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REVIEW Article

Artificial Intelligence - Enhanced Continuous Glucose Monitoring in Diabetes Care

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ABSTRACT

Diabetes Mellitus (DM) represents a major global health burden, with rapidly increasing prevalence, particularly in low- and middle-income countries. Effective glycemic monitoring is essential to prevent complications and optimize long-term outcomes. Continuous glucose monitoring (CGM) has emerged as a transformative technology, providing real-time insights into glucose variability, time-in-range, and hypoglycemic episodes that are not captured by conventional methods such as self-monitoring of blood glucose (SMBG) or glycated hemoglobin (HbA1c). Recent advancements in artificial intelligence (AI) have further enhanced the capabilities of CGM systems by enabling predictive analytics, personalized treatment strategies, and automated insulin delivery. AI-driven algorithms can analyze large-scale CGM datasets to identify glycemic patterns, forecast glucose excursions, and support clinical decision-making. The integration of machine learning models and closed-loop systems, often referred to as artificial pancreas technologies, represents a paradigm shift toward precision diabetes care. This narrative review explores the evolution of CGM technologies, their clinical utility in diabetes management, and the expanding role of AI in optimizing glycemic control. Evidence from clinical trials and real-world studies demonstrate that CGM, particularly when integrated with AI, improves HbA1c levels, reduces glycemic variability, and enhances patient quality of life. However, challenges related to cost, accessibility, data reliability, and patient adherence continue to limit widespread adoption, especially in resource-constrained settings. In conclusion, the convergence of CGM and AI holds significant promise for advancing personalized and predictive diabetes care. Future research should focus

on improving affordability, enhancing algorithm transparency, and evaluating long-term clinical outcomes to ensure equitable implementation across diverse populations.

Keywords
Continuous glucose monitoring, artificial intelligence diabetes mellitus; machine learning, glycemic control, digital health.

SUMMARY

Abbreviations
Continuous Glucose Monitoring (CGM); Self-Monitoring of Blood Glucose (SMBG); Real-Time Continuous Glucose Monitoring (rtCGM); Intermittently scanned Continuous Glucose Monitoring (isCGM); Flash Continuous Glucose Monitoring (FCGM); Artificial Intelligence (AI); Intraventricular Hemorrhage (IVH); Diabetes Mellitus (DM); Type 1 Diabetes Mellitus (T1DM);
Type 2 Diabetes Mellitus (T2DM); Oral Glucose Tolerance Test (OGTT); World Health Organisation (WHO); Blood Sugar Levels (BSL); Flash Glucose Monitoring (FGM); Glycemic Variability (GV); Sodium-Glucose CoTransporter-2 (SGLT2) inhibitors; Diabetic kidney disease (DKD); Clinical decision support systems (CDSS); Organic Electrochemical Transistor (OECT); Hybrid Closed-Loop Systems (HCLS); Diabetes Control and Complications Trial (DCCT); Model Predictive Control (MPC); Proportional-Integral-Derivative (PID); Low and Middle-income countries (LMICs); Negative likelihood ratio (NLR); CLAIR (Continuous Learning Artificial Intelligence Risk); Glycated Hemoglobin (HbA1c); Positive Likelihood Ratio (PLR); Neural network models (NNMs); Root Means Square Error (RMSE); Time in Range (TIR); Machine Learning (ML); Mean Absolute Relative Difference (MARD); Transcutaneous auricular vagus nerve stimulation (taVNS).

1. Introduction

Diabetes Mellitus (DM) is a global health concern with increasing incidence worldwide. In 2024, prevalence reached an estimated 589 million adults (ages 20–79), with a predicted rise to 853 million by 2050. 81% of this disease burden is concentrated in low- and middle-income countries, highlighting a critical public health disparity[1]. The increasing prevalence of DM has not only increased the economic and emotional burden on patients but is also contributing to socioeconomic strain in the healthcare sector[2,3]. Complications like cardio-, cerebro-vascular conditions, blindness, nephropathy, neuropathy, renal failure, amputations, depression, suicide and death are associated with DM[4,5].

Management and monitoring of diabetes has advanced significantly with the introduction of Continuous Glucose Monitoring (CGM)[6]. CGM systems have revolutionized diabetes management by providing real-time data on glucose levels, enabling better glycemic control and reducing the risk of DM-associated complications. Unlike glycated hemoglobin (HbA1c), real-time or intermittently scanned CGM (isCGM) provides insight into glycemic variability, as well as postprandial

hyperglycemia, which are both closely linked to microvascular and macrovascular complications[7]. This has also led to a better understanding of individual metabolic responses to different food types, thereby optimising outcomes in patients with DM, and our understanding of metabolism in non-diabetic individuals[8].

