Chapter 5

AI-Driven Biological Advancements for Diabetes Management and Sustainable Health

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ABSTRACT

Diabetes mellitus, which affects billions of people worldwide, has quietly emerged as one of the largest and most important health crises of our time. As indicated by new estimates, nearly half of the 387 million people living with diabetes are undiagnosed. In this context, artificial intelligence (AI) offers new avenues of hope. AI is helping us revisit how we recruit, track, and treat diabetes based on large volumes of health data to predict patterns and tailor interventions. There is potential to combine

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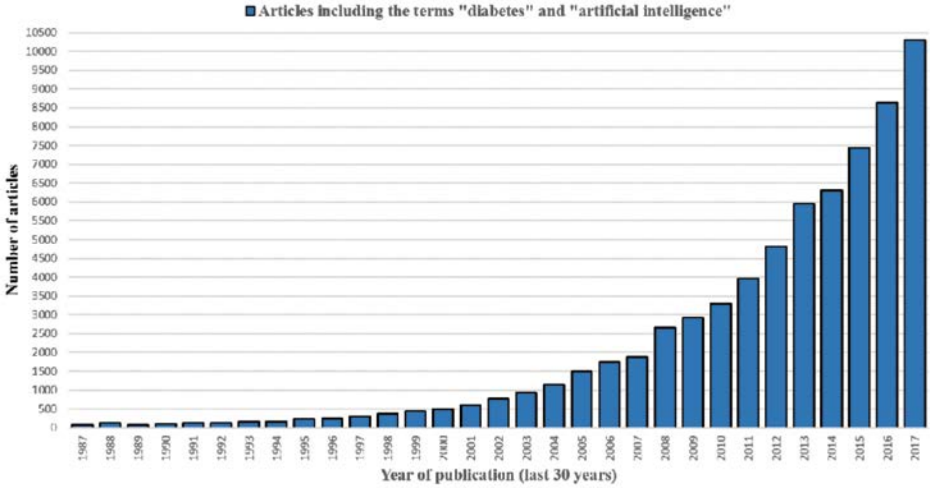
ideas from clinical practice and nutrition science with computational biology to consider prospects and challenges to using AI in achieving patient-centered, sustainable health outcomes. This review focuses on AI driven innovation in diabetes management, AI and precision medicine, AI interventions in nutrient plan and their future perspectives.

1. INTRODUCTION

Diabetes is a non-communicable disease that has an estimated prevalence of 463 million adults plus an ever-increasing number of children and adolescents globally, thus becoming a major health concern for the entire planet. Among the different types of diabetes, type 2 diabetes (T2D) accounts for about 90% of all cases and according to EASD/ADA reports, a serious health problem in the world that imposes a burden on individuals and health systems, will continue to rise rapidly. In spite of the fact that T2D patients are, by and large, provided with the world-class insulin analogues, oral and injectable anti-hyperglycaemic medications for coping with the disease's challenges, they still find it difficult to attain the glycaemic targets set for them and consequently suffer the risk of developing long-lasting micro- and macro-vascular complications (Daly & Hovorka, 2021). Hyperglycemia is the unifying condition that separates the first four categories: type 1 diabetes (T1D), type 2 diabetes (T2D), some diabetes and gestational diabetes mellitus. T1D, which is an autoimmune disorder, leads to the destruction of the insulin-producing pancreatic beta cells by T lymphocytes resulting in an inadequate insulin supply and thus, hyperglycemia. T1D may develop at any age but it represents only 5-10% of all diagnosed cases of diabetes.It typically affects children and teenagers. Insulin resistance (IR) and metabolic syndrome (MS) are often present in type 2 diabetes (T2D), a disease marked by a non-autoimmune, heterogeneously increasing lack of sufficient islet β cell insulin production (Lu et al.,2024; Addissouky et al.,2024).

A group of technologies known as artificial intelligence are utilized to provide results that are on par with human intelligence and critical thinking. Pattern recognition, speech recognition, process automation, data analysis, and other elements are all included in this phrase (Secinaro et al.,2021). AI is being utilized in healthcare for a number of things, including clinical trials, drug management, surgery, and nursing aid. Figure 1, a rough estimate of the number of linked papers in the Google Scholar database, illustrates how swiftly this subject is expanding and how its applications to diabetes research are expanding even more quickly (Contreras & Vehi, 2018).

Figure 1. The number of research articles listed in Google Scholar containing references to both 'diabetes' and 'artificial intelligence'."



The technological innovation in the healthcare sector has created new avenues for the management of diabetes in a more effective way. This is crucial due to the nature of the disease, which requires constant monitoring and adjustments of the treatment plan, and also to the fact that these technologies are now being used in such a way that diabetes care is personalized and made more efficient, including the use of state-of-the-art glucose monitors and computer programs that help with the collection and interpretation of patient data.Artificial Intelligence (AI) is revolutionizing diabetes care in this area by offering improvements in early risk assessment, diagnosis, and individualized treatment. AI improves patient care and results by analyzing big datasets to forecast hazards, correctly interpreting test results, and tailoring treatment regimens (Khalifa et al.,2024). In the past few years, the development of type 2 diabetes has become much more common. As artificial intelligence applications in healthcare have grown, they are utilized for outcome prediction, therapeutic decision-making, and diagnostics, particularly in type 2 diabetes mellitus (Abhari et al.,2019).

