    observable: BOOLEAN
    amount: NUMERICAL
END CONCEPT carbohydrates
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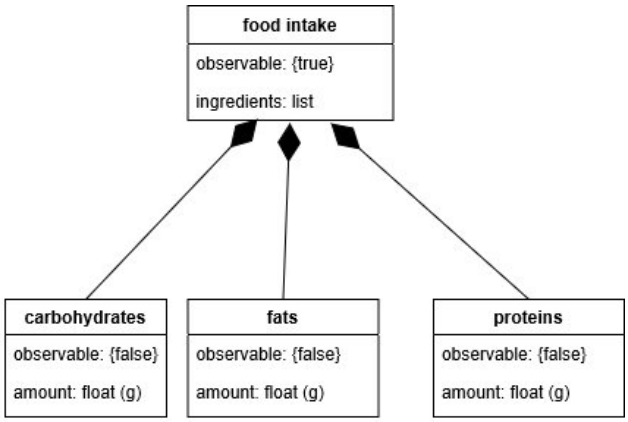


Figure 9: Domain schema describing the nutritional subtype relations of food intake

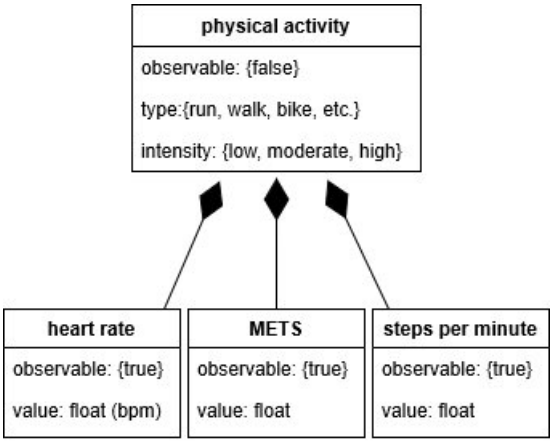


Figure 10: Domain schema describing the subtype relation of physical activity measurements as used for the future blood glucose prediction.

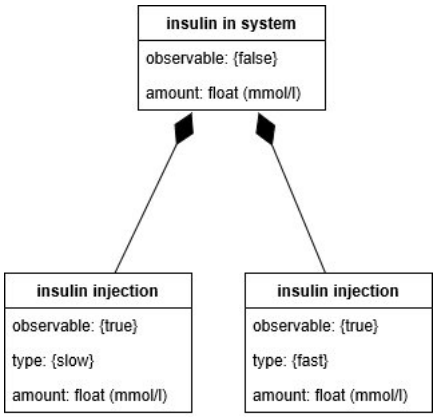


Figure 11: Domain schema describing the subtype relation of insulin in the body and the reported insulin injections as used for the future blood glucose prediction.

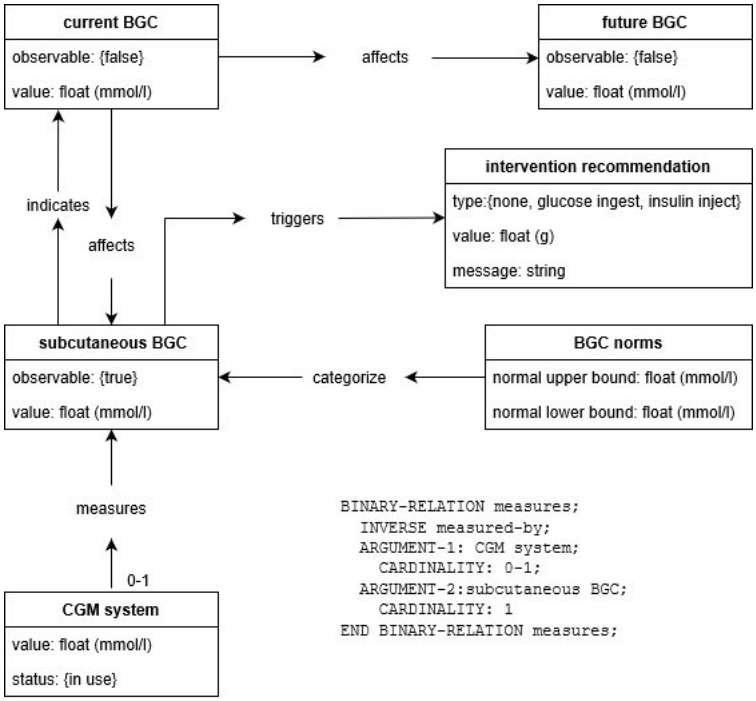


Figure 12: Domain schema describing the relation of different glucose level concepts including their measuring and assessment. BCG = Blood glucose concentration, CGM = continuous glucose monitoring. In every case, the default cardinality 1 applies, meaning that participation in the relation is obligatory.

Rule types

Rule types are special types of relations, that enrich the relations among concepts outlined in the previous subsection of the domain schema. [5] In this case, the same will help construct the cause-effect model, the system uses for its two core tasks: predicting the future blood glucose concentration (BGC) and diagnosing, why abnormal BGCs occur when they occur. For the sake of developing a concisely describable model, we assume additivity of all BCG influence factors.

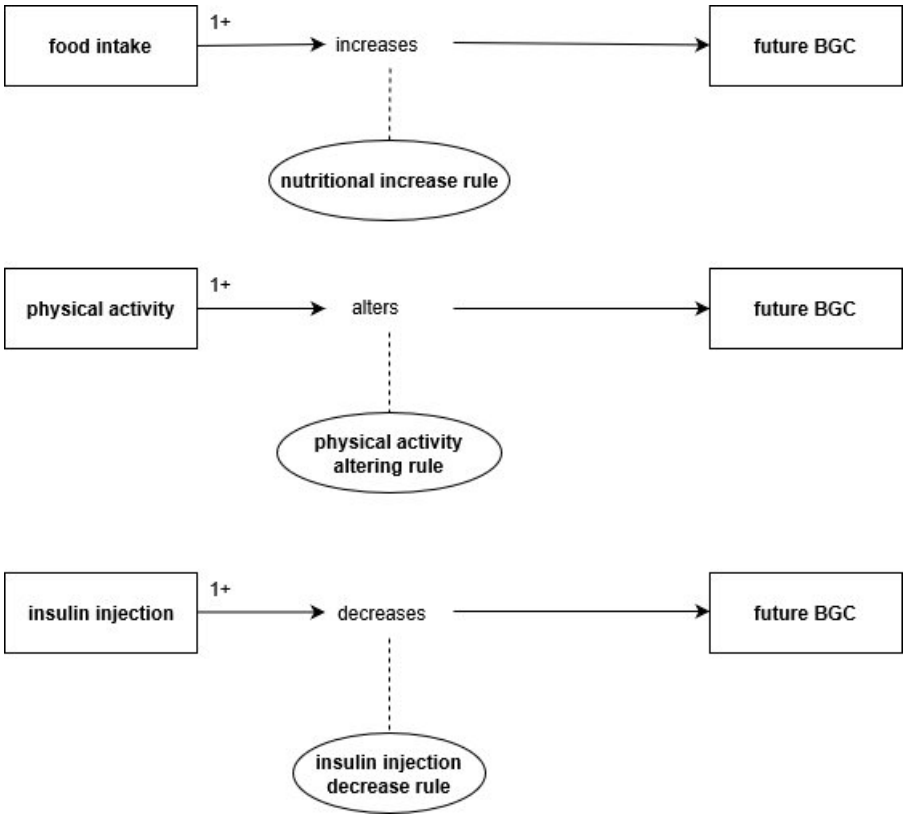


Figure 13: Rule types regarding the three major influence factors on the future BGC.

