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Review article

Artificial intelligence and medical-engineering integration in diabetes management: Advances, opportunities, and challenges

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ABSTRACT

Background: Global incidence and prevalence of diabetes have been rising steadily, leading to increased disability, mortality, and a significant economic burden. Despite advances in medical care, challenges such as shortage of diabetes specialists, unequal distribution of healthcare resources, suboptimal medication adherence, and poor self-management have contributed to inadequate glycemic control in patients.
Objective: This review examines the latest advances in artificial intelligence (AI) applications for diabetes management, evaluating its potential to improve patient outcomes and reduce the economic burden on healthcare systems.
Methods: We comprehensively reviewed recent studies and clinical trials that explore the use of AI in diabetes prevention, diagnosis, and management. Key technologies such as machine learning, predictive analytics, and digital health tools were assessed for their clinical applicability and impact on patient care.
Results: AI-driven approaches, including predictive models for glycemic control, personalized treatment plans, and digital monitoring systems, have shown promising results in enhancing diabetes management. However, challenges remain in integrating these technologies into clinical practice, particularly regarding data privacy, algorithmic transparency, and training of healthcare providers.
Conclusion: While AI presents substantial opportunities for improving diabetes care and reducing healthcare costs, its successful implementation requires overcoming several barriers, including regulatory hurdles and ensuring equitable access to technology. Future research should focus on developing interoperable AI systems that seamlessly integrate into existing healthcare infrastructures and address the diverse needs of diabetic populations.

Abbreviations: ADA, American Diabetes Association; AI, Artificial Intelligence; AU-ROC, Area Under the Receiver Operating Characteristic Curve; ACCORD, Action to Control Cardiovascular Risk in Diabetes; ANN, Artificial Neural Network; BMI, Body mass index; BG, Blood glucose; CGM, Continuous glucose monitoring; CNN, Convolutional Neural Network; DR, Diabetic retinopathy; DL, Deep learning; DM, Diabetes mellitus; DKD, Diabetic kidney disease; DO, Diabetic osteoporosis; DEXA, Dual-energy X-ray absorptiometry; DHTs, Digital health technologies; FDA, Food and Drug Administration; GADA, Glutamic acid decarboxylase antibody; HbA1c, Glycated hemoglobin A1c; HOMA-β, Homeostasis model assessment of β cell function; HOMA-IR, Homeostasis model assessment of insulin resistance; IDF, International Diabetes Federation; IDRA, Implant Disease Risk Assessment; MOD, Mild Obesity-Related Diabetes; MARD, Mild Age-Related Diabetes; NHANES, Nutrition Examination Survey; OP, Osteoporosis; SAID, Severe Autoimmune Diabetes; SIDD, Severe Insulin Deficiency Diabetes; SIRD, Severe Insulin Resistance Diabetes; SVM, Support vector machine; T1D, Type 1 diabetes; T2FSS, Type-2 fuzzy sets; T2DM, Type 2 diabetes mellitus; UKPDS, United Kingdom Prospective Diabetes Study; XGBoost, eXtreme Gradient Boost

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1. Introduction

Diabetes mellitus (DM) is a common endocrine disorder characterized by elevated blood glucose levels due to dysfunction in the blood sugar regulation system.[1] Previously, diabetes was primarily prevalent in economically developed "Western" countries; however, with the rapid development of the global economy, its incidence has rapidly spread worldwide. According to the latest statistics from the International Diabetes Federation (IDF), approximately 537 million adults globally are living with diabetes, including over 121 million in China,[2] making it the country with the highest number of people living with diabetes globally. By 2045, the global prevalence is projected to increase to 783 million cases.[3] Diabetes is not only a health crisis but also a global social disaster. The chronic complications associated with diabetes, including those affecting the heart, brain, kidneys, nerves, and retina, impose considerable suffering and economic burden to patients and their families. However, because diabetes is difficult to prevent and diagnose early, many patients are not diagnosed until years after the onset of the disease. Additionally, the effective management of diabetes involves regular follow-ups for blood glucose control, comprehensive screening for diabetes-related complications, and interdisciplinary collaboration, involving fields such as endocrinology, podiatry, nutrition, nephrology, and ophthalmology. These factors contribute to imbalances in the allocation of healthcare resources, scarcity of advanced medical resources, and insufficiency of primary healthcare capabilities, ultimately leading to suboptimal blood glucose control and target achievement rates among diabetes patients.[4,5] Therefore, it is essential to utilize technological means to assist healthcare professionals in managing diabetes.

Artificial intelligence (AI), as one of the most transformative technologies of the 21st century, has seen rapid development, addressing scientific problems beyond human capabilities.[6] Its application areas are continuously expanding, influencing various aspects of our lives. AI focuses on designing intelligent systems that mimic the human cognitive process to analyze complex environments and make optimal decisions. In recent years, with the global emergence of the concepts of "big health" and medical big data, the strategic importance of public health has further promoted the development of AI in the medical field. Expert systems, artificial neural networks, and deep data-mining programs in AI technology are gradually demonstrating significant application value in healthcare, providing possibilities for high-quality medical assurance and simpler, more effective evaluations of individualized healthcare systems.[7,8] In recent years, AI has also been widely applied in the field of diabetes, leading to numerous advances in disease prediction, diagnosis, complication screening, management, and treatment. This paper reviews these developments.

2. The development of artificial intelligence

Medical knowledge and clinical data are experiencing exponential growth. Medical knowledge and clinical experience that healthcare professionals can access and apply depend on individual medical education and training, as well as the support of the healthcare system they are part of. Working in teams or interdisciplinary collaborations can accelerate the accumulation and growth of medical knowledge and clinical experience. However, the efficient acquisition and transformation of medical knowledge and clinical experience are constrained by individual lifespans and capabilities. As a result, traditional methods of diagnosis, prognosis, and treatment are unable to effectively convert vast amounts of information into therapeutic outcomes, innovative discoveries, and economic benefits.

The digital revolution in medicine began two decades ago,[9] driven by advances in information and communication technology, powerful computational methods, and digital innovations that accelerated the acquisition and transformation of medical knowledge. The integration of AI and medical engineering was pivotal in the digital revolution.[10] In such AI systems, medicine, computer science, economics, and patient-centered humanities are transformed into digital models, enabling intelligent disease management.[10] This is crucial for managing chronic diseases, such as diabetes. AI medical systems, typically developed using real-world big data, address some limitations of traditional clinical trials.[11] AI, including machine learning, has been effectively applied in diabetes for risk stratification, precise diagnosis and treatment allocation, and disease prevention.[12–14] By analyzing data from patient histories, physical examinations, lab results, and diagnostic findings, AI can predict disease occurrence[15–17] and support patient management.[18–21] However, reliable AI models must be based on representative, extensive, and in-depth data and trained by multidisciplinary and multinational teams to avoid biases introduced by developers, statistics, and social attributes.[22] Moreover, understanding complex diseases requires the integration of basic research with disease-related decisive information (e.g. environmental, socioeconomic, infrastructural, behavioral, and social factors).[23] Such applications and models often cannot be developed or validated using only national or institutional-level dataset, necessitating a new collaborative model. Multicenter learning, which uses decentralized data sources to build models and conduct transfer learning, enables multiple institutions to collaborate without changing the physical location of the data. While multicenter learning requires a central coordination, this challenge can be addressed by combining edge computing and blockchain[24,25] technologies.

