

Artificial intelligence for diabetes management – a review

Abstract

Artificial Intelligence (AI) driven algorithms, including machine learning (ML) and deep learning (DL), analyze vast datasets from electronic health records (EHRs), wearable sensors, and continuous glucose monitors (CGMs) to provide accurate predictions and real-time insights. AI applications in diabetes management include automated insulin delivery systems (artificial pancreas), clinical decision support systems (CDSS), dietary and lifestyle coaching, and telemedicine platforms. These innovations improve glycemic control, reduce complications, and empower patients with personalized treatment plans. AI in diabetes care faces challenges such as data privacy concerns, lack of standardization, physician trust issues, and regulatory constraints. Additionally, AI models often suffer from bias due to non-representative datasets, limiting their generalizability across diverse populations. Future advancements will focus on improving AI transparency and explainability, enabling better clinical integration and physician adoption. As AI continues to evolve, its integration into diabetes management holds immense potential to enhance patient outcomes, reduce healthcare burdens, and pave the way for a more efficient, personalized, and data-driven approach to diabetes care.

Keywords: Artificial intelligence, machine learning, deep learning, diabetes mellitus

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Abbreviations: AI, artificial intelligence; ML, machine learning; DL, deep learning; IDF, international diabetes federation; CGM, continuous glucose monitoring; ICMR-INDIAB, Indian council of medical research- India diabetes; CDSS, clinical decision support systems; RRs, relative risks; MRI, magnetic resonance imaging; FDA, food and drug administration; T1DM, type 1 diabetes mellitus; SVMs, support vector machines; RF, random forest; KNNs, K-nearest neighbors; LR, logistic regression; NNs, neural networks; DNNs, deep neural networks; CNNs, convolutional neural networks; RNNs, recurrent neural networks; DME, diabetic macular edema; KNL-Means, k non-local-means; ANN, artificial neural networks; AUC, areas under the receiver operating characteristic curve; EHR, electronic health records; T2DM, type 2 diabetes mellitus; HF, heart failure; IR, infrared; CC, carbohydrate counting; ICR, insulin-to-carbohydrate ratio; ICF, insulin correction factor; IOB, insulin on board; RCT, randomized controlled trial; ICMR-NIN, Indian council of medical research - National institute of nutrition; SAED, smartphone-assisted electronic diabetes; ECG, electrocardiograms; PPG, photoplethysmography; ACC, accelerometers; EDA, electro dermal activity; SKT, skin temperature

Introduction

Artificial intelligence (AI) has emerged as a transformative force across various fields, including healthcare. It refers to computer systems capable of performing tasks that typically require human intelligence, such as pattern recognition, decision-making, and problem-solving.¹ AI encompasses a range of technologies, including machine learning

(ML), deep learning (DL), and natural language processing, which enable systems to analyze large datasets, recognize trends, and provide actionable insights.² AI applications have expanded rapidly in the context of diabetes care, offering innovative solutions for disease prediction, diagnosis, and management. The prevalence of diabetes mellitus is increasing at an alarming rate, making it a critical public health concern. The International Diabetes Federation (IDF) estimates that over 537 million adults worldwide have diabetes, and this number is projected to rise significantly in the coming decades.³ According to the Indian Council of Medical Research- India Diabetes (ICMR-INDIAB) study, the overall weighted prevalence of diabetes in India is 11.4% (95% CI 10.2–12.5). Additionally, prediabetes affects 15.3% of the population, putting millions more at risk of developing full-blown diabetes in the future.⁴ With the growing burden of diabetes, conventional healthcare models are struggling to provide timely and effective care. AI-driven solutions offer the potential to enhance early detection, optimize treatment plans, and support continuous glucose monitoring (CGM), thereby improving overall disease management.

