Generative artificial intelligence in predictive analysis of diabetes and its complications: a narrative review

Ayokunle Osonuga[1], David B. Olawade[2,3,4,5], Manisha Gore[6], Oluwayomi B. Rotifa[7], Eghosasere Egbon[8], Viviane Chinwah[4], Stergios Boussios[3,9,10,11,12,13,14]^

[1]Coltishall Medical Practice, NHS GP Surgery, Norfolk, UK; [2]Department of Allied and Public Health, School of Health, Sport and Bioscience, University of East London, London, UK; [3]Department of Research and Innovation, Medway NHS Foundation Trust, Gillingham, UK; [4]Department of Public Health, York St John University, London, UK; [5]School of Health and Care Management, Arden University, Coventry, UK; [6]Faculty of Medical and Health Sciences, Symbiosis Community Outreach Programme and Extension, Symbiosis International (Deemed University), Pune, India; [7]Department of Radiology, Afe Babalola University Multi-System Hospital, Ado-Ekiti, Nigeria; [8]Department of Tissue Engineering and Regenerative Medicine, Faculty of Life Science Engineering, FH Technikum, Vienna, Austria; [9]Faculty of Medicine, School of Health Sciences, University of Ioannina, Ioannina, Greece; [10]Department of Medical Oncology, Ioannina University Hospital, Ioannina, Greece; [11]Faculty of Medicine, Health and Social Care, Canterbury Christ Church University, Canterbury, UK; [12]Faculty of Life Sciences & Medicine, School of Cancer & Pharmaceutical Sciences, King's College London, London, UK; [13]Kent Medway Medical School, University of Kent, Canterbury, UK; [14]AELIA Organization, 9th Km Thessaloniki-Thermi, Thessaloniki, Greece

Contributions: (I) Conception and design: A Osonuga, DB Olawade; (II) Administrative support: All authors; (III) Provision of study materials or patients: All authors; (IV) Collection and assembly of data: All authors; (V) Data analysis and interpretation: All authors; (VI) Manuscript writing: All authors; (VII) Final approval of manuscript: All authors.

Correspondence to: David B. Olawade, MPH. Department of Allied and Public Health, School of Health, Sport and Bioscience, University of East London, London, UK; Department of Research and Innovation, Medway NHS Foundation Trust, Gillingham, UK; Department of Public Health, York St John University, London, UK; School of Health and Care Management, Arden University, Arden House, Middlemarch Park, Coventry CV3 4FJ, UK. Email: d.olawade@uel.ac.uk.

Background and Objective: Diabetes mellitus (DM), particularly type 2 diabetes (T2D), represents a significant global health crisis, often complicated by severe and progressive conditions such as retinopathy, neuropathy, and cardiovascular disease. Traditional diagnostic approaches frequently detect these complications at advanced stages, limiting the opportunity for early, effective intervention. This review aims to examine how recent advancements in generative artificial intelligence (AI), particularly large language models (LLMs), can transform diabetes management by enabling earlier detection and more personalized interventions.

Methods: A narrative review was conducted to evaluate the current literature on the application of generative AI and LLMs in diabetes care. The review focused on how these technologies analyse multi-dimensional datasets, including medical imaging, electronic health records (EHRs), genetic profiles, and lifestyle factors, and how they process both structured and unstructured data to enhance predictive analytics and risk stratification for diabetes complications.

Key Content and Findings: Generative AI models have demonstrated significant promise in detecting hidden trends and early risk factors for complications such as diabetic retinopathy and neuropathy, often before clinical symptoms manifest. LLMs enhance predictive performance by synthesising unstructured data sources, such as physician notes and patient-reported outcomes, with clinical datasets. Despite limitations concerning data quality, model transparency, and ethical concerns surrounding data privacy, these technologies offer powerful tools for proactive disease monitoring and personalized care.

Conclusions: Generative AI and LLMs are poised to redefine diabetes management by enabling earlier detection of complications and personalised treatment strategies. Their integration into clinical decision

^ ORCID: 0000-0002-2512-6131.

support systems (CDSS) and precision medicine frameworks may reduce the global burden of diabetes, improve patient outcomes, and shift care from reactive to preventative.

Keywords: Generative artificial intelligence (generative AI); large language models (LLMs); diabetes mellitus (DM); predictive analytics; personalized medicine

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Introduction

Diabetes mellitus (DM), particularly type 2 diabetes (T2D), is a global health issue affecting over 537 million adults worldwide, with this number expected to rise significantly in the coming decades (1). T2D is described as a complex metabolic disorder characterized by persistent hyperglycemia due to insulin resistance or insufficient insulin production (2). Its associated complications, including diabetic retinopathy, neuropathy, nephropathy, and cardiovascular diseases (CVDs), pose significant public health challenges and remain leading causes of morbidity and mortality (3). Managing these complications effectively requires early detection and timely interventions, as they tend to progress silently before manifesting into more severe clinical outcomes (4).

Traditional clinical approaches often rely on observable symptoms and well-known biomarkers, such as fasting blood glucose and hemoglobin A1C (HbA1C) levels, to assess disease progression. While these methods have been fundamental in managing diabetes, they are often insufficient for detecting subtle, early changes that precede complications (5). For instance, diabetic retinopathy can go undetected until it has caused irreversible vision damage (6), and diabetic neuropathy might only be diagnosed after patients experience substantial nerve impairment (7). This limitation highlights the need for more advanced, precise methods that can identify early risk factors and changes in disease progression.

Artificial intelligence (AI) has emerged as a transformative tool in healthcare, offering new possibilities for diabetes management in the recent years (8). Generative AI, a subset of AI focused on creating new outputs based on learned patterns from existing data, has demonstrated immense potential (9). Unlike traditional predictive models, generative AI is capable of uncovering complex relationships within vast datasets, including patient medical records, imaging, lifestyle data, and genetic profiles (10). This capability is particularly relevant for diabetes management, where the disease's progression and its complications are influenced by a range of interrelated factors.

Among the most powerful forms of generative AI are large language models (LLMs), such as Generative Pretrained Transformers (GPT) and Bidirectional Encoder Representations from Transformers (BERT). These models have been trained on vast datasets and can process both structured and unstructured data to generate meaningful predictions (11). In the context of diabetes care, LLMs are capable of analyzing diverse information sources, such as electronic health records (EHRs), clinical notes, medical literature, and even patient-reported outcomes (12). This allows for the detection of complex patterns and hidden trends in disease progression, which are often not visible through traditional clinical approaches.

