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Review paper

Advancement of artificial intelligence based treatment strategy in type 2 diabetes: A critical update

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ABSTRACT

In the unrelenting race to strive to dominate type 2 diabetes mellitus (T2DM) care better, this review paper sets out on a significant discovery trip across recent advancements in treatment and the blooming era of artificial intelligence (AI) utilities. Given the considerable global burden of T2DM, innovative therapeutic approaches to improve patient outcomes remain a public health priority. This review first provides an in-depth analysis of the current state of therapy, from novel pharmacotherapy to lifestyle interventions and new treatment methods. At the same time, the rapidly increasing role of AI in diabetes care is woven into the story, mainly targeting how insulin therapy can be modified and personalized through algorithms and predictive modelling. It leaves a deep review of their pre-existing synergies, which helps understand how collaborative opportunities will unlock the future of T2DM care. This critical role is shown by integrating recent therapeutic advances and AI with overall showcasing better screening, diagnosis, and therapeutics decision-making to outcome prediction in T2DM. The review emphasizes how AI applications in insulin therapy have transformative potential in diabetes care. These person-centred approaches to T2DM management, which are more effective and personalized than some traditional strategies, only work because of the often-hidden synergies between AI algorithms in areas such as diagnostic criteria, predictive methods, and familiar classification tools for subgroups with relevant aspects/predictors on prognosis or treatment responsiveness.

1. Introduction

Type 2 diabetes mellitus (T2DM) is a progressive disease with a growing prevalence, posing a significant global health challenge. This condition is associated with an increased risk of complications and profoundly impacts individuals, societies, and healthcare systems. The introduction of new classes of antidiabetic drugs has dramatically changed the landscape of diabetes therapy, yet managing the burden of the disease remains a challenge. Effective management strategies for T2DM include both pharmacological and non-pharmacological interventions. Lifestyle modifications, including losing weight, undergoing metabolic surgery, and adopting aggressive treatments to lower blood sugar levels, have demonstrated effectiveness in initiating diabetes remission. However, the enduring impact of these approaches on the

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long-term complications associated with diabetes is still uncertain [1]. Obesity and T2DM are major public health concerns, often linked with adiposopathy, which describes the pathophysiological changes in adipose tissue. This dysfunctional state of adipose tissue is a significant factor in the aetiology of these conditions, promoting chronic inflammation, dysregulated glucose homeostasis, and insulin resistance. Currently, the most successful strategies for achieving significant weight loss and consequent diabetes remission are metabolic surgery and innovative categories of antidiabetic drugs [2]. A comprehensive lifestyle clinic study demonstrated the impact of non-pharmacological interventions on metabolic health and remission of these conditions, highlighting the importance of personalized physical exercise and nutritional counselling [3]. The integration of recent therapeutic advances and artificial intelligence (AI) is now used for diagnosis, therapeutic decision-making, and outcome prediction in T2DM. AI applications in T2DM care primarily focus on screening and diagnosis in different stages, with machine learning (ML) methods being the most commonly applied techniques. These methods, including support vector machine and naive Bayesian, have shown promise in improving diabetes-related outcomes classification [4]. The development of AI-driven clinical decision support systems (CDSS) integrated with electronic health records (EHR) represents a significant step forward. These platforms assist healthcare providers and individuals in examining pertinent patient data, establishing therapeutic objectives, and considering different treatment options based on forecasts, thus enhancing the support for pharmacological decision-making in T2DM [5]. The importance of precise and personalized management strategies in T2DM care can not be overstated, given the impact of individual characteristics and lifestyle on treatment plans and patient outcomes. AI offers great promise in combining patterns from various data sources with healthcare professionals' expertise to achieve optimal care. Studies have shown that AI-generated individualized feedback can lead to improved health behaviours and better management of T2DM [6] (Figs. 1A and B).

Furthermore, AI interpretation and graph neural networks (GNN) are being used to explore risk factors for complications associated with T2DM, such as cognitive impairment, and to screen potential therapeutic drugs. This approach not only aids in understanding the underlying mechanisms of T2DM complications but also assists in discovering effective treatments [7]. This review aims to provide insights into more effective, personalized, and patient-centric management approaches for T2DM by examining how AI can complement and enhance traditional therapeutic strategies. Hence, the objective of this review is dual: firstly, to present a comprehensive overview of the existing treatment alternatives for T2DM, and secondly, to examine the burgeoning intersection of these therapies with AI. By merging these two aspects, we aim to shed light on the prospective collaborative dynamics that may arise between them. This review is structured to provide a comprehensive understanding of the evolving landscape of T2DM management. The initial sections explore traditional approaches, including pharmacotherapy and lifestyle interventions, emphasising their role in managing the disease's complexity. Subsequently, the review discusses how AI has emerged as a transformative force in diabetes care, offering innovations in predictive analytics, decision-making support, and personalized treatment strategies. The final sections delve into the synergies between these advancements, highlighting the integration of AI with modern therapeutics to create patient-centred and outcome-driven management frameworks. By bridging conventional methods with cutting-edge technology, this review aims to provide insights into the future trajectory of T2DM care. Recent advances like regulation-aware graph learning have demonstrated the potential of leveraging heterogeneous biological networks and connectivity patterns for effective drug repositioning, achieving superior performance in predicting drug-disease associations [8]. Graph representation learning models, such as FuHLDR, have introduced innovative approaches by integrating higher and lower-order biological information, demonstrating enhanced effectiveness in drug repositioning compared to state-of-the-art models [9]. Network-based computational approaches like large-scale graph drug-target interactions (LGDTI), which integrate local and global representations of drugs and proteins, have shown remarkable accuracy in predicting drug-target interactions by leveraging heterogeneous information networks [10]. The fasting plasma glucose (FPG) test requires fasting for at least 8 h and needs confirmation with a second test on a different day if the result is abnormal ($\geq$126 mg/dL or $\geq$7.0 mmol/L) [11]. Oral glucose tolerance test (OGTT) with a 75 g glucose load is conducted following World Health Organization (WHO) guidelines. Diagnosis is confirmed with a second test on a different day, where a 2-h plasma glucose (PG) level of $\geq$200 mg/dL ($\geq$11.1 mmol/L) during the OGTT indicates diabetes [12]. The diagnosis is based on a single haemoglobin A1c (HbA1C) test using the National Glycohemoglobin Standardization Program (NGSP)-certified and Diabetes Control and Complications Trial (DCCT) standardized laboratory method, with an HbA1C level of $\geq$6.5% ($\geq$48 mmol/mol) [13]. The current diagnostic standards for T2DM are summarised in Table 1 [11–13].

2. Therapeutic modalities for T2DM

2.1. Pharmacotherapy

The treatment of T2DM involves a variety of medications that target different aspects of the disease's underlying mechanisms.

2.1.1. Oral antidiabetic agents

Oral antidiabetic agents, commonly called oral hypoglycemic agents or oral hypoglycemics, function through various mechanisms to regulate blood sugar levels, aiming to improve insulin sensitivity, enhance insulin secretion, or reduce glucose absorption from the digestive tract. The development and utilization of oral antidiabetic agents have evolved significantly over the years, reflecting advancements in our understanding of diabetes pathophysiology and the quest for more effective and patient-friendly treatment options. As an integral component of diabetes management, oral antidiabetic agents are often prescribed based on individual needs, considering factors such as the type and severity of diabetes, overall health, and any coexisting medical conditions. The diverse classes of oral antidiabetic agents include biguanides, sulfonylureas, meglitinides, thiazolidinediones (TZDs), dipeptidyl peptidase-4 (DPP-4) inhibitors, sodium-glucose co-transporter-2 (SGLT2) inhibitors, and alpha-glucosidase inhibitors [14,15].