AI has already demonstrated its effectiveness in diabetes care by enabling personalized treatment strategies and automating complex decision-making processes. For example, AI-powered clinical decision support systems (CDSS) assist healthcare providers in recommending the most suitable treatment based on an individual's medical history and real-time health data.⁵ Additionally, AI is being integrated into wearable devices that continuously monitor blood glucose levels, providing predictive analytics to alert patients and physicians of potential complications before they occur.⁶ (Figure 1)

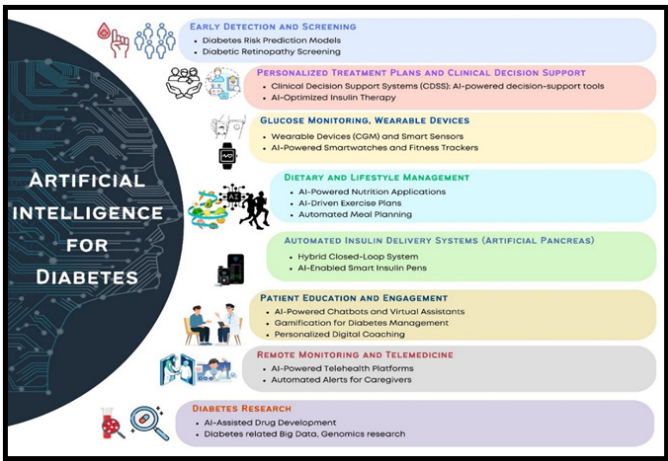


Figure 1 Applications of AI for Diabetes management.

The need for AI in diabetes management stems from the limitations of traditional approaches, which often involve reactive rather than proactive care. Many patients remain undiagnosed or receive treatment only after complications arise, leading to increased morbidity and healthcare costs. AI-driven predictive models can identify individuals at high risk for diabetes, enabling early intervention and lifestyle modifications to prevent disease progression. Moreover, AI can

address disparities in diabetes care by offering remote monitoring and telehealth solutions, particularly in underserved regions with limited access to endocrinologists and diabetes specialists. Looking ahead, AI is poised to play a crucial role in shaping the future of diabetes management. As advancements in ML and big data analytics continue to evolve, AI systems will become increasingly sophisticated, offering more accurate diagnoses, real-time treatment adjustments, and enhanced patient engagement. However, challenges such as data privacy concerns, ethical considerations, and integration into existing healthcare infrastructures must be addressed to fully realize the potential of AI in diabetes care.⁷ Despite these hurdles, AI presents a promising opportunity to revolutionize diabetes prevention, diagnosis, and treatment, ultimately improving patient outcomes on a global scale. According to Khalifa et al.,⁸ AI helps increase care accuracy, empowers individuals to understand diabetes better, and provides personalized, efficient solutions. A systematic review and meta-analysis conducted by Alhalafi et al..⁹ revealed that symptom detection and management consistently demonstrated better outcomes with AI interventions, showing relative risks (RRs) of 0.97 (95% CI: 0.87–1.08, $I^2 = 0\%$) for symptom detection and 0.97 (95% CI: 0.56–1.57, $I^2 = 0\%$) for symptom management.

The history of AI in healthcare spans several decades, with key milestones shaping its development and application in medicine. The evolution of AI in healthcare can be categorized into distinct phases, each marked by significant advancements (Table 1).

Table 1 History of AI in Healthcare^{10,11}

Year	Milestones
1950 – 1979 the foundations of AI in medicine	I. 1950 – Alan Turing introduced the concept of machine intelligence with the "Turing Test," laying the groundwork for AI research.
	II. 1956 – John McCarthy coined the term "Artificial Intelligence," defining it as the science and engineering of making intelligent machines.
	III. 1964—Joseph Weizenbaum developed the first chatbot, ELIZA, to simulate human conversation, showcasing early AI applications in language processing.
	IV. 1972 – MYCIN, an AI system designed to diagnose bacterial infections, was developed at Stanford University, demonstrating AI's potential in medical decision-making.
1980 – 2000 the emergence of expert systems and AI winters	I. 1986 – DXplain, a clinical decision support system (CDSS), was introduced, enabling physicians to generate differential diagnoses based on patient symptoms.
	II. 1990s – AI saw limited growth due to computational constraints and a lack of large datasets, leading to the "AI Winter" phase.
	III. 1997 – IBM's Deep Blue defeated world chess champion Garry Kasparov, illustrating AI's capacity for complex problem-solving, which later influenced AI development in healthcare.
2000 – 2010 The rise of machine learning in healthcare	I. 2007 – IBM's Watson, an AI system capable of analyzing vast amounts of unstructured data, was created. Later, it was adapted for healthcare applications.
	II. 2010 – AI applications expanded to include disease risk prediction and medical imaging analysis, with increasing use in radiology and pathology.
2011 – present the era of deep learning and AI integration in healthcare	I. 2011 – IBM Watson won the Jeopardy competition, showcasing advancements in AI's natural language processing capabilities.
	II. 2017 – The first FDA-approved AI-based medical imaging system, Arterys, was introduced for analyzing cardiac Magnetic resonance imaging (MRI) images.
	III. 2019 – AI-assisted endoscopy tools, such as GI Genius, were developed for automated polyp detection in colonoscopy.
	IV. 2020 – Present – AI in healthcare has seen widespread adoption, with applications in personalized medicine, robotic surgeries, and predictive analytics in disease management.
AI for diabetes care	
1990s early AI applications in diabetes	I. 1999: The U.S. Food and Drug Administration (FDA) approved the first Continuous Glucose Monitoring (CGM) system, marking a significant advancement in diabetes management technology.
2000s advancements in predictive analytics	I. 2006: The FDA approved the first CGM system developed by Dexcom, allowing for real-time data to patients and healthcare providers. ¹²

