Artificial Intelligence for Diabetes Management and Decision Support: A literature Review

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Abstract

Background: Artificial intelligence (AI) methods in combination with the latest technologies, including medical devices, mobile computing, and sensor technologies, have the potential to enable the creation and delivery of better management services to deal with chronic diseases. One of the most lethal and prevalent chronic diseases is diabetes mellitus, which is characterized by dysfunction of glucose homeostasis.

Objective: To review recent efforts to use AI techniques to assist in the management of diabetes, along with the associated challenges.

Methods: We conducted a review of the literature using PubMed and related bibliographic resources. Analyses of the literature from 2010 to 2018 yielded 2641 pertinent articles, of which we selected 140 for detailed review.

Results: We propose a functional taxonomy for diabetes management and AI. We also performed a detailed analysis of each subject category using related key outcomes. This approach revealed that the experiments and studies reviewed yielded encouraging results.

Conclusions: We obtained evidence of an acceleration of research activity aimed at developing AI-powered tools for prediction and prevention of complications associated with diabetes. Our results indicate that AI methods are being progressively established as suitable for use in clinical daily practice, as well as for the self-management of diabetes. Consequently, these methods provide powerful tools for improving patients’ quality of life.

Keywords: diabetes management; artificial intelligence; machine learning; mobile computing; blood glucose

Introduction

Diabetes mellitus refers collectively to a group of diseases resulting from dysfunction of the glucoregulatory system. Hyperglycemia, the hallmark of diabetes, is the primary consequence of this dysregulation. Chronic hyperglycemia in diabetes is associated with long-term complications involving tissue damage and organ failure, which can decrease
life expectancy and even cause death. The International Diabetes Federation estimates that, by 2017, diabetes affected 425 million people worldwide, of whom 4 million people died in the same year. These figures are expected to increase dramatically in the coming decades, placing a rising burden on health care systems².

Diabetes is categorized into three classes: type 1 diabetes (T1D), type 2 diabetes (T2D), and gestational diabetes (GD). Over the long term, T2D patients become resistant to the normal effects of insulin and gradually lose their capacity to produce enough of this hormone. A wide range of therapeutic options are available for patients with T2D. At the early stages of disease, they commonly receive medications that improve insulin secretion or insulin absorption, but eventually they must receive external doses of insulin. On the other hand, T1D patients have severe impairments in insulin production, and must use external insulin exclusively to manage their blood glucose (BG). Treatment of T1D requires consistent doses of insulin through multiple daily injection (MDI) or continuous subcutaneous insulin infusion (CSII) using a pump. GD is treated similarly to T2D, but only occurs during pregnancy due to the interaction between insulin and hormones released by the placenta.

In each class of diabetes, timely diagnosis, education of patients in self-management, and continuous medical care are required to prevent acute complications (e.g., ketoacidosis) and minimize the risk of long-term complications (e.g., nephropathy, retinopathy, diabetic foot, cardiovascular disease, or stroke). In addition to medication, management of diabetes requires adherence to an array of self-care behaviors that are often very burdensome for patients: carefully scheduling meals, counting carbohydrates (CHOs), exercising, monitoring BG levels, and adjusting endeavors on a daily basis. The effects of non-adherence to recommended treatment are not immediately evident, and long-term complications may take years to develop. Accordingly, diabetes therapy is complex, and therapeutic decisions need to take into account diverse medical factors and lifestyle-related activities that must be optimized to improve diabetic patients’ quality of life.

Artificial intelligence (AI) is a quickly growing field, and its applications to medicine and diabetes research are growing even more rapidly, as shown in Figure 1.
At present, intelligent algorithms are achieving substantial success in the application of data-driven methods to support advanced analytics and provide individualized medical aid. The explosive increase in the amount of available information, along with the improved performance of intelligent methodologies capable of handling and processing this information, have led to the development of tools and applications that enhance the effective management of most complicated diseases, including diabetes and cancer.

Over the last decade, the entire paradigm of diabetes management has been transformed due to the integration of new technologies such as continuous glucose monitoring (CGM) devices and the development of the artificial pancreas (AP), along with the exploitation of data acquired by applying these novel tools. AI is attracting increasing attention in this field because the amount of data acquired electronically from patients suffering from diabetes has grown exponentially. By means of complex and refined methods, AI has been shown to provide useful management tools to deal with these incremental repositories of data. Thus, AI has played a key role in the recognition of these systems as routine therapeutic aids for patients with diabetes.

In this manuscript, we describe the latest efforts and advances in the application of AI methodologies in the context of diabetes management and decision support. In the remainder of the Introduction section, we provide the necessary background information on AI methods. We then provide a detailed description of the methodological approach of the review, report the results of our literature analysis and discuss studies on various sub-topics, and conclude with a brief summary of the review and a discussion of future challenges.
**Artificial Intelligence Techniques**

Defining the concept of AI, computational intelligence, or machine intelligence is not a trivial undertaking. In this paper, we refer to AI as a branch of computer science that aims to create systems or methods that analyze information and take actions to handle complexity in diverse application areas (in this case, diabetes management). Although the application of AI algorithms involves highly technical and specialized knowledge, this has not prevented AI from becoming an essential part of the technology industry and making contributions to major advances within the field. This section will provide a short overview of several well-known computational intelligence paradigms. For a more in-depth discussion of various intelligent algorithms, theoretical results, and applications, the reader is referred to\(^3\). In this study, we categorized methodologies with respect to the objective sought: to explore and discover information, to learn using information, or to extract conclusions from information (see Fig. 2).

![Figure 2: A taxonomy of some of the most well-known artificial intelligence methods.](image)

**Learning from Knowledge**

Acquisition of knowledge is a key requirement of solutions intended to exhibit intelligent behavior. Because learning is an effective way to introduce such knowledge, most AI studies to date have employed learning techniques. The primary aim of learning from knowledge is to allow computers to learn automatically without human intervention or assistance. This process could involve any method that includes some inductive component, ranging from a simple Kalman filter to a complex convolutional neural network. No method is inherently better than any other; each is more or less well-suited to different scenarios, e.g., a softer learning curve, faster execution, or more flexible solutions. Furthermore, the performances of various methods are closely related to the quality and quantity of data: when more information is gathered, and less noise is present in the data, better solutions can be obtained. The most important families of techniques are artificial neural networks (ANNs), support vector machines (SVMs),
random forest (RF), evolutionary algorithms (EAs), deep learning (DL), Naïve Bayes (NB), decision trees (DTs), and regression algorithms (RAs).