Food Intake Rule Types

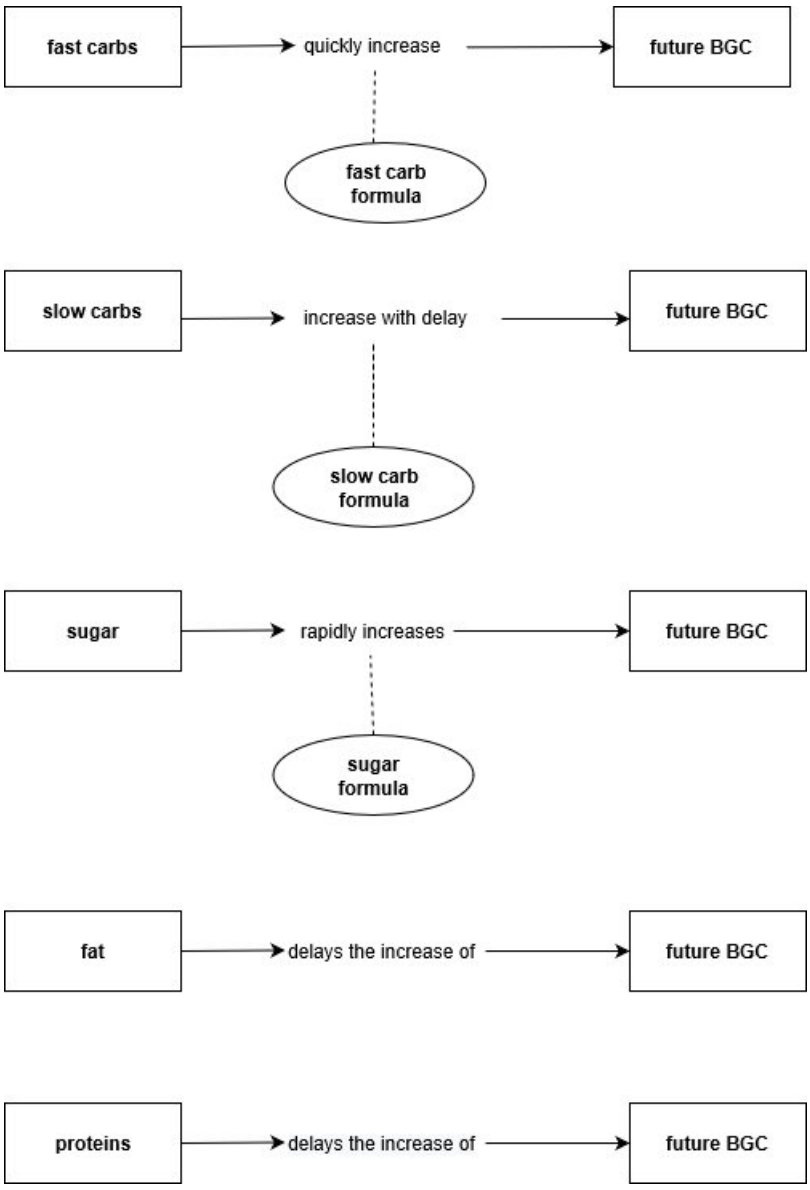


Figure 14: rule types specifically regarding food intake. Used by the system to a) predict the future blood glucose concentration and b) diagnose abnormal glucose values when occuring.

Physical Activity Rule Types

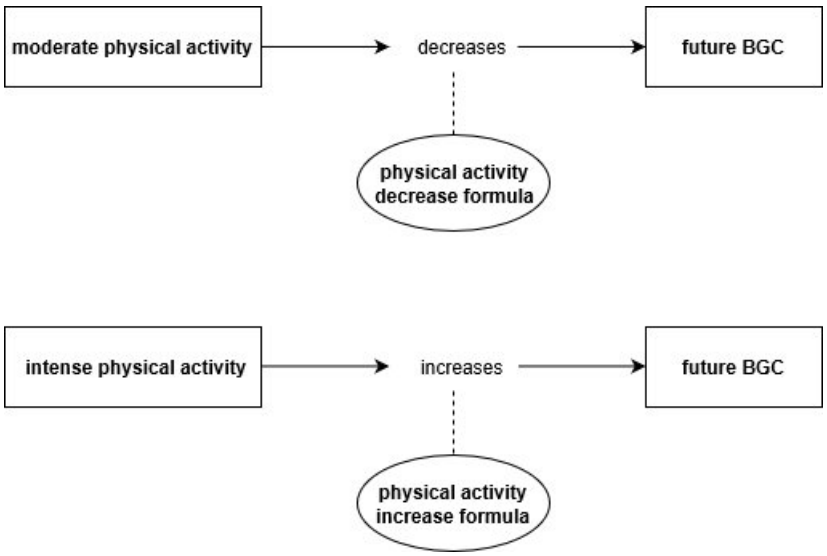


Figure 15: Rule types used to specify the effect of physical exercise on the glucose levels.

Intervention Rule Types

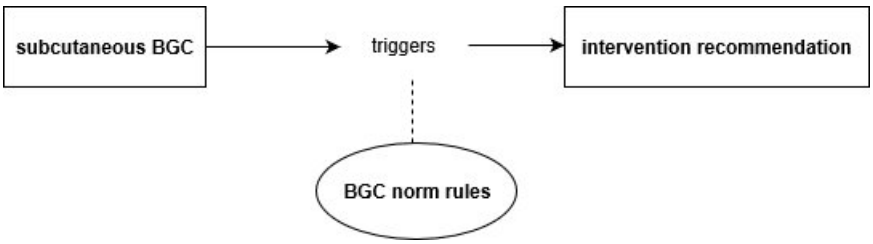


Figure 16: Rule type indicating how the BGC norm rules trigger intervention recommendations of the system. This rule type holds for the case of norm exceeding BGCs where an insulin injection is recommended as well as for norm deceeding BGCs where a glucose ingestion is recommended.

4.3.2 Knowledge Base

Scenario 1

Type 1 diabetes patient Anna eats a medium-sized banana for breakfast and drinks black coffee. This meal contains 89 calories. The nutritional values are composed of 1.1g protein, 12.8g fast carbohydrates, 10g complex carbohydrates, and 12.2g sugar. After entering the nutritional data into the system, it advises her to inject 3 units of fast insulin, which she does after 10 minutes.

```
KNOWLEDGE-BASE insulin-injection-after-meal
    USES:
        fast-carb-formula FROM food-intake-rule-types
        slow-carb-formula FROM food-intake-rule-types
        sugar-formula FROM food-intake-rule-types
        insulin-injection-decrease-formula FROM bgc-influence-rule-types
    EXPRESSIONS:
        /* fast carb formula */
        carbohydrates.type = fast AND carbohydrates.amount = 12.8
        QUICKLY INCREASES future bgc.value = +49.6

        /* slow carb formula */
        carbohydrates.type = slow AND carbohydrates.amount = 10 INCREASES WITH DELAY future bgc.value = +40

        /* sugar formula */
        sugar.amount = 12.2 RAPIDLY INCREASES future bgc.value = +48.8

        /* protein formula */
        protein.amount = 1.1 DELAYS BGC INCREASE by delay.value = +1.1min

        /* insulin injection formula */
        insulin injection.type = fast AND insulin injection.amount = 3 DECREASES future bgc.value = -120
END KNOWLEDGE BASE insulin-injection-after-meal
```

Figure 17: The knowledge base “insulin-injection-after-meal” contains instances of food intake and insulin injection rule types.

