REVIEW PAPER

The promise of artificial intelligence in diabetes management – a narrative review

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ABSTRACT

The incorporation of artificial intelligence (AI) into diabetes management marks a paradigm shift in healthcare, addressing significant limitations of traditional approaches such as financial limits, clinical stagnation, and insufficient access to healthcare services. Healthcare providers can improve long-term patient outcomes by leveraging AI-driven innovations like predictive analytics, continuous glucose monitoring, automated insulin delivery systems, and clinical decision support systems. Furthermore, AI applications in diabetic complications screening, medical nutrition therapy, and personalized exercise regimens help to provide more comprehensive and individualized diabetes care. By addressing important shortcomings of conventional methods, this review examined the revolutionary potential of AI in the management of diabetes.

KEY WORDS: diabetes, management, promise, artificial, intelligence, review.

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Introduction

Diabetes mellitus is a major global health concern, with the prevalence and effect increasing over the last few decades [1]. As of 2021, over 529 million people worldwide had diabetes, with forecasts predicting the number might climb to more than 1.31 billion by 2050. In 2021, the global age-standardized prevalence of diabetes was 6.1%, with the highest rates seen in North Africa, Middle East, and Oceania [1].

Diabetes also dramatically increases morbidity and mortality. Diabetes killed an estimated 5 million people worldwide in 2017 [2]. The condition is a primary cause of comorbidities such as chronic kidney disease, cardiovascular disease, and neuropathy, which exacerbates its health and economic impact [3].

The many drawbacks of traditional diabetes therapy include significant financial limitations that make treatment compliance challenging, particularly in low- and middle-income nations where the issue is made worse by inadequate healthcare infrastructure [4]. The American Diabetes Association emphasizes reducing financial obstacles, as expensive drugs, insulin, and self-monitoring equipment frequently result in poor glycemic control [5, 6]. Furthermore, inadequate access to healthcare services and necessary medications, along with a shortage of educated experts, creates gaps throughout the diabetes care continuum, from diagnosis to treatment [7].

The Academy of Nutrition and Dietetics emphasizes the importance of interprofessional collaboration to address these deficiencies and improve results. Furthermore, traditional techniques frequently lack innovative care models and task-sharing strategies, which could improve therapy delivery [8]. Clinical inertia, patient non-adherence, provider knowledge constraints, and drug management complexity all contribute to the difficulty of providing effective diabetic care. To overcome these constraints, a multimodal strategy is required, including cost-cutting regulatory reforms, the adoption of Artificial Intelligence (AI)-driven and creative care models, and improved training and healthcare infrastructure in resource-limited areas [9].

Artificial intelligence has the potential to change diabetes management and care by overcoming various limitations of existing management approaches, including financial limits, limited access to healthcare services, and clinical inertia [10]. Artificial intelligence can assist minimize budgetary restrictions in diabetes care by optimizing resource utilization and increasing cost-effectiveness. Artificial intelligence-powered systems can continuously and remotely monitor patients' symptoms and biomarkers, decreasing the need for frequent in-person visits and thereby cutting healthcare expenses [11]. Furthermore, AI can improve the efficiency of healthcare services by automating mundane processes and offering decision support, reducing the financial load on both patients and healthcare providers [12].

The ability of AI to analyze vast datasets and deliver predictive analytics can help to reduce clinical inertia, or the failure to accelerate treatment when it is warranted. Artificial intelligence can recognize patterns and predict difficulties, allowing for prompt interventions and personalized treatment strategies. Clinical decision support systems (CDSS) driven by AI can help healthcare providers make evidence-based decisions, minimizing the risk of clinical inertia and increasing patient outcomes [13].

By addressing the major drawbacks of conventional methods, such as budgetary limitations, restricted access to healthcare services, and clinical inertia, this review will explore the revolutionary potential of AI in the treatment of diabetes. It investigated how AI-powered advances, such as predictive analytics, automated insulin delivery (AID), retinal imaging, dietary monitoring, and CDSS, help to enhance disease diagnosis, personalized therapy, and patient compliance. Furthermore, the research emphasized the challenges, ethical considerations, and future perspectives for incorporating AI into diabetes care to improve healthcare outcomes worldwide.

What is AI

Artificial intelligence is the development of computer systems capable of doing activities that normally require human intelligence. These tasks include learning, thinking, problem solving, and decision-making [14].

In the medical industry, AI uses algorithms and massive information to increase diagnostic accuracy, optimize treatment strategies, and improve patient outcomes. Artificial intelligence systems can understand complicated patterns in medical data faster and more correctly than humans, making them valuable AIDS in different healthcare applications, such as diabetes treatment [15].

Artificial intelligence can be classified into many sorts based on its capabilities. Narrow AI (or weak AI) is meant to do narrow tasks, such as image recognition or predictive analytics, but lacks general intelligence. In contrast, general AI (or powerful AI) would have cognitive capacities similar to humans, albeit this is still a speculative concept at this time. Another classification distinguishes AI into rule-based systems, which adhere to predetermined protocols, and machine learning (ML)-based systems, which improve their performance by analyzing massive datasets. Deep learning, a form of ML, uses neural networks to recognize patterns and generate advanced predictions. It is frequently used in medical imaging and disease modelling [16].

