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Application of Artificial Intelligence and Large Language Models in Clinical Decision-Making for Diabetes

Hanyu Yang*

School of Information Science and Technology, Dalian Maritime University, Dalian 116000, China

**Corresponding author: Hanyu Yang.*

Abstract

The global prevalence of Type 2 Diabetes Mellitus (T2DM) and the complexity of its management pose significant challenges to traditional healthcare models. In recent years, the rapid advancement of Artificial Intelligence (AI) technologies—particularly Machine Learning (ML), Deep Learning (DL), and Large Language Models (LLMs)—has provided revolutionary tools for developing intelligent, precise, and personalized Clinical Decision Support Systems (CDSS). This review systematically maps the application landscape of AI and LLMs across the full-cycle management of T2DM, covering the complete chain from risk prediction and precise diagnosis to individualized treatment and long-term prognosis management. In risk prediction, AI models significantly improve early identification of progression from prediabetes to T2DM, as well as diabetic nephropathy, cardiovascular events, and other complications by integrating multidimensional data. At the diagnostic level, in addition to differential typing based on electronic health records, emerging studies have digitized traditional Chinese medicine tongue images and combined them with biomarkers such as oral-gut microbiota through multimodal machine learning, opening new pathways for non-invasive and objective auxiliary diagnosis. In treatment decision support, AI not only recommends glucose-lowering medications and optimizes insulin dosages but also predicts individualized postprandial glucose responses using continuous glucose monitoring data, offering possibilities for dynamic behavioral interventions. LLMs, exemplified by ChatGPT, demonstrate strong potential in interpreting clinical text, simulating doctor-patient communication, and generating preliminary management plans through their powerful natural language processing capabilities, although the reliability and safety of their independent decision-making still require cautious evaluation. Nevertheless, a substantial gap remains between technological advancement and clinical translation. This review further analyzes the core challenges currently faced, including data quality and algorithmic bias, the “black-box” nature of models and insufficient explainability, barriers to integration into clinical workflows, and profound medical ethical issues such as equity, privacy protection, and the risk of marginalizing human decision-making agency. Finally, the paper outlines future directions for the next generation of intelligent CDSS that integrate multimodal data, federated learning, causal inference, and human-centered design principles, emphasizing the need to strike a balance between technological innovation and ethical governance in order to build a safe, effective, equitable, and trustworthy AI-empowered paradigm for diabetes management.

Keywords

type 2 diabetes mellitus (T2DM), artificial intelligence, large language models, clinical decision support system, machine learning, tongue image diagnosis

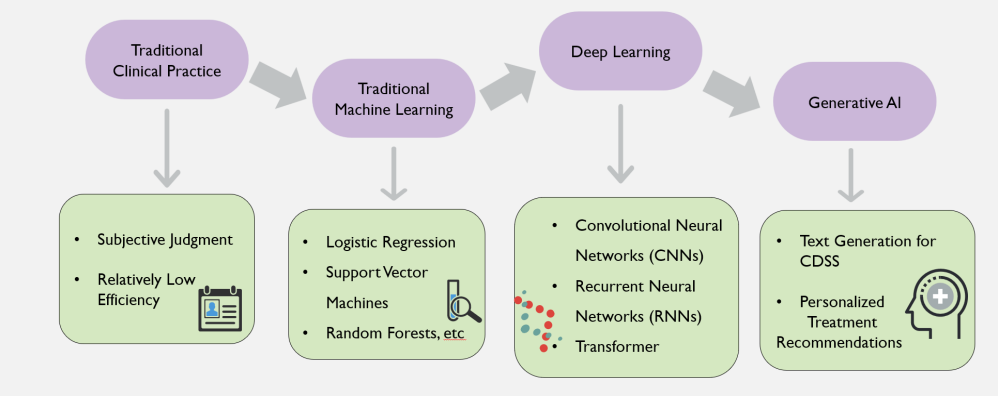
1. Introduction

As a complex chronic metabolic disease, Type 2 Diabetes Mellitus (T2DM) continues to rise in prevalence worldwide, imposing a heavy disease burden and substantial socio-economic costs. Effective management of T2DM goes far beyond simple glycemic control; it is a long-term, dynamic process involving risk assessment, precise diagnosis, individualized treatment, complication monitoring, and behavioral intervention, which places extremely high demands on clinicians' decision-making capabilities. Although traditional "one-size-fits-all" clinical guidelines provide a basic framework, they struggle to adequately address significant inter-individual differences in genetics, phenotypes, comorbidities, and psychosocial factors, potentially leading to under-treatment, over-treatment, or resource misallocation. Against this background, Clinical Decision Support Systems (CDSS) have emerged. Their core objective is to improve healthcare quality and patient outcomes by providing clinicians with patient-specific, evidence-based knowledge and recommendations at the appropriate points in the care process.