Scenario 2

After work. type 1 diabetes patient Peter decides to perform an intensive, 30-minute running workout followed by another 30 minutes of moderate walking. After the high intensity workout, he injects 2 units of fast insulin to counteract the effects of the workout. In order to strengthen himself, he eats a chocolate bar after 40 minutes, during his moderate exercise unit. The same contains 250 calories, 13g fat, 31g (fast) carbs and 4g of proteins.

```
KNOWLEDGE-BASE meal-after-workout
    USES:
        physical-activity-altering-rule FROM bgc-influence-rule-types
        physical-activity-decrease-formula FROM physical-activity-rule-types
        physical-activity-increase-formula FROM physical-activity-rule-types
        fast-carb-formula FROM food-intake-rule-types
        slow-carb-formula FROM food-intake-rule-types
        sugar-formula FROM food-intake-rule-types

    EXPRESSIONS:
        /* physical-activity-increase-formula */
        physical activity.type = run AND physical activity.intensity = high AND
        physical activity.duration = 30 INCREASES future bgc.value = +75

        /* physical-activity-decrease-formula */
        physical activity.type = walk AND physical activity.intensity = moderate AND
        physical activity.duration = 30 DECREASES future bgc.value = -60

        /* fast carb formula */
        carbohydrates.type = fast AND carbohydrates.amount = 28
        QUICKLY INCREASES future bgc.value = +96

        /* sugar formula */
        sugar.amount = 12.2 RAPIDLY INCREASES future bgc.value = +48.8


        /* protein formula */
        protein.amount = 4 DELAYS BGC INCREASE by delay.value = +4min

       /* insulin injection formula */
        insulin injection.type = fast AND insulin injection.amount = 2 DECREASES future bgc.value = -80
END KNOWLEDGE BASE meal-after-workout
```

Figure 18: The knowledge base “meal-after-workout” contains instances of physical activity and food intake rule types.

5 Communication Model

To become effective, produced knowledge has to be transferred to the various parties that use it to perform their own tasks. In brief, a task that is carried out by the knowledge system may produce results in the form of information objects that need to be communicated to the patient and vice versa [5]. Our case presents a rather prototypical, simple example of system-user interaction, where the knowledge system (in form of a smartphone application) presents reasoned results (= intervention recommendations) to the user (= T1DM patient) and alternatively, the patient and app user provides input data to the knowledge system.

5.1 Dialogue Diagram

For the proposed usage, two agents, namely the patient and the system carry out a shared, or rather distributed, task. For successful completion, they need to communicate and exchange information. The communication model consisting of three major components aims to give an overview of all the needed exchanges. The first component is the dialogue diagram shown below. It governs the full dialogue between the patient, the knowledge-based system and supplementary devices used in the process. [5]

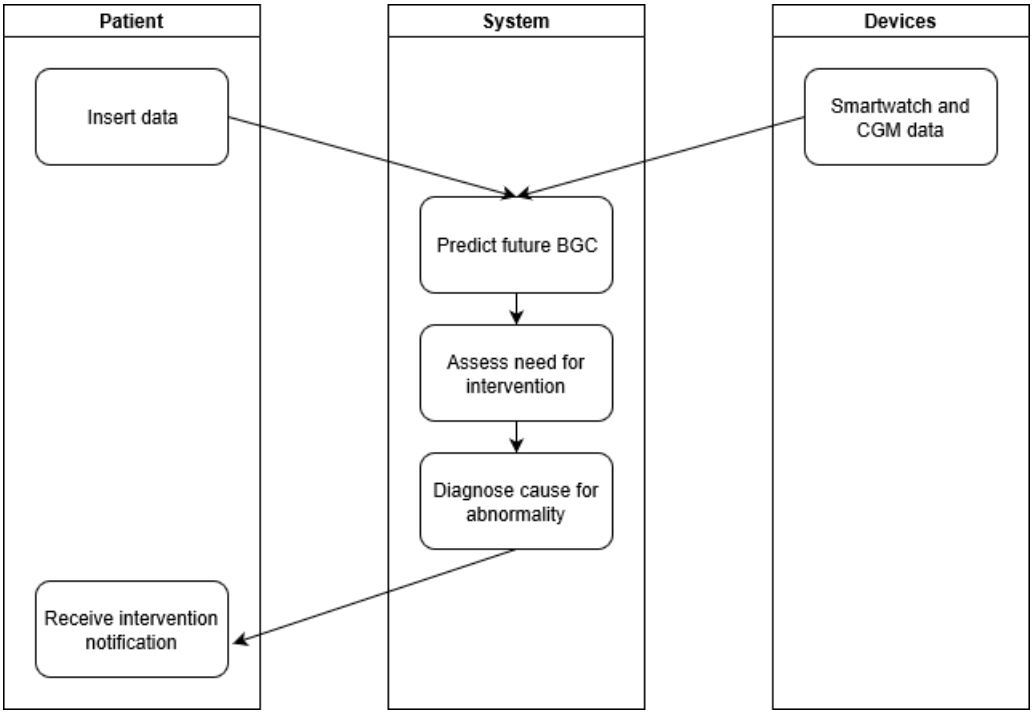


Figure 19: Dialogue diagram of the T1DM support system

5.2 Transaction between Agents

Communication model	**Transaction Description Worksheet CM-1**
TRANSACTION IDENTIFIER/NAME	OBTAIN DIRECT USER DATA The patient inserts data about the type and amount of previous food intake or the type and amount of previously injected insulin. This information message from the patient has a intent a query for information from the knowledge based system. It *asks* the system for information delivery in return.
INFORMATION OBJECT	The type and amount of food intake OR the type and amount of injected insulin linking the patient's data entry to the parameter selection as a prerequisite for BGC prediction
AGENTS INVOLVED	**Sender:** Patient **Receiver:** Knowledge system
COMMUNICATION PLAN	This transaction becomes active whenever the patient decides to make a new data entry. Preferably this corresponds to every time the patient has eaten or injected insulin. See Figure 19.
CONSTRAINTS	The main, required pre-conditions are correctness, accuracy promptness in the specification of the amount and types of food eaten/insulin injected. Post-condition is merely an active, working system application.
INFORMATION EXCHANGE SPECIFICATION	This transaction is of the ask-reply type. No detailed information exchange specication is required.

Table 7: Worksheet CM-1: Specifying the obtain-transactions that makes up the dialogue between the patient and the knowledge system in the communication model.