1.1 ROLE OF AI IN HEALTHCARE

In the healthcare sector, AI may be roughly divided into three categories: patient management, treatment, and diagnostics. The AI has already shown a great deal of potential in the field of diagnostics by reading medical imaging, spotting anomalies, and even making predictions about sickness. For example, current-day AI algorithms are capable of analyzing radiographic pictures for the purpose of accurately classifying diseases, such as infections, tumors, and fractures, at a level that is no less than or may even be better than human radiologists. This contributes to not only greater accuracy but also faster diagnosis, which in turn may lead to improved patient outcomes (Zeb et al.,2024).

In the 1970s, AI with proven medical applications started to gain popularity. The first artificial medical consultant in history, INTERNIST-1, was developed in 1971. Based on the complaints of the patients, the computer system made clinical diagnoses using a search algorithm. Because INTERNIST-1 offered a way for doctors to cross-check their differential diagnoses and had the obvious potential to relieve part of the burden of clinical diagnosis from healthcare providers, it marked a significant shift in AI in clinical research. At this point, the National Institutes of Health sponsored the inaugural AI in Medicine conference at Rutgers University since it was evident that AI had intriguing medical applications (Hirani et al.,2024).

The use of AI in healthcare systems is a complicated integration of multimodal systems that calls for fundamental developments in fields like model performance, optimisation, privacy, and large-scale machine learning. Two crucial ideas need to be addressed in order to successfully integrate AI into healthcare: Analytics with insights and data with security. Complete transparency and trust are necessary for successful integration when it comes to data and security. In a similar vein, data analytics and insight play a critical role. In multimodal applications, AI can synthesise data from several unstructured and structured sources to help make better judgements, identify better solutions, and promote rational discourse (Alhejaily, 2024).

In a broad sense, the human mind is being mimicked by the artificial intelligence. The AI collects, scrutinizes, and interprets huge amounts of data, which leads to the uncovering of patterns and decision-making, almost without human intervention. They are able to change their ways of working and improve their efficiency gradually through the application of algorithms and mathematical processing. AI can accomplish a degree of accuracy and efficiency in activities ranging from pattern recognition to predictive analysis because to this self-improvement mechanism. While machine learning algorithms drive predictive analysis in healthcare, artificial intelligence (AI) technologies like convolutional neural networks (CNNs) are used for medical imaging analysis (Olawade et al.,2024).

1.1.1 Advanced analytics for prediction and early diagnosis

Artificial intelligence has revealed a great deal of promise for early disease diagnosis and risk profiling. The deployment of AI, particularly the utilization of machine learning, permits the analysis of different modalities of data. Among others, medical imaging and genomics can play a significant role in the prediction of cancer, diabetes, or heart disease risks. To give an example, in the mammogram case of breast cancer detection, the human expert confidingly told how much more precise the AI-assisted diagnosis was in comparison with the conventional approaches. Using predictive analytics, the current study discovered that. Early therapies improve patient outcomes by preventing issues in the future (Manik et al.,2021).

1.1.2 Personalised Medicine

Without artificial intelligence (AI) tools to extract information from the data pool, personalised treatment would not be able to flourish. In particular, machine learning (ML), an AI technology, is used to use statistical inference to identify patterns and correlations in the data. This machine learning algorithm can forecast the impact of medication dosage for particular patient populations in pharmacology. For instance, using genetic and non-genetic clinical data, supervised learning (ML algorithm) was taught to predict stable warfarin dosing in Caribbean Hispanic patients classified as “normal,” “low,” or “high” dose patients (Gifari et al.,2021).

1.1.3 Drug Discovery

The pharmaceutical business has taken notice of the effective use of AI tools, especially in biological data processing. Drug-target prediction, bioavailability prediction, and de novo drug design are examples of how AI techniques have been used in drug discovery processes thus far. Several large pharmaceutical companies, including Bayer, Roche, and Pfizer, have also started working with IT firms to develop AI technique-based methods for drug design. The Insilico Medicine business recently used AI to find a medication that treats idiopathic pulmonary fibrosis and has shown promising results in Phase I trials. Therefore, it makes sense to conclude that the field of drug research and development has been modernised by AI approaches (Chen et al.,2023).

2. AI-POWERED BIOLOGICAL ADVANCES IN THE MANAGEMENT OF DIABETES

2.1 CONTINUOUS GLUCOSE MONITORING

Continuous Glucose Monitoring that is CGM system is such a monitor that is attached to a person's body and takes blood glucose levels from a selected body fluid, which in this case is interstitial fluid (ISF), without any break and at very short periods (every 5 to 15 minutes). Typically, a CGM is composed of three parts: a worn sensor,a transmitter that wirelessly transmits readings to a nearby receiver that shows the user the readings (Klonoff et al.,2017). The first reports of continuous blood glucose monitoring in human individuals date back to the 1960s. Many efforts have been made to develop CGM, motivated by the search for an artificial pancreas. For instance, Kadish first tested closed-loop glucose regulation in 1963 using continuous real-time glucose monitoring. Additionally, the idea of an artificial pancreas was put up by Albisser et al. in 1974, and CGM combined with algorithms to automate insulin delivery has showed promise in individuals with Type 1 diabetes (T1D). Miles Laboratory introduced the Biostator, a commercial CGM product, in 1977. Nevertheless, by today's standards, the CGM systems indicated in the latter are regarded as heavy devices. Real-time CGM systems were first used in clinics in 2005. The FDA authorised the MiniMed 670G, the first commercial hybrid closed-loop system, in 2016 (Jin et al.,2023).