2.1.2. Biguanides

Without contraindications, metformin is regarded as the first-line medication for treating T2DM. Metformin appears to reduce blood and liver levels of lipopolysaccharide (LPS), reduction of LPS and mechanism of action of metformin [16–18]. Metformin activates adenosine monophosphate (AMP)-activated protein kinase (AMPK) in liver cells, leading to the activation of AMPK in hepatocytes [19]. It also suppresses adenyl cyclase, which inhibits glucagon-induced cyclic AMP (cAMP) generation, demonstrating its mechanism of action through the suppression of adenyl cyclase [20]. Activation of hepatic AMPK leads to the activation of liver-kinase B1 (LKB1), which describes the mechanism of action by which AMPK activates LKB1 [21,22]. At high doses, metformin inhibits complex I of the mitochondrial electron transport chain, which lowers adenosine triphosphate (ATP) levels and increases

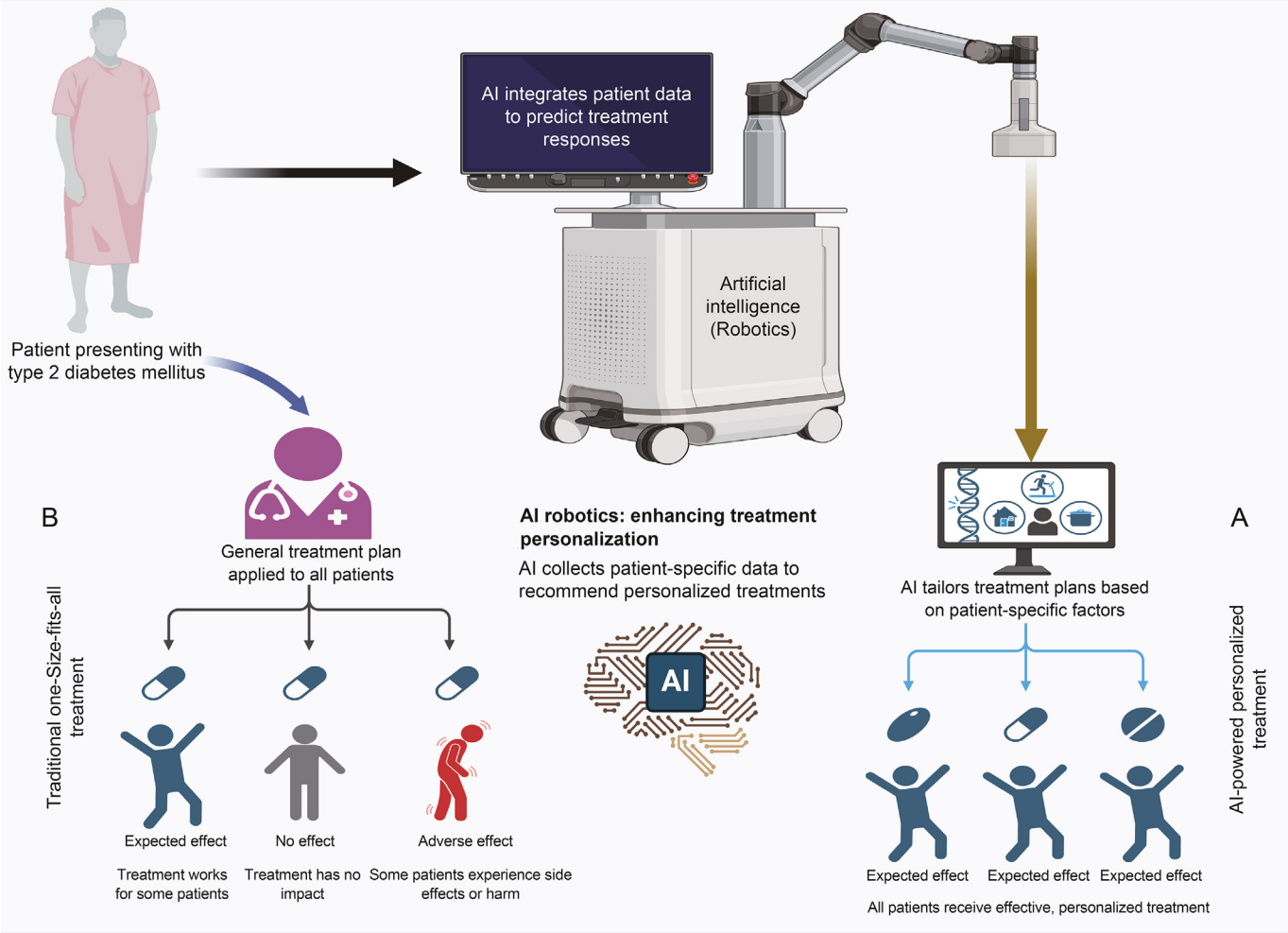

Fig. 1. A comparative schematic representation of two methods. (A) Artificial intelligence (AI)-assisted personalized treatment for type 2 diabetes mellitus (T2DM), showcasing how AI integrates with different treatment modalities to enhance patient-specific outcomes. (B) Traditional method for the treatment of T2DM.

Table 1
Chart summarising the current diagnostic standards for type 2 diabetes mellitus (T2DM).

Diagnostic criteria	Result threshold	Test conditions	Refs.
FPG	≥126 mg/dL (≥7.0 mmol/L)	Fasting for at least 8 h and requires confirmation with a second test on a different day if abnormal	[11]
Random PG	≥200 mg/dL (≥11.1 mmol/L)	Classic symptoms of hyperglycemia or hyperglycaemic crisis, and requires confirmation with a second test	[11]
2-h PG	≥200 mg/dL (≥11.1 mmol/L) during OGTT	OGTT with 75 g glucose load, as per WHO guidelines, and diagnosis confirmed with a second test on a different day	[12]
HbA1C	≥6.5% (≥48 mmol/mol)	NGSP-certified and DCCT standardised laboratory method, and diagnosis is based on a single A1C test	[13]

FPG: fasting plasma glucose; PG: plasma glucose; OGTT: oral glucose tolerance test; WHO: World Health Organisation; HbA1C: haemoglobin A1C; NGSP: National Glycohemoglobin Standardization Program; DCCT: Diabetes Control and Complications Trial.

the AMP/ATP ratio. This mechanism of action involves inhibition of complex I in the mitochondria [23]. Inhibition of mitochondrial glycerol phosphate dehydrogenase (mG3PDH) disrupts gluconeogenesis from lactate [24]. Metformin's component, LKB1, may activate AMPK and contribute to the inhibition of cell growth by activating the tumor suppressor protein LKB1 [25]. Observational research indicates that metformin may reduce the risk of developing cancer by mechanisms that lower cancer risk [26]. Its diverse mechanisms of action and associated effects are listed in Table 2 [16–26].

2.1.3. *Blockers of alpha-glucosidase*

Acarbose, miglitol, and voglibose are the currently approved drugs in this class. Inhibition of alpha-glucosidase in the small intestine's brush border membrane results in decreased absorption of carbohydrates as the conversion of complex non-absorbable oligosaccharides into simple absorbable monosaccharides is blocked by alpha-glucosidase inhibitors [27]. Because alpha-glucosidase inhibitors might cause asymptomatic elevations in liver enzymes and are not advised for individuals with creatinine clearance below 25 mL/min, it is vital to manage liver enzyme levels [28].

Table 2
Possible mechanisms of action for metformin.

Mechanism of action of metformin	Description	Refs.
Reduction of LPS	Metformin appears to reduce blood and liver levels of LPS	[16–18]
Activation of AMPK in hepatocytes	Metformin activates AMPK in liver cells	[19]
Suppression of adenyl cyclase	Metformin suppresses adenyl cyclase, preventing glucagon-induced cAMP generation	[20]
Activation of LKB1 by AMPK	Hepatic AMPK activation leads to the activation of LKB1	[21,22]
Inhibition of complex I in mitochondria	At high doses, metformin inhibits complex I of the electron transport chain in mitochondria, lowering ATP levels and increasing AMP/ATP ratio	[23]
Inhibition of mG3PDH	Inhibition of mG3PDH interrupts gluconeogenesis from lactate	[24]
Activation of tumor suppressor protein LKB1	Metformin's component LKB1 may activate AMPK and contribute to inhibiting cell growth	[25]
Reduction of cancer risk	Observational research suggests metformin may lower the risk of developing cancer	[26]

LPS: lipopolysaccharide; AMPK: adenosine monophosphate (AMP)-activated protein kinase; cAMP: cyclic AMP; LKB1: liver-kinase B1; ATP: adenosine triphosphate; mG3PDH: mitochondrial glycerol phosphate dehydrogenase.