**Figure 3:** General diagram of the learning algorithm process.

**Exploration and Discovery of Knowledge**
The discovery of knowledge revolves around the exploration and creation of algorithms for retrieving potential information from databases, commonly referred to as knowledge discovery in databases (KDD). The primary objective of KDD is identification of valid, potentially useful, and understandable information. KDD involves evaluation and interpretation of patterns and models for making decisions about what does and does not constitute knowledge, i.e., distinguishing between data that are useful and those that are (in the context of interest) useless. Therefore, KDD requires broad and deep knowledge about the area of study.

The overall KDD process is commonly characterized by five stages, presented in Figure 4: selection, pre-processing, transformation, data mining, and interpretation/evaluation. Data mining is the most technical stage of the process. Techniques for data mining have taken much of their inspiration from learning algorithms and statistics, although the two types of approaches have different objectives. The most important data mining tasks involve detection of anomalies, identification of dependencies between variables, regression, clustering, and classification. Examples of representative techniques are k-means, k-nearest neighbor (KNN), and hierarchical clustering (HC).

**Figure 4:** General diagram of the knowledge discovery process.

**Reasoning from Knowledge**
In this discourse, the idea of reasoning from knowledge denotes the creation of precise and effective ways to generate inferences in more precise and robust ways. Thus, reasoning from knowledge involves the use of logical techniques such as deduction and induction to generate conclusions from the available knowledge. The primary objective
of systems that implement reasoning mechanisms is to perform tasks at a human-expert level in a narrow, specialized manner within the domain of interest. Such systems commonly apply heuristics to guide reasoning and reduce the search space of possible solutions.

These systems are based on three main components. First, a knowledge acquisition system is used to gather and collect inferences that can be used for further development. In this context, such a system is used to extract new rules and gather information. Second, a knowledge base, characterized by rules and information that will be used for problem solving. Important aspects here include relations, conditions, recommendations, directives, and strategies. Finally, the inference engine links the knowledge base with the gathered information. Overall, this process facilitates reasoning, whereby the system becomes able to facilitate the realization of the anticipated solution. It is possible for a system structured on this basis to transfer expert knowledge directly to the knowledge base. This, in turn, helps to build new solutions based on previous cases, or to deal with ambiguous concepts and uncertainty. Representatives of these tasks include rule-based reasoning (RBR), case-based reasoning (CBR) (illustrated in Fig. 5), and fuzzy logic (FL).

![Figure 5: Case-based reasoning circle.](image-url)
Methods

A review of the literature was conducted using the PubMed database. This bibliographic system has been validated as a reliable tool for retrieving information about clinical applications and evidence. Only English-language documents published between 2010 and 2017 were considered. The search terms listed in Table 1 were combined to build queries, which were designed to identify terms in the abstract, title, or key words.

Table 1: Terms used in the search queries of the review.

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<td>Diabetes</td>
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<td>Management</td>
<td>Fuzzy logic</td>
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<td>Artificial pancreas</td>
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<td>Artificial intelligence</td>
<td>Clustering</td>
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<td>Particle swarm</td>
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<td>Machine learning</td>
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<td>Blood glucose</td>
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The search terms listed in Table 1 were explored and combined, yielding 349 “hits.” The terms “diabetes,” “management,” “artificial pancreas,” and “blood glucose” were combined with the remaining terms using a conjunctive operator, and these terms were used as keywords to create individual datasets comprising all references to the following phrases: “artificial intelligence” (159), “computational intelligence” (150), “machine learning” (64), “data mining” (88), “deep learning” (2), “k-means” (6), “fuzzy logic” (24), “heuristic” (8), “clustering analysis” (203), “Bayes” (16), “decision tree” (39), “random forest” (20), “particle swarm optimization” (16), “pattern recognition” (26), “genetic algorithm” (33), “supervised algorithm” (9), “unsupervised algorithm” (8), “knowledge-based” (14), “case-based reasoning” (11), “decision support system” (48), “self-organizing map” (3), “evolutionary computation” (2), “neural network” (63), “natural language processing” (22), and “support vector machine” (29). Each of these datasets was then combined to build an objective dataset of articles. A comprehensive review was performed of all references cited in the datasets. Finally, the bibliography of the reviewed articles was thoroughly explored to find titles with relevance to the main focus of this study.

The complete method is summarized in Figure 6. The resultant final collection of articles was divided into various categories, designed to assist in the grouping of studies according to their shared and specific characteristics. Over the course of the systematic review, the sub-categories were fused and fixed to accommodate the merging of information.
Results

Main Findings
Ultimately, 140 papers were included in the review. The potential of AI to enable diabetes solutions has been investigated in the context of multiple critical management issues. In this section, we use the following proposed diabetes management categories to summarize the latest contributions, the state of the art, and the results described in the reviewed articles:

- BG control and modelling of glucose–insulin dynamics
- BG prediction
- Detection of hypoglycemic and hyperglycemic events
- Insulin bolus calculators and advisory systems
- Risk and patient personalization
- Safety and detection of failures, meals, exercise, and stress
- Lifestyle and daily-life support in diabetes management

As seen in Figure 7, most of the papers were published in the last 3 years, reflecting a clear acceleration in the application of AI techniques to diabetes management. In the following, contributions to each of the subdomains are detailed and discussed.

**Blood Glucose Control**
Development of the AP has been intensively pursued over the past decade. An AP consists of an automated system that mimics islet physiology, including a glucose sensor, a closed-loop control algorithm, and an insulin infusion device. The ultimate goal of an AP system is to improve overall diabetes management and reduce the frequency of life-threatening events associated with T1D. The algorithms used by the AP to calculate insulin dosage have been intensively investigated. The major candidate algorithms are derived from traditional control engineering theory; however, AI has become more established over the past few years, and could ultimately provide better candidates to meet the challenges of an AP. Although AI and control engineering have converged to some extent as the two fields incrementally exchange methods, here we will focus on studies dealing with closed-loop algorithms based on AI techniques. We direct interested readers to a recent comprehensive review on AP systems.

Three main AI methodologies have been established as control techniques in recent years: FL, ANNs, and reinforcement learning (RL). Most alternatives to control engineering algorithms are based on FL. Controllers apply FL theory to imitate the lines of reasoning of diabetes caregivers. Thus, the primary benefit of FL over classic control engineering is the ability to deal with nonlinearities and uncertainties. However fuzzy systems have not yet been proven to clearly outperform well-tuned classical approaches.