Table 1 Continued....

2010s integration of AI in diabetes devices	I.	2015: MiniMed 640G, the first predictive insulin suspend algorithm.
	II.	2016:The FDA approved the Medtronic MiniMed 670G, the first hybrid closed-loop insulin delivery system. This system utilized AI algorithms to automatically adjust basal insulin delivery based on CGM reading. ¹³
	III.	2018:The FDA approved the FreeStyle Libre, a flash glucose monitoring system that provided real-time glucose readings without the need for fingerstick calibration. ¹⁴
2020s expansion of AI applications	I.	2023:The NHS in England announced plans to provide individuals with type 1 diabetes mellitus (T1DM) with artificial pancreas devices, which automate blood sugar control by continuously monitoring glucose levels and delivering insulin as needed. ¹⁵
	II.	2024:AEYE Health developed an AI-powered system capable of diagnosing diabetic retinopathy in one minute using a portable camera, facilitating early detection and treatment to prevent vision loss. ¹⁶

AI for early detection and screening of diabetes

AI is transforming the early detection and screening of diabetes by enabling faster, more accurate, and cost-effective diagnosis. AI-driven predictive models analyze patient data to identify high-risk individuals before clinical symptoms appear, allowing for timely intervention and prevention. Several AI models are utilized for diabetes diagnosis, improving accuracy and early detection. Support Vector Machines (SVMs) classify diabetic and non-diabetic individuals with high accuracy (80 to 99.3%),^{17–19} while Random Forests (RFs) use multiple decision trees, achieving around 78–85% accuracy.^{20–22} K-Nearest Neighbors (KNNs) classify patients based on similarity, with performance varying between 66.7% and 94.87%.^{23–25} Logistic Regression (LR), a simpler statistical model, shows lower accuracy (55.5–66.2%) but remains widely used.^{25–27} Advanced DL models, such as Neural Networks (NNs) and Deep Neural Networks (DNNs), provide enhanced accuracy (86–92%),^{28–30} with Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) models improve sequential data analysis.^{24,31} Additionally, ensemble learning approaches, which combine multiple AI models, further enhance diagnostic precision, achieving 80–93.8% accuracy.^{32,33}

According to Han et al.,³⁴ 3D CNN algorithm was designed to be integrated with Magnetic resonance imaging (MRI) to diagnose diabetic macular edema (DME). The diagnostic accuracy of MRI was 93.78 ± 5.32%, significantly improving the accuracy and sensitivity. Ultrasound images of Diabetic kidney disease (DKD) individuals, along with K non-local-means (KNL-Means) filtering algorithm, detected the changes in the levels of renal function.³⁵ Artificial neural networks (ANN) help in understanding the risk factors for diabetes based on the studies by Wang et al.,³⁶ Gholipour et al.,³⁷ and Zhang et al.³⁸ The risk factors included hypertension, dyslipidemia, smoking, inadequate physical activity, erratic eating, and obesity. Clinical data and fundus images were used to identify chronic kidney disease and diabetes with areas under the receiver operating characteristic curve (AUC) of 0.85–0.93.³⁹ ML-based models use an individual’s data [age, height, weight, body mass index (BMI), glycemic values, hemoglobin, serum electrolytes levels, etc.] to classify the risk of diabetes.⁴⁰

