■ REVIEW ARTICLE

A New Era in Diabetes Management: Generative Artificial Intelligence

Meleknur Göktaş [a†], **Tuğba Bilgehan** [b]

[a] Dr. Hulusi Alataş Elmadağ State Hospital , Ankara, Turkey
[b] Department of Nursing, Ankara Yıldırım Beyazıt University Ankara, Turkey.
† meleknur.gkts@gmail.com, corresponding author.

RECEIVED DECEMBER 06, 2024
ACCEPTED MARCH 18, 2025

CITATION Göktaş, M., & Bilgehan, T. (2024). A new era in diabetes management: generative artificial intelligence. Artificial Intelligence Theory and Applications, *5(1)*, 63-81.

Abstract

Diabetes mellitus (DM) is a rapidly increasing global health issue that requires effective self-management to prevent complications and improve quality of life. In recent years, advancements in generative artificial intelligence (GenAI) have created new opportunities to support DM self-management by providing personalized care solutions. This study is designed as a systematic review. Numerous studies in the literature have examined the contributions of GenAI models to DM self-management, and reviewing these studies is essential to provide a general framework on this topic. The primary aim of this study is to systematically examine research that utilizes GenAI in DM management. This systematic review was conducted in accordance with PRISMA guidelines. A comprehensive literature search was carried out between February and October 2024 across PubMed, Scopus, Web of Science, Google Scholar, Ulakbim, Türk Medline, and national databases. Using the keywords "diabetes," "generative artificial intelligence," and "diabetes self-management," studies published between 2018 and 2024 were identified. A total of 19 studies that met the inclusion criteria were analyzed in terms of the GenAI models used, application areas, and reported outcomes. Among the reviewed studies, GPT-based models were predominant, appearing in 53% of the research. In addition, models such as GAN, LSTM, WaveNet, GRU, Markov-Bayes, Google Bard, and Mobiguide were also utilized. Moreover, the findings of this study highlight that GenAI-based systems are widely adopted in DM self-management and possess significant potential to facilitate this process. These systems not only provide information but also incorporate advanced support mechanisms that enhance patient monitoring and clinical decision-making processes. GenAI has made notable contributions to DM care, particularly by developing personalized care plans, offering tailored dietary and exercise recommendations, generating educational materials, predicting blood glucose (BG) levels, providing individualized guidance, and supporting clinical workflows. As GenAI continues to evolve and adapt to the specific contexts and demands of the medical field, its role in DM care is expected to become increasingly prominent. However, several challenges have been reported, including concerns over data security, privacy, misinformation generation, and suboptimal performance in detecting critical conditions such as hypoglycemia. Addressing these ethical, technical, and security-related limitations requires further research and technological advancements. Future studies should prioritize enhancing the reliability, usability, and diagnostic accuracy of GenAI applications to ensure their seamless integration into clinical practice.

Keywords: generative artificial intelligence, diabetes self-management, diabetes

---

Artificial Intelligence Theory and Applications, ISSN: 2757-9778. ISBN: 978-605-69730-2-4 © 2025 İzmir Bakırçay University

1. Introduction

Diabetes Mellitus (DM), a major contributor to multiple health issues, has emerged as an escalating public health problem, significantly impacting a substantial portion of the global population [1, 2]. The prevalence of DM is estimated to rise to 643 million by 2030 and 783 million by 2045 [2, 3]. The primary objectives of DM management are to prevent or mitigate complications and preserve an optimal quality of life. Thus, effective long-term self-management is essential for individuals living with DM as a chronic condition [4]. Individuals with diabetes face an increased risk of developing various complications if they fail to maintain optimal blood glucose (BG) control [5]. The progression of chronic complications not only diminishes quality of life but also has detrimental physical, psychological, and social effects on individuals, while substantially escalating the economic burden of DM on healthcare systems [3,6]. Maintaining optimal glycemic control is a cornerstone of DM management to mitigate the risk of acute and chronic complications. Nevertheless, through comprehensive DM management and strict metabolic control, the onset of these serious complications can be delayed, or in some cases, entirely prevented [1, 3, 5, 7]. Many factors that affect successful DM self-management are modifiable and practical. Key behaviors, including healthy eating, regular physical activity, BG monitoring, adherence to prescribed medication regimens, developing healthy coping strategies, and problem-solving skills, are fundamental components of effective DM self-management [8]. Attaining optimal glycemic control in DM necessitates active participation in self-management efforts, which not only enhances the effectiveness of DM care but also fosters patient empowerment [1].

Each person is unique, and individuals with diabetes may have different preferences, values, and goals for their self-management. Therefore, creating a personalized management plan is essential. Such plans should consider various factors, including the individual’s age, cognitive abilities, work or school schedule, health beliefs, support systems, dietary habits, physical activity level, social situation, financial concerns, cultural factors, and literacy [9]. Furthermore, a comprehensive management approach should integrate factors such as DM history (including duration, complications, and current medication regimen), comorbidities, health priorities, other medical conditions, patient care preferences, and life expectancy [9, 10]. To facilitate this process, a DM care team plays an essential role in supporting individuals with diabetes. However, due to constraints such as time limitations, financial barriers, or other challenges, individuals with diabetes may encounter difficulties in regularly consulting a DM educator [11]. In these cases, a variety of strategies and techniques should be utilized to support self-management efforts. Technology can play a pivotal role in this context, facilitating daily DM self-management activities, including blood glucose (BG) monitoring, physical activity, healthy eating, medication adherence, complication monitoring, and problem-solving. Although the use of technology to support DM self-management is not a new concept, the diversity of technological strategies has expanded as individuals have become more tech-savvy, devices have become more accessible, and new technologies have emerged [12].

Recent advancements in artificial intelligence (AI) and machine learning (ML) techniques have become indispensable in addressing the complexities of DM management, empowering both patients and healthcare professionals in their daily management of DM [13]. AI refers to a set of techniques that enable computers to simulate human intelligence, encompassing ML as a subset. Often referred to as machine intelligence, AI involves the capacity of computer systems to learn from data inputs or historical information. The term 'AI' is commonly used to describe scenarios where a machine mimics cognitive functions of the human brain, such as learning and problem-solving

[14]. Within the healthcare sector, ML models have been effectively applied and are widely recognized as potent tools that enable computers to learn from data [15].

ML is a subset of AI that encompasses techniques enabling machines to enhance their performance in tasks through experience, and includes deep learning (DL). DL, in turn, is a subset of ML that utilizes neural networks, enabling a machine to autonomously train itself to perform tasks. The hierarchical evolution of these technologies can be summarized as follows: AI, ML, and DL [16]. ML models leverage extensively pre-trained data to generate accurate and relevant outputs. In ML, users must define and supply algorithms with sufficient information to generate accurate predictions. In contrast, DL algorithms utilize artificial neural network architectures to autonomously process data, allowing them to learn and generate accurate predictions based on high-level features extracted from the data [17].

ML technology, referred to as GenAI, can generate new data based on the training dataset. Generative models produce data that closely resemble the original dataset. A distinctive feature of GenAI is its capability to perform unsupervised learning, meaning it can identify patterns from data without the need for explicitly labeled examples. Some GenAI models learn how real-world data is distributed and subsequently generate new datasets that are statistically similar to the original dataset (Figure 1) [18, 19].