![Figure 7: Number of articles reviewed, by subdomain and year of publication.](image)
MD-Logic was developed by authors who sought to individualize glycemic control using a fuzzy controller. Two feasibility studies were conducted in cohorts of seven T1D patients to introduce the methodology and test the viability of the controller. Subsequently, a randomized crossover trial was conducted in 12 T1D patients. The results suggested that the fuzzy method could improve the nocturnal BG control without an elevated risk of hypoglycemia. Following these successful feasibility studies, the authors performed a randomized crossover study of 56 young patients over 3 days. The results confirmed a reduced rate of nocturnal hypoglycemia and superior glycemic control in comparison with insulin pump treatment. In a home-based randomized trial of 15 T1D patients, the authors compared the fuzzy AP and sensor-augmented pump over 4 nights; the results confirmed the feasibility, safety, and efficiency of their approach in a home setting. A later extended study of 24 T1D patients during 6 weeks of nocturnal control demonstrated the safety and effectiveness of long-term use of a FL-based controller. In a recent clinical trial evaluating remote patient monitoring of the FL controller, the AP was tested in 75 T1D patients for 4 consecutive nights. The results demonstrated safe and efficient glycemic control. Next year, several studies will evaluate the MD-Logic controller implemented in the MiniMed 690G.

Other research groups have also investigated the application of FL to BG control. For example, the authors of reported a FL controller designed to personalize glycemic control. They tested it in 30 virtual patients on the UVA/PADOVA T1D simulator. Next, to demonstrate the feasibility of their approach, they conducted a pilot study in 12 T1D patients. In a later study, they proposed to stress a fuzzy controller with high-fat meals and exercise, and tested this approach in a trial with 10 T1D patients. The results revealed deficits in their previous approach and ultimately led to improvements in the FL controller.

Other FL approaches have been tested using virtual patients or simulations. For example, the authors of reported a fuzzy controller combined with a learning algorithm that extracted initial patient profiles using open-loop data. Another example was proposed by the authors of, who suggested combining fuzzy and sliding-mode controllers, with the goal of using feedback to govern the insulin delivery rate more aggressively.

Another AI method that has been increasingly adopted in the area of control algorithms is the so-called reinforcement algorithm. The authors of presented an adaptive, patient-specific BG control strategy based on the Actor–Critic learning approach, and tested their approach on 28 virtual T1D patients (adults, adolescents, and children).

Another AP study based on RL was proposed by the authors of, who proposed using an Actor–Critic algorithm to optimize the insulin infusion for personalized glucose regulation, and evaluated the system using virtual patients. The results revealed that their novel tuning method decreased the risk of severe hypoglycemia, especially in patients with low insulin sensitivity. Other AI-related techniques used to support the development of the AP included modeling of glucose metabolism with a SVM.

Over this period, several groups proposed complementary AI algorithms to support AI controllers. The authors of proposed assisting the controller with a genetic algorithm (GA) that optimizes the values for two inputs and one output membership function, with the goal of preventing fluctuations due to derivatives in fuzzy design. Another GA was
used in 24 to support an ANN controller. In that case, the proposed GA optimizes network topology and learning features, instead of using the trial-and-error approach commonly adopted in ANN topology determination. In line with previous studies, the authors of 16 proposed a controller assisted by a particle swarm optimization (PSO) that optimizes the parameters of the glucose–insulin model. Following the trend of combining methods to control BG with metaheuristics, the authors of 15 proposed the use of a Cuckoo search algorithm to optimize the gain of the controller. Optimization AI techniques, aside from their use in conjunction with AI controllers, have been used in other studies to determine controller parameters. For example, the authors of 25 used GA to mine information from patients’ medical histories to generate multiple customized models, and the authors of 26 proposed the use of PSO to adjust the function cost of an economic predictive control model.

Glucose–Insulin Dynamics Modeling
Complementary to advances in control algorithms, efforts have been made to improve models that attempt to capture glucose–insulin dynamics. Since the publication of the seminal paper in this field 27, interest has increased in applying neural networks to identification and control of nonlinear systems. The authors of 28,29 developed a recurrent neural network trained with a real-time recurrent learning algorithm that models the BG kinetics of T1D patients and predicts BG levels using information about meal intake, BG measurements, and infused insulin. The authors of 30 investigated the use of a neurofuzzy network, which attempted to combine the best properties of ANNs and fuzzy systems. Specifically, they implemented a learning system that combines input signals, infused insulin, and BG measurements with a membership initialization based on the fuzzy c-means algorithm. The following year, the authors of 31 performed a more rigorous study using a recurrent neural network trained to model BG in T1D patients. The approach they implemented considered glucose absorption due to CHO consumption and the insulin infusion as inputs. These three neural network studies proposed a model of insulin dynamics as the first step in the design of a control scheme, and then validated the model using T1D patient data. Their results demonstrated that they that were indeed able to capture BG dynamics. More recently, two studies 24,32 presented a complete control scheme using neural networks. Both studies sought to examine the potential of this technique to predict and control BG excursions in T1D using patient-specific models. The first approach was tested based on the hyperinsulinemic–euglycemic clamp technique in 34 rats, and the second was tested using in silico data including BG measurements, administered insulin, exercise information, and ingested food. The results of both approaches demonstrated that ANNs are accurate methods for regulation of glucose levels.

Blood Glucose Prediction
The ability to anticipate BG excursions could provide early warnings regarding ineffective or poor treatments. Thus, information collected from new diabetic technologies, such as the CGM devices, could lead to real-time predictions of future glucose levels. Prediction of BG levels is challenging due to the number of physiological factors involved, such as delays associated with absorption of food and insulin, and the lag associated to measurements in the interstitial tissue. Errors of the CGM also increase the difficulty of predicting BG values (approximately 9% of the mean absolute relative difference for the best sensors 33).
The results of this section are presented in Table 2, which captures the critical information from all studies in which AI methods were used to predict BG values. The table, which is extensive and is presented in two parts (A and B), was designed to provide quick access to information about current technologies being tested. We outline the features of each study using key information, including prediction horizon (PH) in minutes, objective population criteria, number of participants in the cohort, mean number of monitored days per patient, mean number of monitored hours per day, existence of monitoring during the overnight period, type of monitoring technology, and information about physical activity (PA). Finally, we highlight the main AI methods applied in the studies, the bibliographic reference, and the year of publication. AI for BG prediction has been addressed in as many as 13 parallel lines of research. Most of these studies focused on T1D because of the inherent utility of AI in this condition and the availability of high-frequency data collected from patients using a CGM device. The results of our review reveal the range of PHs explored, from 5 to 180 minutes. Short-term predictions were the most frequently explored: 77.5% of studies used PHs below 60 minutes. ANN approaches were the most widely applied methodology, but other machine learning methodologies such as RF, SVM or RAs are being adopted with increasing frequency.