Consequently, CGM has demonstrated clinical utility in predicting the risk of progression toward both Type 1 Diabetes (T1DM) and Type 2 Diabetes Mellitus (T2DM)[9]. Early detection and prediction of predisposition to the disease have therapeutic value, primarily by facilitating lifestyle modifications, which delay onset.

The integration of AI into CGM technology provides a pivotal opportunity to deliver precise, personalized, and predictive diabetes care[10]. Its capacity to identify complex glycemic patterns, analyse large-scale datasets, and generate accurate conclusions has unlocked diverse applications in healthcare. In the context of DM, AI-powered algorithms enhance CGM devices by offering predictive analytics, automated insulin delivery systems, and personalized treatment recommendations.

Figure 1 also shows a diagram illustrating how an AI based closed-loop insulin delivery system works. These innovations with future advancements will help alleviate the burden of diabetic management and improve patients' quality of life [11,12].

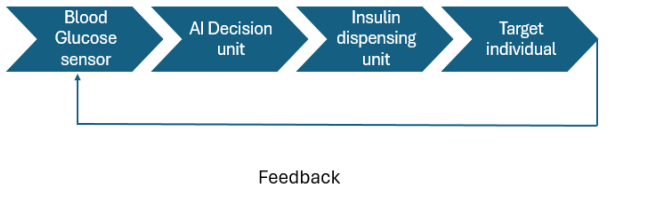

Figure 1. *AI-based closed-loop insulin delivery system.* Adapted from Medanki S, Dommati N, Bodapati HH, et al[13]. Artificial intelligence powered glucose monitoring and controlling system: Pumping module. World Journal of Experimental Medicine. 2024;14(1):87916, under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (CC BY-NC 4.0).

This narrative review aims to explore the latest advancements in CGM technology and the pivotal role AI plays in enhancing DM management. By examining recent studies and technological breakthroughs, this paper highlights the synergistic potential of CGM and AI in optimizing clinical outcomes.

2. Importance of Glucose Monitoring in DM Management

2.1. Standard Diagnostic and Surveillance Methodologies

Routine glucose monitoring is vital for the effective management of DM, it maintains glycemic control, is crucial for patients using insulin or sulfonylureas and is particularly useful during pregnancy, dietary changes, or before surgery, mitigating the risk of complications[14-17]. Among all monitoring methods, postprandial glucose tracking provides superior insight into overall glycemic status compared to fasting plasma glucose levels alone, primarily because postprandial glycemic spikes heavily drive cumulative hyperglycemia. Early diagnosis of DM is also a key factor in its management and prevention of complications. Various methods, such as regular HbA1c and blood glucose screening of at-risk patients, have been employed for this purpose.

The World Health Organization (WHO) diagnostic criteria establish fasting plasma glucose and 2-hour postprandial glucose levels as the diagnostic gold standards [18]. Specifically, a 2-hour oral glucose tolerance test (OGTT) serves as the most sensitive diagnostic assay, where blood glucose levels exceeding 200 mg/dL confirm a diagnosis of DM[19]. Alternatively, cost-effectiveness and accuracy make HbA1c a preferred and a widely used alternative[20].

For ongoing management, persistent self-monitoring of blood glucose (SMBG) is strongly associated with reduced HbA1c levels[21]. In patients with T1DM, executing SMBG at least four times daily can lower HbA1c by approximately 1% compared to a single daily measurement[22]. While SMBG helps patients adjust insulin doses, manage diet and exercise, and make informed decisions about their treatment, its clinical success depends on proper interpretation and healthcare guidance to avoid frustration regarding elevated readings[23,24]. Healthcare costs, emergency visits, and chronic

complications can be reduced by comprehensive SMBG and HbA1c testing.

2.2. Limitations of Capillary Blood Glucose Monitoring (SMBG)

Traditional blood glucose monitoring methods have several limitations, notably procedural discomfort and pain, due to frequent finger pricks, which drastically reduce patient compliance, as well as only providing snapshot data[25]. Compared to emerging matrices, standard invasive methods are more accurate, but they remain costly, painful, and provide only intermittent measurements[26]. Furthermore, SMBG is susceptible to user error, manufacturing variability, and fluctuating environmental conditions[27]. Certain medications and extreme hematocrit values can also compromise reading accuracy[28]. Additionally, glycaemic excursions, including asymptomatic hypoglycemia and postprandial hyperglycemia, frequently evade detection via routine SMBG, as shown even among patients with optimal HbA1c concentrations[29]. Although SMBG is crucial for T1DM and insulin therapy, proper patient training is equally essential to minimize these inaccuracies[30]. Maximal efficacy of monitoring is crucial, as every 1% increase in HbA1c significantly raises healthcare costs due to DM-related complications[31]. Despite its importance, patient adherence to monitoring remains a challenge. Behavioral interventions, such as patient education, problem-solving strategies, and motivational interviewing, have been shown to improve short-term adherence[32]. Literature reviews also recommend an increased emphasis on patient education regarding hypoglycemic symptoms compared to hyperglycemic symptoms for all individuals prescribed anti-diabetic medications.