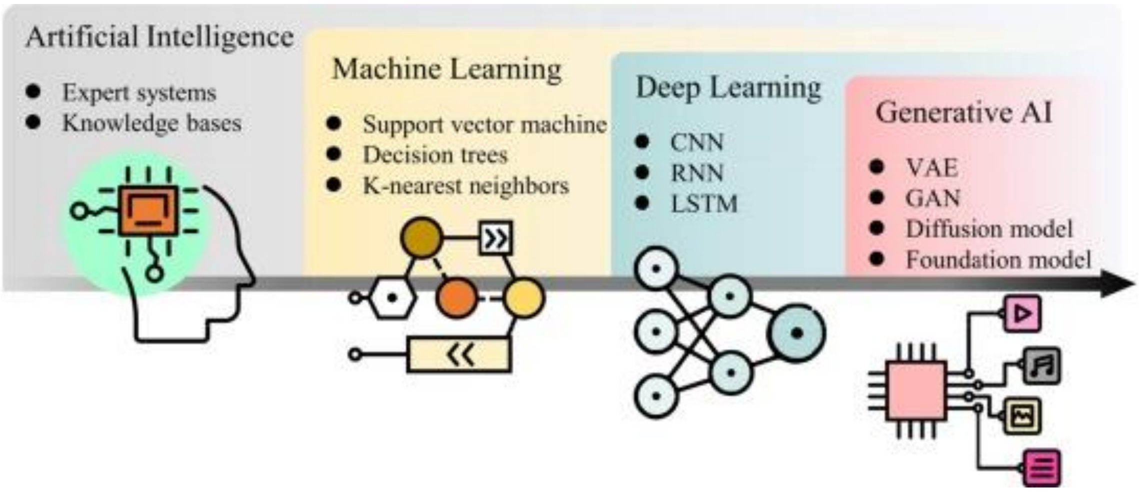

Figure 1: The development of AI and GenAI [19].

GenAI encompasses various models, including Generative Pre-trained Transformers (GPTs), Generative Adversarial Networks (GANs), Bayesian Networks (BNs), Artificial Neural Networks (ANNs), and Large Language Models (LLMs) (Figure 2) [20, 21, 22, 23].

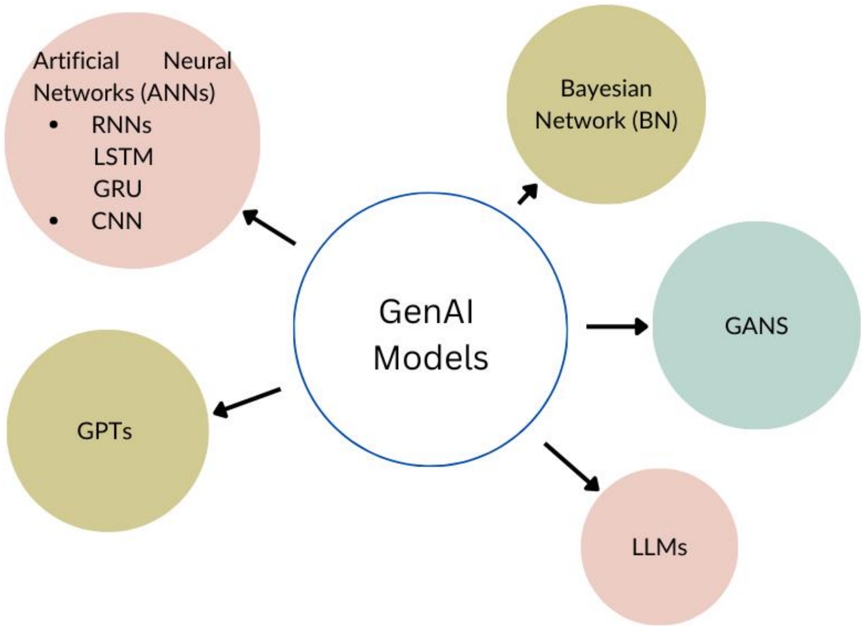

Figure 2: Key Techniques and Models in GenAI [20, 21, 22, 23].

GenAI models are emerging as promising tools within the context of healthcare. These models can analyze an individual's genetic profile, lifestyle, and medical history to provide tailored predictions about treatment options. By considering factors that may influence an individual's response to medication, GenAI can aid in optimizing therapeutic efficacy and improving individual outcomes [24, 13, 25, 26]. By generating personalized scenarios and responses tailored to individual needs, GenAI can effectively address the unique needs of individuals [26]. The predictions generated by GenAI guide the adjustment and optimization of treatments, thereby enabling the provision of more personalized care. Furthermore, by addressing individuals' health concerns and anxieties, GenAI offers supportive responses that help patients feel more reassured and less isolated throughout their healthcare journey [27].

GenAI also demonstrates significant potential in the field of patient education. It can generate personalized educational materials tailored to patients' specific conditions, symptoms, or inquiries. For instance, GenAI can provide individuals with diabetes information on BG management, nutrition, exercise, and medication adherence. Through interactive dialogues, patients can pose questions and receive answers that enhance their understanding of their conditions. This feature is particularly valuable for patients who may feel hesitant or embarrassed to directly ask specific questions of healthcare professionals. Furthermore, GenAI can simplify complex medical concepts by generating visual materials, such as diagrams or infographics. For example, it can illustrate how a specific medication works within the body to enhance patient comprehension [27]. Furthermore, patients with different levels of education and health literacy can improve their health literacy through GenAI-generated content tailored to various reading levels [28]. For instance, GenAI can deliver medication adherence reminders through email or text messages and provide explanations regarding the importance of adhering to prescribed treatment plans. Moreover, to enhance accessibility for individuals whose primary language is not English, GenAI can generate educational materials in multiple languages [29].

By analyzing patient-specific data, GenAI can predict health outcomes, identify potential risks, and recommend personalized treatment plans. Its capacity to extract insights from data presents significant potential for enhancing patient care processes [27]. Acting as a tool for patient engagement, education, and personalized interventions, GenAI provides a promising opportunity to improve DM management and transform healthcare delivery.

A review of the literature indicates that the majority of studies on GenAI have been published in the past three years, highlighting its rapidly growing use in DM management. For example, recent studies have shown that ChatGPT can simplify health information for individuals with diabetes [30], predict disease risks [31], and support patients in achieving positive outcomes by aiding them in managing lifestyle behaviors [32]. Furthermore, GenAI's ability to exhibit human-like empathy is highly regarded by users, as it delivers responses that are comparable to those provided by physicians, thereby fostering a sense of trust and rapport among patients [33].

GenAI demonstrates substantial potential in monitoring treatment adherence in individuals with diabetes and is increasingly recognized as a transformative tool for the future of DM management and care.

2. Materials-Methods

2.1. Purpose, Significance, and Scope of the Study

Purpose and Type of the Study

This research was designed as a descriptive systematic review. Numerous studies in the existing literature have examined the contributions of GenAI models to DM self-management, and reviewing these studies is essential for providing a comprehensive framework on this topic. The primary aim of this study is to systematically examine research that utilizes GenAI in DM management.

Research Question

What methods, applications, and outcomes have been reported in the current literature regarding the use of GenAI in DM self-management?

2.2. Method and Analysis of the Study

Studies on the use of GenAI in DM self-management, published between 2018 and 2024, were reviewed through searches conducted between February and October 2024 in the Scopus, Web of Science, PubMed, Ulakbim, Türk Medline, and Google Scholar databases. The searches were conducted using the keywords 'diabetes,' 'generative artificial intelligence,' and 'diabetes self-management,' either individually or in various combinations.

In the study selection process, relevant keywords were used to search the databases in line with the research question. After applying the inclusion and exclusion criteria, the remaining studies were retrieved, and their titles and abstracts were screened. Studies that did not correspond to the research question were excluded, while the full texts of the remaining studies were evaluated in detail. Ultimately, those meeting the eligibility criteria were included in the final set of studies for this systematic review.

All stages of the study—including article identification, screening, and selection—were conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic

Reviews and Meta-Analyses) guidelines [34]. The PRISMA flow diagram, which outlines the study selection process, has been presented in Figure 3.