The large-scale implementation of AI represents a disruptive advancement in medicine but introduces new risks (e.g., security issues, data manipulation, misuse, unrecognized model limitations, and ethical dilemmas) that need to be carefully weighed against health benefits. Achieving this balance in medicine and healthcare may be one of the most challenging tasks as it involves the most sensitive and vulnerable aspects of our lives, as well as the fields where we can have the greatest positive impact on individuals and society. For instance, ethical dilemmas arise when choosing between two AI-supported decisions and their outcomes, both of which are accurate but equally suboptimal. AI-assisted treatment recommendations can only address the data-driven aspects of personalized medicine, while patients reserve the right to accept or reject treatment recommendations (i.e., opting for potentially less effective treatments for personal reasons).[26] Ultimately, the role of AI algorithms and healthcare professionals is to assist patients (and their families) in making better-informed choices, rather than making decisions for them (Fig. 1).

3. Application of artificial intelligence in the classification of diabetes

3.1. Precise classification of adult-onset diabetes (Including type 2 diabetes mellitus)

According to the 1999 World Health Organization classification criteria, diabetes is mainly categorized into Type 1 diabetes, Type 2 diabetes mellitus (T2DM), gestational diabetes, and other types of diabetes, with more than 90 % of cases classified as Type 2 diabetes.[27] T2DM exhibits significant heterogeneity in terms of etiology, clinical manifestations, and prognosis between different individuals.[28] However, this heterogeneity is often not sufficiently considered in clinical prevention, management, and treatment, with standardized treatment plans being administered to all T2DM patients. This lack of individualized treatment strategies may result in ineffective therapeutic outcomes for some patients, leading to a waste of medical resources and even worsening of the condition of the patient.[29] To better address the high heterogeneity of T2DM, it is crucial to accurately understand the diversity of its pathological mechanisms and achieve further clinical subtyping, which is essential for the precise treatment of T2DM. Researchers are no longer limited to simple clinical phenotypic definitions when characterizing T2DM. Instead, they incorporate multi-omics data

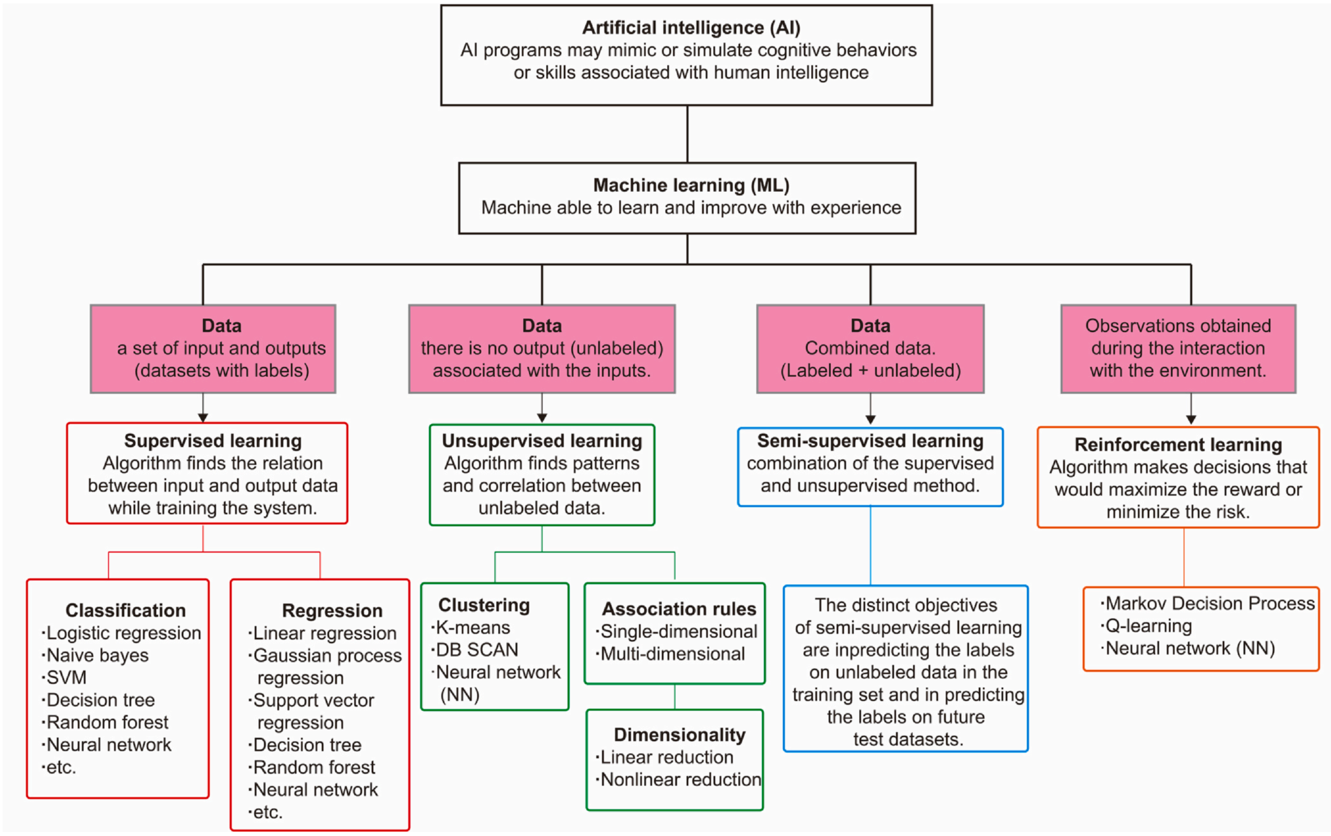

Fig. 1. Technological advances in machine-learning models and algorithms.

(e.g. genomics, metabolomics, gut microbiome), high-resolution (temporal) data, and multi-structural data types (images, texts, etc.), which together more comprehensively depict T2DM.[30] These descriptions involve vast amounts of complex data types, and AI can identify patterns and relationships that are difficult for humans to quantify, efficiently handling large datasets and uncovering intricate associations.

Recently, scholars have begun using serum biomarkers and clinical indicators for clustering analysis of diabetes,[31,32] providing potential pathways for the precise treatment of diabetes. In Sweden, the Ahlqvist team performed a clustering analysis of newly diagnosed diabetes patients using six clinical indicators: glutamic acid decarboxylase antibody (GADA), age at diabetes diagnosis, body mass index (BMI), glycated hemoglobin A1c (HbA1c), homeostasis model assessment of β cell function (HOMA-β), and homeostasis model assessment of insulin resistance (HOMA-IR). They classified diabetes into five subtypes: (1) severe autoimmune diabetes (SAID); (2) severe insulin deficiency diabetes (SIDD); (3) severe insulin resistance diabetes (SIRD); (4) mild obesity-related diabetes (MOD); and (5) mild age-related diabetes (MARD).[31]

The study identified significant variations in clinical characteristics and the risk of complication progression across the subtypes. For instance, the SIDD subtype exhibits the highest risk of diabetic retinopathy, while the SIRD subtype has the highest risk of kidney disease, further confirming the relationship between β-cell function, insulin resistance, and diabetes-related complications.[31] Subsequently, Chinese scholars validated this classification method, confirming that the new diabetes subtypes proposed by Ahlqvist et al. may be universally applicable across different ethnicities and populations.[33] The primary clinical characteristics of these subtypes are consistent across Chinese and American populations, as well as among various ethnic groups. However, this novel stratification method is only for classifying newly diagnosed adult diabetes and does not reliably categorize cases with long-term complications.[33,34] The clinical manifestations of diabetes dynamically change with disease progression, with approximately 20 % to 50 % of gestational diabetes cases developing into T2DM within five years. Recently, a metabolomics-based decision tree algorithm identified 21 small-molecule metabolites, which can predict and precisely intervene in the onset of T2DM far more effectively than traditional clinical fasting glucose screening.[35] This represents an important step towards precision medicine in T2DM classification.