Current evidence underscores the growing role of AI in healthcare, particularly in diabetes care. Various studies have shown that AI algorithms can predict the onset of T2D and its complications with remarkable accuracy (13-15). For example, a study demonstrated that AI could predict the likelihood of T2D onset using data from EHRs, achieving over 90% accuracy (16). Additionally, AI has shown great promise in screening for complications such as diabetic retinopathy, where AI models have matched or even surpassed the diagnostic capabilities of human specialists (17). These advances underscore the potential of AI not only in predicting disease onset but also in identifying early-stage complications before they become clinically apparent (18).

Generative AI builds on these advances by offering deeper insights into complex, multi-dimensional datasets (19). In diabetes care, where factors such as metabolic dysfunction, lifestyle habits, and genetic predispositions all play critical roles, generative AI can integrate these diverse inputs to provide personalized risk assessments (20). By identifying hidden trends that may not be evident to human clinicians, AI models can alert healthcare providers to emerging complications before they progress, allowing for earlier, more targeted interventions (21).

LLMs are especially valuable in this regard. They can process and analyze unstructured data, such as physician notes or patient-reported outcomes, alongside structured data like lab results or imaging studies (22). This ability to synthesize diverse data sources enhances predictive accuracy and provides a more holistic view of each patient's health. For instance, Tan *et al.* worked on how LLMs can identify early signs of diabetic retinopathy by cross-referencing a patient's clinical history with emerging trends in large datasets, providing clinicians with a powerful tool to intervene before irreversible damage occurs (23).

The integration of generative AI into diabetes care represents a significant shift from reactive to proactive management (24). Rather than waiting for complications to become symptomatic, healthcare providers can use AI-driven insights to monitor patients continuously and adjust treatment plans in real time. This proactive approach not only improves patient outcomes but also reduces the long-term healthcare burden by preventing severe complications from developing. It also revolutionizes chronic disease management by enabling predictive modeling that enhances early diagnosis, personalized treatment plans, and proactive healthcare interventions (25).

As these technologies continue to evolve, the future of diabetes care will likely become more individualized and precision-driven (26). A study noted that incorporating genetics, lifestyle, and environmental data into predictive models will enable AI tailor treatment strategies to each patient's unique needs (27). This personalized approach to diabetes management holds great promise for improving both the quality of life and the long-term health outcomes of millions of patients worldwide (28).

The rationale for this review stems from the growing need for more advanced, precise methods to manage DM and its complications, given the limitations of traditional clinical approaches in detecting early signs of disease progression. Despite significant advancements in diabetes care, complications such as diabetic retinopathy, neuropathy, and CVDs often remain undetected until they have reached advanced stages, leading to irreversible damage and increased morbidity. The statement of the problem focuses on the gap in early detection tools, which currently rely heavily on standard biomarkers and observable symptoms, potentially missing subtle yet critical changes that signal the onset of complications. As diabetes continues to be a leading cause of disability and death worldwide, there is an urgent need to leverage emerging technologies to improve early detection and management (29). The objective of this review is to explore the potential of generative AI and LLMs in predictive analysis for diabetes and its complications, assessing how these technologies can uncover hidden patterns in large datasets and facilitate proactive, personalized interventions. This paper aims to provide insight into how AI can shift diabetes care from reactive to preventive, improving patient outcomes and reducing healthcare burdens associated with diabetes-related complications. We present this article in accordance with the Narrative Review reporting checklist (available at https://atm.amegroups.com/article/view/10.21037/atm-25-62/rc).

Methods

This narrative review was conducted to explore and synthesise current evidence on the role of generative AI, particularly LLMs, in the predictive analysis and early detection of DM and its complications. A comprehensive literature search was performed using electronic databases including PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar to identify peer-reviewed articles, reviews, and relevant grey literature published between 1 January 2018 and 31 December 2024.

The search strategy employed a combination of keywords and Boolean operators: ("Generative AI" OR "Large Language Models" OR "LLMs" OR "GPT" OR "BERT") AND ("diabetes" OR "type 2 diabetes" OR "diabetic complications") AND ("predictive analysis" OR "early detection" OR "personalised medicine" OR "AI in healthcare").

Inclusion criteria were as follows:

(I) Articles published in English;
(II) Studies or reviews discussing the use of generative AI or LLMs in diabetes management, early detection, prediction, or complications (e.g., retinopathy, neuropathy, CVD);
(III) Papers that provided technical insights, clinical applications, or future directions of generative AI in the healthcare setting.

Exclusion criteria included articles focused solely on non-generative AI models (e.g., traditional supervised learning) without relevance to diabetes, commentaries without data-backed discussion, and duplicate or outdated sources.

Relevant data were extracted and thematically grouped to align with the objectives of the review:

(I) Articles published in English;

Table 1 The search strategy summary

Items	Specification
Date of search	The search was conducted 24 March 2025
Databases and other sources searched	PubMed, Scopus, Web of Science, IEEE Xplore, Google Scholar; relevant grey literature identified via Google Scholar
Search terms used	Free-text Boolean string used: ("Generative AI" OR "Large Language Models" OR "LLMs" OR "GPT" OR "BERT") AND ("diabetes" OR "type 2 diabetes" OR "diabetic complications") AND ("predictive analysis" OR "early detection" OR "personalised medicine" OR "AI in healthcare"). Where available, database-specific subject headings (e.g., MeSH) were mapped to diabetes and key complications (retinopathy, neuropathy, cardiovascular disease)
Timeframe	1 January 2018 to 31 December 2024
Inclusion and exclusion criteria	Inclusion: English-language peer-reviewed articles and reviews, and relevant grey literature that discuss generative AI or LLMs in diabetes management, early detection, prediction, or complications; studies offering technical insights, clinical applications, or future directions
	Exclusion: items focused only on non-generative AI without diabetes relevance; commentaries without data-backed discussion; duplicates; outdated sources
Selection process	Narrative review approach. Records were screened for thematic relevance to the review objectives by the author team; formal dual independent screening was not undertaken. Disagreements were resolved through discussion and consensus
Any additional considerations, if applicable	No formal quality appraisal due to source heterogeneity; preference given to studies from higher-impact venues or with robust methods and real-world relevance. Data were extracted and thematically grouped. Narrative review design used for transparent reporting rather than exhaustive systematic coverage

AI, artificial intelligence; LLMs, large language models.