Current use of AI in endocrinology

Studies have shown that AI has the ability to diagnose endocrine diseases using facial recognition technologies. Kosilek *et al.* [17] used semi-automatic facial analysis software to identify Cushing's syndrome in women, with an overall accuracy of 91.7% based on texture and geometry in facial photos. Similarly, Kong *et al.* [18] used ML algorithms including support vector machines (SVM) and convolutional neural networks (CNN) to detect acromegaly in facial images. Using pictures from 527 acromegaly patients and 596 healthy controls, the best-performing model had 96% sensitivity and specificity. These results highlight the promise of AI-driven facial recognition as a practical endocrine problem screening tool, with superior diagnosis accuracy on par with conventional methods. Ludwig *et al.* [19] published a review in 2023 on the use of AI in identifying and classifying thyroid nodules, with an emphasis on ultrasonography as the major diagnostic method. The authors examined 930 papers from 2018 to 2022 and chose 33 relevant studies. They discovered that AI, namely ML algorithms, has greatly improved the accuracy of thyroid nodule assessments, assisting in discriminating between benign and malignant cases. Beyond cancer distinction, the review emphasized new AI applications such as cytopathology analysis, frozen section evaluations, and AI interaction with other diagnostic modalities.

Kosilek *et al.* [17] employed a semi-automated approach for analyzing facial texture and geometry to identify Cushing's syndrome in women. However, their small, gender-specific sample limits the applicability of the findings to wider populations and other endocrine disorders. Conversely, Kong *et al.* [18] utilized deep learning models, including CNN and SVM, for detecting acromegaly, achieving a notably high accuracy of 96% thanks to a larger and more diverse dataset. Nonetheless, their results were constrained by reliance on high-quality standardized facial images and the absence of external validation across different ethnic groups. Ludwig *et al.* [19] conducted a systematic review examining AI-based methods for diagnosing thyroid nodules, noting substantial advancements in using ultrasonography to distinguish benign from malignant lesions. However, their analysis revealed considerable variability in study methodologies, training data, and algorithm transparency, hindering reproducibility and clinical applicability. Overall, while AI systems demonstrate encouraging diagnostic accuracy, their effectiveness remains constrained by small and homogeneous samples, limited generalizability, absence of multicenter validation, and inconsistent algorithm performance and interpretability.

AI use in diabetes management

AI in diabetes screening diabetic retinopathy

Artificial intelligence is increasingly being used in the screening and management of diabetes complications, providing sophisticated capabilities for predicting, detecting, and monitoring disorders such diabetic retinopathy (DR), nephropathy, and neuropathy [15].

By analyzing massive datasets such as medical imaging, test findings, and patient histories, AI algorithms can detect tiny trends that traditional methods may not pick up. This allows for earlier diagnosis and more targeted therapy, which improves patient outcomes while lowering the long-term burden of diabetes complications. Artificial intelligence ability to give real-time information and personalized care has the potential to change the management of diabetes complications [20].

Rajalakshmi *et al.* [21] investigated the efficacy of AI in diagnosing DR and sight-threatening DR (STDR) using smartphone-based fundus photography. The researchers used the Remidio ‚Fundus on Phone' device to collect retinal pictures from 301 type 2 diabetes patients. The photographs were analyzed using AI software (EyeArt™) and compared to ophthalmologist assessments. The artificial intelligence had a sensitivity of 95.8% and specificity of 80.2% for detecting any DR, as well as a sensitivity of 99.1% and specificity of 80.4% for recognizing STDR. The study indicated that AI analysis of smartphone retinal imaging gives excellent sensitivity for DR and STDR identification, making it a promising tool for mass retinal screening in diabetic populations.

Studies have shown these early retinal changes, detectable *via* AI methods, position oculomics as a promising tool for noninvasive, early diabetes screening [20–22]. In addition, these methods have shown a sensitivity of 93% and a specificity of 91% to detect DR [22, 23]. Machine learning-integrated models have shown significant potential in automated screening and grading of DR. For example, these models can analyze retinal images to identify and classify DR through image recognition and advanced segmentation of image features, including retinal vasculature extraction from ultra-widefield fluorescein angiography frames [24]. Currently, there are three fully automated AI systems cleared by the US Food and Drug Administration (FDA) to diagnose DR: the IDx-DR (now LumineticsCore), the EyeArt AI diagnostic system, and AEYE Diagnostic Screening [25]. A study by Channa *et al.* [24], also showed that over 5 years, 27 000 fewer Americans would have vision loss with AI-based eye screening compared to screening performed by an eye-care provider.

AI in diabetes medical nutrition therapy

Artificial intelligence is becoming an indispensable tool in medical nutrition therapy (MNT) for diabetes management, delivering innovative methods to customize dietary advice and enhance patient results [10].

Artificial intelligence-powered systems produce personalized nutrition programs by analyzing a variety of data, such as patient demographics, food choices, glucose patterns, and lifestyle factors. These algorithms can forecast the impact of specific foods on blood sugar levels, make real-time modifications, and track progress, ultimately improving the efficacy of MNT [15].