Predictive Models for Onset of Diabetes

Predicting the onset of diabetes plays a crucial role in preventive medicine by identifying individuals who are at a high risk of developing the condition before it manifests clinically. By leveraging advanced diagnostic tools and predictive models, healthcare providers can implement timely interventions, such as lifestyle modifications and personalized treatment plans, to delay or even prevent the progression of diabetes.¹

A machine-based model was developed to predict T1DM by Zou et al. using fasting and postprandial blood glucose, HbA1c, high-density lipoprotein cholesterol (HDL-C), and triglycerides. This model demonstrated strong predictive performance, with an AUC

of 0.80 in internal and external validations.⁴¹ A retrospective study utilized Electronic Health Records (EHR) data to develop an ML model for detecting T1DM misdiagnosed as type 2 diabetes mellitus (T2DM). Key predictors included BMI, age, HbA1c, blood glucose levels, and therapy history. The model demonstrated 17% precision at 10% recall, significantly outperforming the <1% misdiagnosis rate at initial T2DM diagnosis.⁴² Five ML models were developed and implemented with five different ML algorithms, including the RF approach. To identify significant predictors of heart failure (HF), a multivariate logistic regression analysis was conducted, revealing that age, poverty-to-income ratio, history of myocardial infarction, presence of coronary heart disease, occurrence of chest pain, and the use of glucose-lowering medications were independent risk factors associated with HF. The RF model demonstrated the highest accuracy, achieving an AUC of 0.978, making it the most effective model for HF prediction.⁴³ In a study conducted by Ravaut et al., a gradient-boosting decision tree model was developed and trained to assess its predictive performance. The model achieved an AUC of 80.26 (80.21–80.29), indicating strong discriminatory ability. Additionally, it demonstrated good calibration, ensuring reliable probability estimates across different risk levels. The model exhibited robustness across various demographic and socioeconomic factors, including sex, immigration status, race/ethnicity, and area-level marginalization related to material deprivation.⁴⁴

Prediabetes

Machine learning models, particularly ensemble methods like random forests and gradient-boosting machines, analyze clinical and lifestyle variables such as age, BMI, family history of diabetes and hypertension, physical activity, and fasting glucose levels, etc., to predict progression from prediabetes to T2DM.^{45–47} Kushwaha et al.,⁴⁸ developed an ML model to non-invasively screen for pre-diabetes in children and adolescents aged 5–19 years. Researchers tested six models and found XGBoost to be the most accurate, achieving a 90.13% cross-validation score and an AUC of 0.959. Researchers developed and validated a logistic regression model to predict prediabetes risk using EHR data from 22,635 adults, with 26% having prediabetes. The model demonstrated good discrimination (C-statistic: 0.763) and was externally validated using NHANES data from 2,348 participants (30.1% with prediabetes), achieving a C-statistic of 0.787.⁴⁹

Predicting diabetes complications

AI algorithms are increasingly being utilized to predict diabetic complications, offering advanced tools for early detection and personalized intervention. By analyzing vast amounts of patient data, including EHRs, lab results, and medical imaging, AI-driven models can identify individuals at high risk for complications such as diabetic retinopathy, nephropathy, neuropathy, and cardiovascular diseases.

Various systems are doing retinal image analysis^{50,51} and along with genetic details, cardiovascular risk and other complications can be predicted.^{52,53} Clinical data and fundus images were used to identify chronic kidney disease and diabetes with an AUC of 0.85–0.93.³⁹ A study by Khandarkar et al.,⁵⁴ demonstrates the effectiveness of ML in classifying infrared (IR) foot thermograms for early detection of diabetic foot complications. Among the tested networks, the VGG19 CNN achieved the highest performance, with 95.08% accuracy, 95.08% precision, 95.09% sensitivity, 95.08% F1-score, and 97.2% specificity in stratifying severity. A study presents a DL algorithm based on CNN with data augmentation for the automated quantification of the corneal sub-basal nerve plexus in diagnosing diabetic neuropathy. The algorithm accurately quantified nerve fiber length, branch points, tail points, nerve segments, and fractal numbers. The algorithm achieved an AUC of 0.83, a specificity of 0.87, and a sensitivity of 0.68 in classifying diabetic neuropathy based on the Toronto criteria.⁵⁵