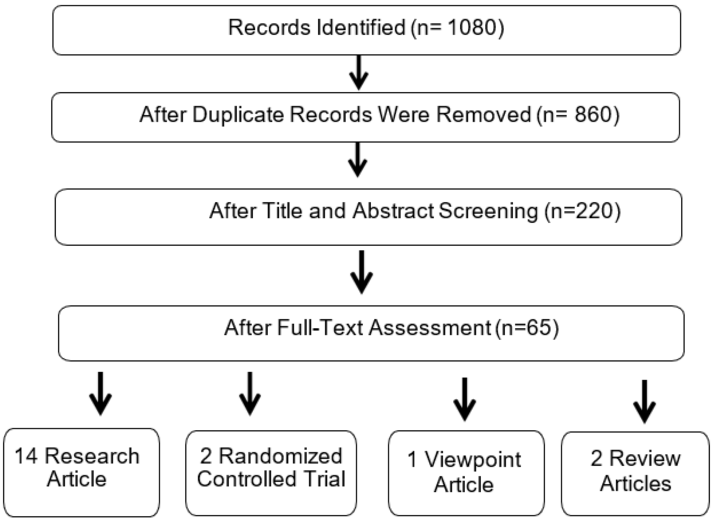

Figure 3. Flow Diagram of the Study

2.3 Inclusion and Exclusion Criteria

Inclusion Criteria:

- Studies addressing the use of GenAI in DM self-management.
- Articles published in English or Turkish.
- Research published between 2018 and 2024.
- Original research articles (including observational studies, experimental studies, clinical studies, and reviews).
- Studies with full-text availability.
- Studies with sufficient methodological quality to be included in a systematic review in accordance with PRISMA guidelines.

Exclusion Criteria:

- Studies related to DM or GenAI that do not focus on DM management.
- Abstracts, conference proceedings, commentaries, book chapters, editorial articles, and theses.
- Articles requiring paid access.

2.4. Data Collection

In the initial stage of the review process, an evaluation form outlining the inclusion criteria was developed. Based on this form, database searches were systematically conducted. As a result of the screening process, a total of 19 studies published between 2018 and 2024, focusing on the use of GenAI in DM management, were identified. All studies that met the inclusion criteria (n = 19) have been included in the review.

In the second stage of the review, a structured checklist was developed, comprising the following components: study title, study type and design, sample group and size, year of publication, and study outcomes. In accordance with this checklist, the titles and abstracts of all relevant articles identified through the database searches were independently reviewed by the author. No other individuals participated in the data collection phase of this study.

3. RESULTS

3.1. Characteristics of the Included Studies

As a result of the review, a total of 19 studies conducted in Turkey between 2018 and 2024 focusing on the use of GenAI in DM management were identified. Among these, 14 (73%) were original research articles, 2 (11%) were review articles, 1 (5%) was a viewpoint article, and 2 (11%) were randomized controlled trials.

3.2. Study Designs and Sample Characteristics

The characteristics of the included studies are presented in detail across separate tables: research articles in Table 1, randomized controlled trials in Table 2, the viewpoint article in Table 3, and review articles in Table 4.

Table 1. Descriptive Characteristics of the Research Articles on the Application of GenAI in DM Self-Management (n=14)

Title of the Study	Type of Study	Theory/Model Used	Sample Group	Study Reference	Study Findings
Blood glucose prediction with deep neural networks using weighted decision level fusion.	Research Article	A fusion of Long Short-Term Memory (LSTM), WaveNet, and Gated Recurrent Units (GRU) architectures.	The study sample is derived from the expanded OhioT1DM dataset, which comprises the BG history of 12 individuals with diabetes over an eight-week period and encompasses 19 distinct data types, including administered insulin doses and physiological sensor readings.	Dudukcu et al., 2021 [35]	The fusion performance of "LSTM + WaveNet + GRU" yielded more successful results in BG prediction. The predicted values are planned to be used for insulin dose calculations, with future development as a mobile application.
Blood glucose prediction for type 1 DM using generative adversarial networks	Research Article	A novel DL model using a modified GAN architecture for predicting BG levels in individuals with type 1 diabetes (T1DM).	BG data from 12 individuals with T1DM over an eight-week period.	Zhu et al., 2020 [36]	In this study, a novel DL model is proposed to predict future BG levels based on past continuous glucose monitoring measurements, meal intake, and insulin administration. When compared to the RNN (Recurrent Neural Network) prediction model, the GAN model demonstrated better validation performance and a smaller RMSE (Root Mean Square Error) for most of the contributors during the training process.

Using an optimized generative model to infer the progression of complications in type 2 diabetes patients	Research Article	Markov Jump Process and Bayesian network	Longitudinal EHRs of 9,298 individuals with type 2 diabetes (T2DM) or prediabetes (2005–2016, China).	Wang et al., 2022 [37]	The findings of this study demonstrated that the system could predict 55.3% of individual complications and 31.8% of complication patterns of progressive T2DM at an early stage, allowing for appropriate management that could potentially delay or prevent these complications.
The Future of Patient Education: AI-Driven Guide for Type 2 Diabetes	Research Article	OpenAI's ChatGPT	70 T2DM-related questions, each asked three times.	Hernandez et al., 2023 [38]	98.5% of responses aligned with care standards, outperforming traditional online search engines, with minimal inappropriate responses (1.5%), underscoring the need for continuous AI improvements.
An AI Dietitian for Type 2 Diabetes Mellitus Management Based on Large Language and Image Recognition Models: Preclinical Concept Validation Study	Research Article	Creating an AI based nutritionist program using advanced language and image recognition models using ChatGPT and GPT 4.0	206 individuals with T2DM and 26 endocrinologists	Sun et al., 2023 [39]	Positive feedback from dietitians and accurate food recognition, enabling personalized meal analysis and dietary guidance. The model developed at the end of this study can identify ingredients from images of a patient's meal and provide nutritional guidance and diet recommendations.
Building Trustworthy Generative Artificial Intelligence for Diabetes Care and Limb Preservation: A Medical Knowledge Extraction Case	Research Article	OpenAI's ChatGPT-4 with a RAG architecture.	NIH Diabetes Self-Management Education Standards knowledge base, 295 articles, 175 questions.	Mashatian et al., 2024 [40]	RAG model effectively delivers reliable medical information for self-education and emphasizes the importance of content validation and prompt engineering.
A Study on the Development of a Chatbot Using Generative AI to Provide Diets for Diabetic Patients	Research Article	OpenAI's ChatGPT	Data from 10 dietary guidelines, adapted for personalized seasonal diet plans.	Lee et al., 2024 [41]	Facilitates personalized diets and supports elderly health management with enhanced services and datasets.
Comparative evaluation of generative artificial intelligence systems for patient queries on age-related macular degeneration and diabetic macular edema	Research Article	ChatGPT-3.5, ChatGPT-4, Google Bard	22 patient queries from 68 anti-VEGF-treated individuals.	Posa et al., 2024 [42]	This study compared the effectiveness of three GenAI systems – Chat GPT-3.5, Chat GPT-4, and Google Bard – in providing clear and concise answers to patient questions about diabetic macular edema. GPT-4 was deemed most effective for patient communication due to its clear and simple language.