3.2. Application of artificial intelligence models in precise classification of type 2 diabetes mellitus

The classification of diabetes is crucial for tailoring individualized treatment plans and predicting disease progression. AI technologies, including linear discriminant analysis, quadratic discriminant analysis, naive Bayesian methods, and Gaussian process classification, are increasingly being used to predict the onset risk of diabetes and classify the disease into different subtypes. These tools, such as islet function assessment or antibody analysis, are particularly valuable for primary healthcare settings that lack specialized tests. AI has demonstrated high accuracy in classifying various forms of diabetes, although further advances in algorithmic capabilities are needed to fully meet the demands of clinical practice.[36–38] However, existing treatments for diabetes are unable to effectively halt the progression of the disease or prevent the onset of chronic complications. This limitation stems partly from the fact that traditional diagnosis relies primarily on glucose levels, which fail to capture the heterogeneity of the disease in terms of clinical presentation and progression. A more refined classification system is needed to identify high-risk individuals and guide personalized treatment strategies. Notably, clustering-analysis techniques such as k-means and hierarchical clustering have been employed to identify distinct subgroups of people living with diabetes with significantly different characteristics and risks of complications. Ahlqvist et al.[31] identified five such clusters in a cohort of 8980 newly diagnosed

European patients based on variables such as glutamate decarboxylase antibodies, age at diagnosis, BMI, HbA1c, and insulin resistance. Subsequent validation of these subgroups in Chinese and U.S. cohorts confirmed the generalizability of this European-centric classification system to different populations.[33,40]

However, existing models based on traditional biomarkers and simplistic classification methods fall short in elucidating the underlying pathogenic mechanisms of diabetes, thereby limiting their clinical utility. These traditional models typically rely on static, stage-based data that do not account for the dynamic nature of the disease across different patient populations. Consequently, there is a increasing focus on integrating multimodal and multi-omics data to deepen the understanding of the interplay between genetic factors, molecular disruptions, and clinical outcomes. This approach emphasizes not only traditional clinical phenotypic factors such as age of onset, BMI, metabolic disturbances, and insulin sensitivity but also incorporates molecular mechanisms and genetic background. By integrating genomics, proteomics, metabolomics, and clinical data, a more detailed and dynamic classification system that adapts to disease progression in real time can be developed. A multimodal AI-assisted classification strategy that combines these diverse data sources would enable more accurate identification of pathogenic sites and inform functional studies. Such strategies are poised to revolutionize the clinical management of diabetes by enhancing diagnostic accuracy and treatment efficacy.

4. Application of artificial intelligence in diabetes and its complication prediction

4.1. Role of artificial intelligence in diabetes prediction

Preventing the onset of diabetes is an effective intervention for reducing diabetes prevalence, managing diabetes progression, and alleviating the burden of the disease. However, this requires accurately screening high-risk populations and predicting their risk of developing diabetes. Developing accurate diabetes prediction methods helps identify high-risk groups and formulate preventive strategies. Diabetes has many well-established risk factors, and predictive models that integrate these risk factors can forecast the risk of diabetes occurrence over a period.[39,40] Machine-learning methods, with their embedded variable selection mechanisms, can detect complex relationships in data, capturing subtle multivariate and nonlinear relationships that traditional statistical methods struggle to uncover. Farran et al.[41] used a support vector machine (SVM) and k-nearest neighbor classifier to assess the risk of diabetes and its complications. Choi et al.[42] employed SVM and artificial neural network (ANN) for prediabetes screening in the Korean population, and both AI models performed better than traditional logistic regression analysis. The random forest method can effectively handle high-dimensional omics data, in addition to performing discrimination and regression analysis, and is valuable for early disease diagnosis. American researchers applied random forest methods, incorporating 93 variables such as body parameters, blood indicators, medical history, and cardiac ultrasound data, to successfully predict the risk of diabetes occurrence after 8 years of follow-up in African Americans from the Jackson Heart Study.[43] Dinh et al.[44] used a data-driven approach and supervised machine-learning models to identify patients with diabetes in the Nutrition Examination Survey (NHANES) dataset. They exhaustively searched for all available feature variables and developed AI models to detect prediabetes and diabetes. The results showed that, in diabetes classification (based on 123 variables), the extreme gradient boost (XGBoost) model achieved an Area Under the Receiver Operating Characteristic Curve (AU-ROC) score of 86.2 % (without laboratory data) and 95.7 % (with laboratory data).[44] For patients in the pre-diabetic group, the ensemble model had the highest AU-ROC score of 73.7 % (without laboratory data), and for laboratory-based data, XGBoost performed best at 84.4 %.[44] The top five predictors of diabetes were waist size, age, self-reported weight, leg length, and sodium intake. For cardiovascular diseases, the models identified key risk factors that contribute to disease progression.[44] Xiong et al.[45] used various AI models (multilayer perceptron, adaptive boosting algorithm, random forest decision tree, SVM, and gradient boosting decision tree) to predict the occurrence of diabetes. The model analysis variables included gender, age, BMI, blood lipids, and blood glucose, showing that the receiver operating characteristic (ROC) curve area (area under the curve, AUC) was between 0.86 and 0.87.[45]

Two key mechanisms within the AI domain can be leveraged to develop decision-support systems for medical predictions: knowledge-based systems, which rely on logic, and probabilistic reasoning systems.[46,47] These approaches offer substantial benefits, including streamlining clinical workflows, conserving time and effort that would otherwise be consumed by non-critical tasks. Furthermore, automated systems can detect subtle and often imperceptible patterns—those that may not be immediately apparent to clinicians or those resulting from complex computations and reasoning processes involving numerous interdependent variables. In the context of diabetes management, AI-driven prediction models can anticipate the onset of diabetes and associated complications. By identifying individuals at high risk at an early stage, these systems can facilitate timely, targeted interventions, ultimately reducing the incidence of diabetes and its complications.

While considerable research has focused on AI applications in diabetes management, several barriers hinder the seamless integration of AI-based digital health technologies (DHTs) into clinical practice. Future investigations must address the diverse sources of bias inherent in AI decision-support systems. A comprehensive, multi-dimensional strategy is required to ensure fairness across the stages of algorithm design, training, validation, and deployment, thus mitigating the potential risks posed by algorithmic bias.[22] Moreover, upcoming studies should prioritize addressing the most pressing clinical needs. To successfully integrate AI-based DHTs into diabetes care, fostering closer collaboration between AI experts and endocrinologists is crucial to developing clinically relevant AI tools that can be adopted in everyday clinical practice. Hospital administrators must also consider the potential disruption to clinical workflows caused by the introduction of these innovative technologies. Additionally, pharmaceutical and technology companies need to establish frameworks for conducting prospective clinical trials to rigorously evaluate the performance of AI systems in real-world clinical settings. Finally, insurers should reassess the value proposition of medical AI systems and adjust reimbursement policies to enhance healthcare delivery, reducing costs while improving overall quality of care.