Artificial Intelligence, especially machine learning and deep learning, can uncover complex nonlinear patterns from vast amounts of electronic health records, medical imaging, genomics, wearable devices, and mobile health data, serving as the core technological driver for the intelligent transformation of CDSS. Early studies primarily focused on constructing risk prediction models for T2DM and its complications using traditional algorithms such as logistic regression, support vector machines, and random forests. With the maturation of deep learning technologies, architectures including convolutional neural networks, recurrent neural networks, and Transformers have been introduced, demonstrating superior performance in processing medical images and time-series physiological signals (such as continuous glucose monitoring data), thereby advancing prediction and diagnosis toward higher accuracy and greater personalization. In recent years, the breakthrough progress of Large Language Models (LLMs), represented by generative pre-trained Transformers, has further expanded the frontiers of AI in healthcare. Leveraging their powerful natural language understanding and generation capabilities, LLMs can not only parse unstructured clinical notes and doctor-patient dialogues but also simulate clinical reasoning, generate patient education materials, and even participate in formulating preliminary management plans, bringing a more natural and interactive new dimension to CDSS.

At the same time, research pathways that integrate traditional medical wisdom with modern technology have also demonstrated unique value. For example, objectifying and quantifying traditional Chinese medicine tongue diagnosis through computer vision techniques, and combining it with molecular biomarkers such as the gut microbiome to construct machine learning models, provides a non-invasive and convenient new approach for early screening and risk assessment of T2DM. However, despite the promising prospects, the widespread application of AI and LLMs in clinical decision support still faces numerous severe challenges. The "black-box" nature of models makes their decision logic difficult to interpret, potentially hindering clinicians' trust and adoption. Inconsistent data quality, selection bias, and privacy and security concerns constitute common obstacles to model development and real-world deployment. More profoundly, potential algorithmic bias may perpetuate or exacerbate existing health inequalities, while over-reliance on technology may lead to de-skilling of clinicians and erosion of decision-making agency, triggering a series of medical ethical dilemmas. This review aims to synthesize recent key literature from authoritative platforms including PubMed, EMBASE, Springer, and *Frontiers* series journals. The core literature consists of empirical studies and systematic reviews published between 2020 and 2025.

Figure 1: Development path of AI-assisted medical decision-making



2. The Key Role of AI in Risk Prediction and Early Identification of T2DM

Early identification of high-risk populations and accurate prediction of disease progression trajectories form the cornerstone for implementing effective interventions to delay or prevent T2DM and its complications. Traditional risk assessment tools (such as questionnaires and simple clinical scoring systems) often reach a performance ceiling due to limited variables and reliance on linear assumptions. AI models, particularly machine learning approaches, can efficiently integrate multidimensional and nonlinear data, significantly enhancing risk stratification capabilities and providing quantitative support for prospective clinical decision-making.

2.1 Risk Warning for Progression from Prediabetes to T2DM

Prediabetes represents the most important reversible stage of T2DM. Precise risk stratification in this population is critical for strengthening preventive interventions. Studies have shown that machine learning models specifically designed for this group can provide superior predictive performance compared to general tools. For example, Zueger et al. developed an ML model based on nearly 14,000 individuals with prediabetes, incorporating 79 predictors (covering demographics, biomarkers, medication history, etc.) to predict the 5-year risk of progression to T2DM [1]. The model demonstrated good discriminative ability (AUC > 0.75). Of greater clinical translational significance, the researchers also developed a simplified model requiring only 8 easily obtainable clinical parameters, which performed comparably to the full model. This design reflects a clinically oriented approach aimed at reducing the burden of data collection, making it easier to integrate into primary care or health management platforms as a decision support tool for identifying high-risk individuals who require prioritized intensive lifestyle counseling.

2.2 Prediction of T2DM Incidence Risk

Predicting the risk of T2DM onset in broader populations is essential for primary prevention in public health. In addition to conventional clinical and laboratory data, emerging non-invasive detection technologies have introduced new dimensions to risk prediction. Leiherer et al. applied the AutoScore framework to develop an interpretable point-based risk scoring model using routine clinical variables from patients at cardiovascular risk. Its performance was comparable to that of complex ML models, yet its transparency made it more likely to gain clinical trust [2].