To counter systemic issues, alternative methods such as sweat, saliva, tear fluid, and transdermal techniques have been explored. However, accuracy continues to be limited by analytical and pre-analytical variables[33]. Research into non-invasive techniques, such as near-infrared spectroscopy, remains an active area of investigation but continues to face persistent challenges[34-36]. Alternative glycemic markers, such as fructosamine and glycated albumin, provide distinct measurement time frames but currently lack standardization and long-term longitudinal data[37].

2.3. The Transition to Continuous Glucose Monitoring (CGM)

The clear limitations of conventional monitoring emphasize the need for advanced monitoring techniques. While SMBG provides discrete data points, and HbA1c remains the gold standard for long-term glycemic control, CGM offers continuous readings, allowing for trend analysis and therapeutic adjustments. Consequently, over the past two decades, CGM has gained substantial popularity and represents an important research area for DM management[38]. CGM systems provide real-time glucose data, including identifying glycemic variability (GV), time-in-range (TIR), hypoglycemic episodes and capture short-term fluctuations[39].

Recent advances in wearable sensors and electrochemical biosensors offer promising, pain-free alternatives, however, further optimization of sensor accuracy is required[30].

Widespread adoption was limited as early devices were expensive and required frequent calibrations. To bridge this gap, intermittently scanned CGM (isCGM), (historically termed flash CGM), emerged as a cost-effective, factory-calibrated alternative that eliminates manual user calibration. As technology progresses, CGM devices are expected to supplant traditional SMBG workflows, improving glycemic control and patient quality of life[40,41].

2.4. Types of CGM, Comparative Clinical Efficacy and Insights

<u>Real-Time CGM (rtCGM), intermittently scanned CGM (isCGM) & their Impact on Glycemic Control</u>

CGM is classified into intermittently scanned CGM (isCGM) and real-time CGM (rtCGM). While rtCGM continuously records glucose data every 5 minutes to a receiver or smartphone app, isCGM requires patients to actively scan the sensor throughout the day to retrieve data trends[42]. IsCGM also helps reduce HbA1c and manage glycemic variability through retrospective trend analysis. However, isCGM's lack of immediate alerts limits its suitability for those needing immediate intervention. Research indicates that CGM systems with threshold user alert alarms significantly reduce the risk of severe hypoglycaemia[43].

A randomised study evaluating 100 patients with T2DM who were not on insulin therapy compared the

efficacy of rtCGM against traditional SMBG by assessing HbA1c changes over a 12-week period. HbA1c decreased by 1.0% with rtCGM vs. 0.5% with SMBG[44]. Insulin initiation was lower in rtCGM users (6%) vs. SMBG (16%). The study concluded that rtCGM may improve HbA1c as a non-pharmacological intervention without medication changes that could induce hypoglycaemia[44].

CGM technology provides detailed glycemic variability (GV) analysis, allowing timely therapeutic adjustments (**Figure 2**). Moreover, insulin analogues, such as degludec, combined with CGM have been shown to reduce glucose variability [45]. Parallel studies evaluating sodium-glucose cotransporter-2 (SGLT2) inhibitors, including canagliflozin and dapagliflozin, demonstrate reduced GV with CGM use[46.] Lastly, a meta-analysis by Chen et al. demonstrated that rtCGM is superior to Flash Glucose Monitoring (FGM; an early form of isCGM) for optimizing glycaemic control in patients with T1DM[47]. Clinical evidence supports the benefit of rtCGM to achieve improved glycaemic control, minimize extreme glucose fluctuations, and lower the incidence of severe hypoglycaemia [48-51]. RtCGM, in particular, has also demonstrated increasing TIR, especially during high-risk activities like exercise[51].

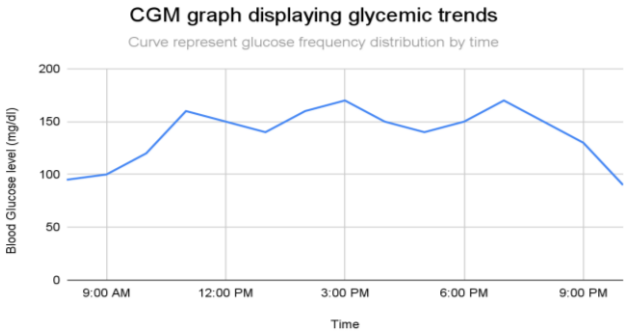

Figure 2. Example of a CGM graph displaying Glycemic trends. Source: Created by the authors for illustrative purposes.