Detection of Hypoglycemia and Hyperglycemia
As with BG prediction, glycemic episode detection encompasses a set of tools that deal with the complexity of effective BG control. However, in this section we will not address glucose values, but instead focus on the appearance of hyperglycemic or hypoglycemic events. These tools enable us to detect the occurrence of glycemic episodes and give us the opportunity to respond promptly to their effects. In contrast to the previous section, most of the reviewed studies on this topic focus on detecting hyperglycemia or hypoglycemia in situations when it is not possible to effectively monitor BG. Therefore, most of these studies deal with real-time approaches rather than predictions of future events. We summarize the studies dealing with detection of BG excursions in Table 3. Each scenario is represented by the following features: PH in minutes, objective population criteria, number of participants in the cohort, mean number of monitored days per patient, mean number of monitored hours per day, existence of monitoring during the overnight period, type of monitoring technology, and inclusion of PA information. Finally, we highlight the main AI methods applied in each study, the bibliographic reference, and the year of publication. More than 64% of the studies focused on real-time detection, and almost 93% specifically focused on T1D. Table 3 shows that over 60% of approaches that exclusively addressed T1D gathered data from CGM sensors, whereas the remainder used a electroencephalogram (EEG) or self monitoring of blood glucose (SMBG) measurements. Studies focusing on T1D were performed with fewer than 15 patients, whereas studies of T2D included larger cohorts. SN and SP were the most common outcomes used to assess the quality of approaches to glycemic detection. Although this section contains fewer papers than the one on BG prediction, we identified more than 10 research groups contributing to this topic. In particular, researchers at the Centre for Health Technologies (Faculty of Engineering and Information Technology, Sydney, Australia) have published five studies on this topic over the last 7 years.
Insulin Bolus Calculators and Advisory Systems
The most common insulin therapies for diabetics, continuous subcutaneous insulin infusion (CSII) and multiple daily insulin injections (MDI), operate according to similar principles. Both utilize basal insulin (injection of long-acting basal insulin and infusion at a constant basal rate, respectively) and bolus insulin (injection of quick-acting bolus insulin and meal boluses, respectively) to cover meals or snacks. The calculation of correct insulin doses and the estimation of the amount of CHO is a regular task in the daily life of many insulin-dependent patients. Bolus advisors are based on previous insulin doses, BG measurements, planned CHO estimates, and other patient-specific parameters, including insulin-to-CHO ratio and insulin sensitivity. Manually calculating bolus doses and counting CHOs can be complex and challenging because individuals must consider multiple parameters to achieve satisfactory glucose control, and miscalculation of these values may result in persistent glycemic episodes.

To support patients in CHO estimation and determination of insulin doses, tools for providing bolus advice and CHO estimates are increasingly being adopted. These tools seek to increase the accuracy of mealtime and correction boluses. AI have been used to provide sets of tools to improve the accuracy of CHO estimates and calculation of the optimal insulin bolus for the ingested meal.

We identified several studies that applied AI to systems aimed at supporting patient decisions by issuing advice regarding meals, exercise, or taking medication. Research groups at the Imperial College London performed an extensive study of an insulin bolus calculator based on a CBR methodology. Their approach, which manages various dynamically optimized diabetes scenarios, was proven in a clinical trial (NCT02053051) to be a safe decision support tool. Additionally, this approach has demonstrated to improve glycemic control in diabetes management when it is combined with an AP system. A similar approach was presented recently by another group, which also proposed an insulin bolus calculator based on CBR but introduced a novel temporal retrieval algorithm. The Center for Biomedical Engineering Research at the University of Bern (ARTORG) performed several important and extensive studies investigating the GoCARB system, which provides dietary advice to diabetic patients based on automatic CHO counting. Their approach is based on the use of computer vision techniques, such as feature extraction and SVM, and pilot studies show it to be an excellent assistive tool. We have also found several studies that validated their approach using the UVA/Padova patient simulator. The authors of proposed the use of a set of insulin delivery profiles optimized by a PSO to find the optimal open- and closed-loop profiles for various meal compositions. More recently, authors of presented an approach based on ANN to optimize the bolus calculation of patients using CGM. Results indicated a significant reduction of blood glucose risk index value when comparing with other approaches. Finally, the authors of proposed an advisory treatment system that provides insulin, meal, and exercise recommendations. Their study, which compared RBR and KNN algorithms, concluded that the KNN algorithm was best suited for this approach.

Risk and Patient Stratification
Most commercially available tools and protocols for managing diabetes are based on general models of the diabetic population or involve subsets of patients defined by simple clusterization features and easily identifiable characteristics. However, the daily lives of diabetic patients are determined by a wide range of management scenarios that
are not represented in these general models. Insulin-dependent patients must manage a highly complex process to maintain suitable levels of BG.

Treatment of diabetes is conditioned by diverse factors, implying high intra- and inter-patient variability. Exercise, nutrition disturbances, age, and cardiovascular complications are just some of the long list of factors that can dramatically impact quality of life and undermine medication adherence even when patients follow their treatment regimen strictly. Such patient variability severely limits the use of general models, which cannot capture the specific physiological behaviors of individuals. Thus, an important step toward better risk detection and intervention is personalization of the system. Over the past decade, major research efforts have been devoted to developing management tools capable of stratifying patients in different segments of the population. Risk assessment and patient stratification methods are important to improving the management of diabetes, and therefore the overall health outcomes of diabetic patients, and consequently have attracted a greater share of attention from the medical community.

This category gathers all reviewed papers that systematically identified individual patients and their risk factors to manage and coordinate their care based on specific conditions and on evidence-based guidelines. Table 4 outlines the type of stratification together with the specific challenge. Main characteristics such as number of years, cohort, and objective population are also included. Finally, the table defines the AI methodology applied, bibliographic reference, and year of publication.