Meanwhile, research pathways combining traditional medical diagnostic indicators with modern AI have attracted considerable attention. Balasubramaniyan et al. utilized panoramic tongue images and deep convolutional neural network models for diabetes diagnosis, validating the potential of tongue images as digital phenotypes in disease identification [3]. More in-depth studies have further fused tongue image features with oral and gut microbiota data. Deng et al. demonstrated that integrating tongue image parameters (such as TB-a reflecting tongue color and perALL reflecting tongue coating thickness) with specific microbial species (e.g., Escherichia and Porphyromonas) using algorithms such as support vector machines could effectively distinguish between healthy individuals, those with prediabetes, and those with

T2DM, achieving an accuracy of 78.9%. This provides an innovative multimodal fusion approach for early non-invasive screening of T2DM [4].

2.3 Early Risk Prediction of Diabetic Complications

Predicting the risk of specific complications after T2DM diagnosis helps optimize the allocation of screening resources and enable early targeted therapy. AI models in this field frequently outperform traditional risk scoring systems. For instance, Allen et al. developed an ML algorithm capable of predicting the risk of progression to different stages of diabetic kidney disease (DKD) within 5 years at the time of initial T2DM diagnosis. The model achieved an AUC exceeding 0.82 for predicting severe endpoints, significantly outperforming traditional scoring tools [5]. Wu et al. employed an interpretable machine learning model (XGBoost) to predict the 1-year risk of renal function progression in T2DM patients with comorbid chronic kidney disease. The internally validated AUC reached 0.906. Using SHAP values, the study provided clear analysis of predictor contributions and ultimately deployed the model as a web application, achieving direct translation into a clinical decision support tool [6]. In the area of cardiovascular complications, Tang et al. integrated a novel imaging biomarker—pericoronary adipose tissue—with clinical factors and developed a model for predicting major adverse cardiovascular events. The model demonstrated excellent performance in both internal and external validation (AUC ≈ 0.81), showcasing AI's capability to enhance predictive accuracy through multimodal data fusion [7]. For diabetic retinopathy, Tsao et al. confirmed that algorithms such as support vector machines can effectively predict its risk, identifying insulin use and diabetes duration as key predictors. These findings can be directly applied to guide personalized screening frequency decisions [8].

Table 1: Contribution of different models/technologies to the diagnosis of T2D

Model/Technology	Diagnostic/Predictive Accuracy	Key Features	Main Contribution
Deng et al. (2024) Tongue-Microbiota Fusion SVM	78.9%	TB-a, perALL, Escherichia, Porphyromonas-A	First to confirm that fusion of tongue images and microbiota can accurately predict diabetes, providing scientific validation for TCM tongue diagnosis
Tian et al. (2024) Tongue-Foot-Clinical ResNet50	95%	Tongue image parameters, foot hardness, BMI, HbA1c	Tongue images provide high-precision, non-invasive indicators for diabetic foot prediction
Thirunavukkarasu et al. (2024) Fusion Thermal Imaging VGG16	94.37%	Fused thermal-visible light image features	Provides a non-contact, early screening tool for diabetes
Balasubramaniyan et al. (2022) ResNet50-RBFNN	98.4%	Multiple tongue image features (color, shape, coating color, teeth marks, etc.)	Achieves high-precision diabetes diagnosis using deep learning

Table 2: AUC of different models/technologies

Researchers	Model/Technology	AUC	Prediction Target
Zueger et al.	ML model (79 predictors)	>0.75	5-year risk of progression from prediabetes to T2DM
Allen et al.	ML algorithm	>0.82	5-year risk of DKD progression after initial T2DM diagnosis
Wu et al.	XGBoost (interpretable ML)	0.906	1-year risk of renal function progression in T2DM patients with CKD
Tang et al.	XGBoost	≈0.81	Major adverse cardiovascular events
Tsao et al.	vector machines	0.839	Identification of DR-related risk factors

3. The Auxiliary Value of AI in Precise Diagnosis and Subtyping Decision-Making for T2DM

Accurate disease subtyping is the starting point for implementing correct treatment. In clinical practice, adult-onset autoimmune diabetes (such as LADA) is easily misdiagnosed as T2DM, leading to treatment delays. At the same time, T2DM itself exhibits high heterogeneity. By deeply analyzing clinical data patterns, AI can provide important assistance in reducing misdiagnosis and achieving precise subtyping.