2.1.4. DPP-4 inhibitors

Different dipeptidyl peptidase inhibitors (iDPPs) are sitagliptin, vildagliptin, saxagliptin, linagliptin, and alogliptin. Incretins are a group of gastrointestinal hormones that play a crucial role in regulating glucose metabolism. The two main incretin hormones are glucagon-like peptide-1 (GLP-1) and glucose-dependent insulinotropic polypeptide (GIP). These hormones are released from the gut in response to food intake and act on pancreatic beta cells to stimulate insulin secretion in a glucose-dependent manner. Additionally, incretins suppress glucagon secretion from pancreatic alpha cells, delay gastric emptying, and promote satiety [29]. The mechanism of action of DPP-4 inhibitors involves inhibiting the enzyme DPP-4, which results in increased levels of GLP-1 and GIP. This leads to enhanced glucose-dependent insulin secretion, suppression of glucagon secretion, slowed gastric emptying, and improved glycemic control. Due to the minimal risk of hypoglycemia and other adverse effects, these drugs are considered as being relatively safe. When using insulin and sulfonylureas together, each of them has an increased risk of hypoglycemia [30].

2.1.5. The insulin secretagogues-sulfonylureas and meglitinides

Although they belong to separate groups of oral hypoglycemic medications, sulfonylureas and insulin secretagogues (meglitinides or glinides) promote insulin release from the pancreatic beta cells. Since they were initially made available for use in clinical settings in the 1950s, sulfonylureas have been the de facto first- or second-line therapy for people with T2DM [31,32]. Although sulfonylureas and glinides bind to the receptor at different sites, they both cause channel closure and cell depolarization, which raises cytoplasmic calcium levels and, as a result, causes the release of insulin. Second-generation sulfonylureas include glimepiride, glipizide, gliclazide, and glyburide [16]. Meglitinides are advantageous for those for whom the objective of avoiding hypoglycaemic episodes is crucial since they typically have a lower risk of hypoglycaemia [33]. Repaglinide and nateglinide are two distinct glinides. The phenylalanine derivative nateglinide differs structurally from sulfonylureas and meglitinide. Sulfonylureas considerably influence FPG concentrations due to their pharmacokinetics, while meglitinides mainly affect postprandial glucose levels [34]. Sulfonylureas are likely to reduce HbA1C by 1.0%–1.5%, although meglitinides are often less efficient in lowering blood sugar (0.5%–1.0%) [16,22]. Hypoglycemia is the most frequent side effect, particularly with long-acting sulfonylureas (such as glyburide/glimepiride) [35–37].

2.1.6. Sodium-glucose co-transporter-2 (SGLT2) inhibitor

In individuals with T2DM, SGLT2 inhibitors renal glucose reabsorption and increases glucose excretion. It works independently of insulin, carries no risk of hypoglycemia, and does not induce fatigue or excessive stimulation of beta cells [38]. Because its method of action depends on proper glomerular-tubular function, individuals with renal insufficiency have decreased SGLT2 efficiency [39]. The three medications that best typify the SGLT2 drug family are empagliflozin, dapagliflozin and canagliflozin [40]. They have proven effective in improving glycemic control and lowering body weight in patients with T2DM [41]. If these medications may also reduce the dosage of insulin, weight loss will be higher. Patients experience more weight loss more quickly [42]. The impact of these medications on the lipid profile is unclear. All of the SGLT2 do not provide the same outcomes. Some studies found them to be lipid-friendly and lipid-neutral in others [43,44]. Finally, since SGLT2 is linked to glomerular hyper-filtration, blocking it may have nephroprotective effects [45]. SGLT2 inhibitors have demonstrated significant cardiovascular protective effects by reducing major adverse cardiovascular events, improving heart function, lowering heart failure risk, and promoting renal health. These benefits extend to individuals both with and without diabetes, suggesting their potential to prevent heart-related complications and improve overall cardiac outcomes [46].

2.1.7. TZDs

Pioglitazone and rosiglitazone are the two TZDs that are marketed in the United States. Because the overall hazards of rosiglitazone outweigh the benefits, the European Medicines Agency has prohibited its use in Europe since 2010 [47]. The mechanism of action of TZDs involves activating peroxisome proliferator-activated receptor gamma (PPARγ), a nuclear receptor primarily found in adipose tissue but also present in other tissues such as the liver, muscle, and pancreas. Activation of PPARγ leads to increased insulin sensitivity in peripheral tissues, such as muscle and adipose tissue. These results in improved glucose uptake and utilization by cells, decreased hepatic glucose production, and reduced circulating levels of free fatty acids [48]. TZDs also affect adipocyte differentiation and adipokine secretion, which can contribute to their metabolic effects [49].

The activation of PPARγ in the central nervous system, promoting heightened appetite, contributes to the weight gain associated with TZD [50]. Because PPARγ is more common in the collecting tubules of the nephron, TZD treatment-induced PPARγ activation results in salt absorption in those cells, causing retention of fluid that may cause or aggravate heart failure [51].

2.2. Injectable antidiabetic agents

Injectable antidiabetic agents constitute a crucial category of medications employed in treating and managing diabetes mellitus. Injectable antidiabetic agents are primarily utilized in cases where oral medications may be insufficient in achieving glycemic control, particularly in individuals with more advanced stages of diabetes or

those who require additional therapeutic interventions [52]. The injectable antidiabetic agents include various classes of medications, each with distinct mechanisms of action targeting different aspects of glucose metabolism. The most common types include insulin and GLP-1 receptor agonists (GLP-1 RAs). Insulin, a hormone produced by the pancreas, is vital for glucose utilization, and injectable insulin is often prescribed when the body's natural insulin production is inadequate [53]. GLP-1 RAs mimic the action of a naturally occurring hormone, GLP-1, which stimulates insulin secretion and inhibits glucagon release. By enhancing insulin activity and suppressing the release of glucose from the liver, GLP-1 RAs contribute to improved glycemic control [54]. Injectable antidiabetic agents are an essential component of diabetes management, offering flexibility and precision in addressing the diverse needs of individuals with diabetes when a more rapid and direct impact on blood glucose levels is required. The selection of injectable antidiabetic agents is based on factors such as the type of diabetes and individual patient characteristics [30].

2.2.1. Insulin

Pre-meal coverage with traditional insulin has a quicker onset and a shorter half-life than long-acting analogues, which allow a once-daily dose. It also shows less daily variation [55]. In addition to long-acting insulins like glargine and detemir, ultra-long-acting insulins like degludec and glargine U-300 and rapid-acting insulins like aspart, lispro or glulisine may be used together. Human insulin and insulin glargine are equivalent, except for the two extra arginine molecules added to the B-chain and the substitution of glycine for asparagine at position A21 [56]. With a half-life of over 25 h and an action of over 42 h, the insulin degludec profile is flatter than other long-acting insulins (glargine and detemir), reducing acute and overnight hypoglycemias [57]. Compared to glargine, insulin degludec demonstrates non-inferiority in lowering HbA1C and a reduced risk of nocturnal hypoglycaemia [58].