The potential of CGM data is further increased when it is integrated with AI, especially machine learning and deep learning technologies. Recent research that merges AI-assisted diabetic management with heart disease risk evaluation has revealed the relations between metabolism and cardiac wellbeing, thus signaling the necessity for interdisciplinary approaches. The use of Deep Neural Networks (DNNs) together with Explainable AI methods can result in highly accurate prognosis of glucose levels after meals by considering various factors such as pre-meal glucose level, insulin dosage, and nutrient content of diet. AI algorithms designed specifically for meal recognition from CGM measurements have been created recently; these algorithms emphasise subtle trends that are difficult for traditional approaches to identify (Ji et al.,2023).

AI incorporated into continuous monitoring systems can help persons with diabetes manage their condition on a daily basis by offering real-time decision support. AI algorithms used in CGM and automatic insulin administration (AID) systems have produced closed-loop systems that resemble artificial pancreas. This method can reduce the need for ongoing diabetes monitoring by making instantaneous insulin dosage decisions based on real-time data processing from CGM sensors. In particular, the creation of closed-loop systems depends on the combination of insulin pumps (like Medtronic or Tandem) with CGM devices (like Dexcom G6 or Freestyle Libre). AI algorithms are used to optimise data processing and make real-time adjustments to insulin administration schemes (Wang et al.,2025).

The glucose sensor, which is a state-of-the-art gadget meant to almost instantaneously monitor the sugar levels in the blood, is the main part of this closed-loop system. This sensor takes the place of the traditional, often painful fingerstick tests by acquiring data in a non-invasive or minimally invasive manner. The AI detection block, which acts as the system's digital brain, receives the collected data with ease. This AI detection block's capacity to interpret and comprehend the intricate glucose data streams it receives from the sensor is what gives it its revolutionary potential.

The dynamic and fluctuating nature of these data streams, which are impacted by things like stress, physical activity, and food consumption, is what defines them. For users who do not use automated insulin delivery (AID) systems because of availability, cost, or personal preference, AI-powered CGM may be especially helpful. In order to control their blood sugar levels and avoid hypoglycemia, particularly during the night, they are far more reliant on their own efforts. Compared to AID users, this group may benefit even more from having access to precise longer-term glucose forecasts (Medanki et al.,2024, Hussain et al.,2025).

A “open-loop glucose controlling system” is a kind of medical technology or process designed to regulate a person's blood glucose levels without requiring continuous input or adjustments based on real-time data. It has several disadvantages in addition to certain benefits. By implementing a feedback system, the disadvantages can be minimised. A promising path for changing diabetes treatment paradigms is provided by recent developments in artificial intelligence (AI) and machine learning. The combination of AI with glucose monitoring devices offers a chance to improve diabetes care's accuracy and customisation. Incorporating AI algorithms allows for the continuous monitoring of glucose levels as well as the analysis of patterns, prediction of future trends, dynamic adjustment of treatment plans, and automation of treatments (Medanki et al.,2024).

For use in the intensive care unit (ICU), Ideal Medical Technologies (IMT) has created an artificial intelligence (AI)-based glucose control algorithm. The natural glucose control system served as the model for this AI-based glucose control program, which has already undergone successful testing in a simulated environment. Furthermore, it was previously combined with two syringe pumps and the Dexcom G4 sensor (which is not CE-marked for usage in the intensive care unit) to form a closed loop glucose control system (artificial pancreas). The safety and efficacy of this prototype system were demonstrated in a brief pilot investigation of severe stress-induced hyperglycemia in a pig model. The infusion pumps in use today are precise and dependable enough to finish a closed-loop glucose management system (Dejournett et al.,2021).

Hospital data, including blood test indicators, clinical registration data, EMRs, prescription data, and data gathered from insulin pumps, pens, different mobile apps, and more, can be connected with the large data produced by CGM. The CGM digital ecosystem is the name given to this integrated system. Researchers and healthcare experts anticipate that future research utilising the CGM digital environment will be increasingly active. Because it can more accurately reflect changes in blood glucose control status than other techniques, CGM is frequently employed in both domestic and international research to assess the effects of biological markers (Ahn et al.,2023).

An error grid analysis revealed that 60%–70% of the interstitial glucose levels acquired from the RT-CGM were clinically correct and defined by a variation of arterial blood glucose level < 20% using the glucometer (Hirani et al.,2024). RT-CGM was first placed in the ICU in 2003. Tighter glucose control has been linked to a higher incidence of hypoglycemic events, but it can also reduce postoperative infection rates, short-term mortality, and lengthen the stay of the patient in the surgical ICU.

Recent studies have indicated that RT-CGM application for interstitial glucose monitoring can enhance the glycemic variability for ICU patients and consequently lead to a reduction in the rate of severe hypoglycemia. More research is needed to determine whether these benefits of RT-CGM can lower the risk of overall mortality in critically sick patients. RT-CGM offers an alternate method of monitoring the blood glucose levels of patients in need of care during the COVID-19 pandemic and lowers the danger of infection for ICU carers because there is less frequent interaction with the afflicted patient just for blood glucose testing. Noninvasive, inexpensive CGM may become more practical in the ICU or for outpatient use in the future (Sun et al.,2021).