(II) Overview of AI in diabetes care;
(III) Predictive applications of generative AI;
(IV) Use of LLMs in synthesising structured and unstructured health data;
(V) Early detection of diabetes complications;
(VI) Challenges, and
(VII) Future directions for clinical integration.

Quality assessment was not formally conducted due to the heterogeneity of the sources included (e.g., primary studies, technical papers, and reviews). However, preference was given to high-impact journals and studies with robust methodologies or significant relevance to real-world clinical practice.

The search strategy, including databases and sources, key terms, timeframe, inclusion and exclusion criteria, and selection process, is summarised in *Table 1*.

The role of AI in diabetes management

AI has transformed many aspects of healthcare, and diabetes management is no exception. AI applications in this field range from supervised machine learning models that predict disease onset to tools that enhance patient self-management (30). However, recent advancements in AI, particularly through the development of predictive analytics, have significantly improved the ability to monitor and manage diabetes (31). AI's capacity to handle large amounts of data and identify complex patterns offers a level of precision and efficiency that was previously unattainable (32).

Supervised machine learning and predictive analytics

Supervised machine learning in DM management, a subset of AI, has been instrumental in diabetes care by using labeled datasets to make predictions based on input variables (33). These models are trained on vast amounts of patient data, including lab results, demographic information, and lifestyle factors, to predict the likelihood of diabetes onset, progression, and related complications using sophisticated feature selection algorithms and machine learning approaches to identify optimal predictors from large datasets (34). Recent advances have demonstrated that anthropometric measures, particularly those estimating abdominal obesity such as waist circumference, serve as powerful predictors in machine learning models for diabetes risk assessment (35).

De Silva *et al.* conducted a comprehensive analysis using the National Health and Nutrition Examination Survey (NHANES) data, employing feature selection algorithms on 156 exposure variables and applying four machine learning algorithms to identify 25 predictors of prediabetes (34). Their models achieved ≥70% area under the receiver operating characteristic curve (AUROC), significantly outperforming the Centers for Disease Control and Prevention (CDC) prediabetes screening tool (34). Remarkably, Buccheri *et al.* demonstrated that a zero-cost screening tool utilising only two variables, age and waist circumference, could achieve 75.3% area under the curve (AUC) for detecting undiagnosed dysglycemia, with sensitivity and specificity of 0.65 and 0.73 respectively (35). This innovative approach, based on Darwinian evolutionary theory principles, highlighted the critical importance of waist circumference as a measure of abdominal obesity in diabetes prediction (35). Further validation through stratified analysis across different demographic groups confirmed the robustness of the age-related waist circumference model, achieving consistent AUC values of 0.69–0.78 across sex and ethnic groups, demonstrating its applicability as a universal screening tool for dysglycemia in diverse populations (36). These algorithms are capable of identifying patients at risk long before they display clinical symptoms, enabling earlier interventions and personalised care strategies. AI's capacity to predict diabetes-related complications, such as CVD, is particularly valuable given the difficulty in assessing individual patient risk using traditional methods alone (31).

AI-powered wearables and mobile applications

Wearable devices and mobile applications powered by AI have become essential tools for real-time diabetes management (37). Continuous glucose monitors (CGMs), smart insulin pens, and AI-driven smartphone apps allow patients to monitor their blood sugar levels, activity, diet, and medication adherence in real-time (38). These devices use machine learning algorithms to analyze data from daily life activities, offering personalized insights and recommendations. For example, CGMs such as the Dexcom G6 and Abbott FreeStyle Libre continuously measured interstitial glucose levels and use AI algorithms to predict blood sugar trends, allowing users to take preventative action to avoid hypo- or hyperglycemia (39,40). Mobile applications like mySugr and Sugar.IQ analyze glucose data and provide users with tailored feedback on diet, exercise, and medication, helping them optimize glycemic control (41). In addition to improving patient outcomes, these tools reduce the cognitive burden on patients by automating much of the day-to-day management of diabetes (42). While these AI-powered technologies have significantly improved self-management, they primarily focus on monitoring. The next frontier lies in AI's ability to go beyond observation and generate novel insights for proactive care, particularly through the use of generative AI models (43).

Generative AI: expanding predictive capabilities

Generative AI, a type of machine learning that creates new data or outputs based on learned patterns, has opened up new possibilities in diabetes management (31). Unlike traditional AI models that are focused on classification and regression tasks, some studies mentioned that generative models are designed to predict and generate new information, offering unique insights into disease progression and complication risks (44,45). These models use large datasets, including clinical data, genetic information, and lifestyle factors, to create highly personalized predictive models (46). One of the most powerful aspects of generative AI is its ability to uncover hidden trends and relationships that are not immediately apparent to clinicians (47). For example, in a study that analyed genetic markers, metabolic data, and cardiovascular risk factors, it was concluded that generative AI models can detect early signs of diabetes-related complications, such as retinopathy, neuropathy, and CVD, before they manifest clinically (48). It was noted that generative AI could be used to screen and diagnose diabetic retinopathy even at an early stage and without the resources that are only accessible in special clinics (49). Generative AI has been used to predict the onset of cardiovascular complications in diabetes patients by analyzing longitudinal data, including heart rate variability, cholesterol levels, and inflammatory markers. A generative model trained on this data can predict the likelihood of a heart attack or stroke in a diabetic patient, offering clinicians valuable insights that can inform preventative treatment plans (50,51).

Individualized risk assessments and personalized interventions

One of the most significant advantages of generative AI in diabetes management is its ability to offer individualized risk assessments (52). While traditional risk calculators rely on generalized population data, generative AI models can analyze multi-dimensional datasets specific to an individual (19). A study emphasized that by incorporating genetic information, metabolic markers, and lifestyle data, these AI models create a more accurate prediction of a patient's risk for developing diabetes-related complications (53). For instance, AI models developed by IBM Watson have been used to predict individual responses to different diabetes medications, helping clinicians tailor treatments to each patient's unique genetic and metabolic profile (54). This precision-medicine approach ensures that patients receive the most effective therapy, minimizing the risk of adverse effects and improving overall outcomes (55). Generative AI can also recommend personalized interventions based on real-time data (56). For example, an AI-driven system might suggest lifestyle modifications, such as dietary changes or exercise routines that are optimized for an individual's metabolism and cardiovascular risk (57). By integrating data from wearable devices, CGMs, and genetic testing, these models can offer real-time, adaptive recommendations that evolve as the patient's condition changes (58).