Zhang *et al.* [26] created „Snap-n-Eat," a smartphone app that identifies and evaluates the nutritional content of foods. Using image recognition algorithms, the software analyses photographs taken with a smartphone camera to identify foods and deliver nutritional information. This application allows users, particularly those with diabetes, to quickly monitor and regulate their dietary intake, resulting in better control of the condition. Vasiloglou *et al.* [27] assessed the accuracy of GoCARB, a computer vision-based smartphone application, in predicting carbohydrate (CHO) content of plated meals for type 1 diabetics. The study compared GoCARB's estimates to those of six expert dietitians for 54 Central European meals, each with three distinct weighed food items. Both GoCARB and dietitians had comparable mean absolute errors in CHO estimate, with GoCARB at 14.8 grams and dietitians at 14.9 grams. The study indicated that GoCARB provides an easy, accurate, and near-real-time approach for calculating CHO content, which may improve diabetic self-management.

Artificial intelligence is rapidly being used in MNT to manage diabetes, providing personalized dietary suggestions that assist patients achieve better outcomes [10]. Artificial intelligence systems produce personalized nutrition regimens by analyzing a variety of characteristics such as patient demographics, eating choices, and glucose trends. These systems can track progress, make real-time adjustments, and predict how particular foods will affect blood sugar [28].

Smartphone apps that employ image recognition to assess nutritional content from food images can help diabetics better track and regulate their diet. Furthermore, AI-powered apps for assessing CHO content provide a practical and accurate technique for improving diabetic self-management [29].

The "dehumanization" of care, socioeconomic inequities, assigning blame for mistakes or malfunctions, and bias in model training and care delivery are some of the issues surrounding the usage of AI. Furthermore, stigma, over-medicalization, and stress may be linked to the prediction of illness onset in high-risk patients [30]. Although health professionals can employ such technologies as part of their work, there is a significant worry that AI systems in the field of nutrition and dietetics may partially replace dietitians. It is also critical to deploy AI applications for those with eating disorders or mental illnesses. Therefore, further rationale is needed for AI-assisted individualized nutrition, and the legal framework needs to be updated frequently to meet ethical concerns and keep up with scientific developments. Individuals and populations may adopt AI more readily if there is a coordinated worldwide focus on these areas [31]. Another worry is that dietitians may be partially replaced by AI systems in the field of nutrition and dietetics [32]. However, rather than replacing medical experts, this should primarily be seen as a shift in the way dietitians and customers communicate. Dietitians may, in fact, deliver and/or employ a number of AI protocols [33, 34]. It is highly advised to identify target users and non-indicated users and to make clear comments about the capabilities of the product in order to reduce such danger. Additionally, a special reminder that all material should be discussed with a physician and/or dietician would safeguard users, particularly those who have health issues. This is especially important for people with eating disorders, mental illness, or high vulnerability. For instance, the onset of an eating disorder may be linked to a teen using a weight-loss app unsupervised [35]. Since cuisine cultures and recipes might vary, there may be a number of variations between the nutrient makeup of photos and actual foods when it comes to dietary assessment using food images [36]. To put it another way, a significant problem is how AI algorithms are implemented. Nonetheless, positive health results can be attained, healthcare expenditures can be decreased, and patient outcomes can be improved if applied correctly [37, 38].

AI in diabetes physical therapy

Artificial intelligence is changing how physical exercise is tracked and optimized for diabetes treatment. Artificial intelligence can use wearable sensors, smartphone applications, and ML algorithms to detect activity patterns, heart rate, and glucose levels in real time and provide personalized exercise recommendations [39]. These AI-powered solutions assist people with diabetes in maintaining optimal physical activity (PA) levels by analyzing their responses to various types of exercise and predicting how activity affects blood sugar control. In addition, AI-powered virtual coaches and adaptive workout regimens provide personalized assistance, assuring safe and successful PA for diabetes prevention and treatment. Artificial intelligence integration in fitness and diabetes care improves self-management, lowers complications, and promotes long-term health [13].

A pilot study assessed the feasibility, acceptability, and efficacy of Sweetch, an AI-powered mobile health platform, in encouraging PA and weight loss among persons with prediabetes. Over three months, 55 individuals demonstrated a substantial increase in PA (+2.8 MET-hours/week, $p = 0.02$) and an average weight loss of 1.6 kg ($p < 0.001$). HbA_{1c} levels fell by a median of 0.1% ($p = 0.04$), although fasting blood glucose remained stable. There were no adverse occurrences reported. The data imply that Sweetch is a safe and effective tool for encouraging lifestyle adjustments in prediabetes, thereby lowering future diabetes risk [40].

It is strongly advised that patients with diabetes have a scientific, individualized, and quantitative exercise regimen that may be a crucial therapeutic agent. However, it is frequently poorly executed because doctors lack the requisite expertise, and participants have low adherence because of flaws in the design (e.g., prescriptions fail to take individual willingness, the attraction of exercise, and complex physical conditions into account). Therefore, it is worthwhile to look into clever, customized prescriptions. A coaching application that provides particular PA recommendations based on contextual information collected in real time was described by Everett *et al.* [40] (e.g., if location data indicate that the patient is in a park, then propose an activity to conduct there). Sun *et al.* [41] looked into whether Chinese middle-aged and older adult community residents' health outcomes could be enhanced by a yearlong, intelligent, tailored exercise prescription intervention based on cloud platforms. These findings imply that middle-aged and older Chinese community members may benefit from this exercise prescription intervention program in terms of cardiovascular function and body composition [40, 41].