3.1 Differential Subtyping and Misdiagnosis Correction

Misdiagnosis of adult-onset Type 1 diabetes is a common clinical challenge. Cheheltani et al. developed an ML model aimed at identifying misdiagnosed cases from electronic health record databases of patients already diagnosed with T2DM [9]. The model was based on multidimensional features including age, body mass index, and treatment response. The study showed that the ML model has the potential to be transformed into a real-time screening or decision support plugin embedded in electronic health record systems, providing early warning alerts when physicians make diagnoses. This would guide precise subtyping from the very beginning of treatment, avoiding ineffective therapy and associated risks caused by misdiagnosis.

3.2 Diagnostic Support Based on Multimodal Data and Causal Discovery

Moving beyond single data sources, AI is being used to integrate and mine the diagnostic value behind multimodal data. In addition to the previously mentioned tongue image–microbiota fusion model, inferring disease-related causal relationship networks from observational data holds significant importance for building more biologically plausible and robust diagnostic support systems. Shen et al. proposed a novel causal structure discovery method and validated it on T2DM data [10]. This method can extract potential causal relationships from observational electronic health record data with relatively high accuracy, laying a methodological foundation for the future development of diagnostic and interventional CDSS that go beyond statistical associations to reflect underlying pathophysiological mechanisms, thereby making the system's recommendations more interpretable and trustworthy.

4. AI-Driven Personalized Treatment Decision Support for T2DM

Treatment decision-making is the core component of T2DM management, involving complex trade-offs across multiple dimensions such as drug selection, dosage adjustment, and lifestyle interventions. AI-driven CDSS is gradually evolving from providing risk information (descriptive and diagnostic) toward directly generating personalized treatment recommendations (prescriptive).

4.1 Medication Recommendation and Regimen Optimization

The selection of glucose-lowering medications is one of the difficult points in clinical decision-making. Singla et al. used a random forest algorithm to directly predict the required type of glucose-lowering medication based on patient characteristics, achieving extremely high prediction accuracy for individual drug classes [11]. Another more complex approach is the "prediction-optimization" framework. Nambiar et al. developed an AI medication and dosage advisory system following this pathway [12]. Given a patient profile, the system first predicts glycemic control outcomes under different medication dosage regimens, then optimizes and recommends the regimen that achieves the best glycemic target with the minimal treatment change, while adhering to clinical guidelines. Retrospective validation showed that the recommended regimens could lead to an expected average improvement in HbA1c of 0.40–0.68%, and received endorsement from endocrinologists regarding the reasonableness of the suggestions. For specific drug responses, Murphree et al. used stacked classifiers to predict glycemic control one year after initiating metformin treatment, helping identify individuals who may respond poorly to first-line therapy and providing a basis for early regimen adjustment [13]. In the field of metabolic surgery, machine learning models can also predict the likelihood of discontinuing glucose-lowering medications after surgery based on real-world data, offering data-driven decision support for patient selection [14].

4.2 Insulin Dosage Titration Support

Insulin dosage adjustment is complex and time-consuming, and is one of the important causes of "clinical inertia." AI-CDSS can provide standardized, data-driven support for this delicate process. Thomsen et al. adopted a user-centered design approach to develop an AI-CDSS specifically for basal insulin dosage adjustment in primary care settings [15]. Through heuristic evaluation, user feedback, and eye-tracking systems to optimize usability, the final prototype achieved extremely high system usability scores. Higher-level clinical evidence comes from Ying et al.'s multicenter randomized controlled trial [16], which directly compared the performance of an AI insulin CDSS with that of senior endocrinologists in insulin titration for hospitalized T2DM patients. The results showed that the AI system was non-inferior to experts in time to

glycemic target achievement, with comparable safety, demonstrating its effectiveness and safety in specific clinical scenarios.

4.3 Non-Pharmacological and Behavioral Intervention Support

The effects of dietary and exercise interventions vary significantly among individuals. To achieve personalized behavioral guidance, Brügger et al. used personalized machine learning models, based on continuous glucose monitoring and meal record data, to predict the risk of the next postprandial glucose excursion for individual patients [17]. The model found that key predictors differed markedly across individuals, providing the possibility for "timely adaptive interventions"—that is, pushing personalized dietary prompts through mobile health applications at appropriate moments based on real-time predicted "glycemic susceptibility states," thereby forming a dynamic behavioral intervention decision support system. Generative AI has also been explored in this field. For example, Harrison et al. used GPT-3.5 to automatically generate behavior change theory-based text messages aimed at improving medication adherence in T2DM patients, significantly increasing the efficiency of intervention content production [18].