AI's role in drug discovery and development

In addition to the clinical applications of AI, generative AI is also revolutionizing diabetes treatment by accelerating the drug discovery process (59). AI models can simulate the biological effects of potential drug compounds on patients with diabetes, predicting efficacy and side effects before clinical trials (60). For example, companies like Insilico Medicine are using generative AI to discover novel compounds for treating metabolic disorders like diabetes (61). These AI-driven approaches significantly reduce the time and cost associated with traditional drug development pipelines. By generating virtual models of how drugs interact with specific proteins and pathways implicated in diabetes, AI can identify promising candidates for further investigation. This capability is particularly important in the search for drugs that can not only manage blood sugar levels but also prevent or reverse diabetes-related complications, such as neuropathy and nephropathy.

The foundation of AI in healthcare: critical datasets for model development

Large-scale, population-representative datasets serve as the cornerstone for developing robust AI models in healthcare, with the NHANES and UK Biobank standing as exemplary resources that have revolutionised AI-driven medical research (62,63). NHANES, which collects comprehensive health and nutrition data from diverse communities across the United States through interviews, health examinations, and laboratory tests, provides researchers with nationally representative samples essential for developing generalisable AI models (62). Similarly, UK Biobank's extensive biomedical database, encompassing half a million participants since 2006, offers researchers worldwide access to imaging data, biomarkers, genetic information, healthcare records, and lifestyle data through its secure Research Analysis Platform (63).

These datasets have proven instrumental in generating breakthrough AI models across multiple internal medicine pathologies, particularly in diabetes research where the complexity and multifactorial nature of the disease demands robust, diverse training data. NHANES data has enabled the development of sophisticated machine learning algorithms for prediabetes prediction, with studies demonstrating superior performance compared to traditional screening tools through feature selection techniques applied to comprehensive exposure variables (34-36). The richness of NHANES data, spanning decades of collection and including detailed anthropometric measurements, laboratory results, and lifestyle factors, has been particularly valuable in identifying novel predictors such as waist circumference as a powerful indicator of diabetes risk (35).

CVD prediction has similarly benefited from these robust datasets, with UK Biobank facilitating the development of ensemble machine learning models that achieve remarkable accuracy improvements by incorporating psychological factors alongside traditional risk parameters (64). Recent studies utilising UK Biobank data have demonstrated how AI-powered electrocardiogram analysis can predict heart failure risk from single-lead recordings, showcasing the potential for scalable community-based risk assessment using portable devices (65). The longitudinal nature of UK Biobank's follow-up data enables researchers to track disease progression over time, providing crucial insights into the temporal patterns that AI models can learn to recognise early warning signs of cardiovascular complications in diabetic patients.

Furthermore, NHANES data has supported the creation of innovative AI-driven screening tools for sarcopenia and muscle mass assessment, demonstrating how anthropometric measurements can effectively substitute costly radiological examinations whilst maintaining high diagnostic accuracy (66,67). These applications underscore the versatility of well-curated datasets in enabling AI models to address multiple health conditions using similar methodological approaches.

The comprehensive nature and rigorous data collection protocols of these datasets ensure that AI models developed from them possess the statistical power and external validity necessary for clinical implementation across diverse populations. Without such foundational datasets, the current advances in generative AI for diabetes care would not be possible, as these models require vast amounts of high-quality, representative data to learn the complex patterns that enable accurate prediction and personalised interventions. As generative AI continues to evolve, the ongoing expansion and enhancement of datasets like NHANES and UK Biobank will be crucial for developing even more sophisticated models capable of addressing the growing global burden of diabetes and its complications.

Generative AI and LLMs

Generative AI and LLMs are emerging as critical tools in revolutionizing diabetes care (68). Their ability to analyze diverse and complex data sources, ranging from structured datasets like medical records to unstructured data like patient notes, sets them apart from traditional AI models. By producing novel insights based on learned representations, these models hold the promise of significantly improving early detection, personalized treatment, and overall management of diabetes and its complications (69).

Overview of generative AI

Generative AI models are designed to analyze vast amounts of data and generate meaningful outputs by learning from underlying patterns (70). These models are particularly useful in diabetes care because of the multifactorial nature of the disease and its complications (71). Diabetes is influenced by various factors, including genetics, lifestyle, metabolic changes, and environmental exposures, making it difficult for conventional models to predict outcomes accurately (72). However, studies showed that generative AI can integrate these data points and produce highly specific and personalized predictions for each patient (73).

One of the most promising aspects of generative AI in diabetes management is its ability to analyze both structured and unstructured data (74). Structured data includes EHRs, laboratory results, medical images, and genetic profiles. These datasets provide quantitative information about a patient's health, which generative AI models can analyze to predict diabetes progression or potential complications. For instance, by examining a patient's blood glucose levels, lipid profiles, and cardiovascular biomarkers over time, generative AI can identify subtle changes that may precede the development of conditions like diabetic retinopathy or nephropathy (75).

Unstructured data, such as patient histories, lifestyle factors, and physician notes, adds another layer of complexity. Traditional models often struggle to incorporate this type of qualitative information into predictive analytics, but generative AI excels in this area (70,73). For example, a patient's diet, exercise patterns, and medication adherence, which are typically recorded in free-text form, can be processed by generative AI models to provide a comprehensive understanding of how these lifestyle factors contribute to disease progression.

Recent studies done have demonstrated the utility of generative AI in detecting early signals of diabetes complications (49,71,76). A notable example comes from research on diabetic retinopathy, in this study, a deep generative AI model was used to analyze retinal images and patient records, identifying subtle retinal changes that precede clinically observable damage (77). These predictions were made well before the onset of symptoms, allowing for earlier interventions that could prevent vision loss. Similar applications have been explored in predicting neuropathy and nephropathy, where generative AI models can detect early signs of nerve and kidney damage by analyzing patient biomarkers and longitudinal health data (78).