Communication model	**Transaction Description Worksheet CM-1**
TRANSACTION IDENTIFIER/NAME	OBTAIN INDIRECT USER DATA The patient's smartwatch continuously tracks data about the patient's heart rate, METS, steps and calories balance and sends it to the patient's smartphone incl. the knowledge based system. The patient's CGM continuously measures the current subcutaneous BGC and sens it to the patient's smartphone. These messages just deliver/present information objects to another agent, namely the knowledge based system. It depicts an independent, informative action without underlying intent or agreement.
INFORMATION OBJECTS	1. heart rate, METS, steps and calories balance and 2. the current subcutaneous BGC, linking data obtainment to parameter selection as a prerequisite for BGC prediction
AGENTS INVOLVED	**Sender:** Supplementary Devices: Smartwatch & CGM **Receiver:** Knowledge system
COMMUNICATION PLAN	This transaction is constantly active. See figure 19.
CONSTRAINTS	Pre-conditions are the untainted functionalities of smartwatch and CGM system.
INFORMATION EXCHANGE SPECIFICATION	This transaction is of the inform type. No detailed information exchange specication is required.

Table 8: Worksheet CM-1: Specifying the transactions that make up the dialogue between two agents in the communication model.

Communication model	**Transaction Description Worksheet CM-1**
TRANSACTION IDENTIFIER/NAME	REPORT REASONED INTERVENTION RECOMMENDATION After the knowledge system completes the listed tasks, it will let the patient know which diagnosis is made and to what extent intervention is needed (e.g. g insulin to inject) and why (e.g. high carb meal).
INFORMATION OBJECT	A smartphone message stating the obtained diagnosis and a detailed recommendation of actions to take.
AGENTS INVOLVED	**Sender:** Knowledge system **Receiver:** Patient
COMMUNICATION PLAN	This transaction automatically takes place whenever the knowledge system finishes the diagnosis step.
CONSTRAINTS	A correct intervention recommendation will depend on the patient's direct and indirect data entries. The required post-condition is that the patient follows the recommendation and documents the taken intervention via the app again.
INFORMATION EXCHANGE SPECIFICATION	This transaction is of the *report* type. see Table 10

Table 9: Worksheet CM-1: Specifying the report transactions that makes up the dialogue between the knowledge system and the patient in the communication model.

5.3 Information Exchange Specification

The following worksheet refines the description of the report transaction shown in Table 9. It specifies internal structure and syntactic form of the sent intervention recommendation.

Communication model	**Information Exchange Specification Worksheet CM-2**
TRANSACTION	*report reasoned intervention recommendation*
AGENTS INVOLVED	1. **Sender**: knowledge system 2. **Receiver**: patient
INFORMATION ITEMS	1. **Role**: *core* object 2. **Form**: canned text + data strings 3. **Medium**: pop-up message of the app on the patient's smartphone
MESSAGE SPECIFICATIONS	1. **Communication type**: report 2. **Content**: Diagnosis as reason for current BGC prediction + Intervention recommendation as the exact amount of insulin to inject/glucose to injest 3. **Reference**: Causal model + intervention model

Table 10: Worksheet CM-2: Specifying the messages and information items that make up an individual transaction within the communication model.

6 Design Model

Main focus of the model design in our case was to preserve the structure of the expertise model and to translate it directly into code. We chose to implement our system in Python for various reasons: Firstly, given the limited scope of the project we did not implement a user interface of android application environment. This reduced the task of our system to a purely computational one with no need of integrating sensory information from different devices. Secondly, Python allowed for an object-oriented implementation approach which easily allowed us to transfer the structure of the knowledge system into code. See the worksheets DM-1 and DM-2 for more detailed description of design decisions.

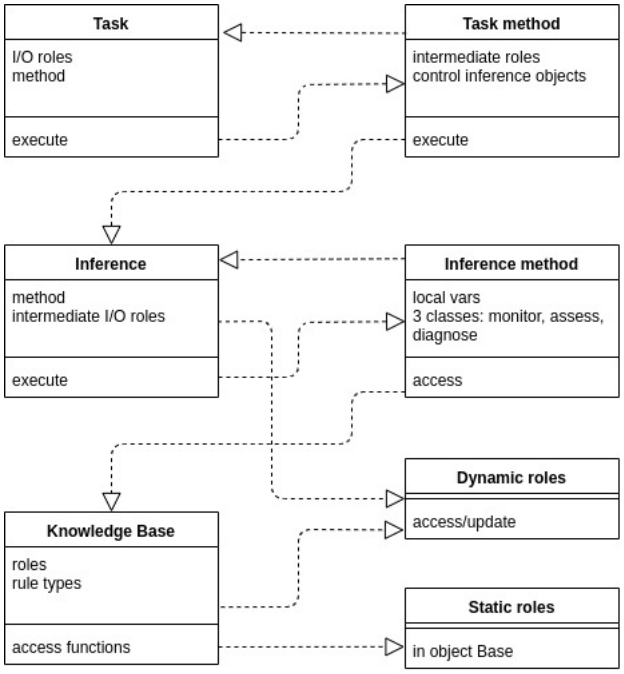


Figure 20: Subsystem decomposition of the application model

Design Model	Worksheet DM-1: System Architecture
Architecture decision	**Format**
SUBSYSTEM STRUCTURE	In our implementation we follow the overall structure of the Model-View-Controller (MVC) architecture. Given the limited project scope we only fully specify the design of the application model (see sub-system decomposition). Briefly summarized, the other two components would have the following functions: **Controller**: Handle incoming sensory data from smartwatch and CGM, as well as nutritional info reports, each timestep it creates a new instance of the monitoring loop and triggers interventions when necessary. **View**: User interface of the smartphone application. Here the user can report his food consumption, check on his current blood glucose levels and intervention messages are displayed here.
CONTROL MODEL	Centralized control that handles input of sensory data at a fixed frequency and delegates tasks to subsystems in a static way.
SUB-SYSTEM DECOMPOSITION	See figure 20. We chose for a simplified version of the application model as described in [5]. **Task**: 1. initializes all classes of task and inference layers and parses input information in the format that is used by methods 2. sequentially executes all task methods and handles I/O of those methods **Task method**: Because each iteration of the control loop relies on the same static function call combination, not a lot of control constructs are needed. The basic elements that are used are iteration, selection and sequencing. **Inference**: In contrast to the structure of the inference object as proposed by [5], a simplified version is used that only allows for the operation *execute*. The operations *has-solution* or *new-solution* where not relevant in this use context. Inference steps are not meant to fail; each case has a solution, rendering those operations unnecessary.
SUB-SYSTEM DECOMPOSITION	**Inference methods**: The inference methods specify the actual computational steps that have to be taken to complete the basic inference steps. We subdivided the methods into three classes which map to the three task types used by the system. Methods do not have direct access to the dynamic or static roles but rather get them as arguments in the function call. **Dynamic roles**: Data types of dynamic roles supported by the system are *elements* and *sets*, with the latter being realized by either lists or dictionary structures that allow for the operations select() and pop(). As discussed above, no mechanisms for truth-maintenance were implemented. **Static roles**: For simplification purposes the static roles are incorporated in the knowledge base object that can easily request values and pass them to inference methods. **Knowledge Base**: As the rule types in the systems implementation require operations on long lists of floats instances of rule types where implemented as knowledge base methods that are called with a certain configuration of arguments. Static roles can be accessed but not modified once the knowledge base object is initialized with a certain value set. No knowledge base modification of analysis functions were implemented