2.2.2. RA-GLP1

After eating, the body secretes the hormone GLP-1, which stimulates insulin release to regulate blood sugar levels. GLP-1 and glucose-dependent insulinotropic polypeptide (GIP), produced by enteroendocrine L-cells in different parts of the digestive tract, play key roles in this process. In T2DM, GLP-1 treatments enhance glucose-dependent insulin secretion, reducing the risk of hypoglycemia. These treatments also lower glucagon levels, slow gastric emptying to moderate postprandial blood sugar spikes, and increase satiety, aiding in weight management and overall blood glucose control [54]. RA-GLP1 are categorized as short-acting or long-acting, depending on how long they persist. Short-acting RA-GLP1 medications include lixisenatide and twice-daily exenatide. Lixisenatide has a considerably longer half-life (2.7–4.3 h) than native GLP1. Additionally, lixisenatide has been used with basal insulin treatment [59,60]. Exenatide long-acting release (LAR) is more effective than the maximum dosage of twice-daily exenatide, sitagliptin, pioglitazone, and insulin glargine in T2DM patients using oral hypoglycemic medications [61–64].

3. Recent therapeutic advances in T2DM management

The landscape of T2DM management is undergoing a transformative era, marked by significant advancements that span a broad spectrum of therapeutic approaches [65]. Recent efforts in this field focus on the potential for disease remission, the innovation and development of new medications, and comprehensive management strategies. These advancements aim to enhance the quality of life for individuals with T2DM by providing more effective glycemic control, reducing complications, and integrating patient-centric care models. The following sections will delve into the latest developments, including promising drugs currently in clinical trials, and explore how these innovations reshape the future of T2DM treatment [66]. Clinical trials of orforglipron are advancing into phase 2, demonstrating its potential as an innovative oral non-peptide GLP-1 RA [67]. Mazdutide is advancing in phase 2 trials, showcasing its promising dual-action mechanism [68]. By functioning as a weak GLP-1 agonist alongside a glucagon receptor agonist, it offers a unique approach to treatment [69]. This promising drug, dorzagliatin, is currently undergoing phase 3 clinical trials and acts as a dual-acting glucokinase activator, targeting both hepatic and pancreatic functions [70]. Imeglimin is currently undergoing a Phase 2 clinical trial and works through a tetrahydrotriazine-based structure, which helps restore and prevent mitochondrial dysfunction in pancreatic β cells [71]. Summarise all ongoing clinical trials of novel therapies for T2DM are listed in Table 3 [67–71].

4. Lifestyle modifications

Modifying dietary habits commonly entails adhering to a controlled diet that emphasizes equilibrium between energy intake and expenditure. This generally translates to a diet low in processed sugars and saturated fats while abundant in whole grains, lean proteins, fruits, and vegetables [72]. Consistent physical activity is key to enhancing insulin sensitivity, managing blood sugar levels, and mitigating cardiovascular risk factors. A well-rounded exercise routine typically includes aerobic activities like walking, swimming, cycling, and resistance training. The objective is to attain a harmonious exercise regimen that facilitates glucose regulation, comprehensive physical fitness, and effective weight management [73]. Sleep is a frequently underestimated facet of lifestyle management for T2DM. Research indicates that obtaining 6–9 h of sleep can diminish cardiometabolic risk factors in individuals with T2DM. On the contrary, insufficient sleep can worsen various complications linked to T2DM, including hypertension, hyperglycemia, insulin resistance, and dyslipidemia. Hence, prioritising sufficient and high-quality sleep is equally significant alongside diet and exercise in the comprehensive management of T2DM [20]. Managing T2DM through lifestyle modifications underscores the significance of adopting a well-rounded strategy encompassing dietary adjustments, physical activity, and sufficient sleep.

Table 3
On-going clinical trials of novel therapies for type 2 diabetes mellitus (T2DM) and their mechanisms of action.

Name of the drug	Phase of clinical trial	Proposed mechanism of action	Refs.
Tirzepatide	Phase 3	Dual GLP-1 and GIP receptor agonist	[67]
Orforglipron	Phase 2	Oral non-peptide GLP-1 RA	[68]
Mazdutide	Phase 2	Dual, GLP-1 (weak) and glucagon receptor agonist	[69]
Dorzagliatin	Phase 3	Dual-acting (hepatic and pancreatic) glucokinase activator	[70]
Imeglimin	Phase 2	Tetrahydrotriazine-based structure, restores/prevents pancreatic β cell mitochondrial dysfunction	[71]

GLP-1: glucagon-like peptide-1; GIP: glucose-dependent insulinotropic polypeptide; GLP-1 RA: GLP-1 receptor agonist.

4.1. Diet

Recent research has spotlighted personalized dietary strategies tailored to individual needs, mainly focusing on approaches like low-carbohydrate diets, Mediterranean diets, and time-restricted feeding. These nuanced dietary interventions have exhibited promising outcomes in enhancing glycemic control and positively impacting metabolic parameters among individuals with T2DM. When individuals adhere to these customised dietary guidelines, the benefits extend beyond glycemic control. Studies have demonstrated a decrease in the prevalence of urinary incontinence among women, alongside improvements in conditions such as sleep apnea, depression, and the overall health-related quality of life. The relationship between obesity and insulin secretion adds complexity to the understanding of T2DM. Exploring these connections sheds light on the intricate interplay between metabolic factors, dietary choices, and overall health in T2DM. By losing weight, one will become more sensitive to insulin, improving one's ability to manage one's blood sugar levels. Consuming enough dietary fibre, particularly fibre that contains natural resources, has been demonstrated to enhance glycemic control and cardiovascular risk factor management, which lowers the risk of cardiovascular mortality in people with diabetes [74,75]. Epidemiological research has linked fats to an increased risk of obesity and cardiovascular disease [76]. Studies on the Mediterranean diet have shown that monounsaturated fatty acids, notably when swapped out for saturated fatty acids, may reduce cardiovascular risk factors and improve glycemic management [77]. Individualized reduced sodium intake should be used when people also have hypertension, which is prevalent [78].

4.2. Exercise

Regular physical activity and exercise have maintained their status as fundamental pillars in managing T2DM. They have demonstrated notable benefits, including enhanced insulin sensitivity, improved glucose control, favourable alterations in lipid profiles and overall cardiovascular health. The positive impact on mental health includes a reduction in depression, emphasising the holistic benefits of incorporating exercise into the routine of individuals with T2DM [72,79,80]. Exercise has proven to be beneficial in preventing the onset of peripheral neuropathy. However, it is advisable to exercise caution, especially in individuals with existing foot ulcers and sores. It is recommended to avoid activities that exert repetitive stress on the lower extremities in such cases. This cautious approach ensures that the positive effects of exercise in preventing peripheral neuropathy are realised without compromising the safety and well-being of individuals with pre-existing foot conditions [81,82]. However, it is crucial to ensure adequate hydration. It is uncommon for T2DM to involve a severe insulin deficit akin to type 1 diabetes (T1D). Maintaining appropriate hydration conditions becomes particularly important in the context of physical activity, contributing to overall health and helping manage the potential effects of hyperglycemia in individuals with T2DM [83].