LLMs in healthcare

Several studies have been carried out on LLMs; a subset of generative AI use in healthcare. All concluded in their studies that LLMs have become particularly influential in healthcare due to their ability to process and synthesize large volumes of textual information (19,79,80). LLMs, such as GPT and BERT, are trained on massive datasets and have the unique capability of understanding both structured and unstructured text (11,81). In diabetes management, this ability to integrate and interpret diverse sources of information is invaluable. LLMs can analyze patient data from a wide range of formats, including EHRs, clinical trial reports, genetic data, and even patient-reported outcomes (31,82). One of the key advantages of LLMs is their ability to comprehend unstructured text, such as physician notes, which often contain critical insights about a patient's condition that may not be captured in structured data fields. These notes can include observations about patient behavior, medication side effects, or subjective symptoms that contribute to the overall understanding of diabetes progression (68).

For instance, a physician might note that a patient has been experiencing more frequent episodes of dizziness or fatigue, which may suggest an underlying issue with blood sugar management or early signs of neuropathy. An LLM trained to analyze these notes, alongside structured data such as lab results and medical imaging, can identify patterns and correlations that might otherwise go unnoticed (83). This capability enhances the predictive accuracy of diabetes models by combining both quantitative and qualitative data, providing a more holistic view of the patient's health (31). Moreover, LLMs can parse vast amounts of research literature, identifying emerging trends in diabetes treatment and complications (84). In clinical practice, this means that an LLM could, for example, cross-reference a patient's genetic profile with the latest findings from genetic research to predict their risk for specific diabetes-related complications, such as nephropathy or CVD. This type of real-time analysis ensures that clinicians are working with the most up-to-date knowledge and can tailor their treatment plans accordingly (85).

The use of LLMs is not limited to text-based analysis. They can also be integrated with other AI models to process multimodal data. For example, LLMs can analyze genetic data alongside medical imaging, lab results, and patient histories to generate more comprehensive predictive models (83,86). This integration enhances the ability of clinicians to detect early signs of complications, offering the potential for more precise and personalized interventions (87). A study demonstrated the use of LLMs in predicting diabetic neuropathy by analyzing a combination of EHR data, physician notes, and patient-reported symptoms (88). The model was able to detect early signs of nerve damage before patients presented with severe symptoms. By recognizing these early patterns, clinicians were able to implement preventative measures, such as medication adjustments and lifestyle interventions, potentially slowing the progression of the disease. Additionally, LLMs are transforming patient care by enabling more efficient and accurate clinical decision-making (89). Their ability to synthesize vast amounts of patient data into actionable insights reduces the cognitive load on clinicians, allowing them to focus on more complex tasks that require human judgment (90). By providing real-time predictions and personalized treatment recommendations, LLMs have the potential to drastically improve patient outcomes and reduce the burden of diabetes-related complications (31).

Applications of generative AI in detecting diabetes complications

Generative AI models have demonstrated immense potential in the early detection and management of diabetes complications (31). These models are capable of processing and analyzing large volumes of diverse data, allowing them to uncover hidden patterns that are difficult or impossible for traditional diagnostic tools to identify. Other studies also noted that by integrating clinical, genetic, lifestyle, and other data sources, generative AI models provide personalized risk assessments that are more accurate and timelier than conventional methods (91). The following sections highlight some of the key applications of generative AI in detecting diabetes-related complications, focusing on diabetic retinopathy, neuropathy, and CVDs. *Figure 1* illustrates the key areas where AI is making an impact in diabetes management.

Diabetic retinopathy

Diabetic retinopathy is one of the leading causes of blindness among people with diabetes, and its progression can be asymptomatic until irreversible damage has occurred (6). Early detection is crucial for preventing vision loss, but traditional screening methods are often limited by their reliance on observable signs such as microaneurysms, hemorrhages, or exudates. These signs typically indicate that significant retinal damage has already occurred, limiting the window for effective intervention (91).

A study mentioned that generative AI models, particularly those using deep learning algorithms, have significantly enhanced the ability to detect diabetic retinopathy at much earlier stages. These models can analyze retinal images in greater detail than human specialists, identifying patterns that precede the visible symptoms of retinopathy (68). A study carried out by Dai *et al.* demonstrated that a deep learning-based AI system could predict the progression of diabetic retinopathy by analyzing subtle changes in retinal microvasculature that are not easily detectable through traditional screening methods (92,93). The AI model was able to predict the likelihood of disease progression,

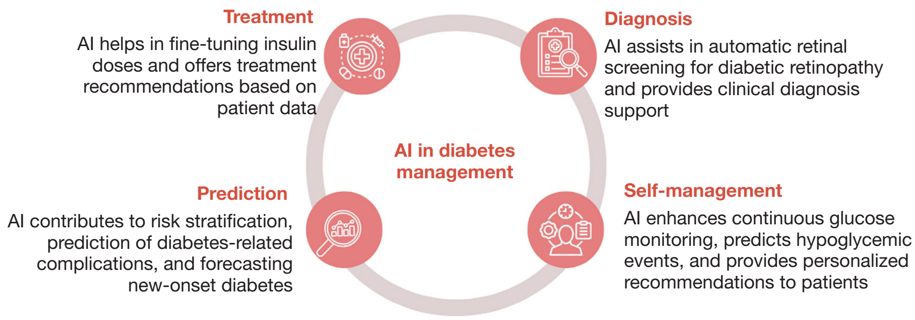

Figure 1 Multifaceted role of AI in diabetes management. AI, artificial intelligence.

improve image collection quality, provide clinical reference, and facilitate diabetic retinopathy screening with an accuracy rate that rivaled expert ophthalmologists, offering the potential for earlier intervention.

Moreover, generative AI models can integrate retinal image analysis with additional patient data, such as glycemic control history, blood pressure, and lipid levels, to provide a more comprehensive risk assessment. By factoring in these additional data points, AI models can offer personalized predictions regarding the likelihood of retinopathy progression for each patient (92). These capabilities allow clinicians to intervene earlier, whether through tighter blood sugar control, laser treatments, or other therapeutic strategies, potentially preventing the progression to severe visual impairment or blindness.