AI for personalized treatment plans and clinical decision support

AI is transforming diabetes management by enabling personalized treatment plans and CDSS that optimize patient care based on real-time data and predictive analytics. Traditional treatment approaches often follow standardized protocols, which may not be equally effective for all individuals due to genetic variations, lifestyle, metabolic responses, and comorbid conditions.⁵⁶ AI-driven models leverage ML algorithms and DL techniques to analyze vast amounts of EHRs, CGM data, and patient history to deliver individualized treatment recommendations. One of the key applications of AI in personalized diabetes care is insulin dose optimization.^{40,57} Advanced ML algorithms, such as reinforcement learning and deep neural networks, process CGM readings, carbohydrate intake, physical activity levels, and insulin sensitivity to provide real-time insulin dosage recommendations. AI-driven platforms like DreaMed Advisor Pro and CamAPS FX assist healthcare providers in fine-tuning insulin therapy for T1DM & T2DM, reducing the risk of hypoglycemia and hyperglycemia.⁵⁸ AI-driven CDSS tools help endocrinologists determine the most effective medication regimens, considering factors such as HbA1c levels, renal function, and cardiovascular risk.

Sinedie, a web-based telemedicine platform, was clinically evaluated over 17 months with 90 gestational diabetes individuals. AI-driven automation significantly reduced clinician workload, cutting patient evaluation time by 27.39% and minimizing face-to-face visits by 88.56%. Patients demonstrated high adherence, measuring glycemia an average of 3.89 times daily and submitting monitoring data every 3.48 days. Additionally, individuals expressed high satisfaction, finding the platform useful and reliable for managing their condition.⁵⁹ A meta-analysis of 108 studies (94 randomized, 14 quasi-randomized) with data from 1,203,053 patients found that CDSS increased adherence to recommended care by 5.8% (95% CI: 4.0–7.6%). Among 30 trials assessing clinical endpoints, CDSS improved guideline-based target achievement (e.g., blood pressure or lipid control) by a median of 0.3% (IQR: -0.7% to 1.9%).⁶⁰ A systematic review and meta-analysis by Jeffery et al.,⁶¹ reported that CDSS improved clinical outcomes (HbA1c, quality of life, hospitalization) in diabetes management.

Hospital-wide glycemic management systems (HGMS) have emerged as essential tools to standardize and improve glycemic control in hospitalized patients with diabetes or stress-induced hyperglycemia.⁶² These systems integrate EHRs, real-time glucose monitoring, CDSS, and multidisciplinary care protocols to facilitate timely insulin adjustment and reduce glycemic variability.⁶³ Sheen

et al.,⁶⁴ demonstrated that implementing an electronic dashboard with a remote management system significantly improved glycemic outcomes in hospitalized patients. The system enabled real-time tracking of glucose data and provided clinicians with decision support, leading to enhanced compliance with glycemic targets and reduced hypoglycemia rates. Another study evaluated the efficacy of an HGMS implemented across multiple wards, finding that it not only improved glycemic control but also reduced hospital length of stay and the incidence of acute glycemic events. A study evaluated the efficacy of HGMS in patients with malignant tumors and hyperglycemia. The intervention group, managed with HGMS, showed significant improvements in glycemic control compared to the control group, including reduced mean blood glucose levels, decreased incidence of hypoglycemia, and higher patient satisfaction rates (97.46% vs. 90.31%, $P < 0.05$).⁶⁵ AI-enabled platforms such as Glucomanager and EndoTool have demonstrated improved glycemic outcomes and reduced hypoglycemia events in inpatient settings.⁶⁶

Glucose monitoring, insulin delivery, self-management, & wearable devices

AI is revolutionizing glucose monitoring by enhancing the capabilities of wearable devices to provide real-time, continuous, and personalized diabetes management.