Artificial intelligence chatbots for the nutrition management of diabetes and the metabolic syndrome	Research Article	GPT-3.5-turbo0301	The total number of requests is 63, with 9 requests entered for each of the 7 conditions.	Naja et al., 2024 [43]	While ChatGPT provided human-like responses, significant gaps were identified, emphasizing that it cannot replace dietitian expertise.
Appropriateness of Artificial Intelligence Chatbots in Diabetic Foot Ulcer Management	Research Article	ChatGPT (OpenAI) GPT-4 (OpenAI) GPT-4 Turbo (OpenAI), GoogleBard (Google LLC), BingAI Balanced-mode (Microsoft Corp.), Perplexity (Perplexity AI) and Claude-2'den (Anthropic)	42 clinical questions on diabetic foot ulcers.	Shiraishi et al., 2024 [44]	Chatbots showed 91.2% accuracy but inconsistent evidence levels. Claude-2 had the highest reference accuracy; ChatGPT had the lowest. Variability and hallucinations highlight the need for cautious clinical use.
Assessment of the information provided by ChatGPT regarding exercise for patients with type 2 diabetes: a pilot study	Research Article	ChatGPT (V.4.0)	14 common patient exercise questions reviewed by two DM care specialists.	Chung and Chang, 2024 [45]	ChatGPT can serve as supplementary educational material but may provide incomplete answers for certain exercise-related questions.
Evaluation of ChatGPT-4 Performance in Answering Patients' Questions About the Management of Type 2 Diabetes	Research Article	ChatGPT-4	24 patient questions	Gokbulut et al., 2024 [46]	It has been observed that, while answering a series of questions related to the pharmacological management of T2DM, no inaccurate information was identified, and responses were highly consistent and reliable. However, readability levels varied, with many responses being classified as difficult to read.
Using Generative AI to Improve the Performance and Interpretability of Rule-Based Diagnosis of Type 2 Diabetes Mellitus	Research Article	GPT	Dataset of 768 instances with eight predictors and one outcome class.	Kopitar et al., 2024 [47]	This study, which explores the combination of association rule mining with GPT-based advanced natural language processing for classifying non-insulin-dependent DM, demonstrates that ChatGPT is effective in predicting diabetic and non-diabetic conditions. However, further research is required to enhance diagnostic accuracy in DM classification.
MobiGuide: guiding clinicians and chronic patients anytime, anywhere.	Research Article	MobiGuide	10 atrial fibrillation patients in Italy and 20 gestational individuals with diabetes in Spain	Peleg et al., 2022 [48]	Higher adherence rates and improved health outcomes were observed, including better glycemic control, with enhanced clinician engagement and patient quality of life.

Table 2. Characteristics of Randomized Controlled Trials on the Use of Generative AI in Diabetes Management (n=2)

Title of the Study	Type of Study	Theory/Model Used	Sample Group	Study Reference	Study Findings
Use of Voice-Based Conversational Artificial Intelligence for Basal Insulin Prescription Management Among Patients With Type 2 Diabetes	Randomized Controlled Trial	Alexa	32 adults with T2DM requiring initiation or adjustment of basal insulin therapy	Nayak et al., 2023 [49]	In this randomized clinical trial of a voice-based conversational AI application for autonomous basal insulin management in adults with T2DM, participants in the AI group demonstrated significantly greater improvements in the time required to achieve the optimal insulin dose, insulin adherence, glycemic control, and DM-related emotional distress compared to those in the standard care group.
Decoding Type 2 Diabetes Through Point-of-Care Testing, Cloud-based Monitoring, and Generative Augmented Retrieval Model-driven Virtual Diabetes Education: A Comprehensive Approach to Glycemic Control	Randomized Controlled Trial	AI-Powered Metabolic Coach Designed to Provide Personalized Recommendations	The study sample consists of 100 individuals aged between 18 and 65 who have been diagnosed with T2DM.	Shaikh et al., 2024 [50]	Participants in the intervention group, who received guidance from an AI-powered metabolic coach designed to provide personalized recommendations, demonstrated superior outcomes in HbA1c improvement, plasma glucose control, and related parameters compared to the control group.

Table 3. Characteristics of the Viewpoint Article on the Use of GenAI in DM Management (n=1)

Title of the Study	Type of Study	Theory/Model Used	Study Reference	Study Findings
ChatGPT in diabetes care: An overview of the evolution and potential of generative artificial intelligence model like ChatGPT in augmenting clinical and patient outcomes in the management of diabetes.	Viewpoint Article	ChatGPT	Dey, 2023 [51]	It can provide personalized care, where individualized treatment plans, glucose monitoring, and medication reminders are generated based on personal patient data. However, ethical considerations and data security must be carefully addressed, and any obtained information should be verified by healthcare professionals.

Table 4. Characteristics of the Review Articles on the Use of GenAI in DM Management (n=2)

Title of the Study	Type of Study	Theory/Model Used	Study Reference	Study Findings
The Future of Diabetes Care: Navigating with Generative Language Models	Review	OpenAI's GPT-3	Khan, 2023 [52]	This review concluded that generative language models can facilitate personalized care by creating customized treatment plans, glucose monitoring, and medication reminders based on individual patient data. However, ethical concerns and data security should be carefully considered, and any recommendations should be validated by healthcare professionals.
Potential and Pitfalls of ChatGPT and Natural-Language Artificial Intelligence Models for Diabetes Education	Review	OpenAI's GPT	Sng et al., 2023 [53]	This review found that ChatGPT performs well in generating comprehensible and generally accurate responses to questions related to DM self-management and education. The application of large language models has the potential to alleviate some of the burden on individuals with diabetes, allowing those with adequate knowledge of their condition to focus on more complex self-management and educational tasks. However, it is important to acknowledge that ChatGPT is constrained by the datasets on which it was trained. These limitations may lead to errors, such as difficulties in distinguishing between different types of insulin or recognizing variations in BG measurement units. The review emphasizes that healthcare providers should exercise due diligence when assessing AI chatbots for clinical care enhancement and patient guidance, ensuring a thorough understanding of both the strengths and limitations of these models.

Tables 1 through 4 reveal that the most commonly used GenAI models were GPT (53%), followed by Google Bard (6%), WaveNet (3.12%), Mobiguide (3.12%), BingAI Balanced-mode (Microsoft Corp.) (3.12%), Perplexity AI (3.12%), Claude-2 (Anthropic) (3.12%), Alexa (3.12%), AI-Powered Metabolic Coach (3.12%), as well as GAN (3.12%), LSTM (3.12%), GRU (3.12%), Markov Jump Process (3.12%), RAG (3.12%), and Bayesian Network (3.12%).

Thematic analysis of the included studies revealed the distribution of GenAI functions in DM self-management, which is presented in Table 5. When examining the areas in which GenAI models used in the studies included in the scope of this systematic review can be applied to DM self-management, it becomes evident that many models can serve common purposes. Additionally, this comparison highlights which model has previously been utilized for specific self-management actions.