Diabetic neuropathy

Diabetic neuropathy is a common complication of diabetes, characterized by nerve damage resulting from prolonged high blood glucose levels (94). This condition can lead to a range of symptoms, from pain and tingling in the extremities to loss of sensation, which increases the risk of injuries and infections. Neuropathy often goes undetected until irreversible damage has occurred, largely because early-stage symptoms can be mild or vague (95). Conventional diagnostic tools, such as nerve conduction studies, are often used after significant nerve damage has developed. Generative AI models are transforming the detection of diabetic neuropathy by analyzing complex datasets, including nerve conduction studies, patient-reported symptoms, and genetic data (20). These models can detect early signs of neuropathy by identifying subtle changes in nerve function that precede more severe symptoms. A study demonstrated how AI-driven analysis of nerve conduction and sensory data could predict neuropathy before symptoms became debilitating, allowing for earlier interventions such as medication adjustments or lifestyle changes (96). *Figure 1* highlights key areas where AI contributes, including diagnosis through automatic retinal screening and clinical support, treatment optimization via insulin dose adjustments and recommendations, self-management enhancements through CGM and personalized advice, and predictive analytics for risk stratification and complication forecasting.

Generative AI models excel in their ability to integrate multiple types of data (47). For instance, these models can combine sensory, motor, and autonomic data with patient-reported outcomes, such as numbness or pain levels, to create personalized risk profiles for neuropathy. By including genetic information related to a patient's susceptibility to nerve damage, AI can further refine predictions, allowing clinicians to tailor treatment plans that mitigate the risk of severe nerve impairment. Early detection of diabetic neuropathy through generative AI can help prevent complications such as foot ulcers, infections, and even amputations, which are common in advanced stages of the disease (97).

Cardiovascular complications

CVD is the leading cause of death among individuals with diabetes, with complications such as heart attacks and strokes being major contributors to diabetes-related morbidity and mortality (98). The multifactorial nature of cardiovascular complications in diabetes, driven by a combination of hyperglycemia, hypertension, dyslipidemia, and lifestyle factors, makes prediction and early intervention particularly challenging. Traditional risk calculators often provide generalized risk assessments based on standard

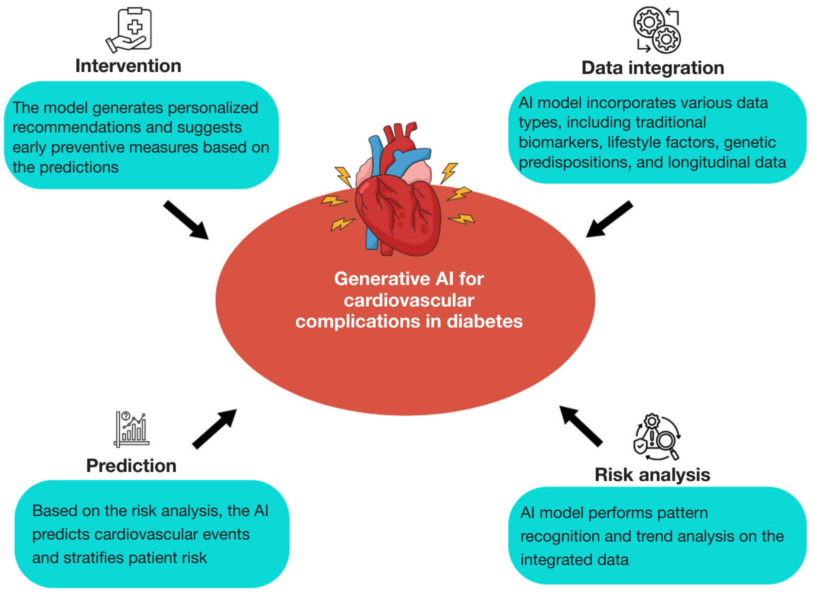

Figure 2 The process of using generative AI to predict and manage cardiovascular complications in diabetes patients. This comprehensive approach highlights the enhanced capabilities of generative AI in addressing the complex interplay of factors contributing to cardiovascular disease in diabetic patients. AI, artificial intelligence.

biomarkers (e.g., cholesterol levels, blood pressure) but may not account for the complexity of individual risk profiles (99). However, Generative AI models have shown superior capabilities in predicting cardiovascular events in diabetic patients by integrating diverse datasets that extend beyond traditional risk factors. These models are able to analyze cardiovascular biomarkers (such as cholesterol levels, heart rate variability, and blood pressure), alongside lifestyle factors like diet, physical activity, and smoking habits, to create highly personalized risk profiles. Additionally, generative AI models can incorporate genetic predispositions to CVDs, which further enhance their predictive accuracy (76).

Generative AI model can analyze longitudinal data from patients with diabetes to predict cardiovascular events, such as myocardial infarctions and strokes, with greater accuracy than conventional risk assessment tools (100). AI models detects subtle trends in cardiovascular markers and metabolic profiles that are indicative of elevated risk, even in patients who appear asymptomatic based on standard clinical evaluations (101). LLMs, which are a subset of generative AI, play a key role in this process by synthesizing and analyzing large volumes of longitudinal data. LLMs can identify hidden relationships between diabetes and cardiovascular markers by processing both structured and unstructured data, including clinical records, lab results, and physician notes (102). For instance, an LLM might detect a pattern of worsening blood pressure and lipid profiles in a patient's clinical history, combined with a family history of CVD, signaling an elevated risk for a heart attack. By recognizing these patterns, LLMs can help clinicians initiate preventive measures, such as optimizing blood pressure management, prescribing statins, or recommending lifestyle changes, well before a cardiovascular event occurs (103). *Figure 2* is a chart depicting the process by which Generative AI predicts and manages cardiovascular complications in individuals with diabetes. The chart outlines four key stages: data integration, where diverse datasets, including traditional biomarkers, lifestyle factors, genetic predispositions, and longitudinal data, are combined; risk analysis, which involves pattern recognition and trend analysis to assess patient risk; prediction, where cardiovascular events are forecasted and risk stratification is performed; and intervention, where personalized recommendations and early preventive measures are generated.

Future directions

The future of generative AI in diabetes management offers immense potential to revolutionize how the disease and its complications are diagnosed, monitored, and treated (104).

As AI technology continues to evolve, and as more comprehensive and high-quality datasets become available, AI models are expected to increase in accuracy and further expand their predictive capabilities (105). These advancements will enable more precise and personalized care for diabetes patients, leading to earlier interventions and better outcomes. Below are some key areas where generative AI is likely to shape the future of diabetes care.