5. AI in diabetes care

Integrating AI in diabetes care represents a transformative shift in managing this chronic and complex condition. Recent studies have illuminated the multifaceted applications of AI in diabetes management, encompassing patient education, clinical decision support, and predictive analytics, each contributing to a more nuanced and practical approach to diabetes care. AI's role in patient education and self-management is particularly noteworthy. AI-driven applications and platforms can provide personalized education, dietary recommendations, and lifestyle advice tailored to individual patient profiles. This personalisation is crucial, as diabetes management depends on patient behaviour and lifestyle choices. AI systems can analyse patient data to offer customised advice and even predict potential challenges a patient might face, enabling preemptive action [84]. In clinical decision support, AI has shown immense potential in enhancing the accuracy and efficiency of diabetes management. AI algorithms can analyse vast amounts of patient data, including blood glucose levels, dietary habits, and exercise routines, to assist healthcare providers in making informed decisions. This can include medication adjustments, insulin dosage recommendations, and identifying patients at risk of complications such as hypoglycemia. By providing real-time, data-driven insights, AI aids clinicians in delivering more precise and effective care. Predictive analytics is another area where AI is making significant strides in diabetes care [85]. AI models can predict the onset of diabetes-related complications, such as diabetic retinopathy or kidney disease, allowing for early intervention. This predictive capability is vital for preventing or delaying complications, often the most challenging and costly aspects of diabetes management. Moreover, AI is revolutionizing the monitoring and management of blood glucose levels. Integrated with AI algorithms, continuous glucose monitoring (CGM) systems can analyse glucose data in real-time, providing patients with actionable insights to manage their condition effectively [86]. These systems can alert patients to potential hyperglycemia or hypoglycemia events, enabling timely intervention. The integration of AI in diabetes care also extends to the development of advanced insulin delivery systems. AI-powered closed-loop systems, also known as artificial pancreas systems, can automatically adjust insulin delivery based on CGM data, significantly reducing the burden of daily diabetes management for patients [87] (Fig. 2). However, integrating AI in diabetes care is not challenging. Issues such as data privacy, the need for extensive and diverse datasets to train AI models and ensuring equitable access to AI-driven tools are critical concerns that need addressing. Additionally, there is a need for collaboration between technologists, clinicians, patients, and policymakers to ensure that AI tools are effectively integrated into healthcare systems and are accessible to all patients, regardless of socioeconomic status. AI's role in diabetes management spans education, clinical decision support, and predictive analytics. Advanced algorithms, such as convolutional neural networks (CNNs), aid in complication prediction, including retinopathy and nephropathy. AI-powered platforms like Information Data Exchange-Diabetic Retinopathy (IDx-DR) exemplify technology integration into clinical practice, providing automated diabetic retinopathy screening. Additionally, AI-driven decision-support systems, such as those used in hospital settings, enhance insulin and drug dosing by analyzing real-time patient data to suggest optimized treatment plans. These tools not only improve efficiency and accuracy in clinical workflows but also contribute to better glycemic control and reduced risks of complications for patients [88]. AI also plays a transformative role in oral drug therapy by predicting drug efficacy and aiding in personalized drug selection. Predictive modelling techniques enable the stratification of patients based on genetic, clinical, and metabolic profiles to identify the most effective oral hypoglycemic agents [89]. Recent studies have highlighted using ML algorithms to analyse patient data and optimize drug responsiveness, improving therapeutic outcomes. For instance, AI has been utilized to predict patient adherence patterns, enabling healthcare providers to pre-emptively address barriers to treatment compliance. This application significantly enhances precision medicine in diabetes care, fostering a more individualized and practical approach to oral pharmacotherapy [90].

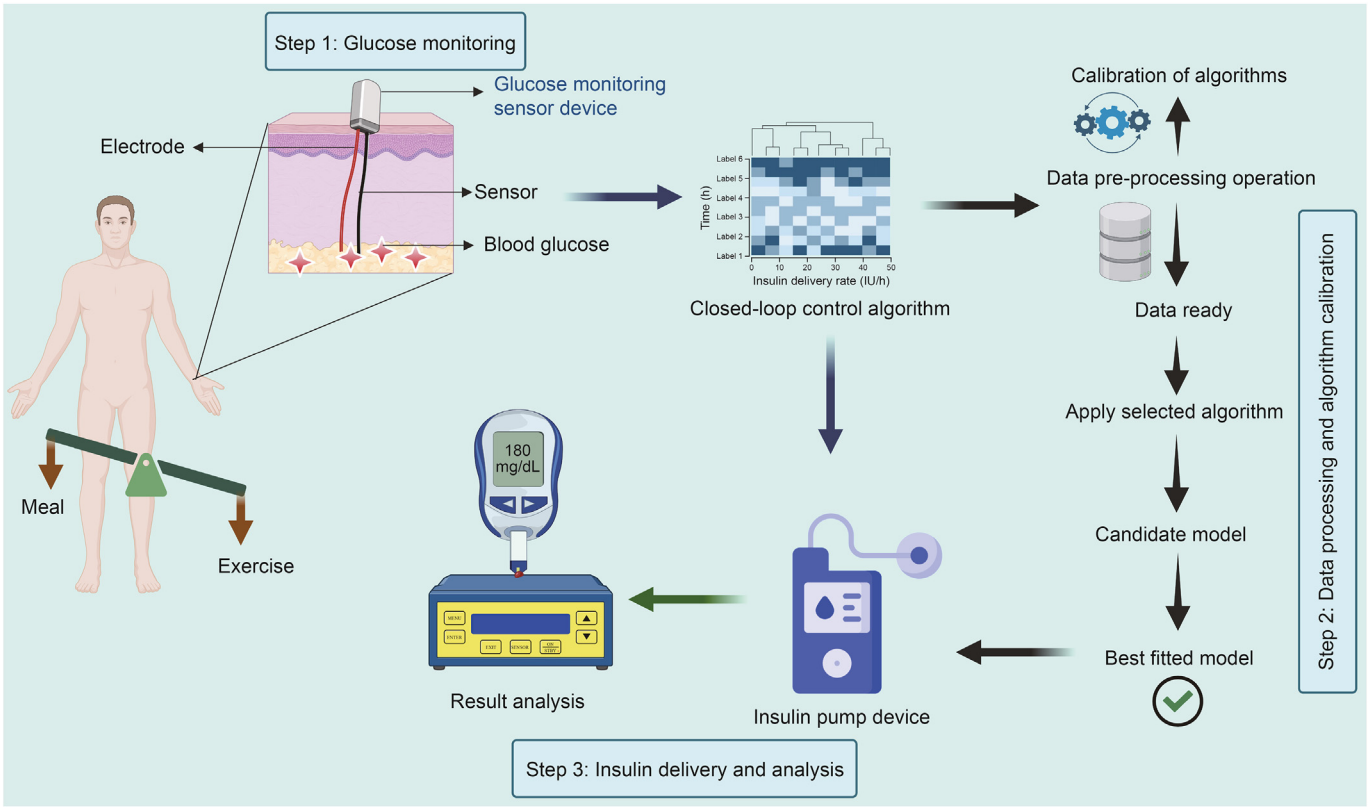

Fig. 2. Detailed workflow of an artificial intelligence (AI)-powered closed-loop system for continuous glucose monitoring (CGM) and automated insulin delivery, highlighting the calibration, data processing, and model application phases.

5.1. Personalized insulin therapy through AI

Personalized insulin therapy has emerged as a promising avenue for improving the management of T2DM. This article explores the role of AI in tailoring insulin therapy to individual patients, thereby enhancing treatment outcomes and patient well-being. Furthermore, AI has the potential to enhance patient engagement and adherence to insulin therapy. Researchers have highlighted the use of AI-driven chatbots to provide real-time support and education to T2DM patients on insulin therapy [91]. These chatbots can answer questions, offer reminders for medication administration, and provide lifestyle recommendations, thereby improving patient self-management. It is worth noting that the integration of AI in personalized insulin therapy is a rapidly evolving field with ongoing research and development. These include ML models, wearable devices, and smartphone applications that continuously monitor and optimize insulin therapy (Fig. 3).

5.2. AI-driven algorithms for insulin dosage

A study by Nayak et al. [92] demonstrated that voice-based conversational AI applications could assist patients with T2DM in titrating basal insulin at home, thus achieving rapid glycemic control. The potential for AI to improve the management of T2DM is clear and holds great promise for the future of diabetes care.