Table 5. The Role of GenAI Applications in DM Self-Management Domains

Self-Management Action	**Included Studies**
Personalized recommendations (e.g., nutrition, exercise, BG management) [1]	Shaikh et al., 2024 [50], Peleg et al., 2022 [48], Hernandez et al., 2023 [38], Sun et al., 2023 [39], Lee et al., 2024 [41], Naja et al., 2024 [43], Shiraishi et al., 2024 [44], Chung and Chang, 2024 [45], Gokbulut et al., 2024 [46], Nayak et al., 2023 [49], Dey, 2023 [51], Khan, 2023 [52], Sng et al., 2023 [53]
Provision of DM education and information	Shaikh et al., 2024 [50], Hernandez et al., 2023 [38], Sun et al., 2023 [39], Mashatian et al., 2024 [40], Posa et al., 2024 [42], Shiraishi et al., 2024 [44], Chung and Chang, 2024 [45], Gokbulut et al., 2024 [46], Nayak et al., 2023 [49], Dey, 2023 [51], Khan, 2023 [52], Sng et al., 2023 [53]
Early detection of complications and complication alerts	Wang et al., 2022 [37], Mashatian et al., 2024 [40], Posa et al., 2024 [42], Shiraishi et al., 2024 [44], Chung and Chang, 2024 [45], Gokbulut et al., 2024 [46], Dey, 2023 [51], Sng et al., 2023 [53]
Emotional support and stress management	Mashatian et al., 2024 [40], Nayak et al., 2023 [49], Dey, 2023 [51]
Insulin and medication management	Shaikh et al., 2024 [50], Mashatian et al., 2024 [40], Gokbulut et al., 2024 [46], Nayak et al., 2023 [49], Dey, 2023 [51], Sng et al., 2023 [53]
Continuous glucose monitoring, BG prediction[2], and personalized analysis	Dudukcu et al., 2021 [35], Zhu et al., 2020 [36], Mashatian et al., 2024 [40], Dey, 2023 [51]
Tracking DM progression and providing lifestyle recommendations	Peleg et al., 2022 [48], Wang et al., 2022 [37], Dey, 2023 [51], Sng et al., 2023 [53]
Communication with healthcare professionals/ decision support for healthcare providers	Peleg et al., 2022 [48], Khan, 2023 [52]
Prediction of future risks and early diagnosis	Peleg et al., 2022 [48], Wang et al., 2022 [37], Posa et al., 2024 [42], Shiraishi et al., 2024 [44], Chung and Chang, 2024 [45], Gokbulut et al., 2024 [46], Kopitar et al., 2024 [47], Dey, 2023 [51], Sng et al., 2023 [53]
Improvements in HbA1C and BG levels	Shaikh et al., 2024 [50], Lee et al., 2024 [41], Hernandez et al., 2023 [38], Sun et al., 2023 [39], Mashatian et al., 2024 [40], Gokbulut et al., 2024 [46], Nayak et al., 2023 [49], Dey, 2023 [51]
Alerts for necessary actions	Peleg et al., 2022, [48], Hernandez et al., 2023 [38], Shaikh et al., 2024 [50], Posa et al., 2024 [42], Shiraishi et al., 2024 [44], Chung and Chang, 2024 [45], Gokbulut et al., 2024 [46], Nayak et al., 2023 [49], Dey, 2023 [51], Sng et al., 2023 [53]

[1] Assessing dietary habits, physical activity, BG levels, and medication adherence based on individual characteristics, climate conditions, and variations in caloric intake.
[2] Predicting future BG levels based on historical continuous glucose monitoring (CGM) measurements, meal intake, and insulin administration.

Table 5 presents a detailed summary of various DM self-management actions and the corresponding studies that contribute to these domains. Key areas frequently explored include personalized recommendations (e.g., nutrition, exercise, BG management) and DM education, underscoring the extensive application of GenAI-powered systems to improve daily self-management practices. Furthermore, key aspects that directly impact clinical management—such as early detection and alert systems for complications, insulin and medication management, continuous glucose monitoring, and BG prediction—have been extensively studied. These findings suggest that GenAI-based systems provide more than simple information and guidance, offering an advanced support framework incorporating in-depth data analysis and patient monitoring. Moreover, the increasing focus on communication with healthcare professionals, decision support, risk prediction, and improvements in HbA1C and BG levels demonstrates the evolving role of AI-driven solutions in DM management. Such systems are anticipated to enhance both patient adherence to treatment and the optimization of clinical decision-making by healthcare professionals. In conclusion, the table highlights the diverse applications of GenAI in DM management, offering valuable insights into how these technologies can support both patients' self-management and healthcare professionals' monitoring strategies. The expansion of GenAI's role in DM self-management, alongside its integration into clinical practice, represents a promising area for future research.

According to the analysis of the studies included in this review, GenAI applications demonstrate considerable potential advantages in DM self-management. However, the studies also highlight several limitations of these applications, as presented in Table 6.

Table 6: Potential Benefits and Limitations of GenAI in DM Self-Management

Advantages	Disadvantages
Personalized guidance	Collection and processing of patients' personal health data
Real-time support	Concerns regarding data security and privacy
Integration of evidence-based best practices	Resistance to the adoption of new Technologies
High accuracy in predicting future BG levels	Sometimes insufficient in detecting a small number of hypoglycemia events
Providing reliable medical information for self-education and self-management of DM	Lack of user trust in the system
Proven improvements in DM self-management	Requirement for comprehensive training and support to use the system effectively
High accuracy of outputs as a result of being trained with accurate books and data sources	Challenges due to insufficient technological infrastructure, especially in low-resource healthcare settings
Ability to offer personalized solutions to complex problems	Possibility of providing misinformation

The studies highlight that GenAI plays a significant role in promoting active patient involvement in self-management processes. Key functionalities such as offering personalized guidance, delivering real-time support, and integrating evidence-based clinical guidelines are central to this enhanced participation. Furthermore, the ability of GenAI to predict future BG levels accurately and provide access to reliable medical information has made DM management more proactive and informed. The high accuracy of GenAI model outputs, ensured by training on high-quality and comprehensive datasets, further strengthens its effectiveness. Additionally, the robust capability of these systems to generate personalized solutions for complex challenges greatly enhances the overall effectiveness of DM self-management. Collectively, these factors contribute to scientifically validated improvements in DM self-care practices.

Foremost among the concerns are data security and privacy, especially with regard to the collection and processing of patients' personal health information. Additionally, challenges such as resistance from healthcare professionals and patients to adopting new technologies, low user trust, and the need for extensive training and technical support complicate the implementation of GenAI solutions. Furthermore, certain models have been found inadequate in detecting critical conditions, such as hypoglycemia, while limited technological infrastructure in certain regions restricts the practical application of GenAI. The potential for GenAI to generate misinformation is also recognized as a significant risk factor. Consequently, while GenAI applications present substantial contributions to DM self-management, critical areas still require development to ensure these systems are more reliable, user-friendly, and ethically compliant (Table 6).

4. Discussion

This review has examined examples of GenAI applications that have had the potential to facilitate and enhance DM management. The analyzed studies highlight the use of GenAI in DM care across various areas, including BG control strategies, detection of hypoglycemia and hyperglycemia, insulin bolus calculators, decision support systems, risk assessment, patient personalization, meal and exercise tracking, error detection, and lifestyle support [48, 49, 50, 52, 53]. DL and GenAI are advancing towards ushering in a new era in DM management. By providing personalized recommendations, simplifying monitoring and follow-up processes, and assisting in error prevention, GenAI significantly contributes to DM self-management [54, 55].

In a randomized controlled trial that has been conducted by Shaikh et al. [50], the effectiveness of an AI-powered metabolic coach designed to provide personalized recommendations has been evaluated over a 12-week period. The study has assessed the impact of the metabolic coach on various glycemic parameters, including HbA1c levels, plasma glucose, glycemic variability (which has been measured using the glucose management indicator score), and predicted postprandial glucose levels. The trial has included 100 individuals aged 18–65 years who have been diagnosed with T2DM and have been willing to utilize digital technology for health monitoring. In this study, in particular, the observed improvement in postprandial glucose regulation has demonstrated that the AI-driven metabolic coach has effectively guided individuals in managing postprandial glucose fluctuations and maintaining stable glycemic control throughout the day. Therefore, the study findings have indicated substantial improvements in both short-term and long-term glycemic control. As a result, participants with T2DM in the intervention group have demonstrated superior outcomes compared to the control group, including significant reductions in HbA1c levels, lower plasma glucose concentrations, and notable decreases in postprandial glucose levels. This AI-driven metabolic coach, which has employed a holistic approach, presents a comprehensive strategy for addressing multiple aspects of metabolic health in DM management. This study has underscored the potential of AI-driven interventions to provide an integrative approach to DM management. The utilization of AI has had the potential to drive significant advancements in personalized care by targeting multiple facets of metabolic health. Consequently, the positive outcomes that have been observed in this study highlight the transformative potential of AI in enhancing the metabolic health of individuals with diabetes through the delivery of personalized healthcare solutions. These findings have provided strong evidence supporting the integration of AI technologies into DM management strategies.