Improved predictive capabilities with larger and more diverse datasets

As the availability of healthcare data continues to grow, generative AI models will benefit from access to larger and more diverse datasets (73). This includes data from CGM, wearable devices, genetic testing, lifestyle tracking, and environmental data. The integration of these diverse data sources will allow AI models to generate more accurate and nuanced predictions regarding disease progression, risk of complications, and responses to different treatments. For example, future AI models could analyze data from millions of patients across different populations, identifying trends and risk factors that are specific to various demographic groups, such as age, gender, or ethnicity (106). This ability to process diverse data will help AI systems account for the unique genetic, metabolic, and lifestyle factors that influence an individual's diabetes risk and tailor treatment plans accordingly. Moreover, as AI continues to learn from new data, its predictive accuracy will improve, leading to more reliable assessments of a patient's future health trajectory (107).

Integration into clinical decision support systems (CDSS)

The most promising future applications of generative AI, is its integration into CDSS (83). AI-driven CDSS can provide physicians with real-time, evidence-based insights into their patients' conditions, supporting more informed and timely decision-making (108). By integrating generative AI into these systems, healthcare providers will have access to advanced tools that offer personalized recommendations based on a comprehensive analysis of patient data. For instance, an AI-powered CDSS could continuously monitor a patient's CGM data, lab results, medication adherence, and lifestyle behaviors, flagging potential risks for complications like diabetic retinopathy or neuropathy before they become clinically apparent (109). Physicians could then receive tailored alerts and recommendations for preventive measures, such as adjusting insulin dosages or initiating dietary changes, without waiting for overt symptoms to develop. Furthermore, the real-time integration of generative AI into CDSS will reduce the cognitive burden on healthcare providers, allowing them to focus on patient care while benefiting from AI-generated insights that guide treatment plans. These systems can also help standardize care by ensuring that evidence-based guidelines are consistently followed, reducing the risk of human error in treatment decisions (110).

Advancements in personalized medicine

Personalized medicine is one of the most promising areas of healthcare where generative AI can have a profound impact (76,86). The ability to analyze an individual's genetic, environmental, and lifestyle factors enables AI to refine treatment protocols specifically tailored to the needs of each patient. In diabetes care, this personalized approach could be transformative, as treatment responses can vary widely based on genetic makeup, lifestyle habits, and comorbid conditions. Generative AI models are uniquely suited to integrate and process these complex data sets to offer highly individualized treatment recommendations. For example, AI could analyze a patient's genetic profile to predict how they might respond to certain medications or dietary interventions, allowing clinicians to select therapies that are most likely to be effective (111). This approach can significantly reduce the trial-and-error period in diabetes management, improving outcomes and reducing the risk of side effects.

In the future, AI-driven personalized medicine could extend beyond treatment selection to the optimization of preventive strategies (112). AI models could identify high-risk individuals based on their genetic predispositions and lifestyle behaviors, enabling clinicians to intervene before diabetes develops or its complications arise. For instance, an AI model might recommend a specific exercise regimen or dietary plan tailored to an individual's metabolic profile, reducing their risk of developing T2D or mitigating the impact of diabetic complications such as CVD or nephropathy.

AI-driven drug discovery and development

Another exciting future direction for generative AI in diabetes care lies in the realm of drug discovery and development (113). AI models have already begun to revolutionize how new drugs are identified and developed, and their applications in diabetes therapeutics are particularly promising (114). Generative AI can simulate the effects of potential drug compounds on diabetic patients by modeling complex interactions between the drugs and biological systems, predicting efficacy, side effects, and optimal dosing regimens before clinical trials even begin. In the context of diabetes, generative AI could accelerate the discovery of novel drugs that target not only glycemic control but also the prevention or reversal of diabetes-related complications (115). For example, AI could identify compounds that have a protective effect on retinal cells in diabetic retinopathy or that enhance nerve regeneration in patients with diabetic neuropathy. AI-driven drug development could significantly reduce the time and cost associated with bringing new diabetes treatments to market, ultimately benefiting patients by providing more effective therapeutic options (116).

Enhanced patient self-management tools

Some studies discussed another future advancement of generative AI in diabetes care. It proposed that the future generative AI in diabetes care will also likely see the continued development of advanced patient self-management tools (117). AI-powered wearable devices, mobile applications, and virtual health assistants can empower patients to take greater control over their diabetes management by providing real-time feedback and personalized recommendations (45). These tools can monitor blood glucose levels, physical activity, diet, and sleep patterns, offering insights that help patients make informed decisions about their health. As generative AI models become more sophisticated, self-management tools will become more proactive, providing patients with anticipatory guidance (118). For example, AI-driven applications could predict fluctuations in blood glucose levels based on past trends, suggesting specific actions—such as adjusting carbohydrate intake or increasing physical activity—to prevent episodes of hyperglycemia or hypoglycemia. Additionally, AI-powered apps could deliver customized health education and motivational support, encouraging patients to adhere to their treatment plans and maintain healthier lifestyles (119).

Strengths and limitations of the review

Table 2 presents a comprehensive summary of the key studies discussed throughout this review, organised by thematic sections. This synthesis demonstrates the extensive evidence base supporting the applications of AI and generative models across various aspects of diabetes care, from early detection and risk prediction to personalised treatment approaches.

This narrative review offers several key strengths, including its comprehensive scope spanning from established supervised machine learning to cutting-edge generative AI and LLMs in diabetes care. The systematic organization across multiple dimensions of diabetes management, from early detection and risk stratification to personalized treatment approaches, provides a detailed technological landscape. A particular strength lies in addressing the full spectrum of diabetes-related complications whilst incorporating critical foundational elements such as major datasets like NHANES and UK Biobank. The review effectively bridges technological innovation with clinical application, offering practical insights into current implementations and future directions for CDSS, personalized medicine, and patient self-management tools, making it a valuable resource for researchers, clinicians, and technology developers.

This narrative review presents a comprehensive synthesis of current evidence on the role of generative AI, particularly LLMs, in the predictive analysis and early detection of diabetes and its complications. However, several limitations should be acknowledged.

First, as a narrative review, the methodology lacks the rigorous systematic framework typically used in systematic reviews or meta-analyses. This introduces the potential for selection bias, as study inclusion was based on relevance and thematic alignment rather than a formal quality appraisal or protocol-driven screening process.

Second, while the search strategy was extensive, it was limited to articles published in English and accessible through major academic databases. As a result, relevant studies published in other languages or not indexed in the selected databases may have been overlooked, possibly limiting the global perspective of the findings.