5.3. Predictive modelling in insulin management

Predictive modelling in insulin management for T2DM has seen significant advancements, particularly through the integration of AI and ML techniques. A key area of development is the use of ML approaches for predicting disease progression and management. Lim et al. [93] provided a comprehensive overview of how predictive modelling, including ML methods, is reshaping the management of T2DM, offering more personalized and effective treatment plans. In a similar vein, Lin et al. [94] developed a deep learning-based glucose trajectory prediction system for individuals with T2DM, showing promising results in controlling glucose levels. However, the system also indicated increased stress levels in participants, pointing to the need for further research to refine these AI-aided health management systems. The LIGHTNING study by Pettus et al. [95] aimed to use ML to predict hypoglycemic event rates in T2DM patients receiving different basal insulin treatments. This study underscores the potential of predictive modelling in identifying patient subgroups at lower risk of hypoglycemia and in foreseeing cost savings related to hypoglycemia. Additionally, Faruqui et al. [96] developed an online nurse-in-the-loop predictive control model that utilized a predictive digital twin trained on participants' self-monitoring data, which provided individualized feedback and recommendations, demonstrating improvements in daily steps and dietary intake for T2DM patients. While these developments are promising, they also bring to light the challenges and need for ongoing research to fully realize the benefits of AI and ML in diabetes care.

5.4. Synergies between therapeutic advances and AI

The synergies between therapeutic advances and AI in the field of T2DM care are rapidly transforming the landscape of diabetes management. AI's integration into diabetes care promises enhanced blood glucose control, reduced complications, and improved patient satisfaction. This integration spans various domains, including automated retinal screening, clinical decision support, predictive population risk stratification, and patient self-

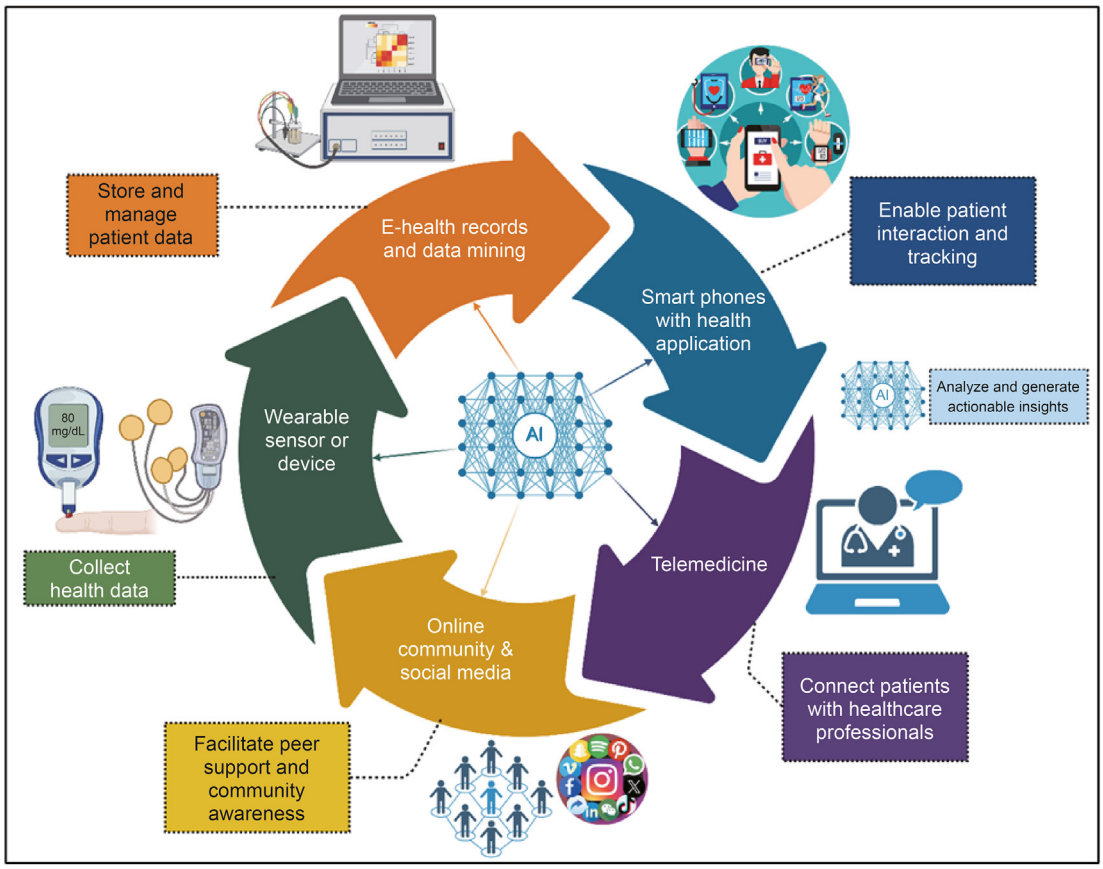

Fig. 3. Overview of artificial intelligence (AI) applications in diabetes management, illustrating a cyclic flow of data among wearable health devices, smartphones, telemedicine platforms, social media, and AI systems for integrated care and personalized insights.

management tools [97]. One notable area where AI is making significant inroads is patient education, revolutionizing how individuals receive information and guidance related to diabetes management. Through personalized and adaptive learning systems, AI contributes to tailoring educational content based on individual needs, fostering a more effective and engaging learning experience for patients. The impact of AI on improving clinical decision-making is evident in the emergence of CDSS for T2DM based on predictive analytics. However, caution is advised based on studies that highlight a gap between the potential of ML to revolutionise diabetes diagnosis and management and the current lack of sufficient evidence to seamlessly integrate these algorithms into routine clinical practice [98]. While there are challenges and barriers to overcome, the potential benefits of AI in enhancing patient care, treatment efficacy, and healthcare efficiency in T2DM are immense.

5.5. Integrating pharmacotherapy with AI

The integration of pharmacotherapy with AI in T2DM care is emerging as a transformative approach, although it is still in the nascent stages of development [99]. Developments in this area include the creation of AI-driven CDSS. These systems utilize predictive analytics to generate treatment pathways, thereby improving chronic disease care and demonstrating potential applicability to other chronic conditions [5]. Lee et al. [100] also highlighted the effectiveness of an integrated digital healthcare platform with AI-driven dietary management, resulting in better glycemic control and more weight loss in adults with T2DM. Wu et al. [101] discussed the potential of an AI-based health education program to improve self-management abilities and blood glucose control in primary healthcare settings. Overall, the integration of pharmacotherapy with AI in T2DM care is a burgeoning field, with studies indicating its potential to enhance diabetes management through improved decision-making, patient education, and personalized care.

5.6. Big data analysis and ML in T2DM

The intersection of big data analysis and ML has revolutionized the management and prediction of T2DM. By using extensive data from EHR genomics, lifestyle factors, and glucose monitoring, these technologies provide valuable insights into disease progression and patient behavior. ML algorithms, capable of learning from complex datasets and improving over time, are particularly well-suited for analyzing the intricate patterns within big data [102]. Navazi et al. [103] highlighted the use of hybrid meta-heuristic ML algorithms for early diagnosis, demonstrating that integrating ML techniques with big data significantly enhances diagnostic accuracy. Similarly, Zhang et al. [104] showed that ML models could effectively predict T2DM development using only self-reported information, underscoring the accessibility and utility of such data in predictive analytics. These findings illustrate the critical role of big data and ML in facilitating early diagnosis and timely intervention in T2DM.

Beyond early diagnosis, big data and ML have also shown promise in predicting complications and personalizing treatment plans for T2DM patients. Studies like those by Abhari et al. [4] and Subramaniyan et al. [105] emphasise the necessity of using large datasets to achieve accurate and generalizable predictive models.

Fregoso-Aparicio et al. [106] highlighted that integrating clinical data with ML enhances the predictive power of diabetes management systems. Moreover, Nibareke and Laassiri [107], and Tigga and Garg [108] demonstrated the utility of multiple ML tools and classification methods in improving diabetes prediction and management. These advancements not only enable healthcare providers to tailor treatment plans based on individual patient profiles but also facilitate the early identification of potential complications, thereby improving patient outcomes and reducing healthcare costs. Overall, the integration of big data and ML in T2DM care represents a significant leap forward in personalized medicine and predictive healthcare.