The primary risks of diabetes are its acute and chronic complications, which lead to higher patient mortality and increased healthcare costs. The complication rate of Type 2 diabetes is very high. In an observational study across 28 countries in Asia, Africa, South America, and Europe, half of patients with Type 2 diabetes had microvascular complications, and 27 % had macrovascular complications.[48] A study incorporating data from multiple countries found that the cost of hospitalization for patients with diabetes without complications was 11 % to 75 % of the per capita income, whereas hospitalization costs for patients with complications were three times higher than that of those without complications.[49] Therefore, actively developing risk prediction models for Type 2 diabetes complications and constructing practical assessment tools is significant for Type 2 diabetes management.

4.2. Role of artificial intelligence in screening and predicting diabetes complications

The earliest models for predicting Type 2 diabetes complications originated from the renowned United Kingdom Prospective Diabetes Study (UKPDS), a landmark randomized controlled trial in the field of diabetes research.[50] Based on this cohort study, Stevens et al. developed one of the first predictive models for Type 2 diabetes-related complications.[51] This model incorporated predictors such as age, gender, ethnicity, smoking history, and HbA1c, focusing on predicting the risk of cardiovascular complications in patients with Type 2 diabetes. Clarke et al.[52] used Weibull regression to develop seven models for predicting complications associated with diabetes, including stroke, heart failure, fatal or non-fatal myocardial infarction, diabetic nephropathy, amputation, and blindness.

Currently, the most rapidly advancing AI application in diabetes complications is in the screening of diabetic retinopathy (DR). In 2017, Gulshan et al.[53] developed and validated a deep-learning (DL) system for DR and related eye diseases based on retinal images from a multiethnic population with diabetes. This study revealed the potential value of automated DL systems in grading DR images from diverse cohorts of patients with diabetes and these systems showed high sensitivity and specificity in DR detection.[53] Subsequent studies validated the operability and feasibility of DL algorithms in Chinese populations with diabetes, demonstrating that DL systems had sensitivity and specificity comparable with those of expert panels. As DR prevalence increased, DL systems effectively screened for DR across diabetes centers nationwide, providing a feasible solution for patients with diabetic retinopathy.[54] In 2017, Professor Ting's team from Singapore used convolutional neural networks to learn from 494,661 fundus images. This model accurately identified DR, glaucoma, and acute macular degeneration with ROC-AUC values of 0.936, 0.942, and 0.931, respectively.[55] In 2018, the Food and Drug Administration (FDA) approved the IDx system (Iowa City, IA) for automatic diagnosis of diabetic retinopathy.[56] Two years later, an AI system named EyeArt also received FDA approval for autonomous DR diagnosis.[57] The application of AI technology has significantly reduced the subjectivity in disease assessment. Currently, AI is primarily used in assisting non-ophthalmologists and in areas with limited medical resources for DR screening. In the future, it is anticipated that AI systems will be developed to independently and accurately diagnose DR. The workflow for AI-based DR screening systems is also continually being researched,[58] providing new insights for exploring the potential of the system.

Over 10 % of patients with Type 2 diabetes suffer from diabetic peripheral neuropathy.[59] Various methods are currently used to screen and diagnose peripheral neuropathy, including nerve conduction velocity tests, vibration threshold tests, nylon filament tests, clinical neurological examinations, Toronto clinical scoring systems, and Michigan neuropathy screening instruments.[60] However, the main diagnostic challenge for diabetic peripheral neuropathy is the lack of a recognized diagnostic gold standard and severity grading criteria. AI can assist in diagnosing and predicting diabetic peripheral neuropathy. Rahmani developed an expert system based on fuzzy logic to diagnose diabetic neuropathy.[61] The final diagnostic parameters of this system included diabetes duration, symptom scores based on the Michigan questionnaire, sign scores based on the Michigan questionnaire, HbA1c levels, fasting blood glucose, serum creatinine, and proteinuria. The final output variable of the system is the severity of diabetic neuropathy, represented as a number between 0 and 10, categorized into four classes: none, mild, moderate, and severe. Reliability studies of this system achieved a sensitivity of 89 %, specificity of 98 %, and accuracy of 93 %.

While AI demonstrates good screening performance for diabetes complications, it also has the potential to predict risks of vascular-related complications. Fan et al.[62] proposed a random forest model for predicting risks, such as coronary heart disease in Type 2 patients with diabetes, providing early personalized risk warnings for clinicians. Makino et al.[63] used machine learning to analyze electronic medical records from 64,059 patients with diabetes, developing a model to predict diabetic kidney disease (DKD) with 71 % accuracy, thereby offering insights into DKD progression and management. In 2019, Professor Katsuki's team applied a convolutional autoencoder model to time-series data from patients with diabetes, identifying high-risk groups for progressive diabetic nephropathy, also achieving a 71 % accuracy rate.[64]

For diabetic osteoporosis (DO), AI can play a significant role in both diagnosis and treatment monitoring. The pathogenesis of DO remains unclear, and dual-energy X-ray absorptiometry (DEXA)—the gold standard for diagnosing osteoporosis (OP)— has certain limitations. Given that T2DM patients have a higher risk of osteoporotic fractures, the ease and accuracy of AI in diagnosing OP make it a research hotspot; it significantly contributes to clinical diagnosis. Wang et al.[65] recruited 289 Chinese patients with T2DM and developed an efficient and simple SVM model incorporating factors such as gender and age, capable of classifying DO with an accuracy rate of 88 %. This suggests that AI has potential applications in clinical DO diagnosis and, owing to its cost-effectiveness, safety, and scalability, it is effective for early detection and routine DO monitoring. In 2020, Jain et al.[66] used an AI model combined with opportunistic abdominal CT image information from diabetes patients to evaluate its diagnostic value compared to DEXA results. The study showed that an L1 attenuation value $\leq$ 160 Hu in CT images had a sensitivity of 91 % in diagnosing osteoporosis, while $\leq$ 110 Hu had a specificity of 80 %, demonstrating that AI models combined with imaging information are helpful in osteoporosis screening in diabetes patients. Thus, AI significantly aids clinicians in predicting diabetes and its complications.

5. Artificial intelligence in diabetes management and blood glucose control

5.1. Health education

Health education aims to make patients with diabetes aware of their condition and enhance their knowledge, facilitating better self-management of the disease. Alotaibi et al.[67] designed an intelligent mobile diabetes management system, which significantly reduced HbA1c levels while enhancing awareness of basic diabetes knowledge in participants. Hamon and Gagnayre applied natural language processing techniques to web forms to identify the knowledge gaps in patients and recommend personalized educational strategies.[68] Recently, Chen et al.[69] evaluated the impact of an intelligent mobile health technology-based diabetes education program on glucose control in patients with T2DM initiating pre-mixed insulin therapy. The 12-week education program, coupled with the initiation of insulin therapy, significantly reduced HbA1c levels in patients with T2DM.