Continuous glucose monitoring (CGM)

Traditional glucose monitoring methods, such as fingerstick blood glucose tests, offer only single-point measurements, limiting their effectiveness in capturing glucose trends. In contrast, AI-integrated CGM systems provide a comprehensive view of daily glucose fluctuations. By analyzing large datasets of glucose readings, AI algorithms can detect patterns, predict future glucose levels, and offer personalized recommendations to help patients maintain optimal blood sugar control.⁶⁷ Wearable devices such as the Freestyle LibrePro and Libre 1, 2, 3 (Abbott), Guardian 3 and 4 (Medtronic), and Dexcom G6 and G7 use AI-driven analytics to improve glucose management. These systems collect real-time glucose data and employ ML models to forecast potential hyperglycemic or hypoglycemic episodes, alerting users in advance.⁶⁸ AI-powered predictive analytics enable individuals to adjust their diet, exercise, and medication regimens proactively, reducing complications associated with diabetes.⁶⁹ Additionally, AI algorithms personalize insulin dosing by considering factors such as food intake, physical activity, stress levels, and sleep patterns, ensuring more precise glucose regulation.

A systematic review and network meta-analysis by Lu et al. (11 studies, 1425 individuals), reported that CGM reduced time above range (-9.06%), time below range (-0.30%), and increased time in range (8.49%).⁷⁰ A study by Tan et al.,⁷¹ reported that CGM reduced HbA1c (-0.40%), time above range (-4.33%), and increased time in range (6.00%). Another systematic review and meta-analysis by Uhl et al. (14 studies), reported HbA1c moderately by 0.32%.⁷² According to Seidu et al., CGM reduced HbA1c (-0.19%), while intermittently scanned CGM reduced HbA1c by 0.31% and improved user satisfaction.⁷³

Applications

Carbohydrate counting (CC) applications like mySugr are crucial in simplifying daily diabetes management by enabling users to log meals, track carbohydrate intake, and analyze their impact on glucose levels. These applications help individuals with diabetes make informed dietary decisions by correlating carbohydrate consumption with blood glucose fluctuations, ultimately supporting better glycemic control. It can be integrated with CGM, allowing real-time tracking

and personalized insights. Other features include insulin dose logging, physical activity tracking, and medication reminders.⁷⁴

Bolus calculators are essential tools in diabetes management, designed to help individuals accurately determine the appropriate insulin correction dose based on various physiological and treatment-related factors.⁷⁵ Bolus calculators consider several key parameters, including the target blood glucose level, current blood glucose reading, insulin-to-carbohydrate ratio (ICR), insulin correction factor (ICF), and the duration of insulin action.⁷⁶ Additionally, they factor in the active insulin on board (IOB) to prevent insulin stacking, reducing the risk of hypoglycemia. mySugr, Bolus Calculator, and GlucoLog RapidCalc are some examples. Ahmad et al. suggested a fully automatic insulin delivery system, which eliminated the need for carbohydrate counting and meal announcements.⁷⁷

Automated Insulin delivery systems (Artificial Pancreas)

The integration of AI with wearable glucose monitoring devices has also facilitated automated insulin delivery systems, commonly known as the artificial pancreas. These closed-loop systems, such as the Tandem Control-IQ and Medtronic MiniMed 780G, leverage AI to automatically adjust insulin delivery based on CGM readings. By continuously analyzing glucose levels and predicting future trends, these systems help prevent glucose excursions, reducing the burden on patients and enhancing their quality of life.

A randomized controlled trial (RCT) evaluated the short-term safety and efficacy of an artificial pancreas system in managing nocturnal glucose levels in individuals with T1DM. The number of hypoglycemic episodes (<63 mg/dL) was lower (7 vs. 22; $P=0.003$), and the duration of glucose levels below 60 mg/dL was shorter ($P=0.02$) compared to the sensor-augmented pump. Median overnight glucose levels were 126.4 mg/dL (7.0 mmol/L) with the artificial pancreas versus 140.4 mg/dL (7.8 mmol/L) with the insulin pump, with no serious adverse events.⁷⁸ According to the FLAIR study, the proportion of daytime glucose levels above 180 mg/dL decreased from 42% at baseline to 34% with an advanced hybrid closed-loop system.⁷⁹

Smartwatches & fitness trackers

Furthermore, AI-powered wearable technology extends beyond glucose monitoring to comprehensive metabolic health tracking.⁸⁰ Smartwatches and fitness trackers, such as the Apple Watch, Galaxy watch 4 and Fitbit, now incorporate AI-driven glucose prediction models, utilizing non-invasive biosensors to estimate blood sugar levels based on heart rate variability, sweat composition, and skin temperature.⁶⁹ These advancements offer non-invasive alternatives for individuals at risk of diabetes, enabling early detection and proactive lifestyle interventions.