Through computer vision-powered video analysis, AI also assists therapists in remotely evaluating the quality of movement. These instruments are as accurate as in-person evaluations in identifying movement restrictions or asymmetries. Without needing to be physically there, therapists can evaluate comprehensive reports or video summaries to make well-informed changes to treatment regimens [42, 43]. The use of AI in customized physical therapy regimens is a revolutionary development in the field of rehabilitation medicine. Artificial intelligence improves physical therapy's efficacy and accessibility by facilitating accurate evaluation, customized therapy planning, real-time monitoring, and remote care. These technologies give therapists strong tools that enhance professional knowledge, boost patient involvement, and facilitate data-driven decision-making. However, issues with data protection, ethics, physician training, and system integration must be resolved for deployment to be successful [43].

AI in diabetes monitoring

Artificial intelligence contributes significantly to diabetes monitoring by improving the precision and personalization of diabetes care [44]. Artificial intelligence algorithms are combined with continuous glucose monitoring (CGM) sensors and wearable devices to analyze vast amounts of patient data. These devices provide real-time insights on blood glucose levels and their rate of change, which are essential for optimizing insulin treatment and predicting undesirable outcomes such as hypoglycemia and hyperglycemia [39, 44]. Furthermore, AI-enhanced CGM systems can increase glucose monitoring accuracy by incorporating real-time signal processing algorithms for denoising, augmentation, and prediction. This can greatly reduce the uncertainty and inaccuracy of CGM sensors, making them more dependable for clinical application [45].

A 2021 randomized clinical study examined the effect of CGM on glycemic control in persons with type 2 diabetes treated with basal insulin alone. The trial, which was conducted in 15 centers across the United States, involved 175 people who were randomly assigned to either a CGM group (n = 116) or a standard blood glucose meter (BGM) monitoring group (n = 59). After 8 months, the CGM group had a significantly lower hemoglobin A_{1c} (HbA_{1c}) level, dropping from 9.1% to 8.0%, compared to the BGM group, which dropped from 9.0% to 8.4%. Furthermore, the CGM group spent more time within the target glucose range of 70–180 mg/dl and less time with glucose levels higher than 250 mg/dl. There were no severe hypoglycemia incidents reported in either group. These data indicate that CGM can successfully improve glycemic control in type 2 diabetes patients treated with basal insulin without the requirement for prandial insulin [46]. Another study demonstrates that CGM causes behavioral changes by delivering real-time feedback on glucose levels. This is expected to assist people with type 2 diabetes make better decisions regarding nutrition, exercise, and medication adherence. The large gains in HbA_{1c} and time in the target glucose range show that CGM promotes healthy habits and self-management without the need for extra insulin therapy [39]. Data analysis and prediction insights are the most important aspects of CGM that make use of AI. Artificial intelligence improves CGM by processing massive volumes of glucose data to find patterns and trends, allowing persons with diabetes to control their condition more effectively [39]. One of the main AI-driven functions in CGM is glucose trend prediction. By analyzing historical glucose data, AI can forecast future blood sugar levels, allowing users to take proactive steps to avoid hypoglycemia or hyperglycemia. These forecasts assist individuals in adjusting their meals, physical activity, or medication timing before glucose levels become troublesome [47]. Personalized alerts and recommendations are another important application of AI. Advanced CGM systems employ AI to tailor alerts to individual glucose trends, delivering real-time warnings and actionable recommendations. This personalized feedback helps people make more educated decisions and promotes adherence to diabetes care strategies [39].

Artificial intelligence also underpins AID systems, which combine CGM and insulin pumps to form hybrid closed-loop systems. These systems, including Medtronic's SmartGuard and Tandem's Control-IQ, use AI to continually alter insulin dose in response to CGM data. By automating insulin delivery, AI decreases user strain while improving glycemic control [48]. In addition, AI improves behavioral coaching by analyzing CGM trends and offering personalized insights *via* digital health platforms such as Dexcom Clarity and LibreView. These platforms provide personalized advice on nutrition, exercise, and medication adherence, enabling better self-management of diabetes [49].

Finally, AI-driven big data analytics contributes significantly to population health by analyzing CGM data from huge groups of patients. This enables healthcare providers to discover trends, improve treatment tactics, and create more successful diabetes control plans [28]. Overall, AI revolutionizes CGM by enhancing accuracy, personalization, and automation, making diabetes treatment more efficient and user-friendly [10].

AI in automated insulin delivery

Automated insulin delivery systems for diabetes treatment combine an insulin pump, CGM technology, and a control algorithm to optimize insulin dose and improve glycemic control [50]. These systems constantly alter insulin delivery based on real-time glucose readings from the CGM, with the control algorithm regulating insulin administration by increasing, reducing, or pausing it to keep glucose levels within a target range, often 100–120 mg/dl. Automated insulin delivery systems include hybrid closed-loop systems, low-glucose suspend systems, and CGM-augmented open-loop systems, which are all intended to improve glucose regulation and lessen the burden of diabetes treatment [50, 51]. Hybrid closed-loop systems automatically alter basal insulin delivery based on real-time CGM data, while the user manually administers bolus dosages at meals. These systems can forecast glucose trends and modify insulin delivery every 5 minutes to keep glucose levels within a specified range, usually 100–120 mg/dl [52].

Low-glucose suspend devices briefly stop insulin delivery when glucose levels are expected to fall below a certain threshold, thereby preventing hypoglycemia. These devices continue insulin delivery once glucose levels have stabilized [52]. Continuous glucose monitoring augmented open-loop systems provide the user with real-time glucose data, which is then used to manually alter insulin delivery. While not completely automated, these technologies can enhance glucose management by delivering constant input [52].