2.2 AUTOMATED RETINAL SCREENING FOR DIABETIC RETINOPATHY (DR)

The most frequent complication of the disease, diabetic retinopathy, is found in 97% of people who have been diabetic for a long time. Diabetic retinopathy was estimated to be a worldwide issue affecting 103 million adults in the year 2020, while this is expected to rise to 160 million by 2045. The two main characteristics of this ischemic eye disease are the death of retinal nerves and the development of small blood vessel leaks with the resulting bleeding in the retina. Later on, the phenomena of intraretinal microvascular anomalies, venous beading, and cotton wool patches may come to be seen. Proliferative diabetic retinopathy (PDR) which is characterized by the development of very fragile retinal capillaries at the interface with the vitreous can be seen as a consequence of a long period of oxygen deprivation and the subsequent release of the vascular endothelial growth factor (VEGF) (Grauslund et al., 2022).

Although the density of ophthalmologists varies throughout nations and areas, their diagnosis depends on the availability of skilled ophthalmologists. The unequal distribution of personal resources in ophthalmology is further exacerbated by the disparities in the clinical experience of ophthalmologists. As a result, there is growing interest in developing dependable and economical screening techniques for retinal disorders. The lack of skilled ophthalmologists in developing nations may be addressed by deep learning (DL)-based patient screening and referral. Diabetic retinopathy (DR) and other retinal disorders can be automatically detected with near-expert performance using DL systems trained on colour fundus pictures (Dong et al.,2022). AI-based automated DR detection enables uniform interpretation and real-time reporting of results in addition to giving diabetic patients routine exams. Automated solutions can improve patient access to screening and are more affordable than human grading. Furthermore, physician workload related to manual image grading is decreased by automated DR screening systems. There have been reports of a number of automated DR image evaluation systems, including EyeArt from Eyenuk Inc., IDx-DR from Digital Diagnostics Inc., SELENA from Singapore Eye Research Institute, Retmarker from Retmarker Ltd., and Automated Retinal Disease evaluation from Google LLC. The US Food and Drug Administration (FDA) has approved the AI system for the identification of more-than-mild DR (mtmDR), and diagnostic research has demonstrated that IDx-DR is sensitive and specific for DR screening (Ipp et al.,2021).

AI-based image interpretation has been developed in the medical industry. Traditional machine learning techniques based on feature extraction or pattern recognition provided by professionals manually for DR characterisation and classification have been used to study automated analysis of retinal images for DR over the past 20 years (Cheung et al.,2019). AI has been suggested as a viable way to improve diagnostic performance and save human resources because diabetic retinopathy screening is difficult and time-consuming for medical experts. Machine learning (ML) has long been verified as a first-generation approach for assessing diabetic retinopathy. These early techniques relied on automatic detection of lesions associated with diabetic retinopathy, such as haemorrhages and retinal microaneurysms. In the end, recognition results in a general category for diabetic retinopathy based on well specified inputs for disease categorisation, such as the shape, colour, and anticipated locations of specific lesions (Grauslund et al.,2022).

Artificial intelligence (AI) based on deep learning (DL) represents a breakthrough that has significantly improved the state-of-the-art in many tasks, including speech recognition, image processing, and text generation, in tandem with advancements in imaging and the digitalisation of healthcare. By facilitating the development of computer-aided diagnosis systems (CADx) with expert-level accuracy, DL has proved most effective in the medical arena when it comes to medical image analysis. There are numerous instances in radiology, gastrointestinal, ophthalmology, and dermatology. Actually, the first autonomous AI licensed by the US Food and Drug Administration (FDA) is a DR screening tool (Font et al.,2022).

2.3 AI algorithm development of DR

The first step in creating AI algorithms for DR screening from retinal photos is to create a sizable dataset of photos of DM patients, each of which is annotated with the degree of DR. The DL algorithms may then be developed using about 80% of the data (photos with labels), with the remaining 20% saved for algorithm evaluation. This stage is similar to the preclinical development approach for new medications and is known as “in silico evaluation” or “internal validation.” Next, fresh datasets of retinal photos of DM patients are used to validate the algorithms. This stage, commonly referred to as “external validation” or “offline validation,” is specific to AI development because medication development methods do not incorporate it. Similar to phase 1 and phase 2 studies for small-scale safety and efficacy evaluation in drug development programs, the algorithms may then be prospectively verified in the “early live clinical prospective validation” phase. The “comparative prospective evaluation” phase, which is similar to phase 3 trials in drug development programs, is the next stage for AI. Both AI algorithms and medication research initiatives go through a similar final post-market surveillance phase (Grzybowski et al.,2023).

2.4 Limitations of using AI in detecting DR

The fact that AI algorithms trained to identify retinal illnesses mostly rely on features from fundus photos, which may not provide a complete picture of the deep layers of the retina and choroid, is one drawback. certain retinal condition. In contrast, a significant percentage of patients have several retinal disorders, which limits the usefulness of this AI software in an actual clinical situation. Therefore, creating AI algorithms that can identify several retinal illnesses at once in a single detection is becoming more and more necessary due to clinical practice and community screening efforts (Bai et al.,2022).