5.2. Dietary guidance

AI is also widely applied in dietary guidance and treatment plan selection. In 2022, Professor Edlitz's team from Israel used a gradient-boosting regression tree model to predict postprandial blood glucose levels based on parameters from 800 healthy individuals, including hematological indicators (HbA1c, cholesterol, ALT, CRP), lifestyle factors (diet, exercise), physical examination (BMI, waist circumference, blood pressure), and gut microbiota.[70] The model was tested on 100 healthy individuals, demonstrating a significant correlation with actual measurements ($R = 0.70$). Subsequently, the authors used the model to predict individualized “healthy” (lower postprandial blood glucose, stable blood glucose) and “unhealthy” (higher postprandial blood glucose, unstable blood glucose) diets in 12 healthy individuals. The predictions aligned closely with those of professional nutritionists[71]; this achievement was recognized as one of the top ten results of the year by *Cell*. In 2018, Professor Basu’s team in the U.S. used a gradient forest decision tree model to identify three factors influencing the effectiveness of intensive glucose management among 10,251 Type 2 diabetes patients in the Action to Control Cardiovascular Risk in Diabetes (ACCORD) study. These factors were age, BMI, and HbA1c. They inferred that younger patients, those with lower BMI, and those with lower HbA1c levels were more likely to benefit from intensive glucose management.[72]

5.3. Managing different types of diabetes

Unlike many other medications, insulin dosing requires titration, meaning that the dose must be adjusted based on real-time indicators such as current blood glucose levels or recent food intake. This complexity in insulin dosing requires that healthcare providers perform intricate calculations to determine the optimal dose. Errors in insulin dosing can be perilous, as incorrect doses may lead to severe adverse outcomes, including hypoglycemia, which can be fatal. Prior research has focused on optimizing insulin dosing strategies for both patients and clinicians. For patients with Type 1 diabetes (T1D), Tyler et al.[73] applied k-nearest neighbor methods to generate insulin dosing recommendations within the framework of a quality control algorithm. Pesl et al.[74] employed case-based reasoning in the ABC4D (Advanced Bolus Calculator for Diabetes) to provide meal-time dosing advice. In T2DM, Bergenstal et al.[75] demonstrated, in a multicenter randomized controlled trial, that the combination of automated insulin titration guidance and healthcare professional support resulted in superior glycemic control compared to professional support alone. For clinicians, early AI-enabled decision-support systems were typically designed to assist healthcare providers in optimizing insulin dosing strategies for their patients. This model remains relevant today, as most patients with diabetes do not use automated insulin delivery systems, either due to personal preference or the relatively high costs associated with these systems. In T1D, Fong et al.[76] predicted future blood glucose (BG) levels to lie within predefined ranges (rather than exact values) and generated dosing recommendations based on these predictions. This approach remains pertinent today, given the continued use of self-monitoring of BG and non-rapid-acting insulins in many regions. For T2DM, Wang et al.[77] framed insulin dosing guidance as a constrained optimization problem. In both T1D and T2DM, Nguyen et al.[78] used tree-based methods to predict whether patients would require more than 6 units of daily insulin, achieving an AUROC of 0.85. A key challenge in evaluating the alignment between expert and AI-generated recommendations is that, even when discrepancies arise, both may be valid owing to the inherent variability in the priorities and risk preferences expressed by human clinicians (and AI developers). Therefore, it may be more useful to position AI recommendation tools as aids to human decision-making rather than substitutes.

For patients using insulin, adjusting insulin doses according to individual conditions is a major challenge. AI has significant advantages in assisting diabetes patients with insulin dose adjustments.[79] In 2022, Professor Zhou from the U.S. used a fuzzy-logic model to build a closed-loop artificial pancreas and tested it in 12 patients with T1D.[80] In 2016, Professor Reddy's team from the UK developed an insulin dose calculator that can be used on mobile platforms using a case-based reasoning model and tested it on 10 patients with T1D.[81] The automatic closed-loop artificial pancreas system that uses reinforcement learning methods consists of three parts: a continuous glucose monitoring system, a control algorithm, and an insulin pump capable of precise insulin infusion. The control algorithm acts as the "brain" of the artificial pancreas. To make the control algorithm more accurate, engineers have proposed various control theory algorithms to address the problem of adjusting insulin doses in artificial pancreas systems. However, these algorithms have limitations and; thus, have not yet been fully implemented in clinical practice.[82,83] AI-based neural network glucose controllers can maintain BG levels between 3.9–7.8 mmol/L for 97.8 % of the time in patients in intensive care units.[83] As it is well-known that diabetes patients must manage BG while minimizing hypoglycemia, which can cause severe consequences such as loss of consciousness, seizures, or even death, DL frameworks using heart rate and corrected QT interval ECG signals as hypoglycemia response parameters can early detect hypoglycemia in T1D (Fig. 2).[84]

AI systems that regulate insulin delivery through insulin pumps, based on continuous glucose monitoring (CGM) values, are already used in T1D. The prediction of BG levels remains a critical area of research, as it can enhance diabetes management. While BG prediction can be incorporated into specific treatment-related applications (e.g. AI systems), scientific literature often focuses solely on the general performance of BG predictors. An essential aspect of contextual information is meal data. Accurate meal timing and content can be established through qualitative trend analysis based on CGM data.[85] Additionally, hypoglycemia prediction via CGM is particularly significant owing to the immediate negative effects of hypoglycemic events, representing another area where AI can have a positive impact. The rapid advances in DL technology and its applications in clinical settings have led to a marked increase in the number of approved AI-based medical devices in recent years.[85]

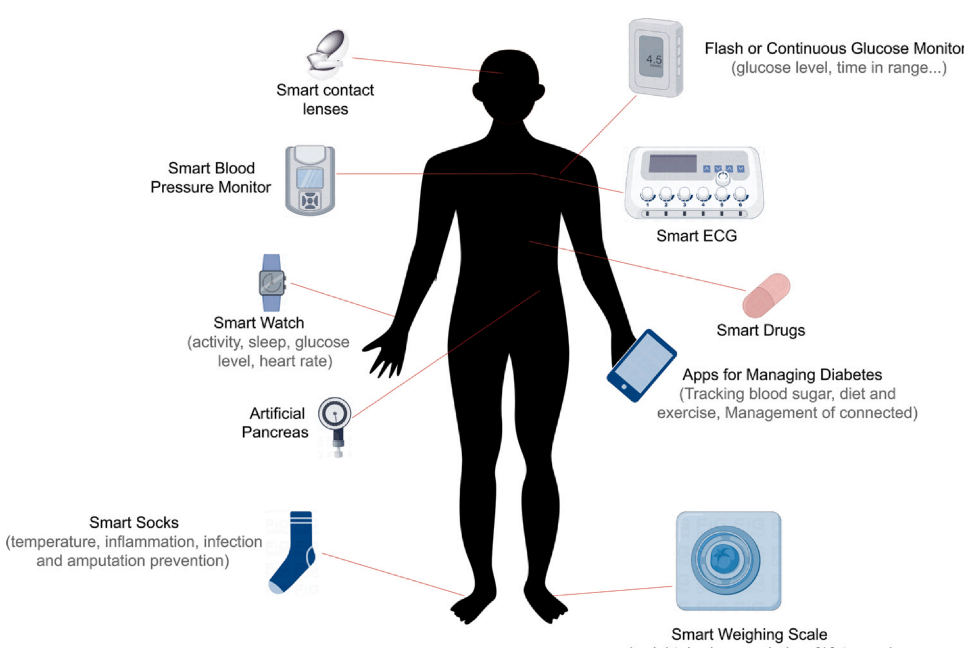

Fig. 2. Wearable devices used to support patients with diabetes.