A systematic review by Ahmed et al. evaluated AI in wearable devices for blood glucose prediction using the QUADAS-2 tool. ML models, particularly ensemble-boosted trees (random forest), were the most commonly used approaches. Wrist-worn devices frequently employed photoplethysmogram and near-infrared sensors, highlighting the trend toward non-invasive glucose monitoring.⁸¹ Another systematic review reported that wearable devices could benefit individuals with diabetes, researchers, and healthcare professionals.⁸²

Dietary and lifestyle management

AI is transforming dietary and lifestyle management for diabetes by providing personalized meal plans, exercise recommendations, and behavior modification strategies.⁸ AI-driven systems analyze

real-time health data, dietary intake, glucose fluctuations, and lifestyle patterns to offer tailored interventions, enhancing blood sugar control and overall well-being.¹ A food image analysis system can be used (semi-automatic or automatic) for food recognition, calorie intake calculation, and segmentation.⁸³ ML-based algorithms can be used to create personalized diets integrating parameters (diet, physical activity, etc.) for better glycemic response.⁸⁴ NutriAIDE mobile application is an advanced AI-driven nutrition tool developed by the Indian Council of Medical Research - National Institute of Nutrition (ICMR-NIN). The application enables users to monitor both macronutrient and micronutrient intake with precision. An AI-based photo recognition tool that allows users to capture images of their meals, automatically identifying foods and providing detailed nutritional information. It encourages users to assess their eating patterns, engage in regular physical activity, and evaluate their overall food environment, promoting holistic lifestyle changes.⁸⁵

An RCT by Lee et al.,⁸⁶ suggested that AI-integrated digital platforms (AI-based diet management) helped in reducing HbA1c and weight when compared to routine diabetes care. A web-based AI-driven nutrition platform, personalized meal planning, and recipes showed a reduction in weight (MD: 4.5 kg/m²) and waist circumference (MD: 3.9 cm).⁸⁷ The Sweetch application helped deliver specific physical activity recommendations in real time and reduced weight and HbA1c in individuals with prediabetes.⁸⁸

Recent advancements in fuzzy logic, particularly Type-2 Fuzzy Set Systems (T2FSS), have contributed to developing more nuanced AI-based dietary monitoring frameworks.⁸⁹ T2FSS can model the uncertainty and vagueness inherent in nutritional assessments, including subjective food portion estimations and varied metabolic responses. One such system, the Type-2 Fuzzy Set-based Implant Disease Risk Assessment (T2FS-IDRA) method, integrates dietary intake data with metabolic and behavioral parameters to provide personalized dietary risk profiling.⁹⁰ These systems are increasingly being tested for diabetes risk monitoring, leveraging intelligent rule-based architectures that adaptively manage food intake recommendations and glycemic responses.⁹¹

Patient education/ self-management and engagement

AI provides personalized learning experiences, real-time feedback, and interactive support systems. AI-driven solutions, such as chatbots, virtual health assistants, and mobile applications, offer on-demand, adaptive education tailored to individual needs, helping patients make informed decisions about their health.^{92,93} AI-powered chatbots and virtual assistants, integrated into mobile apps and telemedicine platforms, provide real-time answers to patient queries, medication and glucose monitoring reminders, and personalized lifestyle recommendations. A systematic review and meta-analysis (25 studies) reported that chatbot intervention provided personalized diet, physical activity, and medication recommendations. They also helped in lowering blood glucose (MD: 0.30).