2.5 Diabetic Patient Self Management

Education in self-management for patients with diabetes (DSME) is considered to be a very effective way of enhancing the patient's condition and of reducing the medical costs incurred by the patient. The National Standards for Diabetes Self-Management Education and Support define DSME as a “continuous process of making possible the knowledge, skill, and capacity required for prediabetes and diabetes self-care”. This procedure is based on evidence-based guidelines and takes into account the needs, objectives, and life experiences of the individual with diabetes or prediabetes. Patients and their families must consistently practise daily self-care in order to effectively control their diabetes (Sharma et al.,2024). By the cooperative process of DSME and educational programs, individuals with developing diabetes or at risk for the disease acquire the knowledge and abilities necessary to successfully self-manage the condition and change their behaviour in order to improve health outcomes. Healthy diet, compliance with medication, self-monitoring of blood sugar (SMBG), and prevention behaviour for diabetes complications are the elements of DSME (Shah et al.,2015). Dedicated patient self-management, in which people actively participate in their health-related behaviours and decisions, can lead to effective long-term treatment of type 2 diabetes. Regular exercise, monitoring food consumption and glucose in the blood levels, and taking medications are some of the aspects of T2DM individual management (Yingling et al.,2019). Technology can extend the reach of diabetes education and support when primary care resources are insufficient or patient resources and access to care are limited. Patients may have difficulty scheduling and attending diabetes education classes or meeting regularly with a diabetes educator due to time, financial, or other constraint. Education can be provided using technological resources so that patients learn new practices and routines related to diabetes management. Technology can support the daily diabetes self-management activities of blood glucose monitoring, exercising, healthy eating, taking medication, monitoring for complications, and problem-solving. Visual feedback of clinical information, including these self-management activities, improves patients' ability to see how diabetes is affected by their behaviors and promotes decision-making and problem-solving (Hunt et al.,2015).

2.6 AI in patient self management

The health care industry's previous approach of anticipating a sickness to appear before treating it has gradually been replaced with a strategy that uses signals to prevent the condition. The acceleration of health information from multiple sources, including smartwatches, genomic information, electronic health records, and sensors for the environment, is the cause of this change. AI and ML experts can use big data analytics to identify people who are most likely to develop specific diseases so that they can be promptly treated to prevent the onset or aggravation of numerous diseases (Adetunji et al.,2022). Patients are empowered and informed thanks to AI. Health care systems are greatly impacted by digital solutions because they affect patient comorbidities, behaviours, the amount of time spent in medical facilities, and the necessity of frequent travel to and communication with healthcare professionals. Additionally, AI has enhanced the flow of patients into and out of hospitals. Patients have the opportunity to connect and gain knowledge from the experiences of others via online diabetes communities and support groups. Patients' well-being and desired results are positively impacted by this cooperative approach to learning more about the different facets of the illness, which is interesting for both patients and carers (Ellahham et al.,2020).

Chatbots are interactive devices that employ artificial intelligence (AI) to converse with people in natural language, whether through text or voice, at any time or location. A growing number of health chatbots are being developed for different purposes. Chatbots and other health technology solutions are rarely deployed in healthcare after the initial pilot study phase. Instead of quantitatively analysing chatbot logs, previous research on health chatbots has mostly relied on questionnaires or interviews. Examining chatbot exchanges may provide valuable information for future advancements (Begum et al.,2025).

Knowledge graphs are a type of graph used in AI research that contains entities, properties, and relationships between things. These relationships are often kept as inter-connecter triples. Particularly in the medical field, KG-based technologies are being developed to extract structured knowledge from large data, which is thought to be an essential component for the development of AI in conjunction with big data and deep learning. Medical information retrieval, medical knowledge intelligent question and answering (QA), diagnosis, and treatment are possible uses of KG technology in type 2 diabetes. Knowledge-based question answering is a kind of QA processing that makes use of a knowledge database to quickly and accurately respond to user-written questions expressed in plain language (Wu et al.,2023).

Even if self-management plans can help manage diabetes, a survey of more than 100 diabetic individuals revealed that a technology-driven approach might be the catalyst for better diabetes self-management. Although the relevant app stores (such as Google's Play Store and Apple's app Store) currently offer a wide range of diabetes self-management solutions, they usually differ in their core feature sets and, specifically, they usually consist of a simple structure with no complicated features like a nutrition system which keeps track of the diet, and makes recommendations that are appropriate according to a clinician's plan (Joachim et al.,2022).

Diabetes patients are very much aware of the primary benefits of the wearables such as keeping track of their health all the time, sharing their data with health systems even easily, and even getting support for changing their lifestyles. These advantages are the basis for allowing the medical professionals and the patients to work together more frequently and make decisions based on more information, and also to improve the patients' behavior through the use of one of the methods applied in psychology such as reinforcement. Among the factors that support the adherence to the good practices are motivational tools like goal setting and accomplishment notifications, which are especially effective in case of diabetes. However, even though the situation is favorable in this respect, there are still numerous obstacles that the industry must overcome before the full acceptance of the wearable technology and its integration into the patients' daily lives in the long run (Alzghaibi, 2025).