Safety and Detection of Failures, Meals, Exercise, and Stress
Because people with both types of diabetes need support to successfully manage their disease, solutions with higher accuracy that require less user interaction are associated with higher-quality diabetes treatments. Tools or algorithms capable of early detection of critical events affecting glycemic control, such as exercise, a meal, or an infusion set failure, are critical for systematic automation of both closed-loop and open-loop systems. Insulin-dependent patients monitoring their glucose with CGM devices use BG measurements to calculate insulin infusion rates. Consequently, failure of these devices can lead to episodes of hyperglycemia or hypoglycemia. The authors of \(^{48}\) proposed an approach using SVM to detect correct and incorrect measurements in real-time CGM. They tested their system on 23 critically ill patients, and obtained promising results in patients with sepsis or septic shock. The same objective was pursued in \(^{49}\), authors used a KNN algorithm for diagnosis of faults; data from 51 patients were used to validate the performance of their approach. Focusing on the detection of inaccurate measurements by glucose meters, the authors of \(^{50}\) developed a SVM algorithm to minimize the effects of hematocrit on glucose, and tested their method on 400 BG samples.

Physical activity offers multiple benefits for diabetic patients, but also complicates the management of diabetes, especially in T1D patients. Some of the factors affecting BG dynamics during exercise include the intensity, duration, and type of exercise, insulin on board, and the carbohydrate absorption rate. Tools and systems focused on automated detection of exercise could improve the accuracy of treatments. The authors of \(^{51}\) proposed the use of a KNN classification algorithm to automatically detect exercise type and intensity in an AP system. They tested their approach in five T1D patients, and reported a SN of 98.37%. A similar aim was addressed by the authors of \(^{52}\), who
proposed to automatically detect physical exercise by a regression model and the use of an accelerometer and heart rate sensors worn on the body. The system was assessed on 13 T1D patients, yielding a SN of 97.2% and a SP of 99.5%.

Meal detection is an important feature, both for AP systems that do not permit manual meal announcements and as a safety system for patients who may forget to enter meal information manually. The authors of 53–55 investigated the development of a meal detection system based on analysis of CGM signals using an unscented Kalman filter and a fuzzy system to estimate the carbohydrates content. Their approach was validated in silico using 30 T1D patients from the UVA/Padova simulator which revealed a SN of 91.3% and an error of 23.1% in CHO estimation, and then, in vivo using data from 11 T1D patients which provided a SN of 93.5% for meals and 68.0% for snacks.

Failures of insulin pumps may result in prolonged hyperglycemia or diabetic ketoacidosis. Early detection of failures could minimize the associated risk. The authors of 56 proposed the use of a time-varying autoregressive model to develop a system of patient alerts. Validation with data from nine T1D patients during 18 weeks of infusion set wear revealed that the system had 50% SN and 66% SP.

Lifestyle and Daily-Life Support in Diabetes Management
Lifestyle management is a fundamental aspect of diabetes care. Sedentary living, stress, non-adherence to medication, lack of regular medical exams, and bad habits can lead to discontinuation of treatment for patients with diabetes. From the time of diagnosis, patients are required to optimize their lifestyles to manage complications and other comorbid conditions, with the overall goal of enhancing their own care. Current technologies and data warehouses enable solutions that model data and make quality decisions based upon them. Decision support systems (DSSs) consist of tools focused on helping patients or doctors to manage diabetes therapies. These systems usually have monitoring features that facilitate systematic recording of information about diet, PA, medication, glucose measurements, etc., and combine it with tools to support both patients and clinicians, with the overall goal of enhancing therapeutic outcomes.

Multiple studies aimed at developing DSSs to manage diabetes have been proposed since 2010. One of the most prolific efforts is the METABO project 57–62. The system developed by this project involves monitoring and advanced features including tools to prevent future excursions, dynamically optimize care pathways, extract patterns by knowledge discovery, and guide weight loss programs. The authors conducted several pilots, including a usability tests in 36 T1D patients. Another important effort is being made in the MOISAC project 63–66 which is focused on the development of a DSS for T2D management, with a special focus on the risk assessment of related complications using data mining methods. Another daily-life support system was presented in 67, a DSS that provides advanced tools such as a recommender system that employs CBR and an integrated BG prediction tool based on evolutionary computation.

The authors of 68 proposed a DSS based on a RL algorithm that automatically sends messages to patients who are following a personalized plan for physical exercise. The approach was validated with 27 sedentary T2D patients. Daily-life support systems using AI tools for GD were also investigated. A weight management proposal was presented in the MediClass 69 system. The system based on the application of a natural
language processing (NLP) algorithm was validated in postpartum visits of 600 GD patients. Authors of 70 also investigated tools related to GD patients. They proposed a mobile application based on an AI-augmented telemedicine DSS as a tool for helping patients with GD. Later, they presented a platform71 to remotely evaluate patients using a classifier based on a clustering algorithm and a DT learning algorithm. The system was evaluated with 90 GD patients. Results indicated a reduction in time devoted by clinicians to patients and in face-to-face visits per patient.

Six other studies have proposed alternatives to manual creation of patient care workflows. The studies offer support for the design and deployment of the diabetes management protocols, as well as ways to continuously improve the patient tracking throughout the entire process. The authors of 72,73 presented a system aimed at decreasing cardiovascular risk of T2D patients by enhancing patient care workflows. The authors validated their system by administering questionnaires to 3391 T2D patients. Next, the authors of 18 used a machine learning approach to extract sequences of drug prescriptions from electronic health record (EHR) data and identify factors associated with patient care flow deviations. Another DSS with care flow tools was presented in 74. This system focuses on the management of T2D patients using advanced features such as computerized alerts and reminders. It was tested with 20 T2D patients for 6 months, resulting in reduced HbA1c levels and improved diabetes awareness. Fourth, the authors of 75 proposed using data mining methods to enable the dynamic design of care protocols, but highlighted the need for mechanisms to reduce the Spaghetti Effect and make DSSs usable by experts. Fifth, the authors of 76 developed a diabetes management system to integrate a series of AI models and tools with an engine to manage diabetes care flows. Finally, the authors of 77 proposed a dynamic care flow system that applied data clustering and association rule mining techniques to prioritize required user tasks.

Other tools have been proposed for improving daily-life support for diabetes therapies. Four different tools have been designed to analyze online discussion forums or social networks in order to extract relevant information. First, authors of 78 compared multiple machine learning techniques (DT, SVM, Bagging and Bayes) to analyze patients online comments in order to predict the patient assessment about hospital performances. Second, the authors of 79 proposed using a k-means clustering analysis to identify communication patterns both on and off Facebook. They validated their tool in a cohort of 700 T2D patients. Third, The authors of 80 proposed clustering based on repeated bisecting k-means with the goal of obtaining patient experience information, including emotional and temporal aspects of diabetes management. Finally, the authors of 81 proposed using NLP methods to extract information about patients’ skills related to diabetes management.