Similarly, in a study conducted by Zhu et al. [36], a novel DL model has been developed utilizing a modified Generative Adversarial Network (GAN) architecture to predict future BG levels in individuals with T1DM, based on historical continuous glucose monitoring (CGM) measurements, meal intake, and insulin delivery. To train the model, BG-related data have been collected over eight weeks from 12 individuals with T1DM. The dataset included BG levels recorded every five minutes via CGM, insulin delivery data from insulin pumps, self-reported events (such as meals, work, sleep, psychological stress, and physical exercise) through a smartphone application, and physical activity data captured by a sensor band. The developed model has been found to provide appropriate treatment recommendations regardless of prediction error, demonstrating high clinical accuracy. For individuals with T1DM, maintaining BG within the target range is essential to prevent periods of hypoglycemia and hyperglycemia, which can lead to severe complications. Accurate BG prediction can reduce this risk and facilitate early interventions to improve DM management. However, DM management remains challenging due to the complex nature of glucose metabolism and the wide range of lifestyle factors that can affect it. For this reason, the DL model developed by Zhu et al. [36], which incorporates personalized data to predict future BG levels, holds promise as an innovative tool for advancing DM management.

In a study conducted by Dudukcu et al. [35], a fusion model has been developed using the extended OhioT1DM dataset, which includes historical BG data from 12 individuals with diabetes. The model has combined Long Short-Term Memory (LSTM), WaveNet, and Gated Recurrent Units (GRU) architectures, incorporating decision-level fusion of these models. The study has demonstrated that the fusion model incorporating 'LSTM + WaveNet + GRU' architecture has achieved superior performance in BG prediction. Dudukcu et al. [35] plan to utilize the prediction values generated by the fusion model in calculating the required insulin doses. If these efforts prove successful, the developed system is planned to be converted into a mobile application. This would provide individuals with diabetes access to more accurate BG prediction and insulin dosage guidance through a GenAI-powered DM management tool, offering the added convenience of mobile use. In another study by Peleg et al. [48], the Mobiguide application has been tested with 10 atrial fibrillation patients in Italy and 20 gestational individuals with diabetes in Spain. Additionally, Mashatian et al. [40] have developed an AI-based question-answering model using a Retrieval-Augmented Generation (RAG) architecture to address inquiries related to DM and diabetic foot care. In this study, Pinecone has been utilized as a vector database alongside GPT-4, developed by OpenAI. The NIH National Standards for Diabetes Self-Management Education have served as the foundation for training the model. A total of 58 keywords have been used to select 295 articles, and the model has been tested with 175 questions covering various topics. According to the results, the RAG model is considered a promising tool for delivering reliable medical information to the public for self-education and self-management in the field of DM.

In a study that has been conducted by Lee et al. [41], a chatbot using GenAI has been developed to provide dietary recommendations for individuals with diabetes. The chatbot has been trained using an additional dataset that has been produced expressly for the system, and it is based on OpenAI's ChatGPT model. This approach allows patients to access personalized diet plans that have been tailored to their physical needs, including options that have considered seasonal changes. When compared with existing applications, the system has demonstrated superior capabilities in managing the health status of elderly individuals by incorporating additional data sources and offering a wider range of services. As a result, through this system, a new chatbot has been made accessible, which has focused on dietary guidance, has assumed the role of an expert, and has performed precise caloric calculations to help individuals with diabetes manage their health effectively.

In another study, Wang et al. [37] have developed a generative Markov-Bayes-based model, which has been based on previous GenAI models. In this study, longitudinal electronic health records from 9,298 individuals with T2DM or prediabetes, which have been collected from a large regional healthcare delivery network in China between 2005 and 2016, have been utilized to generate 5,000 synthetic disease trajectories. The findings have shown that 55.3% of individual complications and 31.8% of complication patterns associated with progressive T2DM can be predicted early and appropriately managed, potentially delaying or preventing them through lifestyle modifications that reduce the risk of DM development or progression.

However, there are several limitations associated with the use of GenAI. These include the production of inaccurate or fabricated content, reliance on unreliable information sources, and the provision of incorrect answers to user queries. In addition, various practical challenges exist within clinical applications [56, 57]. These findings indicate that GenAI stands out for its role in facilitating DM self-management and delivering information on DM care, while highlighting the need for further improvement in critical areas such as emotional support and medication adherence. As GenAI continues to adapt and develop in response to the unique settings and requirements of the medical field, it is expected to play a more significant role in DM care [50]. Based on evidence-based models that examine perceived usefulness and ease of use—key factors influencing the adoption of new technologies—these elements appear to be critical for the successful integration of GenAI into clinical practice [58].

5. Conclusion

The findings of this systematic review demonstrate that GenAI technologies have gained increasing significance in DM self-management, offering powerful tools that support patients in managing their own care processes. The majority of the reviewed studies indicate that GenAI applications are being effectively utilized in various areas, such as providing personalized recommendations, delivering DM education, early detection of complications, and offering emotional support. GenAI-powered solutions have been shown to make significant contributions in critical aspects of DM management, including BG prediction, dietary management, exercise recommendations, insulin dose optimization, and the generation of patient education materials. However, the limitations highlighted in the literature are also noteworthy. Issues such as data security and privacy, ethical concerns, the risk of misinformation, challenges in predicting critical situations like hypoglycemia, and limited access to technology in low-resource healthcare settings have been identified as areas requiring further development for GenAI applications. Additionally, hesitations regarding technology adoption among healthcare professionals and patients, as well as the need for technical support and comprehensive training to ensure effective use of these systems, pose challenges to their implementation.

Overall, the results of this review highlight the innovative solutions and potential benefits offered by GenAI in DM self-management, while also emphasizing the need for improvement to make these technologies more reliable, transparent, user-friendly, and ethically sound. In this context, there is a need for the development of larger datasets, increased interpretability of GenAI models, and more comprehensive evaluations of these systems. Future research is recommended to focus on developing strategies that enhance data security, accuracy, interpretability, and user satisfaction to strengthen the integration of GenAI applications into clinical practice.

Acknowledgement

This paper is a comprehensively expanded version of the proceedings abstract presented at the IV. International Congress on Artificial Intelligence in Healthcare.

References

[1] The Society of Endocrinology and Metabolism of Turkey. (2024). *Guidelines for the diagnosis, treatment, and monitoring of diabetes mellitus and its complications-2024.* https://file.temd.org.tr/Uploads/publications/guides/documents/diabetesmellitus2024.pdf

[2] Republic of Türkiye Ministry of Health. (2023). *Türkiye diabetes program 2023 – 2027.* https://hsgm.saglik.gov.tr/depo/birimler/saglikli-beslenme-ve-hareketli-hayat-db/Dokumanlar/Programlar/Turkiye-Diyabet-Programi.pdf

[3] Magliano, D. J., Boyko, E. J. IDF Diabetes Atlas 10th edition scientific committee. (2021). *Idf diabetes atlas*. (10th ed.). International Diabetes Federation. https://pubmed.ncbi.nlm.nih.gov/35914061/

[4] World Health Organization. (2003). *Adherence to long-term therapies: evidence for action*. https://iris.who.int/handle/10665/42682

[5] American Diabetes Association. (2023). *Standards of care in diabetes-2023.* https://www.portailvasculaire.fr/sites/default/files/docs/2023_ada_diabete_standards_of_care_in_diabetes_diab_care.pdf

[6] Harding, J. L., Pavkov, M. E., Magliano, D. J., Shaw, J. E., & Gregg, E. W. (2019). Global trends in diabetes complications: a review of current evidence. *Diabetologia*, *62*, 3-16. https://doi.org/10.1007/s00125-018-4711-2