Deep learning has emerged as a powerful tool for predicting complications associated with T2DM. CNNs have demonstrated exceptional capabilities in the early detection of diabetic retinopathy through retinal image analysis, outperforming traditional diagnostic methods in accuracy and sensitivity [86]. These models excel at identifying microaneurysms and other subtle retinal changes that may not be apparent to human evaluators. Similarly, advanced neural network architectures are being utilized to predict diabetic nephropathy by analyzing a combination of clinical, biochemical, and imaging data. These models enable the identification of high-risk individuals and facilitate early interventions to prevent or mitigate kidney damage. Integrating such deep learning techniques into routine care provides an unprecedented opportunity for precision diagnostics, allowing for timely and targeted management of diabetes-related complications [109].

5.7. Future directions and implications for use of AI

The future directions and implications of integrating AI in T2DM care are multifaceted, offering exciting prospects for enhancing patient care and management. While specific studies focusing solely on T2DM are limited, the broader implications in diabetes care and AI applications provide valuable insights. The effectiveness of AI in obesity management, a common comorbidity in T2DM, suggests potential collaborative opportunities. Hinchliffe et al. [110] noted the role of digital health technologies, including ML and AI, in automating and personalizing interventions in obesity care. An essential area of future exploration is the potential for AI-enhanced technologies to support individuals with diabetes during significant life transitions, such as moving from home to university for young adults. Research findings consistently point to the pivotal intersection where technological innovation converges with the personalized needs and experiences of individuals grappling with the management of T1D. This critical juncture highlights the potential for technology to be tailored and responsive to the diverse and unique requirements of those navigating the complexities of T1D [87]. Identifying and analysing factors that influence the usability of these applications is crucial for their effective implementation in diabetes care [85]. Stein and Brooks [111] investigated the effectiveness of a standalone, fully automated text-based mobile coaching service in promoting weight loss and related health behaviours, demonstrating the potential of AI to increase access to compassionate health care via mobile health platforms. By providing personalized insights, real-time feedback, and actionable recommendations, the combination of an AI digital coach and a consumer-friendly glucose meter encourages individuals to make informed decisions and adopt healthier lifestyle choices [112]. The consistent decrease in HbA1C levels reflects not only the efficacy of this integrated approach but also hints at the transformative impact on the long-term health outcomes of individuals with diabetes. This shift in self-management practices signifies a departure from conventional approaches, highlighting the potential of technology-driven interventions to enhance the effectiveness of diabetes care. The future directions in AI and T2DM care are geared towards enhancing patient support through technology, improving data usability and interpretation, and exploring novel ways to manage diabetes more effectively.

5.8. Potential barriers and challenges in the use of AI

Implementing AI in the care of individuals with T2DM encounters numerous potential barriers and challenges, necessitating thoughtful solutions to unlock its maximum benefits. Research indicates that complex technological concerns, the active engagement of patients, ethical considerations, safeguarding data privacy, health disparities, reservations among clinicians, regulatory constraints and the requirement for well-balanced strategies and collaborative research initiatives emerge as pivotal challenges that require careful attention and resolution [113]. Goldstein et al. [114] further emphasise that hurdles such as regulatory approval, reimbursement processes, updates to quality measures, and the localised optimisation of clinical workflows pose additional challenges in integrating AI into diabetes care [115]. The conceptualisation and development of a prototype for virtual assistant software designed to facilitate self-care among older adults managing T2DM underscore a crucial aspect of healthcare innovation. In recognising the diversity within the T2DM patient population, particularly among older adults, the prototype highlights the importance of moving beyond one-size-fits-all solutions. By tailoring virtual assistant software to cater specifically to the distinct requirements of older adults, the approach becomes more personalized and attuned to the unique challenges and preferences prevalent in this demographic [116].

Furthermore, patient perceptions of AI applications in healthcare play a crucial role. The research conducted by Esmaeilzadeh and colleagues indicates that the medical condition and the clinical interaction affect factors such as privacy worries, trust dilemmas, communication obstacles, apprehensions about regulatory norms, liability hazards, and the willingness to utilize services. This underscores the importance of building trust and ensuring transparency in AI applications [117]. Another challenge identified by Dvey-Aharon and Huhtinen [118] is finding reliable and convenient methods for screening diabetic retinopathy using AI algorithms, which is crucial for early detection and treatment. The lack of transparency and potential for bias in AI and ML applications are significant concerns, necessitating using Bayesian methods to foster trust in medical AI/ML applications [119]. Shah et al. [120] highlight the accessibility of diabetic retinopathy screening in primary care settings as a barrier, emphasising the need for widespread and accessible screening methods. The future implementation of AI in T2DM care is laden with challenges related to technology, ethics, regulation, patient engagement, and trust. Addressing these barriers requires multidisciplinary efforts, regulatory framework development, patient-centric approaches, and continuous research and innovation.

6. Bridging the gap between AI and therapeutics in T2DM management

Integrating AI into managing T2DM can revolutionise patient care by enhancing diagnostic accuracy, personalizing treatment plans, and improving overall health outcomes. However, despite AI's promising capabilities, significant barriers impede its seamless incorporation into therapeutic strategies. Addressing these challenges through interdisciplinary collaboration, education, and robust regulatory frameworks is crucial for harnessing the full potential of AI in diabetes care. This section explores the multifaceted challenges of integrating AI with therapeutics in T2DM management and proposes comprehensive solutions to bridge these gaps [6].

6.1. Challenges in integration

Integrating AI into T2DM management presents numerous technological, ethical, and practical challenges. One primary challenge is data standardisation and integration. AI systems require vast amounts of high-quality data to function effectively, but the data used in healthcare often comes from disparate sources and in various formats. This lack of standardisation makes compiling and analysing data efficiently tricky [87]. Additionally, data quality can vary significantly, with issues such as missing information or inaccurate entries further complicating the integration process [117].

Ethical concerns also pose significant barriers. AI systems in healthcare must navigate the complex landscape of patient privacy and data security. Ensuring that AI applications comply with regulations like the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) is crucial to maintaining patient trust and protecting sensitive health information [118]. There are also concerns about bias in AI algorithms, which can result from biased data sets or algorithmic design, potentially leading to unequal treatment outcomes among different patient populations [119].

From a practical standpoint, healthcare providers' acceptance and adoption of AI technologies can be slow. Clinicians may be sceptical about the reliability of AI systems or may lack the necessary training to use these tools effectively. Furthermore, integrating AI into existing healthcare workflows requires significant changes in infrastructure and processes, which can be resource-intensive and disruptive [120]. Financial constraints also play a role, as developing and implementing AI technologies involves substantial investment, which may not be feasible for all healthcare settings [121].

Integrating AI into diabetes management faces several challenges that hinder its seamless adoption and widespread application. One significant barrier is the lack of data standardization, as healthcare data often originates from disparate sources and formats. Developing standardized data-sharing protocols is essential for efficient AI model training and application. Another critical issue is ensuring patient privacy, as AI systems require access to sensitive health information. Solutions like advanced encryption techniques and federated learning frameworks can mitigate privacy concerns while maintaining robust data utilization. Furthermore, integrating AI into clinical workflows requires comprehensive training programs for clinicians to enhance their understanding and usability of AI tools. By addressing these challenges through technological advancements and education, AI can achieve its full potential in improving diabetes care.

6.2. Potential solutions

To overcome these challenges, a multi-faceted approach involving interdisciplinary collaboration, education and training, standardisation and regulation, and patient-centric approaches is necessary.

6.2.1. Interdisciplinary collaboration

Effective integration of AI into T2DM management requires collaboration between diverse fields, including computer science, endocrinology, data science, and ethics. Such interdisciplinary collaboration can ensure that AI systems are designed with a comprehensive understanding of both the technological possibilities and the clinical realities. For instance, collaboration between data scientists and clinicians can help identify relevant clinical variables to include in AI models, improving their accuracy and utility [84]. Additionally, involving ethicists in the development process can help address potential biases and ensure ethical considerations are incorporated from the outset [113].