A Smartphone-Aided Electronic Diabetes (SAED) system was evaluated for T2DM management. There were significant improvements in the intervention group, with a notable reduction in HbA1c levels compared to the control group. Additionally, diabetes awareness increased among SAED users.⁹⁴ Another application-based education program showed similar results, with decreased initiation of insulin and improved glycemic control.⁹⁵

Remote monitoring and telemedicine

AI provides real-time, data-driven solutions for diabetes management. AI-powered telemedicine platforms enable continuous monitoring, early detection of complications, and personalized

treatment adjustments, improving patient outcomes and healthcare accessibility. AI-driven telemedicine platforms also facilitate virtual consultations between patients and healthcare professionals.⁴⁰ Patients can receive timely medical advice, medication adjustments, and lifestyle recommendations without visiting a clinic through secure video calls, mobile applications, and AI-powered chatbots. AI-powered mobile applications provide interactive health coaching, dietary tracking, and medication reminders, helping patients maintain better control over their condition.⁹⁶ Studies have shown that the outcomes of telemedicine care are similar to normal care.^{97,98} A systematic review by Marsh et al. reported that diabetes education by telemedicine improved adherence and reduced HbA1c levels.⁹⁹

Diabetes research

Traditional research methods often rely on manual data analysis and lengthy clinical trials, which can be time-consuming and resource intensive. AI-driven approaches, particularly ML and DL algorithms, enable researchers to process vast datasets efficiently, identify patterns, and generate actionable insights to improve diabetes prevention and management.¹⁰⁰ One of AI's most significant contributions to diabetes research is its ability to analyze multi-omics data, including genomics, proteomics, and metabolomics, to identify genetic risk factors and potential therapeutic targets.⁵⁶ AI also plays a crucial role in drug discovery and development for diabetes treatment.^{101,102} AI-driven digital biomarkers offer non-invasive, continuous, and personalized monitoring using data from wearable devices, mobile health technologies, and EHRs. AI models leverage data from electrocardiograms (ECG), photoplethysmography (PPG), accelerometers (ACC), electrodermal activity (EDA), and skin temperature (SKT) sensors to detect early physiological changes.¹⁰³ AI-enhanced retinal imaging tools such as IDx-DR and EyeArt have demonstrated high sensitivity and specificity in detecting diabetic retinopathy.¹⁰⁴

Challenges and limitations of AI

Despite AI's transformative potential in diabetes care, several challenges and limitations hinder its widespread adoption and effectiveness.^{1,7,40,56,92} Addressing these limitations ensures that AI can effectively support personalized, efficient, and equitable diabetes management. (Figure 2)

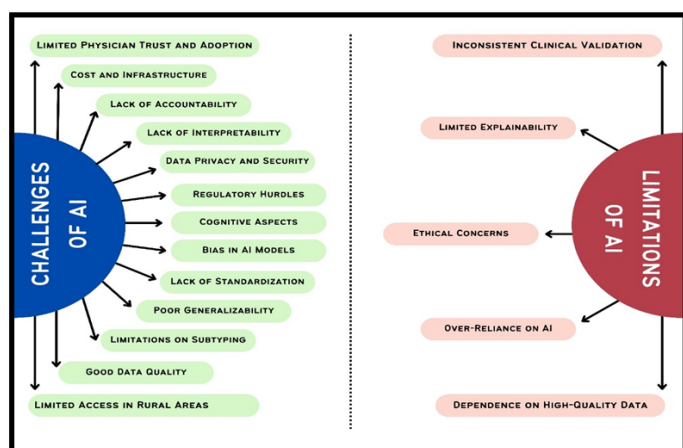


Figure 2 Challenges and limitations of AI.

Conclusion

AI has become a powerful tool in diabetes care, revolutionizing early detection, personalized treatment, glucose monitoring, patient

education, and remote management. Despite its significant potential, data privacy, model transparency, physician trust, and regulatory barriers must be addressed to ensure widespread clinical adoption. Future advancements will focus on improving AI transparency and explainability, enabling clinicians to understand and trust AI-driven recommendations. Expanding affordable AI-driven remote monitoring will enhance access to real-time glucose tracking and telemedicine, particularly in resource-limited regions. Additionally, regulatory advancements will establish standardized guidelines for AI approval, ensuring safety, accuracy, and ethical implementation in healthcare. Furthermore, global AI collaboration in diabetes research will foster inclusive, diverse, and representative datasets, leading to more generalizable and effective AI models. By overcoming existing challenges and leveraging future innovations, AI has the potential to transform diabetes management, making care more precise, accessible, and patient-centric while improving long-term health outcomes.

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Conflicts of interest

The author declares that there are no conflicts of interest.

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