[7] American Diabetes Association. (2024). 2. Diagnosis and Classification of Diabetes: Standards of Care in Diabetes-2024. *Diabetes Care, 47*(1), 20-42. https://doi.org/10.2337/dc24-S002

[8] American Association of Diabetes Educators. (2009). AADE Guidelines for the Practice of Diabetes Self-Management Education and Training (DSME/T). *The Diabetes Educator, 35*(3), 85-107. https://doi.org/10.1177/0145721709352436

[9] Williams, D. M., Jones, H., & Stephens, J. W. (2022). Personalized type 2 diabetes management: an update on recent advances and recommendations. *Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy*, 281-295. https://doi.org/10.2147/DMSO.S331654

[10] Khor, X. Y., Pappachan, J. M., & Jeeyavudeen, M. S. (2023). Individualized diabetes care: Lessons from the real-world experience. *World Journal of Clinical Cases*, *11*(13), 2890. https://doi.org/10.12998/wjcc.v11.i13.2890

[11] Song, M., Choe, M. A., Kim, K. S., Yi, M. S., Lee, I., Kim, J., Lee, M., Cho, M.Y., & Shim, Y. S. (2009). An evaluation of Web-based education as an alternative to group lectures for diabetes self-management. *Nursing & health sciences*, *11*(3), 277-284. https://doi.org/10.1111/j.1442-2018.2009.00458.x

[12] Hunt, C. W. (2015). Technology and diabetes self-management: An integrative review. *World journal of diabetes*, *6*(2), 225–233. https://doi.org/10.4239/wjd.v6.i2.225

[13] Sheng, B., Pushpanathan, K., Guan, Z., Lim, Q. H., Lim, Z. W., Yew, S. M. E., Goh, J. H. L., Bee, Y. M., Sabanayagam, C., Sevdalis, N., Lim, C. C., Lim, C. T., Shaw, J., Jia, W., Ekinci, E. I., Simó, R., Lim, L. L., Li, H., & Tham, Y. C. (2024). Artificial intelligence for diabetes care: current and future prospects. *The Lancet. Diabetes & Endocrinology*, *12*(8), 569–595. https://doi.org/10.1016/S2213-8587(24)00154-2

[14] Goel, A.K., & Davies, J. (2020). Artificial Intelligence. In R. J. Sternberg (Ed.), *The Cambridge Handbook of Intelligence* (602-625). Cambridge: Cambridge University Press.

[15] Cahn, A., Akirov, A., & Raz, I. (2018). Digital health technology and diabetes management. *Journal of diabetes*, *10*(1), 10–17. https://doi.org/10.1111/1753-0407.12606

[16] Aggarwal, M., & Murty, M. N. (2021). Deep learning. *Machine Learning in Social Networks: Embedding Nodes, Edges, Communities, and Graphs* (35-66). Springer Singapore. https://doi.org/10.1007/978-981-33-4022-0_3

[17] Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and vascular neurology*, *2*(4). https://doi.org/10.1136/svn-2017-000101

[18] García-Peñalvo, F. J., & Vázquez-Ingelmo, A. (2023). What do we mean by GenAI? A systematic mapping of the evolution, trends, and techniques involved in Generative AI. *International Journal of Interactive Multimedia and Artificial Intelligence, 8*(4), 7-15. https://doi.org/10.9781/ijimai.2023.07.006

[19] Liu, S., Chen, J., Feng, Y., Xie, Z., Pan, T., & Xie, J. (2024). Generative artificial intelligence and data augmentation for prognostic and health management: Taxonomy, progress, and prospects. *Expert Systems with Applications,* 255, 124511. https://doi.org/10.1016/j.eswa.2024.124511

[20] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. *Advances in neural information processing systems,* 27.

[21] Hernandez-Matamoros, A., Fujita, H., & Perez-Meana, H. (2020). A novel approach to create synthetic biomedical signals using BiRNN. *Information Sciences, 541*, 218-241. https://doi.org/10.1016/j.ins.2020.06.019

[22] Wu, T., He, S., Liu, J., Sun, S., Liu, K., Han, Q. L., & Tang, Y. (2023). A brief overview of ChatGPT: The history, status quo and potential future development. *IEEE/CAA Journal of Automatica Sinica*, *10*(5), 1122-1136. https://doi.org/10.1109/JAS.2023.123618

[23] Balasubramaniam, S., Chirchi, V., Kadry, S., Agoramoorthy, M., Gururama, S. P., Satheesh, K. K., & Sivakumar, T. A. (2024). The road ahead: Emerging trends, unresolved issues, and concluding remarks in generative AI—A comprehensive review. *International Journal of Intelligent Systems*, *2024*. https://doi.org/10.1155/2024/4013195

[24] Howell, M. D. (2024). Generative artificial intelligence, patient safety and healthcare quality: a review. *BMJ Quality & Safety*, *33*(11), 748-754. https://doi.org/10.1136/bmjqs-2023-016690

[25] Kline, A., Wang, H., Li, Y., Dennis, S., Hutch, M., Xu, Z., Wang, F., Cheng, F., & Luo, Y. (2022). Multimodal machine learning in precision health: A scoping review. *npj Digital Medicine*, *5*(1), 171. https://doi.org/10.1038/s41746-022-00712-8

[26] Yang, K., Ji, S., Zhang, T., Xie, Q., & Ananiadou, S. (2023). On the evaluations of chatgpt and emotion-enhanced prompting for mental health analysis. arXiv preprint

[27] Reddy, S. (2024). Generative AI in healthcare: An implementation science informed translational path on application, integration and governance. *Implementation Science*, *19*(1), 27. https://doi.org/10.1186/s13012-024-01357-9

[28] Gabrielson, A. T., Odisho, A. Y., & Canes, D. (2023). Harnessing generative artificial intelligence to improve efficiency among urologists: welcome ChatGPT. *Journal of Urology*, *209*(5), 827-829.

[29] Hiba, A., Al-Qudheeby, M., Kheyami, Z. A., Khalil, R., Khamees, N., Hijjawi, O., Sallam, M., & Barakat, M. (2024). Cross-linguistic evaluation of generative AI models for diabetes and endocrine queries. *Jordan Medical Journal*, *58*(4). https://doi.org/10.35516/jmj.v58i4.3369

[30] Ayre, J., Mac, O., McCaffery, K., McKay, B. R., Liu, M., Shi, Y., Rezvan, A., & Dunn, A. G. (2024). New frontiers in health literacy: using ChatGPT to simplify health information for people in the community. *Journal of General Internal Medicine*, *39*(4), 573-577. https://doi.org/10.1007/s11606-023-08469-w

[31] Chen, A., Chen, D. O., & Tian, L. (2024). Benchmarking the symptom-checking capabilities of ChatGPT for a broad range of diseases. *Journal of the American Medical Informatics Association*, *31*(9), 2084-2088. https://doi.org/10.1093/jamia/ocad245

[32] Huang, R. S. T., Lu, K. J. Q., Meaney, C., Kemppainen, J., Punnett, A., & Leung, F. H. (2023). Assessment of resident and AI chatbot performance on the University of Toronto family medicine residency progress test: comparative study. *JMIR Medical Education*, *9*, e50514. https://doi.org/10.2196/50514

[33] Ayers, J. W., Poliak, A., Dredze, M., Leas, E. C., Zhu, Z., Kelley, J. B., Faix, D. J., Goodman, A. M., Longhurst, C. A., Hogarth, M., & Smith, D. M. (2023). Comparing physician and artificial intelligence chatbot responses to patient questions posted to a public social media forum. *JAMA internal medicine*, *183*(6), 589-596. https://doi.org/10.1001/jamainternmed.2023.1838

[34] Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & the PRISMA Group. (2009). Reprint—preferred reporting items for systematic reviews and metaanalyses: The PRISMA Statement. *Physical Therapy, 89*(9), 873-880.