The American Diabetes Association emphasizes that AID systems use AI algorithms to analyze CGM data, forecast glucose trends, and alter insulin delivery. These systems can control insulin delivery by increasing, reducing, or halting insulin in response to CGM feedback, projected glucose levels, and the pace of glucose change. This integration of AI boosts the precision and personalization of insulin delivery, resulting in enhanced time in range (TIR) and lower risk of hypo- and hyperglycemia [52]. In addition to the types of AID systems previously discussed, several specific commercially available systems have distinct features and functionalities that integrate CGM and AI to optimize insulin dosing and improve glycemic control [52]:

- Medtronic MiniMed 780G: This hybrid closed-loop system employs the Guardian 3 sensor and incorporates an advanced algorithm that modifies basal insulin delivery every 5 minutes based on real-time CGM data. It also offers automatic correction boluses to treat hyperglycemia, increase TIR, and reduce hypoglycemia. The 780G/AHCL is safe and meets established glycemic objectives, according to a multi-center study by Carlson *et al.* [53]. Time in range improved (reported TIR up to ~75% with 100 mg/dl target), and there was no severe hypoglycemia or diabetic ketoacidosis occurrences during the trial period;
- Tandem t: slim X2 with Control-IQ: This device works with the Dexcom G6 sensor and has an algorithm that adjusts basal insulin delivery and provides automatic corrective boluses. It has features including a sleep mode for better nightly glucose control and an exercise mode to minimize insulin administration during physical activity. Pooled randomized data from Beck *et al.* [54] showed that Control-IQ was effective for all ages and baseline control levels. The results of the study demonstrated that the effects of Control-IQ are constant and especially beneficial for individuals with greater baseline HbA_{1c};
- Omnipod 5: This tubeless patch-pump device also incorporates the Dexcom G6 sensor and an adaptive algorithm that learns individual insulin requirements over time. It modulates insulin administration every 5 minutes and enables customizable glucose objectives. Forlenza *et al.* [55] found benefits in type 1 diabetes in pivotal trials and demonstrated positive glycemic outcomes across ages in a sizable retrospective real-world population. The usefulness of Omnipod 5 across a large user base is supported by this enormous real-world dataset;
- Tidepool Loop: An open-source, hybrid closed-loop system that works with a variety of insulin pumps and CGM systems. It is intended to give consumers flexibility and customization, although it is not yet generally available in a commercial format. Research has shown that adults and children with type 1 diabetes can safely and efficiently use the Loop open-source system, which can be started with community-developed resources [56, 57].

These systems use AI algorithms to analyze CGM data, anticipate glucose changes, and alter insulin delivery dynamically. This integration improves the precision and personalization of insulin administration, resulting in enhanced glycemic control and a lower risk of hypo- and hyperglycemia. One of the potential breakthroughs in AI-driven AID systems is "meal detection technology", which automatically identifies food consumption based on CGM data without the need for manual meal announcements [58]. This technology leverages deep learning and ML algorithms to detect glucose level changes indicative of meals, enhancing postprandial glucose control [58, 59].

Traditional hybrid closed-loop systems require users to announce meals manually, which can be time-consuming and error-prone. Meal detection technology automates this process, allowing AID systems to respond more accurately and efficiently to glucose fluctuations related by food consumption. Deep learning frameworks for meal detection and CHO estimate have been found in studies to improve mean blood glucose levels and TIR while without significantly increasing the risk of hypoglycemia. Furthermore, meal detection algorithms have showed earlier and more precise meal recognition, resulting in better insulin dosing and lower postprandial hyperglycemia [60].

Integrating meal detection technology with "multivariable AID systems" enables the automatic delivery of insulin boluses based on anticipated CHO intake, hence improving glycemic control. This innovation brings AID systems closer to totally closed-loop operation, decreasing the cognitive strain on users while boosting the effectiveness and convenience of diabetes control [60, 61].

The bionic pancreas is an advanced AID system that mimics the endocrine function of a healthy pancreas to help people control diabetes. It uses a CGM, an insulin pump, and a control algorithm to self-regulate blood glucose levels. The bionic pancreas can be either unihormonal, giving only insulin, or bihormonal, administering both insulin and glucagon to treat hyperglycemia and hypoglycemia, respectively [60, 61].

Clinical trials have shown that the bionic pancreas improves glycemic management. For example, a multicenter randomized trial found that the bionic pancreas lowered glycated hemoglobin levels and kept glucose levels within the target range more efficiently than normal treatment [61]. Another study found that the bihormonal bionic pancreas provided better glycemic management with fewer hypoglycemia episodes than standard insulin pump therapy [60]. Artificial intelligence improves glucose prediction and insulin dosing in AID systems, increasing their functionality and effectiveness. Artificial intelligence algorithms analyze CGM data to forecast future glucose trends and optimize insulin delivery, lowering the risk of hypoglycemia and hyperglycemia. AI-driven decision support systems can provide personalized suggestions for insulin changes, enhancing TIR and reducing hypoglycemia [39]. Overall, AI is changing AID systems into more intelligent, adaptable, and autonomous technologies that improve glycemic management, extend range, and reduce the risk of hypoglycemia and hyperglycemia. As AI-driven technologies advance, the future of diabetes treatment approaches a fully closed-loop system that greatly enhances the quality of life for diabetics [61].