3. PREDICTIVE MODELING AND RISK STRATIFICATION

Predictive analysis can foresee within the field of healthcare the likelihood of a specific patient developing a disease or suffering a complication. The generated data can be a great help in the doctors' and patients' mutual decision making and may also result in the patient being more satisfied with the overall medical care provided to him or her.. Because to the presence of unknown risk factors, unbalanced data, time-varying dynamics data, and different illness therapies, predicting the development of disease complications is a difficult procedure. Predicting problems accurately may enable more focused interventions to stop or limit their progression. Predictive analytics combined with AI has enormous potential to enhance the treatment of common chronic illnesses with high morbidity and death rates. It also plays a significant role in preserving a healthy lifestyle, taking medication, and keeping an eye on glycaemic state (Hassan et al.,2023, Gosak et al.,2022). It can be difficult for medical practitioners to diagnose diabetes mellitus early and accurately, especially in its early stages. As a guide, artificial intelligence and machine learning methods can assist them in learning the basics of this illness and lowering their workload. Numerous studies have been conducted to use machine learning and ensemble approaches to automatically predict diabetes (Tasin et al.,2023).

In one of Canada's biggest and most varied communities, the three-year AI for Diabetes Prediction and Prevention (AI4DPP) CIFAR Solution Network will apply verified machine learning (ML) models to forecast diabetes incidence and complications. The needs and experiences of structurally marginalised communities were given particular consideration while designing these machine learning algorithms for application in community health settings. In particular, the models have shown excellent predictive performance and strong overall and sub-group performance. They were developed using routinely collected health administrative data, which includes records on diagnoses, procedures, medications, and demographics of patients accessing a single-payer health system (Rosella et al.,2025).

A prospective cohort of 4746 and 4615 people in Finland in 1987 and 1992, respectively, served as the basis for the creation of the FINDRISC. The criteria for the FINDRISC model include age, gender, body mass index (BMI), blood pressure drugs, a history of high blood glucose, physical activity, daily consumption of fruits, vegetables, or berries, and a family history of diabetes. The FINDRISC can be applied as a logistic regression (LR) model or as a scorecard model.

The German Diabetes probability Score (GDRS), which calculates the 5-year probability of developing type 2 diabetes, is another widely used scoring prediction model. 9729 men and 15,438 women between the ages of 35 and 65 from the European Prospective Investigation into Cancer and Nutrition (EPIC)-Potsdam research served as the basis for the GDRS (Edlitz & Segal, 2022).

3.1 Biological Precision Medicine and AI

In order to accomplish accurate diagnosis, treatment, prognosis prediction, and preventative strategies at the individual level, precision medicine is a new approach to medicine that utilises clinical large-scale data, encompassing clinical, omics, and imaging data. Among these, imaging data makes up a sizable amount of medical data and has a crucial reference value in disease diagnosis, treatment plan development, and disease prognosis because of its noninvasiveness and accessibility. The capacity to handle medical big data, which calls for massive processing power and top-notch computer tools, is another crucial component in the development of precision medicine (Li et al.,2023). With the goal of "bringing us closer to curing diseases like cancer and diabetes," President Barack Obama introduced the Precision Medicine Initiative in 2015. Since then, it has attracted a lot of attention. Precision medicine makes superior medical and health recommendations for a person by using data such as genetics, environmental factors, and lifestyle to improve disease prediction, prevention, diagnosis, and/or treatment. The core idea of precision medicine is to prevent and treat illness by taking individual patient variability into consideration (Kaurich et al.,2025).

It is challenging for diabetics to maintain target blood glucose levels since bolus insulin dosages increase the risk of hypoglycemia. AI-driven algorithms have developed to analyse complex, multidimensional data in order to identify high-risk individuals, risk factors, and biomarkers linked to type 2 diabetes, as well as to direct tailored preventative measures. AI methods forecast T2D risk by evaluating multidimensional data using multimodal models (Ghosh et al.,2025). The following factors make type 2 diabetes treatment a strong choice for a precision medicine strategy. Following metformin, there are other medication groups that share the same primary goal of lowering blood glucose but have distinct methods of action. The glucose-lowering response to each medication seems to differ significantly at the individual level. Apart from a small percentage of people with particular difficulties, there isn't a definite "best" general treatment. For the remainder, there is no information in the current treatment guidelines regarding which drug class is most effective for decreasing blood glucose for which individuals. Because the clinical phenotype of type 2 diabetes varies greatly, it is conceivable that individuals with distinct underlying pathophysiologies will react differently to the various medication classes, depending on the drug's mode of action (Dennis, 2020). Personalised medicine is at the forefront thanks to AI-driven solutions. For instance, automated insulin delivery systems—also known as II artificial pancreas—integrate CGM data with insulin pumps and make real-time dose adjustments to maintain ideal glycaemic control. AI has made it easier to find new biomarkers for early identification and disease monitoring, which lessens the daily load on patients with type 1 diabetes while lowering long-term problems. For example, type 2 diabetes-related genetic variations have been found using sophisticated machine learning algorithms, providing new targets for medication development. AI-powered simulations are speeding up the testing of novel treatments and drastically cutting down on the time and expense involved with conventional clinical trials (Gunatilake et al.,2025). Patient records, medical notes, prescriptions, audio interview transcripts, pathology, and radiology reports are just a few examples of the unstructured medical text that machine learning (ML) can learn from. ML techniques will be used in daily applications in the future to arrange the increasing amount of scientific literature, making it easier to access and extract valuable knowledge from it. In the clinic, ML can leverage the potential of electronic health information to accurately anticipate medical events. The variety of clinical or healthcare provider-specific electronic health records, which is a feature of modern medical practice worldwide, can be solved by adding a rating mechanism to the content network (Filipp et al.,2019).