AI solutions are being developed not only to support diabetes diagnosis but to mimic the "hidden insights of treatment by a specialist," such as insulin dosage adjustments. One such example is Advisor Pro, developed by DreaMed Diabetes, Ltd., which received FDA approval in 2018. This device leverages AI to determine and recommend whether remote insulin dose adjustments are required by transmitting data from CGM and self-monitored BG to a cloud server. Subsequently, healthcare providers can evaluate these recommendations and communicate them to patients.[86] In a non-inferiority trial involving 108 patients with T1D, participants were randomly assigned to one of two groups: one managed manually by a diabetes specialist and the other managed by an AI system. The results indicated that the AI-guided group maintained targeted BG levels and experienced hypoglycemia rates that were not inferior to those of the expert-managed group.[87]

The Medtronic Guardian Connect System, which integrates a smartphone application with CGM data, is another example of an AI system that received FDA certification in 2018. This system uses AI to predict hypoglycemic events up to one hour in advance and notifies the patient. According to product data, the accuracy of these alerts is 98.5 %, occurring approximately 30 min before the onset of hypoglycemia. Using this technology, patients receive alerts for impending hypoglycemia based on their biometric data, which can sometimes be challenging to interpret. This allows patients to take preventive measures, such as consuming glucose tablets, to avert hypoglycemia and its associated complications.[87]

5.4. Physical therapy

A scientific, personalized, and quantitative exercise prescription is considered a potentially essential therapeutic approach for patients with diabetes. However, it is often poorly implemented owing to lack of necessary knowledge and skills by clinicians, while patients exhibit low adherence due to design flaws (e.g., prescriptions failing to consider individual willingness, the appeal of exercise, and complex physical conditions). Therefore, intelligent, personalized exercise prescriptions warrant further investigation. Everett et al.[88] developed a coaching application that delivers specific physical activity recommendations based on real-time contextual information (e.g., if location data indicates that the patient is in a park, the app suggests an activity suitable for the location). Sun et al.[89] investigated whether a year-long, cloud-based intelligent personalized exercise prescription could improve health outcomes for Chinese middle-aged and older adult community dwellers. The program enhanced certain health outcomes, such as cardiovascular function and body composition, in middle-aged and older Chinese community residents.

6. Artificial intelligence in diabetes dietary management

6.1. Artificial intelligence -based dietary recommendations

Dietary management is a crucial aspect of diabetes care. Recommending appropriate diets helps reduce carbohydrate intake, maintain BG levels near normal, lighten the burden on pancreatic β-cells, and correct metabolic disturbances.[90] Lee et al.[91] proposed a new ontology model based on interval Type-2 fuzzy sets (T2FSS) and applied it to personal diabetes dietary recommendations. Experts and relevant personnel found that the proposed T2FS-based Implant Disease Risk Assessment (IDRA) method had higher satisfaction compared to existing methods. Khan et al.[92] developed more professional dietary content based on expert user interactions with the system, achieving better results than traditional case-based reasoning methods. Norouzi et al.[93] designed a nutrition recommendation system based on mobile devices, combining constraint-based reasoning with roulette wheel algorithms, and built a knowledge base according to the American Diabetes Association (ADA) guidelines. The system recommended snack menus based on the preferences and conditions of patients. It recommended various snacks to patients with diabetes with 100 % accuracy based on season and 90 % accuracy based on personal interests. Marji et al.[94] used optimal domain algorithms to design a dietary planning expert system that recommends nutrient content to minimize errors from preset nutrient levels. They developed a mobile application named SlimLine, which was able to match nutritional needs within a 25 % range.

6.2. Artificial Intelligence -Based Automatic Dietary Monitoring

Studies have shown that manual reporting of food intake is often inaccurate and impractical, highlighting the need for automated dietary monitoring solutions.[95] A typical image-based dietary monitoring system requires users to take food photos with a smartphone, which are sent to a server for analysis to estimate the nutritional characteristics. Report results are sent to the user while analysis reports are generated for healthcare professionals.[96] Food image analysis systems include food image segmentation, food recognition and classification, volume estimation, and calorie conversion. Researchers first segment the food plate to define the food area, then apply region growing methods to segment the food parts, and detect candidate regions using deformable part models, circular detectors, and JSEG region segmentation methods.[97] Chen et al.[98] used Otsu's thresholding and morphological operations to segment food from background images, which serves as the basis for volume calculations, with an average error of 10 % for irregularly shaped objects. Pouladzadeh et al.[99] improved the accuracy of recognizing non-mixed and mixed foods by 5 % and 15 %, respectively, using graphical, color, and texture segmentation in the segmentation step. He et al.[100] developed a multi-view food-recognition algorithm using multi-core SVM, achieving about 90 % recognition rate for general foods. Kogias et al.[101] introduced a food image classification system adjustable to the nutritional needs of diabetes patients, using a two-level image classification scheme with Convolutional Neural Network (CNN), achieving 84.18 % and 85.94 % classification accuracy in the first and second levels of the NTUA-Food 2017 dataset, respectively. McAllister et al.[102] demonstrated that pre-trained ResNet-152 and GoogleNet systems could provide sufficient generalizability for various food image classification tasks, showing that deep CNN features are effective for food image classification. Vasiloglou et al.[103] designed a smartphone system "GoCARB" based on computer vision, specifically for patients with T1D, to estimate carbohydrate content in meals, with an accuracy comparable to that of nutritionists. Zhang et al.[104] developed a mobile food recognition system that can automatically identify foods and estimate their calorie and nutritional content without user intervention, achieving over 85 % accuracy in testing 15 different foods. These results suggest that AI has the potential to improve the accuracy of image-based dietary assessments. Although AI has shown great potential in diabetes dietary management, it is still in the early stages of research. Most studies are still based on laboratory settings and specific scenarios, and dietary recommendations and monitoring in complex real-world environments remain immature. Therefore, the practical application of AI in the field of diabetes dietary management still needs improvement (Fig. 3).

7. Glycemic management of hospitalized patients with diabetes in non-endocrine wards

Approximately 8.3 % of hospitalized patients are diagnosed with diabetes upon admission, but diabetes is not the primary reason for hospitalization in most cases. More than 90 % of patients with diabetes are hospitalized in departments other than endocrinology.[105] Effective glycemic management during hospitalization is a critical clinical issue, as proper BG management can improve patient outcomes, shorten hospital stays, enhance medical efficiency, and conserve healthcare resources.[106] After the initial approach where primary physicians adjust BG levels, AI-driven management models have made the management of hospitalized patients with diabetes more efficient in clinical practice. However, since AI-based intelligent management systems are still in their early stages, the decision-making in disease management is not entirely accurate, leading to low compliance with AI intelligent management models among some patients and healthcare professionals. Moreover, the AI intelligent management