AI in screening of complications

By combining ML algorithms, deep learning models, and big data analytics, AI is transforming the screening and early identification of diabetes-related problems. Diabetes is a multisystem illness that causes consequences like DR, nephropathy, neuropathy, and cardiovascular disease. Identifying these consequences is critical for limiting disease progression and improving patient outcomes [21].

One of the most commonly used AI applications is DR screening, in which deep learning models analyze retinal pictures to detect microvascular damage with high accuracy [21]. For a dataset of 6,500 patients in Iran, Tapak *et al.* [62] used artificial neural networks, SVM, fuzzy c-means, random forests, logistic regression, and linear discriminant analysis. Ten risk indicators were included as predictors (information pertaining to blood glucose was excluded). The study showed that SVM outperformed logistic regression and linear discriminant analysis in terms of under the curve. In a similar vein, Maniruzzaman *et al.* [63] contrasted linear discriminant analysis, quadratic discriminant analysis, and naive Bayes with Gaussian process-based methods using various kernels (linear polynomial and radial basis). The Gaussian process approach with a radial kernel produced the best accuracy. Second, there are more opportunities for AI diabetes screening thanks to the advancement of diverse sensing technologies and the creation of related new datasets. Using eight texture extractors, Shu *et al.* [64] thoroughly investigated the impact of texture features recovered from facial-specific regions on diabetes detection. Using SVM, the optimal texture feature extractor for diabetes mellitus detection may obtain 99.02% accuracy, 99.64% sensitivity, and 98.26% specificity. Li *et al.* [65] used ML approaches to predict the risk of pre-diabetes and diabetes and developed a non-invasive diabetes risk prediction algorithm based on tongue feature fusion. With an average accuracy of 0.821 and an average area under the receiver operating characteristic curve (AUROC) of 0.924, their model performed at its best. Zhang *et al.* [66] showed that DL models with AUROCs of 0.85–0.93.66 may be utilized to identify T2D from fundus images alone or in conjunction with clinical information. Furthermore, AI models have been created to predict diabetic kidney disease (DKD). Dong *et al.* [67] investigated the 3-year risk of DKD using ML models applied to electronic medical information. Using a variety of clinical variables, including laboratory tests, the study accurately predicted DKD progression. Specific model performance parameters such as accuracy, sensitivity, and specificity were highlighted, emphasizing ML potential to improve early detection and management of DKD in diabetic patients. Shi *et al.* [68] conducted another investigation on the automatic identification of DKD in type 2 diabetes patients by combining retinal vascular measures with clinical factors using AI. The model showed good sensitivity (84.5%) and specificity (84.5%) in detecting DKD, indicating its potential as a useful tool for early detection and diabetes treatment. Artificial intelligence models, by merging retinal imaging and clinical data, provide a promising technique to identify problems like DKD in diabetes patients.

Diabetic neuropathy (DN) is a common consequence of diabetes that can cause a variety of neurological disorders. Early detection is critical for controlling and avoiding future issues. Mengarelli *et al.* [69] developed a computer-aided screening system to identify DN through standing balancing exercises. The study used center of pressure data to divide individuals into non-neuropathic, asymptomatic neuropathy (AN), and symptomatic neuropathic categories. The first method produced over 86% accuracy in identifying the three groups, whereas the second pathway, separating symptomatic and AN, obtained over 97% accuracy, ensuring no asymptomatic patient was missed. Meng *et al.* [70] investigated the application of AI to diagnose peripheral neuropathy using corneal confocal microscopy pictures. The researchers used a binary classification algorithm to analyze the photos and identify indicators of diabetic neuropathy. The artificial intelligence model performed well, with a sensitivity of 94.7% and a specificity of 94.9%. This study demonstrates how AI can be efficiently used to increase diagnostic accuracy and early diagnosis of DN using non-invasive approaches, hence improving clinical decision-making.

Diabetic foot is a significant consequence of diabetes mellitus caused by a combination of peripheral neuropathy, peripheral artery disease, and poor wound healing. Patients with diabetic feet are more likely to develop infections, ulcers, and, in severe situations, amputations. Neuropathy impairs protective sense, but vascular insufficiency limits blood supply, making wound healing more difficult. Even minor injuries, if left untreated, can lead to chronic ulcers, infections, and gangrene, reducing quality of life [71].

Khandakar *et al.* paper described a novel AI-based approach for identifying the severity of diabetic foot problems using thermographic imaging. The researchers used k-means clustering to evaluate plantar temperature changes, which are a crucial indicator of ulcer risk. Both classical ML models and CNN were tested, with the VGG19 CNN scoring 95.08% accuracy and 97.2% specificity. Additionally, a stacking classifier integrating gradient boost, XGBoost, and random forest algorithms showed equivalent performance [72].

Artificial intelligence has shown tremendous promise in diagnosing and managing diabetes-related problems such as DR, nephropathy, neuropathy, and diabetic foot. Artificial intelligence models, which use deep learning, ML, and big data analytics, can improve diagnosis accuracy, forecast illness development, and enable timely therapies [10]. Studies have demonstrated that AI-driven techniques, such as retinal image analysis, electronic medical record-based predictions, and thermographic imaging, can considerably improve patient outcomes by allowing for early detection and personalized treatment plans. As AI technology advances, its incorporation into ordinary clinical practice will be critical to lowering diabetes-related morbidity and mortality. Additional research and validation across varied demographics are required to optimize AI applications and enable universal clinical use [10].