Digital health records assessed by AI can predict a disease's future evolution, reveal hidden patterns in patient clusters, and even recommend preventive measures personalized to every patient's condition. Thus, this approach leads not only to improved outcomes for single patients but also enhances public health initiatives in general. Still, the integration of AI into precision medicine has a lot to offer, but the reasons like patient privacy problems, consent acquisition, and the handling of the ethical challenges posed by AI decision-making are still there (Chen et al.,2025).

3.2 AI in peritoneal Dialysis Treatment

Another area where AI is showing promise is fluid management. For dialysis patients, particularly those with diabetes, anticipating and preserving the ideal fluid balance is essential since fluid excess can worsen cardiovascular issues. AI algorithms have been created to assist medical professionals in maximising ultrafiltration rates in individuals with Parkinson's disease. These algorithms can predict fluid overload by evaluating patient data, thereby averting consequences such as heart failure. Due to the combined difficulties of glycaemic control, the use of higher concentration dextrose solutions, and fluid retention, personalised hydration management is especially crucial for PD patients with diabetes. Dialysis prescriptions are also being customised using AI-driven technologies according to the unique characteristics of each patient (Mahdevi et al.,2025).

4. FUNCTIONAL FOODS, PROBIOTICS AND AI

Functional foods are dietary components that, because they include essential bioactive chemicals, offer health advantages beyond simple nutrition. Recent studies have shown that the bioactive substances that may be present in food have a major impact on reducing the risk of chronic illnesses, supporting gut health, lowering inflammation, strengthening the immune system, improving cognitive function, and helping with weight management (Arshad et al.,2025). Consumers are increasingly demanding solid scientific proof for nutritional claims, as seen by market trends, and they are educating themselves to comprehend the significance and veracity of Functional Food Ingredients (FFIs) and the related health claims. gaining the self-assurance to voice their opinions on the advantages and safety of food goods and determining which aspects of food, like sustainability and naturalness, are significant to them (Doherty et al.,2021). The introduction of AI technology into the food sector is a calculated reaction to upcoming societal shifts and the increasing industry convergence. In contrast to other disciplines like biotechnology, economics, and medicine, its uptake has been delayed. Probiotics, antioxidants, and fibres are examples of functional substances that have been scientifically shown to improve human health, however traditional techniques of finding these ingredients are frequently laborious and constrained. The quick and accurate identification of functional substances is now possible because to recent developments in big data and artificial intelligence. These technologies make it possible to identify bioactive chemicals by analysing large datasets, such as metabolomic, genomic, and food consumption trends (Hong et al.,2024).

Chauhan et al. (2021) used a set of neural networks to create a predictive model after discovering a functional constituent with glucose-modulating activity. According to Casey et al. (2021), the study's predictive algorithm found several validated peptides with blood glucose regulation action. In short, a dataset of glucose-regulating peptides that was constructed by combining data from literature with proprietary internal data established from mass spectrometry and in vitro investigations was used to train neural network models based on stacks of recurrent and dense layers in fold cross-validation. For the training sequences, two sets of models were trained with varying degrees of internal redundancy. The final predictive model for glucose-upregulating peptides was an ensemble of the models that performed the best on the test sets. Several plant proteomes were screened in silico using the predictor, with an emphasis on the most prevalent proteins for each plant. Pisum sativum was given priority for in vitro testing since it was the top-ranked natural source based on counts of peptides that the predictor identified as active in the area of glucose regulation. As a result, it has been shown to lower the HbA1c in prediabetics (Chauhan et al.,2021).

By improving formulation accuracy, predictive modelling, and customised nutrition, developments in optimisation techniques, machine learning, and artificial intelligence have the potential to revolutionise the production of functional foods. As demonstrated by studies on flavonoid-rich Quranic mixed foods and natural antimicrobial formulation, cutting-edge optimisation techniques like simplex-centroid mixture design have already shown considerable promise in fine-tuning complex food formulations to maximise the efficacy and stability of bioactive compounds. Predictive modelling and quick, high-throughput screening are made possible concurrently by AI and machine learning. They assist scientists in finding new functional chemicals and connecting food compositions to illness risk. Citrusinol, for instance, was found to be a promising substance for muscular health by an ensemble model (Karantonis et al.,2025).

4.1 AI in the discovery of probiotic strain

Microbiotics, which are made up of probiotics, prebiotics, postbiotics, and synbiotics, are key factors in the process of regulating gut microbiota composition and through that, the whole body's immune and metabolic stability. Probiotics, the live beneficial microorganisms, and prebiotics, the non-digestible fibres that promote the good microbes, are both taken in to maintain the balanced microbiota which is essential for optimal gut functioning. Along with the microbial metabolic byproducts - postbiotics, and the combinations of probiotics and prebiotics - synbiotics, they also play a role in gut health by the support of a good microbiome (Lam et al., 2025). In microbiomics, artificial intelligence (AI) has become a game-changing tool that presents fresh approaches to these problems. AI facilitates large-scale, quick functional analysis of genomic data and opens up new avenues for the development and commercialisation of probiotics by improving the speed and accuracy of probiotic screening. For example, tRNA sequence information has been found by machine learning (ML) models as a crucial genetic characteristic that sets probiotics apart from intestinal pathogens, opening the door for creative approaches to probiotic creation (Han et al.,2025).