Furthermore, tools have been developed to analyze clinical appointments, medication, and therapy adherence. For example, a machine learning approach to examining medication adherence thresholds and risk of hospitalization was implemented in 82. The system implemented in 83 promotes patient empowerment and adherence to therapy based on the automatic generation of feedback messages. The authors of 84 proposed a clinical DSS that issues medication interaction alerts based on clusters with similar management recommendations. A fuzzy approach was also presented by authors of 85 to support the problem of medication selection in T2D patients. Finally, the authors of 86...
proposed to use a machine learning algorithm to predict missed clinical appointments and help patients continue regular doctor visits.
Discussion and Conclusion

The increased availability of digitized health data from diabetic populations, along with the emerging applications of AI and research trends such as the AP and personalized medicine, suggests that we are moving toward a new paradigm for management of diabetes. This new outlook proposes to achieve custom delivery of diabetes care while tailoring professional practices, medical decisions, and treatments to individual patients.

By systematically examining high-quality articles in the PubMed database, we identified a series of studies with the goal of evaluating the latest efforts of AI-enabled solutions for diabetes management. The topics we reviewed suggest that prediction and prevention are currently being revitalized and reinforced by AI applications, whereas “safety and failure detection” has been less extensively reviewed, constituting fewer than 6% of the studies we encountered. Similarly, few investigations have delved into the application of AI techniques to early detection of critical issues such as exercise, meals, infusion set failures, and so forth. Exploiting the latest AI techniques to improve the safety of both AP systems and open-loop tools has the potential to dramatically improve performance. By contrast, research on closed-loop systems has been the most prolific area for application of AI methods, representing 24% of the reviewed studies. Most of these efforts addressed fuzzy techniques, but the application of other methodologies has begun to attract increasing interest. In our opinion, researchers in this field should continue to take advantage of the latest improvements in AI and to combine them with development of the AP. A considerable number of the reviewed studies investigated BG, either to develop models that enable accurate predictions of BG concentrations (19%) or to detect possible BG events (9%). Multiple studies reported accurate prediction and detection tools that promise to improve management resources for current and future therapies. These tools include bolus advisors, as well as both lifestyle and patient stratification.

Our findings show the increasing importance of AI methods for diabetes management. We think their potential may encourage researchers to explore the use of AI methods to learn, discover, and reason from diabetic data. In general, the most striking advances in the application of AI techniques come from data-driven methods that learn from large datasets. The ability to collect information from individual diabetic patients has led to a shift in diabetes management systems; accordingly, systems that lack access to valuable data will face substantial hurdles. Diabetes management is geared toward tailored management of therapies, at the level of smaller strata of patients or even individuals. Thus, management protocols provided to diabetic patients should be tailored to address their needs at various points during their illness. Furthermore, the availability of genetic data, such as that provided by metabolomics analysis, has also empowered the application of AI methods to personalization of diabetes management.

A large number of studies have already been published on the application of AI to diabetes in a broad range of management domains. Our dive into PubMed demonstrates an acceleration in the pace of research on AI-powered tools designed to predict and prevent the complications associated with diabetes. Although the available technologies and methods for diabetes management are growing exponentially in terms of quantity and quality, the potential of AI to boost effective and accurate management of diabetes has already been demonstrated in both open- and closed-loop therapies. Research in this
field should continue, and should seek to discover the opportunities and advantages of applying AI methodologies in diabetes management that differentiate these strategies from other classical approaches.

Table 2: Summary of reviewed studies addressing blood glucose prediction.