Table 12: Worksheet DM-1: System Architecture

Design Model	Worksheet DM-2: Target Implementation Platform
SOFTWARE PACKAGE	Android OS using Python 3.6
POTENTIAL HARDWARE	Smartphones, Smartwatches, Tablets, Televisions
TARGET HARDWARE	Smartphone
VISUALIZATION LIBRARY	Many available, but need to be adapted for this specific purpose.
LANGUAGE TYPING	Python is weakly/dynamically-typed.
INTERACTION PROTOCOLS	inter-process communication library (CORBA, IPC) with client-server communication method
COMMONKADS SUPPORT	No

Table 11: Worksheet DM-2: Target Implementation Platform

7 Implementation

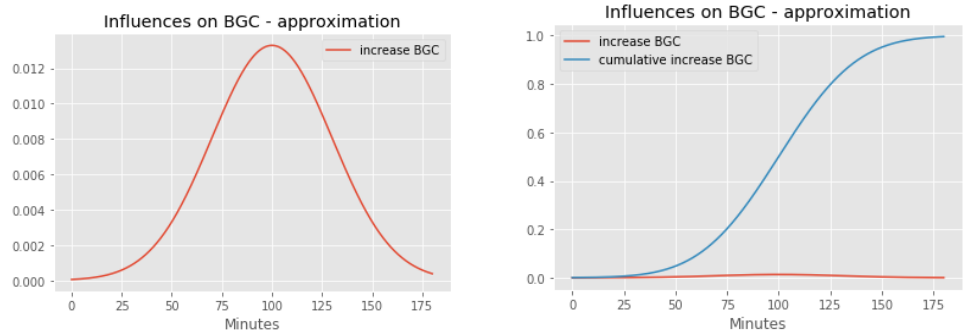
7.1 General Structure

To maintain the structure of the knowledge system as developed using the CommonKADS approach, we created five different classes: a task class, three inference classes, and a knowledge base class. Besides those main classes we used two helper classes which were responsible for generating message strings as well as storing the series of predictions made by the system. Each of the main classes implemented the methods that corresponded to the responsibilities as described by the knowledge model. The task class had three main methods, named after the three types of task used in the system: monitor, assess and diagnose. All three of the inference classes also corresponded to each one of the task types, and implemented methods that corresponded to the atomic steps of that specific task type. The knowledge base class implemented all static knowledge roles as well as one method for each rule instance used in our knowledge model. The general data pipeline for a single monitoring case consisted of initializing new objects for all classes, and passing them as input args to the task object, which organized the information flow exactly as described in the knowledge model. Because the goal use of our system is a constant monitoring loop, we built a rough draft of a controller instance on top of this hierarchy that created a list of sample data observation that iteratively got fed into the pipeline. We also implemented an interactive console application that each iteration generated some output, an intervention message when needed and queried the user whether action should be taken (eat x grams of sugar/ inject x units of fast insulin). Those actions were then incorporated into the next iteration of the system.

7.2 Predicting Future BGC

7.2.1 Single Factor Influence

A major challenge of the system was the implementation structure of the blood glucose prediction. The mathematical functions that describe the impact of certain factors on blood glucose levels can only be described on a conceptual level as the factual values of those functions depend on too many factors that cannot be assessed, e.g. individual patient factors (sleep quality, mood, hormones), time of the day, temperature and many more. Expecting patients or even trained medical specialist to quantify those functions exactly would be absurd. In order to nevertheless extract the valuable expert knowledge we decided upon a strategy that approximates those functions in a way that allows us to directly relate the parameters of those functions to intuitive expert knowledge.



(a) Magnitude of the increase in blood glucose levels over time.

(b) Cumulative increase in blood glucose levels over time.

Figure 21: Note that y axis values are not inherently meaningful for this graph as for modelling purposes we chose the total impact on blood glucose to be 1.

After the first interview with our experts we knew that the increase in blood glucose levels should approximately follow the function as shown in figure 21a. In order to bring it conceptually closer to the absolute change in blood

glucose levels we compute the cumulative increase as shown in figure 21b. Albeit more intuitive to understand, it still did not allow to extract meaningful parameters from the function. This however could be achieved, using a simple piece wise linear function approximation of that function, as shown in figure 22. On a conceptual level, this function can be described using three parameters: the delay of the onset of the effect, the total increase at the end of the effect and the duration of the effect. All three of those parameters describe the function in terms that can easily be described by diabetes experts.

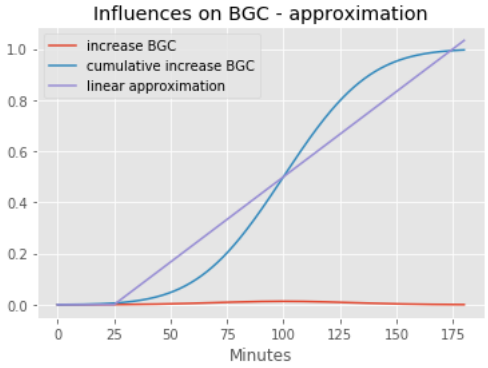


Figure 22: Linear approximation function of the cumulative increase function describing the increase of blood glucose given a certain influence factor.

Using those linear functions, we were able to describe all rule types for factors that increase or decrease the blood glucose levels. In order to account for the delaying effects of other factors, i.e. uptake of protein or fat, we just needed to alter the given effect function such that the first part of the linear function (effect=0) was prolonged. This approximation system thus allowed us to describe and combine all factors that influence blood glucose level in a simple and intuitive way.

7.2.2 Multiple Factor Influence

The linear approximation also enabled for a straightforward implementation of the general prediction model given a set of influence factors in each iteration of the monitoring loop. In order for this approximation to work we also had to assume that the case of multiple factors influencing blood glucose could be described using an additive model without any interaction between those factors. Given this assumption we could simply add all influences and the current prediction of the blood glucose timeline, rendering us with an aggregated piecewise linear function describing both the blood glucose prediction function and all factors influencing blood glucose. This is illustrated in an example in figure 23.

7.2.3 Code Implementation

Given the additive model approximation, the implementation into software was straightforward. Both predicted blood glucose curves and cumulative influences were segmented into 10 minute timesteps and stored in arrays. This thus does not yet realize the intended event-driven monitoring system, but rather a time based iteration approach that each timestep aggregates data from the past iteration period. Simplifying the monitoring frequency however allowed to construct more intuitive and easy to follow example scenarios and should not limit the generalization of this prototypical system to a more complex setting. Each iteration of the monitoring loop the output blood glucose array from last iteration would be passed to the system, new influence arrays were created according to the knowledge model and aggregated into the blood glucose array. After each iteration all influence arrays were discarded and only the resulting blood glucose array was passed on further down the pipeline.
For better illustration purposes we used the data from the two scenarios from section 4.3.2 to create two traces including system output describing all atomic steps, intervention messages and plots for each monitoring iteration.