3. Evolution of Continuous Glucose Monitoring (CGM)

3.1. History of Glucose Monitoring Methods

The history of glucose monitoring dates back to the 19th century (**Figure 3**), with early methods focused on measuring glucose in urine. A key milestone was the introduction of Benedict's copper reagent in 1908, followed by Clinitest in 1941 and Clinistix in 1956, which introduced enzymatic urine testing[52]. These methods were indirect and lacked immediate glucose data.

The conceptual foundation for enzyme-based glucose sensing was established by Clark and Lyons in 1962, who proposed the first enzyme electrode for glucose detection. Building on this principle, Ames introduced Dextrostix in 1965, a glucose oxidase–based reagent strip that transformed blood glucose testing. Although the test was semi-quantitative and required large blood samples, it paved the way for future advancements. The introduction of blood glucose testing with Dextrostix in 1965 was followed by the Ames Reflectance Meter in 1970, the first glucose meter designed for use with Dextrostix in clinical settings, although its accuracy was limited. The Dextrometer, launched in 1980, made true home blood glucose monitoring more accessible[53].

3.2 First-Generation CGM Devices

Conventional glucose monitoring methods were limited by the need for frequent finger pricks and their inability to provide continuous glucose data, prompting the development of CGM systems. CGM systems utilize the physiological equilibration between blood glucose and interstitial fluid in the subcutaneous tissue, enabling minimally invasive continuous monitoring.

First-generation CGM systems marked a significant step forward by using subcutaneous electrochemical sensors to measure interstitial glucose levels. One of the first retrospective subcutaneous CGM systems became commercially available in 1999. Concurrently, the GlucoWatch Biographer, approved in 2001, was one of the first transdermal devices to use reverse iontophoresis to extract glucose across the skin. Despite their innovation, early devices faced persistent challenges like skin irritation, frequent calibration needs, and limited accuracy, especially in hypoglycemic ranges. Early clinical trials demonstrated CGM's ability to reveal glycemic patterns missed by SMBG, but accuracy remained a concern. Advances in sensor biocompatibility and calibration set the stage for modern CGM systems. Consequently, contemporary CGMs have transitioned from niche diagnostic devices into widely adopted, patient-facing tools.