ML is especially useful for researching the human gut microbiota since it sheds light on how this intricate microbial population affects both health and illness. Machine learning (ML) approaches such as feature selection, biomarker identification, disease prediction, and treatment recommendation may efficiently analyse and understand high-dimensional, heterogeneous data. Our comprehension of intricate microbial communities has been transformed by the application of machine learning techniques to microbiome data. Microbiome samples have been effectively classified and host phenotype has been predicted using supervised learning techniques like random forests and support vector machines (D'Urso & Broccolo, 2024).

Groups of bacteria and human health are remarkably correlated, according to AI technology, which can analyse vast datasets to identify significant links. AI is also developing predictive models for the interactions between microorganisms. These models describe how different microbial populations interact in the gastrointestinal system and how these interactions affect the host's immunity and metabolism. These results are crucial for both epidemiology and the development of targeted treatments meant to reverse the extinction of keystone taxa. One of the most cutting-edge areas of medicine today is the search for bacterial biomarkers. The unique microbiological signatures linked to different medical disorders can be captured by AI (Alexandrescu et al.,2025).

5. ETHICAL COMPLICATIONS IN USING AI IN HEALTHCARE

Managing and safeguarding patient data in AI systems is one of the main ethical issuesThe use of enormous amounts of private medical data to generate forecasts and prescriptions raises the main issue concerning security and privacy. Patients need to feel that their personal data is handled correctly. For this, strong data security measures, including but not limited to authentication, confidentiality, and stringent access controls, are required (Igwama et al., 2024). The principal cause of privacy being tagged as an ethical issue is that compromising it and disclosing patient information inappropriately can inflict various harms on the data subjects, e.g., discrimination in employment or insurance, emotional distress, and losing trust. Inadequate protection of patient data can have the detrimental effects mentioned above because it is sensitive and used in training, validation, and diagnosis. Abdullah et al. identified data ownership as a bioethical concern and defined it as “authority to control, process, or access data.” Additionally, it communicates profitability through the capacity to sell data or get paid. Property laws and/or intellectual property rules should determine ownership of medical data, just as they do for physical property (Crew et al.,2025).

An AI system diagnosing a patient incorrectly or proposing a poor treatment option will also raise serious issues about responsibility and blame. The question of who will be held responsible—the company, the physician, or the developer—remains a complicated legal matter. It is necessary to establish clear rules for human-machine partnership, medical supervision, and distribution of liability to avert legal disputes and ensure safety in patient care.AI's clinical integration can overcome these challenges with a number of strategies. AI ensures that doctors remain actively involved in the decision-making process by using human-in-the-loop (HITL) as an assistive tool rather than an autonomous decision-maker. Regulatory platforms offered secure environments for testing AI models in real-world situations prior to their widespread usage, allowing developers and healthcare providers to assess performance and resolve problems early (Deivayanai et al.,2025). In medical settings, a heavy dependence on AI has detrimental effects on human healthcare professionals. Medical professionals continue to be the primary authority in healthcare applications, even while AI technology helps with decision-making. Reassuring the audience of the beneficial effects of AI on the future of healthcare, AI technologies should collaborate with medical staff to manage monotonous chores so that physicians may provide better patient care (Kothinti et al.,2024).

Because algorithms may contain biases, AI-driven retinal illness diagnosis raises ethical concerns. A notable medical university's researchers carried out a case study where they discovered that the accuracy of AI systems in recognizing diabetic retinopathy (DR) was different depending on the demographic group of patients. The algorithm, the study reported, highlighted a major difference in performance while diagnosing DR between Caucasian and African American patients. This emphasises how crucial it is to overcome algorithmic biases in order to guarantee that all patient populations have fair access to proper diagnosis and treatment. These prejudices have the potential to worsen disparities in access to high-quality care and maintain current healthcare disparities (Fathima et al.,2024). There are potential and challenges associated with the ethical integration of AI in public health and healthcare. AI, for instance, has the potential to improve diagnosis accuracy and speed operations, but it also raises concerns about dehumanisation in healthcare and a decrease in patient-provider relations. Working partners in public health and medicine can use AI to enhance population health and health care outcomes while upholding a commitment to ethical practice by proactively addressing these ethical issues (Dankwa-Mullam, 2024).

6. CONCLUSION

Innovative strategies to address the rising prevalence of diabetes worldwide are driving the changing landscape of diabetes management. The intricacy of glycaemic regulation cannot be well captured by conventional metrics like HbA1c, underscoring the need for more thorough measurements. With the help of CGM technology, these measurements offer real-time data that helps patients and medical professionals manage diabetes as effectively as possible. By anticipating dangers and customising treatment regimens, AI algorithms further improve this process by addressing both short-term fluctuations and long-term stability.

Sustainable gains depend on empowering patients with AI-driven self-management tools and community involvement. While integrating PROs with AI allows for dynamic, individualised interventions, gamified apps and social media groups improve adherence and offer peer support.

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