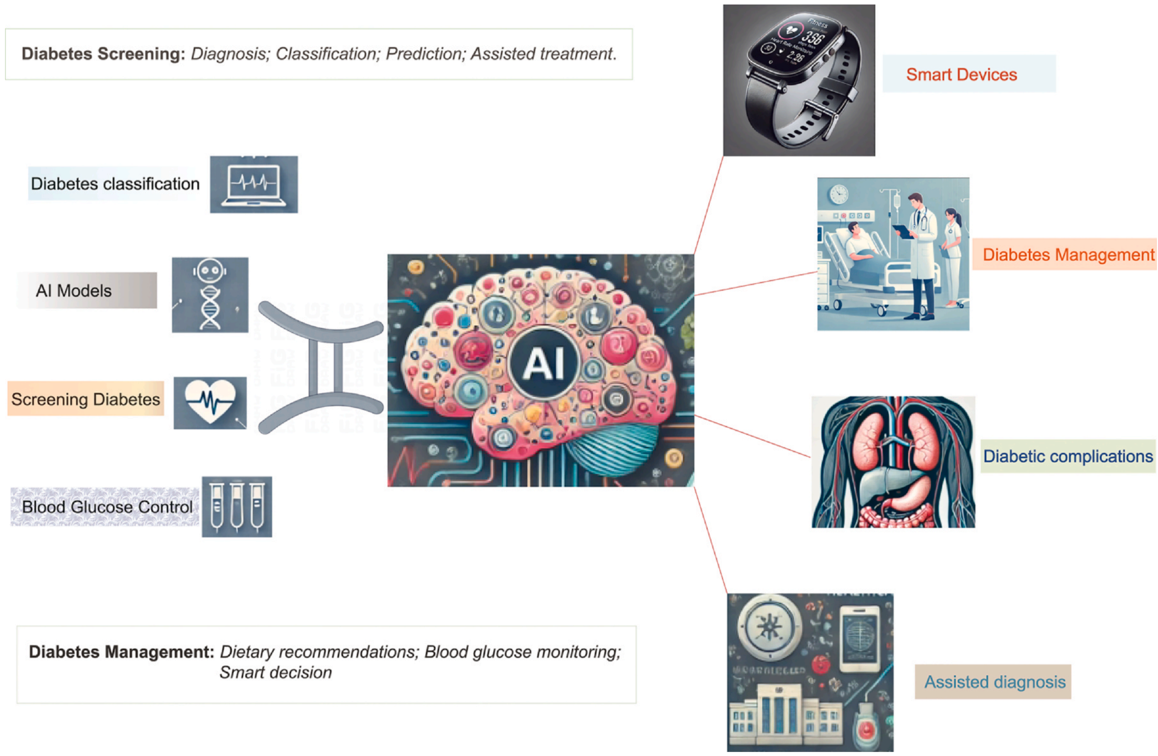

Fig. 3. Overview of AI application in diabetes management.

system relies on hospital information systems as its foundation, which requires hospitals to deploy robust computer and network systems to maintain the operation of the AI system. Many hospitals lack the infrastructure for building both the foundational platform and the functionalities based on electronic medical record systems. Additionally, there is currently no commercial platform that can provide proactive BG management, which requires hospitals to develop these functions on their own. While large information technology companies have relatively mature function development technologies, communication between engineers and clinicians regarding their needs has become a bottleneck in platform development. At the same time, differences in the models of basic information infrastructure across hospitals pose significant obstacles to this project.

7.1. Hospital-wide glycemic management programs

The foundation of hospital-wide glycemic management programs is the hospital information system. This system can systematically and accurately collect patient history, test results, treatment progress, lifestyle information, and more. Endocrinologists can access the hospital information system to quickly understand the condition of the patient and adjust glycemic management plans accordingly.[107] Some hospitals have also implemented multidisciplinary collaborative models, where endocrinologists work with nutritionists, health education nurses, rehabilitation therapists, and other specialists to provide comprehensive BG management.[108] Hospital-wide glycemic management programs can be divided into two models: on-demand consultation and proactive management.

In the on-demand consultation model in the U.S., after training, pharmacists, internists, general practitioners, nurses, and nutritionists form a diabetes management team to achieve multidisciplinary collaboration.[109] When a patient exhibits abnormal BG levels, the primary physician can request a consultation with the glycemic management team. Team members review the medical history of the patient, test results, and treatment progress, arrange laboratory tests, adjust treatment plans, and, if necessary, involve nutritionists, diabetes educators, and rehabilitation therapists to implement a multidisciplinary approach. This model applies to all hospitalized patients, including surgical patients.[110,111] In China, most hospital-wide glycemic management systems integrate bedside BG monitoring systems with hospital information systems. After a BG management request from the primary physician, endocrinologists can remotely access patient information and provide timely glycemic management recommendations, conduct bedside health education if needed, or initiate multidisciplinary management. In contrast, the proactive management model differs from the on-demand consultation model by enhancing the autonomy of the glycemic management team. In a hospital-wide glycemic management project at the University of California, endocrinologists identified patients needing glycemic management by reviewing hospital-wide BG monitoring records. They then provided treatment adjustment recommendations to primary physicians after reviewing electronic medical records. During the operation of the project, the incidence of hyperglycemia and hypoglycemia among patients decreased compared to before.[112] In 2019, Australia launched a more proactive glycemic management project, where diabetes management team members used electronic medical records to identify patients with diabetes or hyperglycemia on the day of admission, proactively visited the bedside, assessed patients, and arranged medication and other treatments. Patients receiving this intervention reported a 23 % reduction in abnormal BG levels and an 80 % reduction in hospital-acquired infections.[113] This indicates that the proactive management model better highlights the role of professionals and further improves healthcare service efficiency.

7.2. Intelligent glycemic management decision-support systems

Intelligent glycemic management decision-support systems are built on the proactive management model by integrating information technology, AI, and visualization tools. These systems use both clinically interpretable domain knowledge and opaque AI techniques to help clinicians more comprehensively, quickly, and accurately assess patient conditions and assist in formulating treatment plans. In 2005, Davidson et al.[114] developed and reported an algorithm for adjusting intravenous insulin doses to help non-specialist caregivers stabilize BG levels of patients. An international multicenter study involving 777 critically ill patients confirmed the feasibility of this algorithm in managing BG levels in hospitalized patients.[115] Some glycemic management decision-support systems issue alerts and provide corresponding actions when patients show or are likely to show abnormal BG levels. These systems have proven effective in improving BG control and reducing hypoglycemia.[116,117] Similar systems have also been proven effective in non-ICU and perioperative patients.[118,119] However, current intelligent glycemic management decision-support systems are still in the early stages of development and application. Decision-support systems used in clinical practice need to provide well-justified recommendations that are easily understandable by clinicians and patients. Currently, mainstream AI algorithms often operate as "black boxes" with intermediate processes that cannot be directly explained using clinical knowledge. Recommendations generated by these algorithms may hinder effective communication or shared decision-making between doctors and patients. Therefore, high-quality evidence-based clinical practice guidelines, especially those that are transparent, publicly available, and easily convertible into structured domain knowledge, are essential for the development and application of intelligent glycemic management decision-support systems.

8. The future and challenges of intelligent medicine

AI, as an emerging interdisciplinary field, has rapidly developed over the past decade and has provided substantial benefits to medicine. However, it must be recognized that AI faces certain challenges and even controversies in medicine. In the development and application of AI-assisted healthcare, particularly in the realm of ethics, there are still numerous obstacles: (1) Cognitive Aspects of AI: Diseases evolve, and the quality and reliability of databases used for AI development are uncertain. Issues such as data-sharing difficulties and data heterogeneity can lead to AI providing insufficient or incorrect conclusions for cases outside its training set. (2) Universality of AI: Owing to objective distribution differences in data, AI might be biased towards certain groups, potentially leading to unfairness for others. (3) Accountability for Errors: It is difficult to hold AI accountable for errors that harm patient health, making it challenging to prevent similar damages from occurring in the future. (4) Patient Privacy: The explosive growth of healthcare big data and the integration of various databases using AI can easily lead to the inference of personal health information. Balancing privacy protection with public interest is a sensitive issue, particularly for chronic disease databases with long timelines and multiple data sources.