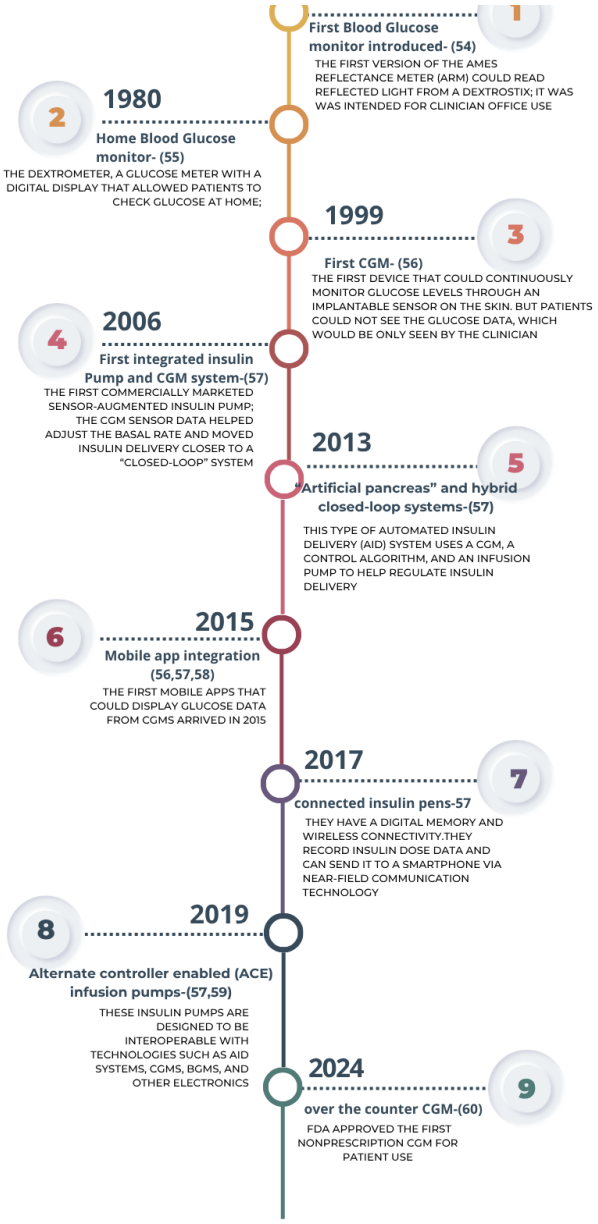

Figure 3. *Timeline of CGM Technological advancements*

3.3. Digital Integration and Automation of CGM

Between 2006 and 2017, CGM technology transitioned from isolated diagnostic tools to integrated consumer and automated systems. In 2006, Medtronic launched the MiniMed Paradigm REAL-Time, the first system to display CGM data directly on an insulin pump. Sensor wear time subsequently extended from three to seven days, and algorithmic advancements reduced the Mean Absolute Relative Difference (MARD) below 10%, aligning sensor accuracy with standard blood glucose meters. In 2015, the Dexcom G5 Mobile introduced direct Bluetooth telemetry to smartphones, enabling real-time remote monitoring for caregivers. These systems have advanced rtCGM technology with factory calibration, extended sensor life, and insulin pump integration, helping reduce hypoglycemic episodes and improve TIR in T1DM[61].

This culminated in two major regulatory milestones: the 2016 approval of the Medtronic MiniMed 670G, the first commercial hybrid closed-loop (HCLS) "artificial pancreas" system that automated insulin delivery based on sensor data, and the 2017 approval of the Abbott FreeStyle Libre, which introduced the is CGM.

3.4. Non-Invasive and Implantable CGM

Technological advances have led to implantable CGM systems, such as Eversense, featuring subcutaneous sensors with six-month lifespans and wireless data transmission.

Non-invasive CGM aims to measure glucose without penetrating the skin, using techniques like spectroscopy and electrochemical biosensors. Optical methods such as near-infrared spectroscopy are being explored for infection-free monitoring, though accuracy and environmental sensitivity remain a challenge[62].

Table 1 compares the different methods used to monitor glucose levels. It shows that CGM systems provide more detailed and continuous glucose information than traditional SMBG, helping improve diabetes management and glycemic control.

4. Evaluating CGM: Benefits and Limitations

4.1. Patient-Centric Benefits for CGM

Real-time glucose data empowers patients to make informed decisions about diet, exercise and medication. The integration of CGM with mobile apps and cloud platforms enhances patient-provider communication, enabling personalized care. Customizable alerts for hypo- and hyperglycemia improve adherence and reduce anxiety.

Table 2 summarizes important clinical trials comparing CGM with traditional glucose monitoring. Overall, these studies demonstrate that CGM improves blood sugar control by lowering HbA1c levels, minimizing hypoglycemia, and increasing CGM adoption reportedly rose from 6% in 2011 to 38% in 2018 among T1DM patients[67]

Table 1. Comparison of glucose monitoring methods

Method	Invasiveness	Cost	Accuracy	User experience	Benefits
Standard Blood glucose monitoring (SMBG)	Minimally invasive [64]	Less cost Effective [63]	Provides accurate glucose measurements when performed correctly, although accuracy may be affected by user technique and meter type[64]	User Friendly [65]	Greater HbA1c control. Helps protect patients by immediately confirming hypoglycemia and hyperglycemia. Helps with patient self-management education. [65]
rtCGM (Real time continuous glucose monitoring)	More invasive Due to continuous sensor wear [65]	Higher cost than SMBG [63]	Accurate levels of glucose are depicted [66]	User friendly devices can be placed on the arm, thigh or belly. Continuous readings are shown on the sensor [66]	Greater HbA1c control** and reduces hypoglycemia by alarming the patient continuously of low glucose levels. [66]
IsCGM (intermittently scanned continuous glucose monitoring)	Less Invasive [66]	More cost effective than rtCGM [66]	Same accuracy as rtCGM under most clinical conditions [64]	Less user-friendly devices as they can be placed on the arm only. A scan is required in order for the glucose levels to be displayed [66]	Greater HbA1c control** but not efficient in reducing hypoglycemia as the sensor is required to be scanned manually. [66]

** *Haskova et al discusses the efficacy of rtCGM and isCGM*

Table 2. Landmark studies Demonstrating the clinical efficacy of Continuous Glucose Monitoring (CGM)