6.2.2. Education and training

To effectively embrace AI technologies in healthcare, we must prioritize comprehensive education and training for healthcare providers. This investment will empower them to leverage these advancements confidently and improve patient care. Training programs should focus on enhancing the digital literacy of clinicians, helping them understand how AI tools work, how to interpret AI-generated insights, and how to integrate these tools into their clinical practice. Continuous education initiatives can also help clinicians stay updated with the latest advancements in AI and its applications in diabetes care [100]. Furthermore, fostering a culture of openness to technological innovation within healthcare institutions can help mitigate resistance to adopting new technologies [111].

6.2.3. Standardisation and regulation

Standardisation of data formats and protocols is crucial for the seamless integration of AI into healthcare. Establishing typical data collection, storage, and sharing standards can facilitate the development of robust AI models that can be applied across different healthcare settings. Regulatory frameworks should also be adapted to address AI's unique challenges in healthcare. This includes developing guidelines for the ethical use of AI, ensuring transparency in AI decision-making processes, and implementing mechanisms for monitoring and evaluating the performance of AI systems [120]. Regulatory bodies need to work closely with AI developers, healthcare providers, and patients to create regulations that protect patients while encouraging innovation [97].

6.2.4. Patient-centric approaches

Incorporating patient perspectives into the design and implementation of AI technologies is essential for ensuring these tools meet the needs of those they are intended to help. Engaging patients in the development process can provide valuable insights into their preferences, concerns, and needs, leading to the creation of more user-friendly and effective AI applications. Moreover, educating patients about the benefits and limitations of AI can help build trust and encourage them to participate actively in their care [101]. Personalized AI-driven tools that provide tailored recommendations and support can enhance patient engagement and adherence to treatment plans, ultimately improving health outcomes [92].

7. AI-driven CDSS

AI-driven CDSS have revolutionized the management of T2DM by enhancing predictive analytics, risk stratification, and personalized treatment recommendations. These systems leverage ML algorithms to analyse vast amounts of patient data, identifying patterns and trends that enable the prediction of health outcomes such as hypoglycemia and hyperglycemia events. This predictive capability allows healthcare providers to intervene proactively, adjusting treatment plans before adverse events occur, thereby improving patient safety and outcomes. AI-CDSS can categorise patients into different risk levels, prioritising high-risk individuals for more intensive management, which is crucial for preventing complications associated with T2DM, such as cardiovascular disease and diabetic nephropathy. Moreover, AI-CDSS generates personalized treatment recommendations by considering many factors, including genetic data, lifestyle choices, and comorbid conditions. This tailored approach enhances treatment adherence and efficacy, aligning closely with patients' needs and preferences. AI-CDSS can optimize insulin therapy by continuously monitoring

glucose levels and other relevant parameters, suggesting precise insulin dosages and timing, thus reducing the risk of errors and enhancing glucose management. These systems also facilitate shared decision-making by providing options and potential outcomes, empowering patients to actively participate in their care, which has been shown to improve satisfaction and adherence [122]. However, the implementation of AI-CDSS in diabetes care faces significant challenges. Data standardisation and integration with existing healthcare infrastructure are critical issues that must be addressed to ensure seamless interoperability. Additionally, there are concerns about data privacy and security, as AI systems require access to sensitive patient information. Ensuring robust safeguards and compliance with regulatory standards like GDPR and HIPAA is essential.

Furthermore, the acceptance and trust of AI among healthcare providers can be hindered by a lack of understanding or scepticism about the accuracy of these systems. Education and training programs are crucial to build confidence and familiarity with AI technologies. Finally, continuous evaluation and validation of AI-CDSS are necessary to ensure their reliability and effectiveness in real-world settings [123].

Addressing these issues through robust regulatory frameworks, interdisciplinary collaboration, and continuous evaluation is essential for maximising the potential of AI-CDSS in diabetes care. Studies have demonstrated that AI-CDSS can significantly enhance clinical decision-making, improve glycemic control, and reduce complications, promising a transformative impact on diabetes management. As AI technologies continue to evolve, they hold the potential to further revolutionise diabetes care by enabling more precise, proactive, and personalized management strategies [124].

8. Predictive modelling for complication prevention

Predictive modelling has become crucial in managing T2DM by enabling early identification and preventing complications. These models use ML algorithms to analyse extensive patient data, identifying patterns and risk factors associated with diabetes-related complications such as cardiovascular disease, nephropathy, retinopathy, and neuropathy. Early detection through predictive modelling allows healthcare providers to implement timely interventions, significantly improving patient outcomes and reducing healthcare costs. By incorporating variables like demographic data, clinical parameters, and lifestyle factors, predictive models can assess the risk of complications, enabling personalized treatment plans. For example, patients at high risk for diabetic nephropathy can be monitored more closely and advised on lifestyle changes, thereby enhancing treatment adherence and efficacy [125]. However, implementing predictive models faces several challenges, including data quality, privacy concerns, and the need for continuous model validation. Ensuring robust data protection and compliance with regulations like HIPAA is essential for maintaining patient trust.

Additionally, integrating predictive models with EHR systems enhances their utility by providing real-time data analysis and risk assessment, facilitating prompt and informed decision-making. Despite these challenges, the future of predictive modelling in T2DM management looks promising, with advancements expected to incorporate a broader range of data sources, including wearable devices and genomic data. These developments could further enhance the precision and utility of predictive models, paving the way for more proactive and personalized diabetes care, ultimately transforming T2DM management by enabling early intervention and reducing complications [126].

9. Conclusion

In conclusion, integrating AI in managing T2DM presents a paradigm shift with vast potential to improve patient outcomes. This article has highlighted key findings that emphasise the transformative impact of AI in various aspects of T2DM care, including predictive analytics, personalized treatment regimens, patient self-management, and the enhancement of clinical decision-making processes. The key findings underscore AI's capability to analyse complex health data, offering more accurate predictions and personalized care plans. AI-driven predictive models can forecast disease progression and treatment responses, aiding early interventions. In pharmacotherapy, AI algorithms optimize drug dosages and reduce adverse effects, while AI-powered lifestyle management tools provide tailored dietary and exercise recommendations. However, the implementation of AI in T2DM care is not without challenges. Issues such as data privacy and security, potential biases in AI algorithms, and the need for clinician education and acceptance have been identified as significant barriers. Future research should focus on improving the quality and diversity of data used in AI systems, ensuring that these technologies are representative of and effective for diverse patient populations. Ethical considerations, particularly regarding data privacy and algorithmic bias, must be a central focus, ensuring that AI-driven healthcare advances ethically and equitably. Clinically, there is a need for a concerted effort to integrate AI tools into healthcare workflows seamlessly. This integration requires technological advancements and a focus on educating healthcare providers about AI capabilities and limitations. Additionally, healthcare systems must address accessibility and affordability issues to ensure that the benefits of AI in T2DM care are available to all patients, regardless of socioeconomic status or geographical location. As research and development in this field continue to advance, the collaborative efforts of scientists, clinicians, and policymakers will be crucial in harnessing the full potential of AI for improving the lives of individuals living with T2DM.

CRediT authorship contribution statement

Aniruddha Sen: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Palani Selvam Mohanraj:** Writing – original draft, Supervision, Methodology, Formal analysis. **Vijaya Laxmi:** Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Data curation. **Sumel Ashique:** Writing – original draft, Visualization, Supervision, Methodology, Formal analysis. **Rajalakshimi Vasudevan:** Writing – original draft, Visualization, Methodology, Funding acquisition, Formal analysis. **Afaf Aldahish:** Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis. **Anupriya Velu:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis. **Arani Das:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis. **Iman Ehsan:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis. **Anas Islam:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Sabina Yasmin:** Writing – review & editing, Visualization, Supervision, Methodology, Funding acquisition, Formal analysis. **Mohammad Yousuf Ansari:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that there are no conflicts of interest.

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