AI in clinical decision support systems

Artificial intelligence in CDSS involves the integration of ML and advanced analytics into healthcare decision-making procedures [73]. By analyzing massive datasets such as patient information, medical histories, and real-time clinical data, AI can help healthcare providers diagnose illnesses, forecast outcomes, and personalize treatment strategies. This technology improves decision-making by providing evidence-based suggestions, minimizing human error, and increasing patient care efficiency. Artificial intelligence-powered CDSS is quickly revolutionizing healthcare by making it more precise, efficient, and responsive [28].

Tarumi *et al.* [74] examine the use of AI to improve chronic illness management, with an emphasis on pharmacological decision assistance for type 2 diabetes mellitus. The authors investigated the use of ML approaches to help healthcare practitioners optimize pharmacological therapies for type 2 diabetes patients. Artificial intelligence-powered decision support systems are designed to personalize treatments, improve results, and reduce clinician burdens. The research emphasizes the necessity of incorporating AI technology to improve chronic illness care, notably in the management of type 2 diabetes.

Ljubic *et al.* [75] employed advanced ML models to predict ten complications of type 2 diabetes mellitus (DM2) from electronic medical records. Recurrent neural network (RNN) models, notably the gated recurrent unit model, outperformed classic methods like random forests, with prediction accuracy of 73–83% for complications such as myocardial infarction and chronic ischemic heart disease. The accuracy increased as the training data contained more hospitalizations and patient data. This work demonstrates the potential of deep learning for early prediction of DM2 problems.

Artificial intelligence has showed great potential in CDSS by increasing diagnostic accuracy, personalizing treatment recommendations, and improving patient outcomes. Artificial intelligence can analyze large datasets using ML models and prediction algorithms to deliver real-time recommendations, eliminate human error, and detect possible problems early on. These improvements allow healthcare providers to make informed, data-driven decisions, hence improving care for those with chronic illnesses such as diabetes. As technology advances, AI's position in CDSS is anticipated to become even more integrated into clinical practice [74, 75]. A comparison between outcomes: traditional vs. AI-augmented diabetes management is illustrated in Table 1.

Challenges and ethical considerations

Artificial intelligence in diabetic care poses various problems and ethical concerns [13]. One key concern is the possibility of bias in AI systems, which can result from skewed training data or decision-making procedures, leading to discrepancies in healthcare results [80]. It is critical to ensure that AI systems are egalitarian and do not worsen existing health inequities [81]. Another ethical consideration is the transparency of AI systems. Many AI models behave like „black boxes", making it impossible to comprehend how decisions are made. This lack of transparency can undermine trust between patients and healthcare providers. Ensuring that AI algorithms are explainable and their decision-making processes are transparent is critical for building trust and making educated clinical decisions [82].

Data privacy and security are also top priorities. Because artificial intelligence systems rely on large volumes of sensitive patient data, protecting these data from unauthorized access, breaches, and malicious cyberattacks is essential to preserving patient privacy and maintaining public trust. Compliance with regulatory criteria, such as those set by the FDA, is required to assure the safety, efficacy, and ethical integrity of AI-powered diabetic care applications [83]. Furthermore, the use of AI in clinical practice presents difficulties with patient autonomy and informed consent. Patients must be fully informed about the use of AI in their care, including the possible dangers and benefits. Ensuring that AI systems comply with ethical obligations from design to deployment is critical for their responsible and equitable integration into healthcare [84].

The effective application of AI technologies in rural and low-resource settings is hampered by a number of clinical and operational issues, despite its significant potential in the management of diabetes [85]. First, the efficacy of AI algorithms that depend on constant data input from wearable sensors like glucose monitors is hampered by inadequate digital infrastructure, such as poor internet access and a lack of cloud-based data storage [86, 87]. Second, low-income patients cannot afford AI-enabled insulin pumps, CGM devices, or smartphone-based apps [86, 88]. Lastly, underutilization or abuse of these tools results from a lack of qualified healthcare workers and data literacy needed to comprehend AI outputs and incorporate them into clinical processes [89]. Furthermore, the accuracy of forecasts in non-urban or ethnically diverse groups may be lowered by algorithmic bias, which results from the underrepresentation of varied populations in AI model training [90].

In conclusion, Table 2 summarizes the major forms of artificial intelligence and their key applications in diabetes care. It demonstrates how several AI approaches are being incorporated into different facets of diabetes treatment, from reinforcement learning and natural language processing to conventional ML and deep learning. Together, these methods improve clinical decision support, AID, tailored treatment optimization, and illness prediction. When taken as a whole, they show how AI can revolutionize precision medicine, simplify diabetic care procedures, and eventually enhance patient outcomes.