<table>
<thead>
<tr>
<th>Prediction horizon</th>
<th>Population</th>
<th>Cohort</th>
<th>Days</th>
<th>Time</th>
<th>Overnight PA</th>
<th>AI methods</th>
<th>Ref.</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>15, 30 and 45 min</td>
<td>T1D</td>
<td>15 RP</td>
<td>28</td>
<td>10 h</td>
<td>✓</td>
<td>ANN</td>
<td>87</td>
<td>2010</td>
</tr>
<tr>
<td>30 min</td>
<td>T1D</td>
<td>12 RP</td>
<td>10</td>
<td>24 h</td>
<td>✓</td>
<td>ANN</td>
<td>28</td>
<td>2010</td>
</tr>
<tr>
<td>75 min</td>
<td>Critical Care</td>
<td>1 RP</td>
<td>16</td>
<td>15 h</td>
<td>✓</td>
<td>ANN</td>
<td>88</td>
<td>2010</td>
</tr>
<tr>
<td>75 min</td>
<td>T1D</td>
<td>27 RP</td>
<td>5</td>
<td>24 h</td>
<td>✓</td>
<td>ANN</td>
<td>89</td>
<td>2011</td>
</tr>
<tr>
<td>30 min</td>
<td>T1D</td>
<td>5 VP</td>
<td>7</td>
<td>24 h</td>
<td>✓</td>
<td>ANN</td>
<td>90</td>
<td>2011</td>
</tr>
<tr>
<td>30 and 45 min</td>
<td>T1D</td>
<td>30 VP</td>
<td>8</td>
<td>24 h</td>
<td>✓</td>
<td>ANN</td>
<td>91</td>
<td>2012</td>
</tr>
<tr>
<td>15, 30, 60 y 120 min</td>
<td>T1D</td>
<td>27 RP</td>
<td>13</td>
<td>24 h</td>
<td>✓</td>
<td>RF</td>
<td>92</td>
<td>2012</td>
</tr>
<tr>
<td>30 min</td>
<td>T1D</td>
<td>20 VP</td>
<td>11</td>
<td>24 h</td>
<td>✓</td>
<td>ANN</td>
<td>93</td>
<td>2012</td>
</tr>
<tr>
<td>30 min</td>
<td>T1D</td>
<td>10 RP</td>
<td>3</td>
<td>24 h</td>
<td>✓</td>
<td>SVR, RA and ANN</td>
<td>94</td>
<td>2013</td>
</tr>
<tr>
<td>15, 30 and 45 min</td>
<td>T1D</td>
<td>23 RP</td>
<td>6.1</td>
<td>24 h</td>
<td>✓</td>
<td>RA and ANN</td>
<td>95</td>
<td>2013</td>
</tr>
<tr>
<td>15, 30, 60 y 120 min</td>
<td>T1D</td>
<td>27 RP</td>
<td>13</td>
<td>24 h</td>
<td>✓</td>
<td>SVR</td>
<td>96</td>
<td>2013</td>
</tr>
<tr>
<td>30 min</td>
<td>T1D</td>
<td>20 RP</td>
<td>3</td>
<td>24 h</td>
<td>✓</td>
<td>ANN</td>
<td>97</td>
<td>2015</td>
</tr>
<tr>
<td>15,30, 45 y 60 min</td>
<td>T1D</td>
<td>6 RP</td>
<td>11</td>
<td>24 h</td>
<td>✓</td>
<td>ANN</td>
<td>98</td>
<td>2015</td>
</tr>
<tr>
<td>30,60 and 120 min</td>
<td>T1D</td>
<td>10 RP</td>
<td>6</td>
<td>24 h</td>
<td>✓</td>
<td>ANN</td>
<td>99</td>
<td>2015</td>
</tr>
<tr>
<td>30 min</td>
<td>T1D</td>
<td>15 RP</td>
<td>13</td>
<td>24 h</td>
<td>✓</td>
<td>ANN</td>
<td>100</td>
<td>2015</td>
</tr>
<tr>
<td>30 min</td>
<td>T1D</td>
<td>5 VP – 1 RP</td>
<td>30</td>
<td>24 h</td>
<td>✓</td>
<td>SVR</td>
<td>101</td>
<td>2016</td>
</tr>
<tr>
<td>Not specified</td>
<td>Fasting Glucose</td>
<td>346 RP</td>
<td>1</td>
<td>NO</td>
<td>✓</td>
<td>ANN</td>
<td>102</td>
<td>2016</td>
</tr>
<tr>
<td>5, 15, 30, 45 and 60 min</td>
<td>T1D</td>
<td>15 RP</td>
<td>13</td>
<td>24 h</td>
<td>✓</td>
<td>Kernel least mean square</td>
<td>103</td>
<td>2016</td>
</tr>
<tr>
<td>60 min</td>
<td>T1D</td>
<td>5 RP</td>
<td>90</td>
<td>24 h</td>
<td>✓</td>
<td>EC</td>
<td>104</td>
<td>2016</td>
</tr>
<tr>
<td>24h</td>
<td>T1D &amp; T2D</td>
<td>8 RP</td>
<td>3</td>
<td>24 h</td>
<td>✓</td>
<td>DT</td>
<td>105</td>
<td>2016</td>
</tr>
<tr>
<td>30 min</td>
<td>T1D</td>
<td>3 RP</td>
<td>10</td>
<td>24 h</td>
<td>✓</td>
<td>EA</td>
<td>106</td>
<td>2016</td>
</tr>
<tr>
<td>30 and 60 min</td>
<td>T1D</td>
<td>17 RP</td>
<td>6</td>
<td>24 h</td>
<td>✓</td>
<td>RA</td>
<td>107</td>
<td>2017</td>
</tr>
<tr>
<td>60, 120, 150 and 180 min</td>
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<td>20 VP</td>
<td>14</td>
<td>24 h</td>
<td>✓</td>
<td>EA</td>
<td>108</td>
<td>2017</td>
</tr>
<tr>
<td>0</td>
<td>T2D</td>
<td>3 RP</td>
<td>23</td>
<td>Not specified</td>
<td>✓</td>
<td>NB</td>
<td>109</td>
<td>2017</td>
</tr>
<tr>
<td>30, 60, 90 and 120 min</td>
<td>T1D</td>
<td>10 RP</td>
<td>10</td>
<td>24 h</td>
<td>✓</td>
<td>KNN, RF and EA</td>
<td>110</td>
<td>2017</td>
</tr>
<tr>
<td>120 min</td>
<td>T1D</td>
<td>100 VP</td>
<td>14</td>
<td>24 h</td>
<td>✓</td>
<td>EA</td>
<td>111</td>
<td>2017</td>
</tr>
<tr>
<td>30, 60 and 90 min</td>
<td>T1D &amp; T2D</td>
<td>106 RP</td>
<td>&lt;7</td>
<td>24 h</td>
<td>✓</td>
<td>RA and ANN</td>
<td>112</td>
<td>2017</td>
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</table>
Table 3: Summary of reviewed studies addressing detection of hyperglycemia and hypoglycemia.

<table>
<thead>
<tr>
<th>Prediction horizon</th>
<th>Population</th>
<th>Cohort</th>
<th>Days</th>
<th>Time</th>
<th>Nigt</th>
<th>Measurement</th>
<th>PA</th>
<th>Methods</th>
<th>Ref</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 min</td>
<td>T1D</td>
<td>6 RP</td>
<td>1 day</td>
<td>10 h</td>
<td>✓</td>
<td>EEG</td>
<td></td>
<td>ANN</td>
<td>113</td>
<td>2010</td>
</tr>
<tr>
<td>0 min</td>
<td>T1D</td>
<td>30 RP</td>
<td>80–247 days</td>
<td>6 h</td>
<td>✓</td>
<td>SMBG</td>
<td>✓</td>
<td>RF and SVM</td>
<td>114</td>
<td>2012</td>
</tr>
<tr>
<td>0 min</td>
<td>T1D</td>
<td>15 RP</td>
<td>1 day</td>
<td>10 h</td>
<td>✓</td>
<td>CGM</td>
<td></td>
<td>ANN and PSO</td>
<td>115</td>
<td>2012</td>
</tr>
<tr>
<td>0 min</td>
<td>T1D</td>
<td>10 RP</td>
<td>30 days</td>
<td>4 h</td>
<td>✓</td>
<td>CGM</td>
<td>✓</td>
<td>SVM</td>
<td>116</td>
<td>2013</td>
</tr>
<tr>
<td>30 min</td>
<td>T1D</td>
<td>15 RP</td>
<td>12.5 days</td>
<td>24 h*</td>
<td>✓</td>
<td>CGM</td>
<td>✓</td>
<td>SVM</td>
<td>117</td>
<td>2013</td>
</tr>
<tr>
<td>60 min</td>
<td>T1D</td>
<td>10 RP</td>
<td>4.5 days</td>
<td>6 h</td>
<td>✓</td>
<td>CGM</td>
<td></td>
<td>SVM</td>
<td>118</td>
<td>2013</td>
</tr>
<tr>
<td>30 min</td>
<td>T1D</td>
<td>10 RP</td>
<td>17.3 days</td>
<td>24 h*</td>
<td>✓</td>
<td>CGM</td>
<td></td>
<td>DT</td>
<td>119</td>
<td>2013</td>
</tr>
<tr>
<td>Next 24 h</td>
<td>T2D</td>
<td>163 RP</td>
<td>344 data points</td>
<td>6 h</td>
<td>✓</td>
<td>SMBG</td>
<td>✓</td>
<td>RF</td>
<td>120</td>
<td>2015</td>
</tr>
<tr>
<td>0 min</td>
<td>T1D</td>
<td>15 RP</td>
<td>1 day</td>
<td>4 h</td>
<td>✓</td>
<td>CGM</td>
<td></td>
<td>ANN</td>
<td>121</td>
<td>2014</td>
</tr>
<tr>
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<td>T1D</td>
<td>10 RP</td>
<td>18 data points</td>
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<td>SMBG; ECG</td>
<td>✓</td>
<td>ANN</td>
<td>122</td>
<td>2014</td>
</tr>
<tr>
<td>2, 7, 30, 61–90 days</td>
<td>T1D &amp; T2D</td>
<td>201 &amp; 323 RP</td>
<td>787 data points</td>
<td>6 h</td>
<td>✓</td>
<td>SMBG</td>
<td></td>
<td>Pattern recognition</td>
<td>123</td>
<td>2014</td>
</tr>
<tr>
<td>0 min</td>
<td>T1D</td>
<td>15 RP</td>
<td>1 day</td>
<td>10 h</td>
<td>✓</td>
<td>ECG</td>
<td>✓</td>
<td>ANN</td>
<td>124</td>
<td>2016</td>
</tr>
<tr>
<td>Past events</td>
<td>T2D</td>
<td>119695 RP</td>
<td>&gt;12 days</td>
<td>6 h</td>
<td>✓</td>
<td>EHR</td>
<td></td>
<td>NLP</td>
<td>125</td>
<td>2016</td>
</tr>
<tr>
<td>0 min</td>
<td>T1D &amp; T2D</td>
<td>500 RP</td>
<td>1 day</td>
<td>2 h</td>
<td>✓</td>
<td>Invasive BG</td>
<td></td>
<td>DT and ANN</td>
<td>126</td>
<td>2017</td>
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</table>
Table 4: Summary of reviewed studies addressing risk and patient stratification.