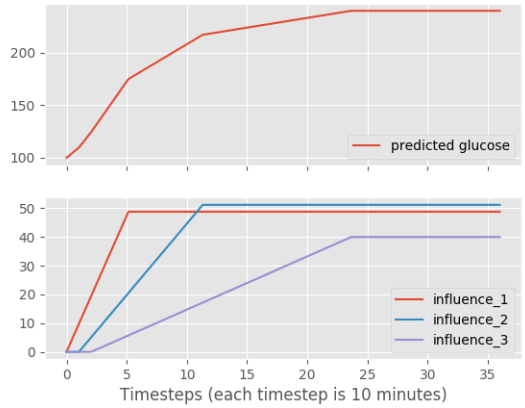


Figure 23: Aggregating the effects of multiple factors onto the function describing the blood glucose concentration curve. This model assumes only additive effects. The blood glucose level before applying all factors to it was a constant value of 100.

7.3 Example Scenario 1

For this scenario we assume that Anna stays seated for the whole sequence (represented by physical exercise data: 0 steps, heart rate 70, 1 METS). The whole sequence spans 60 minutes, i.e. 6 timesteps.

7.3.1 After 0 minutes - eats banana and drinks black coffee

```
Starting control loop with current BGC: 100
Starting monitoring sequence with current blood glucose concentration 100.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min... Done
BGC +60 min will be 182.02
Full prediction timeline for the next 90 min:
[100.   109.76 124.64 141.42 158.21 174.99 182.02 189.04 196.07]
Comparing predicted to optimal... Done
Diffscore: 82.02
Starting assessment sequence with diffscore 82.02.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
An intervention should be sent because blood glucose will be too high
Starting diagnose sequence with current blood glucose concentration 100,
future blood glucose concentration 182.02, and intervention = (True, 'upper')
Generating set of possible hypotheses... Done
hypotheses ['food', 'intense_exercise']
Specifying the observables for hypothesis intense_exercise... Done
```

```
Obtaining observable exercise... Done
Verifying hypothesis intense_exercise... Done
Specifying the observables for hypothesis food... Done
Obtaining observable nutrition... Done
Verifying hypothesis food... Done
```

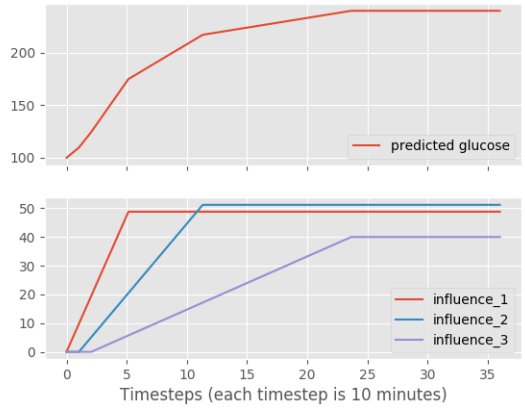


Figure 24: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 1 of scenario 1

```
###### INTERVENTION MESSAGE ######

I detected that your blood sugar will be too high within the next 60 minutes.
It seems like this is due to the following actions you took:

You ate a carbohydrate rich meal recently

I would advise you to inject 3.0 units of fast insulin in order to keep your
glucose levels in the goal range.
Do you want to inject insulin? Select an amount of units of fast insulin between 0 and 10:
3
```

7.3.2 After 10 minutes - injects 3 units of fast insulin

```
Starting control loop with current BGC: 109.76
Starting monitoring sequence with current blood glucose concentration 109.76.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min... Done
BGC +60 min will be 146.69
Full prediction timeline for the next 90 min:
[109.76 117.58 127.31 137.03 146.76 146.72 146.69 146.66 146.62]
Comparing predicted to optimal... Done
Diffscore: 46.69
Starting assessment sequence with diffscore 46.69.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
Blood glucose will be in the acceptable range. No intervention needed
```

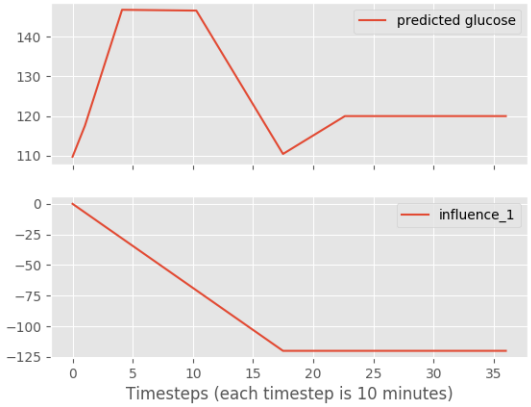


Figure 25: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 2 of scenario 1

7.3.3 After 20 minutes - no action

```
Starting control loop with current BGC: 117.58
Starting monitoring sequence with current blood glucose concentration 117.58.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min...Done
BGC +60 min will be 146.66
Full prediction timeline for the next 90 min:
[117.58 127.31 137.03 146.76 146.72 146.69 146.66 146.62 146.59]
Comparing predicted to optimal... Done
Diffscore: 46.66
Starting assessment sequence with diffscore 46.66.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
Blood glucose will be in the acceptable range. No intervention needed
```

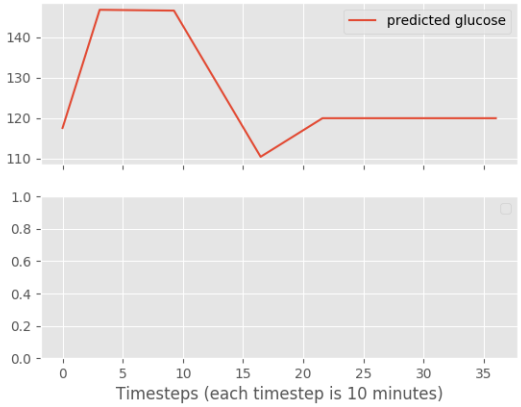


Figure 26: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 3 of scenario 1

7.3.4 After 30 minutes - no action

```
Starting control loop with current BGC: 127.31
Starting monitoring sequence with current blood glucose concentration 127.31.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min...Done
BGC +60 min will be 146.62
Full prediction timeline for the next 90 min:
[127.31 137.03 146.76 146.72 146.69 146.66 146.62 146.59 146.55]
Comparing predicted to optimal... Done
Diffscore: 46.62
Starting assessment sequence with diffscore 46.62.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
Blood glucose will be in the acceptable range. No intervention needed
```

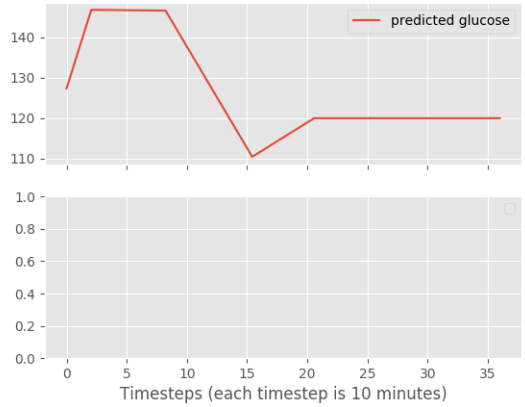


Figure 27: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 4 of scenario 1

7.3.5 After 40 minutes - no action

```
Starting control loop with current BGC: 137.03
Starting monitoring sequence with current blood glucose concentration 137.03.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min...Done
BGC +60 min will be 146.59
Full prediction timeline for the next 90 min:
[137.03 146.76 146.72 146.69 146.66 146.62 146.59 146.55 141.4 ]
Comparing predicted to optimal... Done
Diffscore: 46.59
Starting assessment sequence with diffscore 46.59.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
Blood glucose will be in the acceptable range. No intervention needed
```