Conclusions

Artificial intelligence in diabetes treatment provides a paradigm shift in healthcare by overcoming significant shortcomings of traditional approaches, such as financial limitations, clinical stasis, and restricted access to healthcare services. Healthcare providers can improve long-term pa-

Table 1. Comparative outcomes: traditional vs. artificial intelligence-augmented diabetes management

System/study	Design	Sample size	Comparator	Key outcomes (glycemic control parameters)	Main conclusions
Medtronic MiniMed 780G/ Advanced Hybrid Closed-Loop System [53]	Multicenter randomized controlled trial	157 adolescents and adults with type 1 diabetes	Sensor-augmented pump therapy (manual insulin adjustments guided by CGM)	Glycated hemoglobin (HbA_{1c}) decreased by 0.5%; time in range (70–180 mg/dl) increased by 68–75%; time below range (hypoglycemia < 70 mg/dl) remained < 2%	The AI-driven automated correction algorithm significantly improved glucose regulation and reduced glycemic variability compared with conventional pump therapy
MiniMed 780G/ Real-World Study [76]	Prospective observational study (6-month follow-up)	235 individuals with type 1 diabetes	Pre-AID baseline using manual control	Time in range increased by 12%; mean glucose level decreased by 18 mg/dl; no cases of severe hypoglycemia reported	Demonstrated sustained improvement in glycemic outcomes and excellent safety of AI-enabled AID in real-world settings
Tandem t: slim X2 with Control-IQ Technology [54]	Multicenter randomized controlled trial	168 adults with type 1 diabetes	Sensor-augmented pump therapy (manual control)	Time in range improved to 71% vs. 59% in the comparator group; HbA_{1c} reduced by 0.33%; only one episode of severe hypoglycemia occurred	The closed-loop Control-IQ algorithm markedly enhanced glucose control and safety relative to traditional insulin delivery methods
Control-IQ/ Pediatric Trial [77]	Multicenter randomized controlled trial	101 children aged 6–13 years with type 1 diabetes	Standard insulin pump combined with CGM	Time in range increased by 11%; HbA_{1c} decreased by 0.4%; time spent in hypoglycemia (< 70 mg/dl) reduced by 0.9%	The AI-driven Control-IQ system safely optimized insulin delivery in pediatric populations and achieved better glycemic outcomes than standard therapy
Omnipod 5/ Pivotal Trial [78]	United States multicenter, single-arm pivotal clinical trial	241 adolescents and adults with type 1 diabetes	Baseline manual or hybrid insulin therapy (pre-trial)	HbA_{1c} reduction of 0.5–0.7%; time in range improved by 65–74%; hypoglycemia time < 2%	The Omnipod 5 hybrid closed-loop system significantly enhanced glycemic control while maintaining a very low incidence of hypoglycemia
Omnipod 5/ Real-World Evidence Study [55]	Retrospective analysis of real-world data (69,902 users)	–	Historical pre-system user data	Median time in range 73%; mean glucose 147 mg/dl; severe hypoglycemia 0.08 events per patient-year	Large-scale real-world evidence confirms the safety, reliability, and effectiveness of the AI-integrated Omnipod 5 system in everyday use
Tidepool Loop Study [79]	Prospective observational study and FDA regulatory submission	558 users with type 1 diabetes	User baseline data from open-loop or manual insulin delivery	Time in range increased by 13%; HbA_{1c} decreased by 0.4%; no cases of diabetic ketoacidosis or severe hypoglycemia	The Tidepool Loop became the first FDA-cleared open-source AI-based closed-loop insulin delivery application, demonstrating safety and efficacy comparable to commercial systems

AI – artificial intelligence, AID – automated insulin delivery, CGM – continuous glucose monitoring, FDA – Food and Drug Administration

Table 2. Overview of artificial intelligence types and applications in diabetes management

AI type/method	Description	Examples of techniques	Key applications in diabetes management
Machine learning [91]	A data-driven approach that enables algorithms to identify patterns and make predictions or classifications from structured datasets	Decision trees, random forests, support vector machines, gradient boosting	Used for forecasting glucose fluctuations, estimating insulin needs, detecting hypoglycemia risk, and predicting diabetes-related complications
Deep learning [92]	An advanced form of machine learning utilizing multi-layered neural networks to recognize complex relationships, particularly in large or unstructured data such as images or sensor outputs	Convolutional neural networks, recurrent neural networks, long short-term memory models	Applied in interpreting CGM data, analyzing retinal images for diabetic retinopathy, and supporting insulin dose prediction
Reinforcement learning [93]	A self-learning method where models optimize actions through feedback and rewards to improve performance over time	Q-learning, deep Q-networks	Facilitates adaptive insulin dosing and enhances the performance of automated closed-loop (artificial pancreas) systems for glucose regulation
Natural language processing [94]	A branch of AI that enables computers to interpret and derive meaning from human language in text or speech form	Text mining, sentiment analysis, transformer-based models (BERT, GPT)	Supports intelligent clinical decision-making, virtual patient education tools, and automated extraction of information from electronic health records

AI – artificial intelligence, CGM – continuous glucose monitoring

tient outcomes by leveraging AI-driven innovations like predictive analytics, CGM, AID systems, and CDSS. Furthermore, AI applications in diabetic complications screening, medical nutrition therapy, and personalised exercise regimens help to provide more comprehensive and individualised diabetes care. One of the most significant benefits of AI in diabetes treatment is its capacity to assist early identification and intervention, lowering the risk of serious consequences such DR, nephropathy, neuropathy, and cardiovascular disease. Artificial intelligence-powered screening technologies that use ML and deep learning algorithms have shown greater sensitivity and specificity in detecting certain disorders at earlier stages than traditional diagnostic approaches. Similarly, AI-driven CDSS helps doctors make evidence-based treatment decisions, reducing clinical inertia and assuring rapid therapeutic modifications.

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