[35] Dudukcu, H. V., Taskiran, M., & Yildirim, T. (2021). Blood glucose prediction with deep neural networks using weighted decision level fusion. *Biocybernetics and Biomedical Engineering*, *41*(3), 1208-1223. https://doi.org/10.1016/j.bbe.2021.08.007

[36] Zhu, T., Yao, X., Li, K., Herrero, P., & Georgiou, P. (2020). Blood glucose prediction for type 1 diabetes using generative adversarial networks. In *CEUR workshop proceedings* (Vol. 2675, pp. 90-94).

[37] Wang, X., Lin, Y., Xiong, Y., Zhang, S., He, Y., He, Y., Plasek, J. M., Zhou, L., Bates, D. W., & Tang, C. (2022). Using an optimized generative model to infer the progression of complications in type 2 diabetes patients. *BMC Medical Informatics and Decision Making*, *22*(1), 174.

[38] Hernandez, C. A., Gonzalez, A. E. V., Polianovskaia, A., Sanchez, R. A., Arce, V. M., Mustafa, A., Vypritskaya, E., Gutierrez, O. P., Bashir, M., & Sedeh, A. E. (2023). The future of patient education: AI-driven guide for type 2 diabetes. *Cureus*, *15*(11).

[39] Sun, H., Zhang, K., Lan, W., Gu, Q., Jiang, G., Yang, X., Qin, W., & Han, D. (2023). An AI dietitian for type 2 diabetes mellitus management based on large language and image recognition models: preclinical concept validation study. *Journal of medical Internet research*, *25*, e51300.

[40] Mashatian, S., Armstrong, D. G., Ritter, A., Robbins, J., Aziz, S., Alenabi, I., Huo, M., Anand, T., & Tavakolian, K. (2024). Building trustworthy generative artificial intelligence for diabetes care and limb preservation: a medical knowledge extraction case. *Journal of Diabetes Science and Technology*, 19322968241253568. https://doi.org/10.1177/19322968241253568

[41] Lee, H. E., Jun Woo, C. H. O. I., & Kang, M. S. (2024). A Study on the development of a chatbot using generative AI to provide diets for diabetic patients. *Korean Journal of Artificial Intelligence*, *12*(3), 25-31. https://doi.org/10.24225/kjai.2024.12.3.25

[42] Posa, K. N., Peralta, G. E. Q., Hidalgo, I. F., Prat-Oriol, B., & Abreu, R. (2024). Comparative evaluation of generative artificial intelligence systems for patient queries on age-related macular degeneration and diabetic macular edema. *Investigative Ophthalmology & Visual Science*, *65*(7), 2326-2326.

[43] Naja, F., Taktouk, M., Matbouli, D., Khaleel, S., Maher, A., Uzun, B., Alameddine, M., & Nasreddine, L. (2024). Artificial intelligence chatbots for the nutrition management of diabetes and the metabolic syndrome. *European Journal of Clinical Nutrition*, *78*(10), 887-896. https://doi.org/10.1038/s41430-024-01476-y

[44] Shiraishi, M., Lee, H., Kanayama, K., Moriwaki, Y., & Okazaki, M. (2024). Appropriateness of artificial intelligence chatbots in diabetic foot ulcer management. *The international journal of lower extremity wounds*, 15347346241236811. https://doi.org/10.1177/15347346241236811

[45] Chung, S. M., & Chang, M. C. (2024). Assessment of the information provided by ChatGPT regarding exercise for patients with type 2 diabetes: a pilot study. *BMJ Health & Care Informatics*, *31*(1), e101006. https://doi.org/10.1136/bmjhci-2023-101006

[46] Gokbulut, P., Kuskonmaz, S. M., Onder, C. E., Taskaldiran, I., & Koc, G. (2024). Evaluation of ChatGPT-4 performance in answering patients' questions about the management of type 2 diabetes. *Medical Bulletin of Sisli Etfal Hospital*, *58*(4). https://doi.org/10.14744/SEMB.2024.23697

[47] Kopitar, L., Fister Jr, I., & Stiglic, G. (2024). Using generative AI to improve the performance and interpretability of rule-based diagnosis of type 2 diabetes mellitus. *Information*, *15*(3), 162. https://doi.org/10.3390/info15030162

[48] Peleg, M., Shahar, Y., & Quaglini, S. (2022). MobiGuide: guiding clinicians and chronic patients anytime, anywhere. Communications of the ACM, 65(4), 74-79. https://doi.org/10.1145/3511596

[49] Nayak, A., Vakili, S., Nayak, K., Nikolov, M., Chiu, M., Sosseinheimer, P., Talamentes, S., Testa, S., Palanisamy, S., Giri, V., Schulman, K., & Schulman, K. (2023). Use of voice-based conversational artificial intelligence for basal insulin prescription management among patients with type 2 diabetes: a randomized clinical trial. *JAMA network open*, *6*(12), e2340232-e2340232. doi:10.1001/jamanetworkopen.2023.40232

[50] Shaikh, A., Baluni, S., Malpani, N., Lodha, P., & Meena, A. (2024). Decoding type 2 diabetes through point-of-care testing, cloud-based monitoring, and generative augmented retrieval model-driven virtual diabetes education: A comprehensive approach to glycemic control. *International Journal of Diabetes and Technology*, *3*(1), 25-31. https://doi.org/10.4103/ijdt.ijdt_5_24

[51] Dey, A. K. (2023). ChatGPT in diabetes care: An overview of the evolution and potential of generative artificial intelligence model like ChatGPT in augmenting clinical and patient outcomes in the management of diabetes. *International Journal of Diabetes and Technology*, *2*(2), 66-72. https://doi.org/10.4103/ijdt.ijdt_31_23

[52] Khan, S. (2023). The Future of Diabetes Care: Navigating with generative language models. *Indus Journal of Medical and Health Sciences*, *1*(1), 109-116. https://induspublishers.com/IJMHS/article/view/58

[53] Sng, G. G. R., Tung, J. Y. M., Lim, D. Y. Z., & Bee, Y. M. (2023). Potential and pitfalls of ChatGPT and natural-language artificial intelligence models for diabetes education. *Diabetes Care*, *46*(5), 103-105. https://doi.org/10.2337/dc23-0197

[54] Thyde, D. N., Mohebbi, A., Bengtsson, H., Jensen, M. L., & Mørup, M. (2021). Machine learning-based adherence detection of type 2 diabetes patients on once-daily basal insulin injections. Journal of diabetes science and technology, 15(1), 98-108. https://doi.org/10.1177/1932296820912411

[55] Cordeiro, R., Karimian, N., & Park, Y. (2021). Hyperglycemia identification using ECG in deep learning era. Sensors, 21(18), 6263. https://doi.org/10.3390/s21186263

[56] Megahed, F. M., Chen, Y. J., Ferris, J. A., Knoth, S., & Jones-Farmer, L. A. (2024). How generative AI models such as ChatGPT can be (mis) used in SPC practice, education, and research? An exploratory study. Quality Engineering, 36(2), 287-315. https://doi.org/10.1080/08982112.2023.2206479

[57] Kanitz, R., Gonzalez, K., Briker, R., & Straatmann, T. (2023). Augmenting organizational change and strategy activities: Leveraging generative artificial intelligence. *The Journal of Applied Behavioral Science, 59*(3), 345-363. https://doi.org/10.1177/00218863231168974

[58] Stamler, J., Vaccaro, O., Neaton, J. D., Wentworth, D. (1993). Diabetes, other risk factors, and 12-yr cardiovascular mortality for men screened in the multiple risk factor intervention trial. *Diabetes care*, *16*(2), 434-444. https://doi.org/10.2337/diacare.16.2.434