5. The Emerging Role and Evaluation of Large Language Models in T2DM Clinical Decision Support

Jang et al. evaluated the ability of GPT-4 to recommend glucose-lowering medications based on patient clinical information [19]. The study found that for initial monotherapy, ChatGPT showed relatively high consistency with physicians' prescriptions; however, consistency decreased significantly as treatment complexity increased (dual or triple therapy). Prompt engineering techniques (such as few-shot learning) helped improve its performance. Mondal et al. compared the ability of GPT-4 with physicians in generating management plans for real T2DM patients [20]. The results showed that GPT-4 performed better in reducing unnecessary medication prescriptions, but its generated plans were inferior to those of physicians in terms of completeness and carried a certain proportion of safety risks (such as potential drug interactions).

These empirical studies indicate that although current LLMs possess the potential to assist clinical reasoning, provide a "second opinion," or handle standardized consultations, they are not yet capable of independently undertaking full-process management decisions for complex patients. Their outputs must undergo strict review and oversight by clinicians. In the future, LLMs are more likely to serve as "augmented intelligence" components, integrated into broader multimodal AI-CDSS frameworks, to handle clinical text, generate patient communication summaries, explain complex medical concepts, and other tasks, thereby enhancing the overall usability and accessibility of the system.

6. Future Perspectives

Despite the enormous potential demonstrated by AI and LLMs in T2DM decision support, the path toward widespread, safe, and effective clinical application remains fraught with challenges across technological, clinical, ethical, and regulatory dimensions.

Future research will evolve along several key directions:

a) Deep personalization and multimodal fusion: Integrating genomic, proteomic, metabolomic, imaging, digital phenotype (e.g., from wearable devices), and social determinants of health data through multimodal LLMs or federated learning frameworks to construct more comprehensive patient digital twins, enabling hyper-personalized risk prediction and intervention simulation.

b) Enhanced causal reasoning and dynamic decision-making: Advancing CDSS from association-based prediction toward causal relationship-based decision support, capable of providing adaptive recommendations according to dynamic changes in patient status [10].

c) User-centered design and full-cycle management: Further optimizing the human–machine interaction experience of CDSS and extending its application scenarios from hospitals to communities and homes, supporting patient self-management and remote monitoring, and building an integrated intelligent management ecosystem spanning hospital–community–home.

d) Robust evaluation and governance systems: Establishing standardized clinical evaluation processes, fairness audit standards, and ethical guidelines for AI medical products to safeguard the safe, effective, and equitable implementation of innovative technologies.

7. Conclusion

This review systematically outlines the latest advances, application value, and multifaceted challenges of artificial intelligence and large language models in full-cycle clinical decision support for Type 2 Diabetes Mellitus. From early risk warning based on multidimensional data, to auxiliary diagnosis integrating novel biomarkers such as tongue images and microbiota; from data-driven individualized medication recommendations and insulin titration, to dynamic interventions supporting behavioral change; and the new potential demonstrated by LLMs in natural language interaction—AI technologies are profoundly reshaping the management paradigm of T2DM. A successful CDSS is not only the product of high-performance algorithms but also the result of deep integration of human factors engineering, clinical workflows, and user-centered design.

However, the brilliant prospects of technology must be examined against reality. Data bias, algorithmic "black-box" characteristics, barriers to clinical integration, and the resulting ethical dilemmas concerning equity, privacy, accountability, and the marginalization of humanistic care constitute the core constraints on the deep development of AI in healthcare. Moving forward, the healthy advancement of this field must rely on close interdisciplinary and multi-stakeholder collaboration: clinicians and data scientists working together to ensure the clinical relevance and safety of models; human factors engineers and designers optimizing system usability and user experience; and policymakers and ethicists constructing forward-looking, agile, and responsible governance frameworks. Ultimately, the most promising pathway for AI in diabetes management is not to replace clinicians, but to serve as their powerful "augmented intelligence" partner. By providing data-driven deep insights, reducing cognitive load, and optimizing decision-making processes, AI can empower healthcare professionals to jointly deliver more precise, efficient, equitable, and human-centered care for patients with Type 2 Diabetes Mellitus. This new model of human–machine collaboration and ethics-first intelligent healthcare will be the key to addressing the global diabetes challenge.

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