Study	Year	Study Design	Population	Sample Size	Key Findings
Deiss et al. [68]	2006	Randomized Controlled Trial (RCT)	Type 1 Diabetes Mellitus (T1DM)	156	Frequent CGM use significantly improved HbA1c compared with SMBG, demonstrating the value of continuous monitoring.
JDRF CGM study group [69]	2008	Multicenter RCT	T1DM patients aged equal to and >8 years	322	CGM significantly reduced HbA1c in adults and improved glycemic control without increasing severe hypoglycemia.
Ehrhardt et al. [70]	2011	RCT	Insulin treated T2DM	100	rtCGM users achieved greater HbA1c reduction than SMBG users despite no medication intensification.
DIAMOND Trial (Beck et al.) [71]	2017	RCT	Adults with T1DM using multiple daily Insulin Injections	158	CGM resulted in significantly lower HbA1c and improved glycemic control compared with conventional monitoring.
GOLD Trial (Lind et al.) [72]	2017	RCT	Adults with T1DM on multiple daily injections	161	CGM reduced HbA1c, increased TIR, and decreased hypoglycemic episodes compared with SMBG.
Charleer et al [73]	2020	Prospective Real world Cohort Study	Adults with T1DM using intermittently scanned CGM	1905	Long-term CGM use improved quality of life and glycemic outcomes under routine clinical practice.
Wright et al.[74]	2021	Retrospective Observational study	T2DM patients using basal insulin or non insulin therapy	1034	isCGM use was associated with significant HbA1c reduction in routine clinical care.

4.2. Limitations and Challenges of CGM

Despite its benefits, CGM has limitations in accuracy, cost, and accessibility. Sensor performance can be suboptimal in detecting hypoglycemia, particularly in patients with impaired hypoglycemic awareness. High costs and inconsistent insurance coverage hinder widespread adoption, especially in low-resource settings. Modern CGM devices, such as Dexcom G7[75,76] and FreeStyle Libre 3[77,78], offer improved accuracy but vary in sensor metrics[79]. Integration with automated insulin delivery has enhanced patient outcomes, yet inpatient CGM use is not FDA-approved[80,81]. Limitations also include low patient literacy, alarm fatigue, interference from certain substances, high discontinuation rates, and inadequate reimbursement[82]. Moreover, CGM accessibility to low income and underdeveloped countries requires further improvement.

Patient adherence can be challenging due to device fatigue, discomfort or the psychological burden of constant monitoring. Patient education is also required to interpret glucose trends effectively.

Addressing these barriers necessitates advances in sensor reliability, cost reduction and improved patient support. Telemedicine enhances DM management by providing continuous monitoring with remote consultations and has also proven effective for HbA1c monitoring[83,84,85]. However, it is limited by resource constraints, lack of awareness, accessibility and regulatory concerns[86,87].

5. Integration of Artificial Intelligence in Continuous Glucose Monitoring and Diabetes Management

5.1. Integration of Artificial Intelligence in CGM

Recent innovations focus on evaluating Artificial Intelligence (AI)-integrated digital health platforms for DM management. Combining AI with CGM is transforming care by enabling accurate glucose trend forecasting and personalized insulin dosing. AI models analyze real-time and historical CGM data to predict glucose fluctuations, facilitating timely actions such as insulin adjustments or dietary alterations[88].

In an RCT by Lee et al., an AI-driven digital platform was evaluated in adults with T2DM. Over 48 weeks, the intervention improved HbA1c metrics without escalating hypoglycemia risk, while also driving significant weight loss by week 24. When paired with CGM data and structured clinical feedback, patient outcomes improved significantly compared to standard care[89].

In a neonatal context, Galdersi et al. conducted a retrospective study using CGM data linked to an AI-derived Continuous Learning Artificial Intelligence Risk (CLAIR) index to assess glucose variability during the first 72 hours of life. The CLAIR index was the sole significant predictor of intraventricular hemorrhage (IVH) compared to traditional clinical variables, highlighting its potential as an early risk-detection biomarker[90].

5.2. AI Algorithms in CGM Data Analysis

AI algorithms are capable of processing complex datasets to uncover glucose patterns often missed by standard analyses. By integrating data from CGMs, insulin delivery systems, and digital health metrics, these models deliver individualized treatment recommendations. Derozie et al. emphasized that visualizing AI output enhances interpretability for both healthcare providers and patients alike. In their study, daily glucose readings were structured over time and clustered into similar glycemic patterns. These clusters revealed common daily glucose trends, establishing a baseline for more tailored DM management strategies[91]. AI applications in DM include complication prediction, diagnosis, improved prevention strategies and treatment response, with successful implementation for self-management and education[92,93].

5.3. Machine Learning for Personalized Management Using CGM

Machine learning (ML) architectures excel at interpreting the rich data stream provided by CGM devices, which measure interstitial glucose levels at 5-minute intervals. A meta-analysis of 46 studies evaluated ML models for glucose prediction across multiple forecasting horizons. The average root means square error (RMSE) for prediction horizons of 15, 30, 45, and 60 minutes was 18.88 mg/dL, 21.40 mg/dL, 21.27 mg/dL, and 30.01 mg/dL, respectively, with neural network models (NNMs) demonstrating superior overall performance[94].