Third, much of the current research on generative AI in healthcare, including diabetes care, is still emerging. Some of the included studies are preprints or based on preliminary findings, and long-term clinical validation of AI models remains limited. This means that many of the reported outcomes, although promising, may not yet be generalisable or reproducible across different populations and healthcare settings.

Table 2 Summary of main articles considered in diabetes AI review

Section	Study/reference	Key focus	Main findings/applications	Dataset/technology
Supervised machine learning and predictive analytics	De Silva *et al.* (34)	Feature selection and ML for prediabetes prediction	Achieved ≥70% AUROC, identified 25 predictors, outperformed CDC screening tool	NHANES 2013–2014 (n=6,346)
	Buccheri *et al.* (35)	Zero-cost screening tool for dysglycemia	75.3% AUC using only age and waist circumference, sensitivity 0.65, specificity 0.73	NHANES 2007–2016 (10 years)
	Buccheri *et al.* (36)	Stratified analysis of waist circumference model	Consistent AUC 0.69–0.78 across sex and ethnic groups	NHANES data stratification
AI-powered wearables and mobile applications	Dexcom G6 & Abbott FreeStyle Libre (39,40)	Continuous glucose monitoring	AI algorithms predict blood sugar trends, prevent hypo/hyperglycemia	CGM technology
	mySugr & Sugar.IQ (41)	Mobile diabetes management	Tailored feedback on diet, exercise, medication for glycemic control	Smartphone applications
Generative AI: expanding predictive capabilities	Genetic markers study (48)	Early complication detection	Detect retinopathy, neuropathy, CVD before clinical manifestation	Genetic/metabolic data
	Cardiovascular prediction models (50,51)	Heart attack/stroke prediction	Longitudinal analysis of heart rate variability, cholesterol, inflammatory markers	Longitudinal datasets
Individualized risk assessments and personalized interventions	IBM Watson (54)	Personalized medication prediction	Individual responses to diabetes medications based on genetic/ metabolic profiles	Clinical/genetic data
AI's role in drug discovery and development	Zhavoronkov *et al.* (61)	Novel compound discovery	Generative AI for discovering metabolic disorder treatments	Virtual drug modeling
The foundation of AI in healthcare: critical datasets for model development	Dorraki *et al*. (64)	Cardiovascular prediction with mental health	85.13% accuracy incorporating psychological factors	UK Biobank (n=375,145)
	Dhingra *et al*. (65)	Heart failure prediction from ECG	AI-enabled single-lead ECG analysis for HF risk stratification	Multi-national cohorts
	Buccheri *et al*. (66,67)	Sarcopenia screening	AI simplification of muscle mass loss detection, zero-cost variables	NHANES 1999–2006
Overview of generative AI	Deep generative model (77)	Diabetic retinopathy early detection	Identify subtle retinal changes before clinical symptoms	Retinal images + patient records
	Neuropathy/nephropathy prediction (78)	Early nerve/kidney damage detection	Biomarker analysis and longitudinal health data	Patient biomarkers
LLMs in healthcare	LLM neuropathy study (88)	Diabetic neuropathy prediction	Early nerve damage detection before severe symptoms	EHR + physician notes + patient symptoms
Diabetic retinopathy	Dai *et al*. (92,93)	Deep learning retinopathy detection	Predict progression via retinal microvasculature analysis, rival expert accuracy	Retinal imaging + clinical data
Diabetic neuropathy	AI-driven neuropathy analysis (96)	Early neuropathy detection	Predict neuropathy before symptoms become debilitating	Nerve conduction + sensory data
Cardiovascular complications	Cardiovascular events prediction (100)	MI/stroke prediction in diabetes	Superior accuracy vs conventional risk assessment tools	Longitudinal patient data
	LLMs cardiovascular analysis (102)	CVD pattern recognition	Synthesize structured/unstructured data for cardiovascular risk	Clinical records + lab results + notes
Future directions	Various studies (104-119)	Multiple future applications	CDSS integration, personalized medicine, drug discovery, self-management tools	Emerging technologies and datasets

AI, artificial intelligence; AUC, area under the curve; AUROC, area under the receiver operating characteristic curve; CDC, Centers for Disease Control and Prevention; CDSS, clinical decision support systems; CGM, continuous glucose monitor; CVD, cardiovascular disease; ECG, electrocardiogram; EHR, electronic health record; HF, heart failure; LLMs, large language models; MI, myocardial infarction; ML, machine learning; NHANES, National Health and Nutrition Examination Survey.

Furthermore, the field of generative AI is rapidly evolving. New developments, models, and applications may have emerged after the time of writing, potentially limiting the review's ability to capture the most recent innovations and technologies.

Finally, while this review aimed to highlight the opportunities and challenges associated with generative AI, it did not include a formal risk-benefit analysis or stakeholder perspectives from patients, clinicians, or developers, which are critical for real-world implementation.

Despite these limitations, this review provides a valuable foundation for understanding how generative AI is reshaping diabetes care and serves as a springboard for future research and interdisciplinary dialogue.

Conclusions

Generative AI, particularly LLMs, is revolutionizing the management of diabetes and its complications. By harnessing the power of these advanced models to analyze vast, multi-dimensional datasets, clinicians are gaining new insights into the hidden patterns of disease progression, metabolic dysfunction, and risk factors that were previously undetectable. This capability enables earlier detection of complications such as diabetic retinopathy, neuropathy, and CVDs, allowing for more timely and personalized interventions. As generative AI continues to evolve, it is poised to shift diabetes care from a reactive to a proactive approach, where individualized treatments are based on a patient's unique genetic, lifestyle, and clinical data. AI-driven tools are already beginning to empower both clinicians and patients with real-time insights, improving glycemic control, reducing complications, and enhancing overall quality of life. The integration of AI into CDSS, personalized medicine, and patient self-management platforms will further enhance the precision and effectiveness of diabetes management. While challenges related to data availability, model transparency, and ethical considerations remain, ongoing advancements in AI technology are expected to address these issues. As the field moves forward, generative AI will play an increasingly central role in diabetes care, improving outcomes for millions of patients worldwide by enabling more tailored, proactive, and effective treatment strategies. In the years to come, this transformative technology will be integral to reducing the global burden of diabetes and its associated complications.

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Footnote

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