The integration of AI into healthcare has the potential to significantly transform patient management and healthcare delivery. This transformative potential extends to various aspects, including the reduction of healthcare costs, improvement of patient outcomes, and enhancement of diagnostic accuracy. However, challenges remain, particularly in the context of diabetes management, where AI models exhibit limitations in subtype classification. Additionally, a comprehensive comparison between AI and traditional screening methods is essential for understanding the best approaches to patient care. AI technologies can enhance healthcare delivery by streamlining processes, optimizing resource allocation, and reducing the costs associated with chronic disease management. For instance, predictive analytics powered by AI can identify patients at high risk and enable early interventions to prevent costly complications. Research indicates that AI-driven tools can lead to a reduction in healthcare costs by up to 30% through more efficient management strategies and personalized treatment plans.[120] Moreover, AI can facilitate timely diagnosis and treatment adjustments, significantly improving patient outcomes. For example, AI algorithms that analyze patient data can predict adverse events, allowing clinicians to intervene before critical issues arise.[121] Despite the advantages, current AI models face several limitations, particularly in the classification of diabetes subtypes. Many models exhibit poor generalizability across diverse populations, leading to discrepancies in diagnostic accuracy. For instance, a study found that certain AI models achieved high accuracy (up to 90%) in identifying diabetes subtypes in white populations, but accuracy fell below 60% for other racial and ethnic groups.[122–124] This inconsistency highlights a critical challenge in deploying AI in clinical settings, as misclassification can result in inappropriate treatment decisions and adverse patient outcomes. Furthermore, the lack of interpretability in AI algorithms complicates their integration into clinical practice, as healthcare providers may struggle to trust and understand AI-driven recommendations. To fully appreciate the potential of AI in diabetes management, it is vital to compare its performance with traditional screening methods. Traditional approaches, such as questionnaire-based assessments and biochemical testing, have long been the standard in identifying diabetes and its complications. While these methods are well-established, they may overlook subtle indicators of disease progression, particularly in complex cases. In contrast, AI can analyze a broader range of data, including electronic health records, lifestyle factors, and social determinants of health, to provide a more comprehensive risk assessment.

However, traditional methods have the advantage of interpretability and established clinical guidelines, which can foster trust among healthcare providers and patients. In some instances, relying solely on AI for screening may lead to overdiagnosis or unnecessary interventions, increasing healthcare costs and patient anxiety. Thus, a hybrid approach that combines the strengths of both AI and traditional

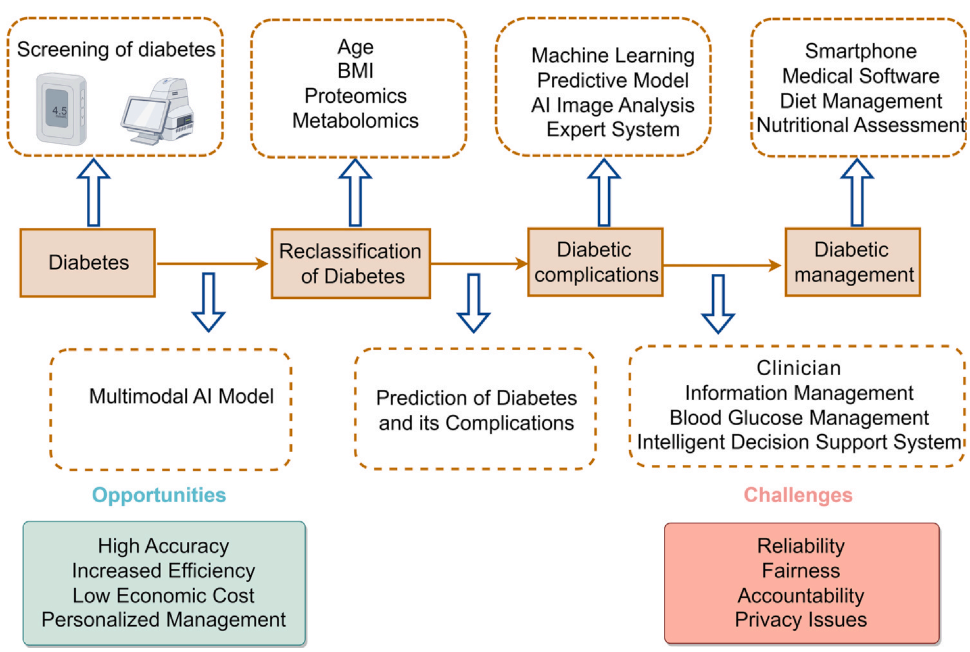

Fig. 4. Artificial intelligence in diabetes management: Advances, opportunities, and challenges.

screening methods may offer the most effective solution. By integrating AI-driven insights with conventional assessments, healthcare providers can enhance diagnostic accuracy and optimize patient care.

As AI rapidly advances, questions arise about whether AI can replace humans, given its effectiveness, accuracy, and comprehensiveness in various medical fields. Is AI a friend or foe to humanity? Medicine is both a science and an art; disease definition is not simply a binary issue, and treatment is not just a straightforward diagnosis and treatment correspondence. Medicine has a human element, especially in chronic diseases like diabetes. In complex situations, AI cannot replicate real doctor-patient interactions or simulate treatment decisions influenced by emotions, non-verbal communication, values, personal preferences, and social environment. Face-to-face communication between doctors and patients may be more beneficial than interacting with a cold machine. Therefore, AI currently serves as a supportive tool in diagnosis and treatment rather than replacing doctors entirely (Fig. 4). The goal is for AI to augment human capabilities in diabetes management, ensuring more effective treatment outcomes.

9. Conclusion

AI has achieved relatively mature development in the field of diabetes, with some technologies already in preliminary clinical application, such as AI-assisted diagnosis of retinal images for diabetic patients. However, other areas, such as obesity and fatty liver, remain in the early stages of exploration and require further research. With the geometric growth of vast and complex medical data, clinical physicians increasingly find it challenging to manage and control these data directly. Therefore, leveraging AI to streamline data management, accurately analyze data, provide clinical decision support, and assist in treatment is particularly crucial for clinicians. We anticipate that AI will play a pivotal role in the field of diabetes in the near future, with promising prospects.

Ethics approval

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CRediT authorship contribution statement

Shizhan Ma: Funding acquisition. **Mian Zhang:** Project administration, Writing – review & editing. **Wenxiu Sun:** Writing – original draft. **Yuhan Gao:** Writing – original draft. **Mengzhe Jing:** Writing – original draft. **Ling Gao:** Project administration, Funding acquisition, Supervision. **Zhongming Wu:** Writing – review & editing, Supervision, Funding acquisition. All the authors have read and approved the final version of this manuscript

Data availability

Not applicable

Declaration of Competing Interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work and there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript titled, "Artificial intelligence and medical-engineering integration in diabetes management: Advances, opportunities, and challenges".

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