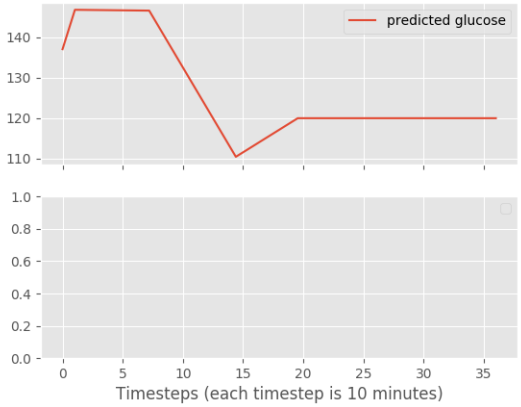


Figure 28: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 5 of scenario 1

7.3.6 After 50 minutes - no action

```
Starting control loop with current BGC: 146.76
Starting monitoring sequence with current blood glucose concentration 146.76.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min...Done
BGC +60 min will be 146.55
Full prediction timeline for the next 90 min:
[146.76 146.72 146.69 146.66 146.62 146.59 146.55 141.4  136.25]
Comparing predicted to optimal... Done
Diffscore: 46.55
Starting assessment sequence with diffscore 46.55.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
Blood glucose will be in the acceptable range. No intervention needed
```

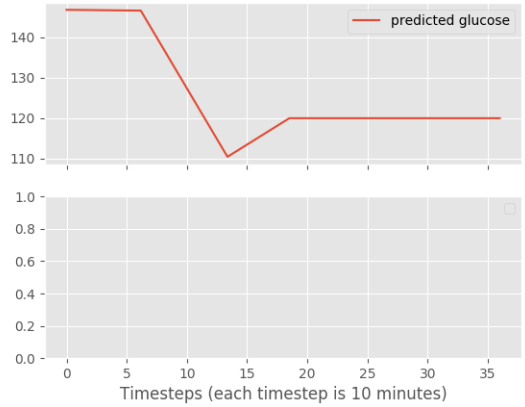


Figure 29: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 6 of scenario 1

7.4 Example Scenario 2

7.4.1 After 0 minutes - vigorous exercise

```
Starting control loop with current BGC: 100
Starting monitoring sequence with current blood glucose concentration 100.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min... Done
BGC +60 min will be 125.0
Full prediction timeline for the next 90 min:
[105. 110. 115. 120. 125. 125. 125. 125. 125.]
Comparing predicted to optimal... Done
Diffscore: 25.0
Starting assessment sequence with diffscore 25.0.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
Blood glucose will be in the acceptable range. No intervention needed
```

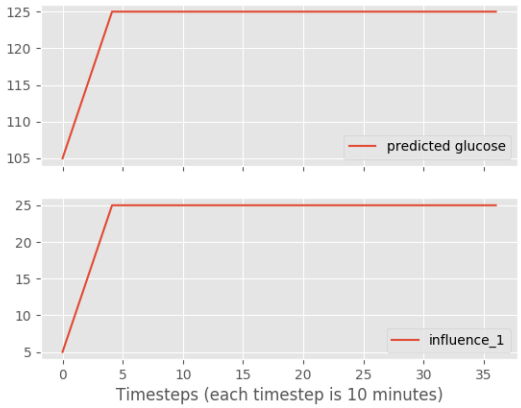


Figure 30: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 1 of scenario 2

7.4.2 After 10 minutes - vigorous exercise

```
Starting control loop with current BGC: 110.0
Starting monitoring sequence with current blood glucose concentration 110.0.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min... Done
BGC +60 min will be 150.0
Full prediction timeline for the next 90 min:
[115. 125. 135. 145. 150. 150. 150. 150. 150.]
Comparing predicted to optimal... Done
Diffscore: 50.0
Starting assessment sequence with diffscore 50.0.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
Blood glucose will be in the acceptable range. No intervention needed
```

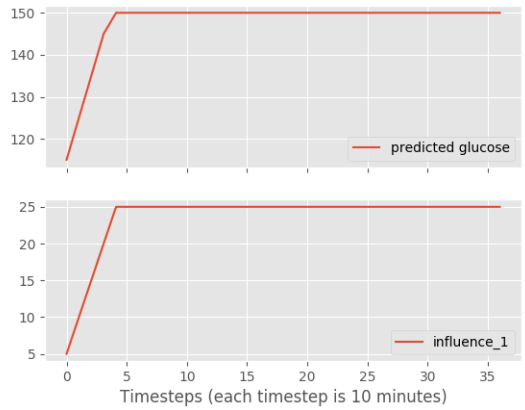


Figure 31: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 2 of scenario 2

7.4.3 After 20 minutes - vigorous exercise

```
Starting control loop with current BGC: 125.0
Starting monitoring sequence with current blood glucose concentration 125.0.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min... Done
BGC +60 min will be 175.0
Full prediction timeline for the next 90 min:
[130. 145. 160. 170. 175. 175. 175. 175. 175.]
Comparing predicted to optimal... Done
Diffscore: 75.0
Starting assessment sequence with diffscore 75.0.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
An intervention should be sent because blood glucose will be too high
Starting diagnose sequence with current blood glucose concentration 125.0,
future blood glucose concentration 175.0, and intervention = (True, 'upper')
Generating set of possible hypotheses... Done
hypotheses ['food', 'intense_exercise']
Specifying the observables for hypothesis intense_exercise... Done
Obtaining observable exercise... Done
Verifying hypothesis intense_exercise... Done
Specifying the observables for hypothesis food... Done
Obtaining observable nutrition... Done
Verifying hypothesis food... Done
```

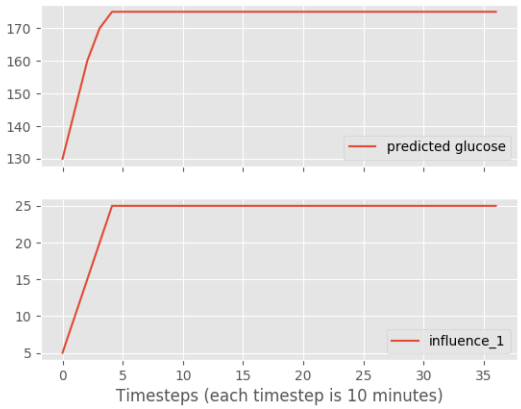


Figure 32: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 3 of scenario 2

```
###### INTERVENTION MESSAGE ######

I detected that your blood sugar will be too high within the next 60 minutes.
It seems like this is due to the following actions you took:

You are currently exercising at high intensity
I would advise you to inject 2.0 units of fast insulin in order to keep your
glucose levels in the goal range.
Do you want to inject insulin? Select an amount of units of fast insulin between 0 and 10:
2
```