For hypoglycemia prediction, pooled analysis yielded a positive likelihood ratio (PLR) of 8.3 and a negative likelihood ratio (NLR) of 0.31. For

detection, the PLR and NLR were 2.4 and 0.37, respectively. While ML models can accurately predict impending hypoglycemia, their sensitivity in capturing active, acute events remains a limitation[94].

5.4. Predictive Alerts for Glucose Excursions

The Diabetes Control and Complications Trial (DCCT) definitively established that tight glucose control reduces microvascular complications in T1DM but increases the risk of severe hypoglycemia[95]. Consequently, optimizing HbA1c requires rigorous monitoring to avoid hypoglycemic events.

A pilot study (n=15) using a DexCom long-term CGM demonstrated that real-time monitoring helps reduce hypoglycemia risk. However, larger adequately powered trials are needed to confirm long-term benefits on HbA1c[96,97]. Predictive alerts using ML show potential but often produce false positives due to the statistically relative rarity of hypoglycemic events. Improving model specificity and generalizability remains key for practical use.

5.5. Closed-Loop Systems (Artificial Pancreas)

Closed-loop systems, or the artificial pancreas (AP), automate glycemic management by synthesizing a CGM sensor, a control algorithm, and an insulin pump into a continuous feedback loop:

- **CGM Sensor:** Continuously monitors interstitial glucose trends.
- **Control Algorithm:** Processes real-time data to recommend insulin delivery.
- **Insulin Pump:** Subcutaneously delivers the modulated insulin doses.

A primary algorithmic approach utilizes Model Predictive Control (MPC), which anticipates future glucose levels and adjusts insulin, accordingly, improving stability and reducing hypo- or hyperglycemia risks [98]. For instance, Control-IQ technology employs an MPC algorithm that predicts glucose levels 30 minutes in advance. The system upregulates insulin delivery upon anticipating hyperglycemia and suspends insulin administration if it predicts impending hypoglycemia[99].

Concurrently, alternative models incorporate Proportional-Integral-Derivative (PID) controllers within the decision unit. These mathematical frameworks calculate the appropriate insulin dose, which is then automatically delivered by the pump which demonstrates adaptability in maintaining glucose control even during acute glycemic fluctuations[100] (**Table 3**).

6. Ethico-legal Considerations

Determining liability for AI-driven clinical errors remains a complex legal challenge[112-114]. When machine learning algorithms recommend incorrect treatments that cause patient harm, liability is ambiguously distributed among healthcare providers, developers, and institutions. This opacity is compounded by the evolving nature of algorithms and human automation bias, where clinicians may over-rely on AI. Furthermore, third-party cloud processing of CGM metrics demands strict compliance with GDPR and HIPAA regulations. Ethical frameworks must ensure that AI tools augment, rather than replace, human clinical judgment[115,117,118].

6.1. Data Security, Privacy, and Blockchain Integration

To mitigate data breaches, AI-driven CGM platforms require robust encryption, access controls, and anonymization throughout their lifecycle. Integrating blockchain technology offers a decentralized, immutable ledger where CGM data transactions are encrypted and timestamped to prevent unauthorized tampering[115]. This supports secure, real-time data streaming and enables conditional data sharing. Blockchain enhances electronic health record (EHR) interoperability, feeding secure data into AI models for personalized clinical interventions while maintaining verifiable regulatory compliance[115].

6.2. Algorithmic Trust, Explainability, and Equity

Fostering clinician and patient trust requires explainable AI techniques to make complex algorithmic decision-making transparent. Algorithms must also account for patient demographic differences to ensure equitable treatment. Because over 75% of global diabetes deaths occur in LMICs, mitigating data underrepresentation is vital to avoid compounding healthcare inequities[116]. Federated learning addresses this bias by enabling multi-institutional model training without exchanging raw patient data, while adversarial debiasing further reduces demographic disparities.

Table 3. Current and Emerging AI Applications in CGM[80]