<table>
<thead>
<tr>
<th>Stratification</th>
<th>Challenge</th>
<th>Period</th>
<th>Cohort</th>
<th>Population</th>
<th>Methods</th>
<th>Year</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complications</td>
<td>Group risks of retinopathy</td>
<td>5 years</td>
<td>55</td>
<td>T1D</td>
<td>DTs and ANNs</td>
<td>2010</td>
<td>127</td>
</tr>
<tr>
<td>Disease complexity</td>
<td>Group combinations of comorbid conditions</td>
<td>2 years</td>
<td>15480</td>
<td>Chronic diseases</td>
<td>Hierarchical clustering</td>
<td>2011</td>
<td>128</td>
</tr>
<tr>
<td>Disease complexity</td>
<td>Group management profiles</td>
<td>3 months</td>
<td>239</td>
<td>T1D</td>
<td>Hierarchical clustering</td>
<td>2011</td>
<td>129</td>
</tr>
<tr>
<td>Disease complexity</td>
<td>Group management profiles</td>
<td>3.5 months</td>
<td>70</td>
<td>T2D</td>
<td>K-means</td>
<td>2012</td>
<td>130</td>
</tr>
<tr>
<td>Complications</td>
<td>Group biomechanical foot profiles</td>
<td>6 months</td>
<td>97</td>
<td>T1D &amp; T2D</td>
<td>K-means</td>
<td>2013</td>
<td>131</td>
</tr>
<tr>
<td>Disease complexity</td>
<td>Group by drug purchases</td>
<td>7 years</td>
<td>953</td>
<td>T2D</td>
<td>Knowledge discovery</td>
<td>2015</td>
<td>66</td>
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<tr>
<td>Complications</td>
<td>Group risks of renal disease</td>
<td>3 years</td>
<td>109</td>
<td>T2D</td>
<td>K-means</td>
<td>2015</td>
<td>132</td>
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<tr>
<td>Complications</td>
<td>Group risks of complications</td>
<td>10 years</td>
<td>1441</td>
<td>T1D</td>
<td>Learning models</td>
<td>2015</td>
<td>133</td>
</tr>
<tr>
<td>Complications</td>
<td>Group risks of complications</td>
<td>5 years</td>
<td>84</td>
<td>T1D &amp; T2D</td>
<td>RA and ANN</td>
<td>2015</td>
<td>134</td>
</tr>
<tr>
<td>Complications</td>
<td>Group risks of retinopathy</td>
<td>&lt;1 year</td>
<td>345</td>
<td>T2D</td>
<td>SVM, RF, DT and NB</td>
<td>2015</td>
<td>135</td>
</tr>
<tr>
<td>Disease complexity</td>
<td>Groups of blood glucose profiles</td>
<td>4 months</td>
<td>10</td>
<td>T1D</td>
<td>Hierarchical clustering</td>
<td>2016</td>
<td>136</td>
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<tr>
<td>Complications</td>
<td>Group personal networks types</td>
<td>5 years</td>
<td>1862</td>
<td>T2D</td>
<td>RA and K-means;</td>
<td>2016</td>
<td>137</td>
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<tr>
<td>Disease progression</td>
<td>Group risks of T2D progression</td>
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<td>2017</td>
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<td>2017</td>
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<tr>
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<td>Group by retinopathy, neuropathy, or nephropathy</td>
<td>3,5,7 years</td>
<td>943</td>
<td>T2D</td>
<td>RF and Logistic Regression</td>
<td>2018</td>
<td>63</td>
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Acknowledgments
This work was funded by the Spanish Government through grant DPI2016-78831-C2-2-R and the European Union through Fondo Europeo de Desarrollo Regional (FEDER).

Conflicts of Interest
None
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Abbreviations

AC, accuracy
AI, artificial intelligence
ANN, artificial neural network
AP, artificial pancreas
BG, blood glucose
CBR, case-based reasoning
CGM, continuous glucose monitoring
CHO, carbohydrate
CSII, continuous subcutaneous insulin infusion
DCP,
DSS, decision support system
DT, decision tree
DL, deep learning
EA, evolutionary algorithm
FL, fuzzy logic
GA, genetic algorithm
KDD, knowledge discovery in databases
KNN, k-nearest neighbor
MDI, multiple daily injection
NB, Naïve Bayes
NLP, natural language processing
PA, physical activity
PH, prediction horizon
PSO, particle swarm optimization
RA, regression algorithm
RBR, rule-based reasoning
RF, random forest
RMSE, relative mean square error
SN, sensitivity
SP, specificity
SVM, support vector machine
T1D, type 1 diabetes
T2D, type 2 diabetes
GD, gestational diabetes