7.4.4 After 30 minutes - moderate exercise, injected 2 units of insulin

```
Starting control loop with current BGC: 145.0
Starting monitoring sequence with current blood glucose concentration 145.0.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min... Done
BGC +60 min will be 126.76
Full prediction timeline for the next 90 min:
[140.   145.29 145.59 140.88 136.18 131.47 126.76 122.06 117.35]
Comparing predicted to optimal... Done
Diffscore: 26.76
Starting assessment sequence with diffscore 26.76.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
Blood glucose will be in the acceptable range. No intervention needed
```

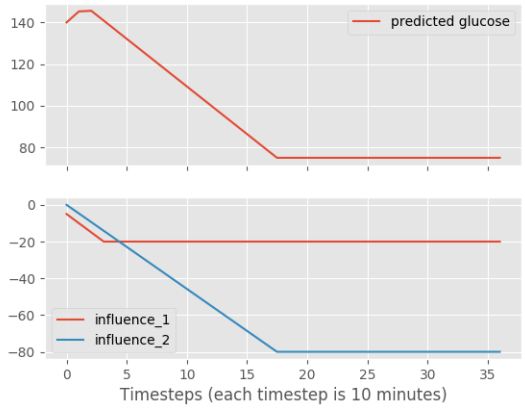


Figure 33: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 4 of scenario 2

7.4.5 After 40 minutes - moderate exercise, ate chocolate bar

```
Starting control loop with current BGC: 145.29
Starting monitoring sequence with current blood glucose concentration 145.29.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min... Done
BGC +60 min will be 102.06
Full prediction timeline for the next 90 min:
[140.29 135.59 125.88 116.18 111.47 106.76 102.06  97.35 105.05]
Comparing predicted to optimal... Done
Diffscore: 2.06
Starting assessment sequence with diffscore 2.06.
Specifying the norms...,  Done
Selecting relevant norm for the case... Done
Selected upper norm 60
Evaluating diffscore against upper norm... Done
Matching norm value to decision category... Done
Blood glucose will be in the acceptable range. No intervention needed
```

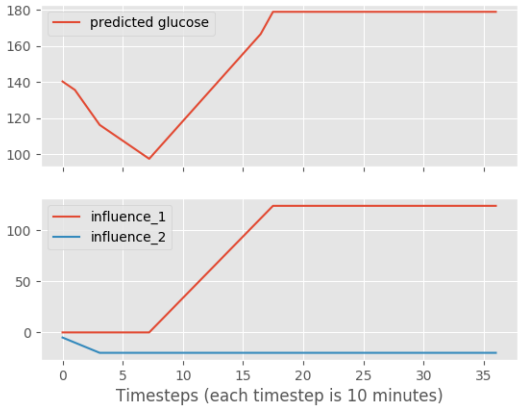


Figure 34: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 5 of scenario 2

7.4.6 After 50 minutes - moderate exercise

```
Starting control loop with current BGC: 135.59
Starting monitoring sequence with current blood glucose concentration 135.59.
Receive datapoints... Done
Select relevant parameters... Done
Predicting future blood glucose concentration +60 min... Done
BGC +60 min will be 77.35
Full prediction timeline for the next 90 min:
[130.59 115.88 101.18  91.47  86.76  82.06  77.35  85.05  92.74]
Comparing predicted to optimal... Done
Diffscore: -22.65
Starting assessment sequence with diffscore -22.65.
Specifying the norms...  Done
Selecting relevant norm for the case... Done
Selected lower norm -30
Evaluating diffscore against lower norm... Done
Matching norm value to decision category... Done
Blood glucose will be in the acceptable range. No intervention needed
```

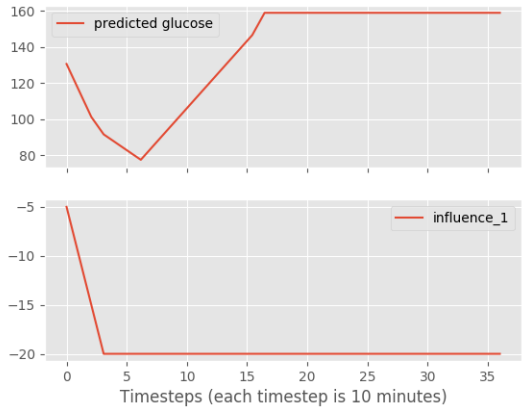


Figure 35: All factors influencing blood glucose as well as the aggregated blood glucose forecast for timestep 6 of scenario 2

8 Conclusion

The process that lead to the development of the final version of the implemented system was not always straightforward (as expected), but regarding the scope of the project with regard to time and resource constraints the result did satisfy most of the expectations that formed in the initial phase of the project. A major contributor to this result most likely is that we were able to get into close contact with our experts early in the project which allowed us to have access to expert knowledge right away. This facilitated developing the overall structure of our system already having access to an end goal structure. It is likely that this saved us much time going back and forth restructuring our system because of unexpected structural challenges.

The final expert system developed in this project is able to satisfy many of the initial tasks that it was expected to perform and can surely be seen as a successful proof of concept while serving as a starting point to further developing a more extensive system that also is embedded in the target implementation platform. While combining multiple task types as described by the CommonKADS framework it represents a more complex task structure that is stable in handling the continuous task nature of daily T1DM disease management. By approximating the real life relations inherent to T1DM with intuitive and easy to compute set of linear equations it potentially allows for a computationally low cost implementation on the target platform smartphone.

A lot of the groundwork for developing a system that effectively is practical for T1DM patients has been done in this project, but there are some limitations of the system that have to be addressed or at least considered in further research. First, the initial vision was to make use of existing food ontologies to extract the macro-nutrient composition of food items in order to ease the patients manual food intake reports. However, the granularity of those databases did not meet the requirements for application in T1DM management, as not only the total number of carbohydrates was relevant, but also the decomposition thereof in sugars, simple carbohydrates and complex carbohydrates. Implementing such an ontology given one of the many food databases out there is certainly a crucial aspect to the goal of developing a user friendly application that also educates new patients on the different carbohydrates and their implications.

Second, even though the approximations and assumptions in the present project allowed for an easy and straightforward design and implementation process, they are likely to impair the performance of the system to a degree that is yet to be determined. Further research on the interaction of the different factors on blood glucose levels is needed and in how far those can be implemented onto a system that fits the capacities of toady's smart devices. Defining and quantifying the costs of the simplifications we took is necessary to ensure that the system we developed does indeed produce reliable results. This is especially important given the use case of an application that is designed to recommend actions to patients that can have extreme health consequences given inaccurate or malfunctioning algorithms.

Finally, a general flaw of this application type that surfaced during interviews with the expert is the fact that a large part of T1DM management consists of the patients knowledge about the factors that influence blood glucose and adaptation of a lifestyle that allows for minimization of blood glucose fluctuations. The most powerful tool in a T1DM patients arsenal is anticipation and any system, however powerful, can only react to the factors that will eventually influence blood glucose levels in the future. While the present work can be seen as an indicator that it is possible to develop a system that is capable to react to external factors accurately, it is important to keep in mind that the competence of this technology is bound by its fundamental structure. The present research nevertheless shows that such a system can be developed to support inexperienced patients in gaining an initial understanding of the processes underlying T1DM disease management.

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