Current Applications in CGM[101]			
Applications	**Characteristics**	**Benefits**	**User Experience**
Dexcom G5 [101]	Earliest CGM device used to provide real time accurate glucose levels. It requires calibration.	Provides real time alerts and saves up the record for 7 days in the sensor.	Confirmatory fingersticks are required prior to treatment and have less sensor life.
Dexcom G6 [101]	Latest generation which does not require calibration.	Real time accurate results and can store the data in the sensor for 10 days.	Cost-effective and thinner transmitter making it highly user friendly.
FreeStyle Libre 14 day[102]	Factory Calibrated and thus decreasing the errors due to physiological lag time between blood and interstitial glucose levels.	Disposable sensors and single readers can scan and activate multiple devices in the office.	No alerts are provided by the sensor which has a life of 14 days.
FreeStyle Libre 2 [103]	Similar characteristics except that it provides hyperglycemic alerts.	Thinnest CGM device	User friendly as it provides both spectrums of sugar levels.
Emerging AI Applications in CGM-[104]			
Medtronic 670G [104]	First FDA approved artificial pancreas system that provides basal insulin delivery after every 5 minutes.	Reduces HbA1c levels and improves the time in target range [105].	Discontinuation is higher due to sensor issues, availability issues and preference for injections [106]
Tandem T [107]	Use a calibration free Dexcom G6 sensor which provides extended bolts upto 2 hours.	Improvements in hypoglycemia, mean glucose and HbA1c along with increased percentage time in target levels [108]	Device related treatment satisfaction and improved emotional wellbeing.
Omnipod 5 [109]	Tubeless insulin delivery system which has no bolus automation.	Greater reduction in HbA1c levels [110]	Not as user friendly as the algorithm is adjusted after every 3 days.
iLet Bionic Pancreas [111]	Closed loop system that delivers insulin based on body weight and meal requirement	Greater reduction A1c as compared to hybrid loop system but no difference in hypoglycemia.	User friendly as it only requires carbohydrates amount and estimates the user's insulin need and delivery. However, it is expensive.

6.3. Medical Society Endorsements and Technical Standards

Medical and technical societies are actively establishing consensus guidelines to bridge implementation gaps:

- Diabetes Technology Society (DTS): Advocates for rigorous cybersecurity standards (e.g., IEEE 2621) using security-by-design frameworks, memory protections, and continuous threat monitoring via the Malware Information Sharing Platform (MISP)[118].
- ADA and EASD: Recognize AI's expanding role through joint consensus reports and expert reviews, though formal, standalone clinical guidelines are still maturing.
- European Diabetes Forum (EUDF): Emphasizes that AI-driven clinical decision support systems (CDSS) can minimize clinical inertia, providing a clear roadmap for safe integration and strategic governance in primary care[118].

7. Future Directions

Ongoing advancements in digital technology, connectivity, and data analytics is shifting the management of DM toward seamless, real-time, and minimally invasive CGM systems[119, 120, 121]. However, several critical questions remain. These include determining HCLS potential to replace traditional insulin therapies as the gold standard of care[122]. Large-scale investigations must assess the cost-effectiveness, clinical reliability, long-term patient adherence, and real-world implementation of these systems.

CGM is now increasingly used in patients with chronic renal failure and coronary atherosclerosis[123,124]. Artificial intelligence (AI) is also playing a vital role; AI-driven nutritional

platforms optimize personalized dietary choices, while algorithms for diabetic kidney disease (DKD) synthesize complex genetic and clinical biomarkers to tailor patient-specific interventions[125,126]. Notably, recent investigations evaluating ChatGPT for nutritional guidance have exposed critical gaps in structured dietary interventions, highlighting the need for medically validated AI frameworks.

Wearable CGM devices, including smartwatches and wristbands, offer real-time, non-invasive glucose monitoring and are compatible with mobile applications[127,128]. While most commercial CGM systems rely on the traditional glucose-oxidase electrochemical principle, newer OECT-based CGM designs enhance precision and device longevity[129,130]. Future integration directions also lie in combining AI, CGM hardware, and transcutaneous auricular vagus nerve stimulation (taVNS); a novel non-pharmacological intervention for glycemic control[131]. This multimodal approach could enable real-time neuromodulation while minimizing medication dependence across a broader patient demographic[132].

8. Conclusion

This narrative review aims to evaluate and summarize the evolution of CGM technology and the significant role of AI in DM management. The review found that CGM provides a more comprehensive glucose profile as compared to SMBG, improving glycemic control and patient quality of life. It is of particular benefit in alerting patients of asymptomatic hypoglycemia and postprandial hyperglycemia with acceptable HbA1c levels.

We further highlight the use of Machine learning models, digital platforms and devices that enhance self-management and treatment. The evolution of hybrid closed-loop insulin delivery systems (the artificial pancreas) has revolutionized DM care by optimizing insulin delivery and reducing patient intervention[127,128].

However, limitations like cost, ethico-legal considerations and perception of inaccuracy remain. Future research should explore the cost effectiveness, patient adherence, reliability and real-world implementation of these systems, particularly in diverse populations. Additionally, we need to explore algorithms in AI and CGM technology which can improve the early detection and timely management of complications. However, challenges like high cost of CGM devices and their accessibility in low-income regions must also be addressed for widespread adoption[129].

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Autor contribution

US, UB, SK were involved in conceptualization and administration, All authors were involved in writing the original draft and interpretation of data. Literature search: US, FYS, SC, HI Substantial revisions to the final draft performed by HI, FYS, SC, US. Mentorship by SIAS. Images and tables designed by FYS. All authors have read and approved the final manuscript.

Conflict of Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

AI use statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

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