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DIGITAL TECHNOLOGIES IN DIABETES MANAGEMENT: THE ROLE OF CONTINUOUS GLUCOSE MONITORING AND ARTIFICIAL INTELLIGENCE IN MODERN ENDOCRINOLOGY

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ABSTRACT

The ongoing development of digital technologies, when used appropriately in diabetes care, has a significant impact on the management of patients with diabetes. New technologies enable the monitoring and adjustment of treatment in patients without the need for face-to-face appointments. The aim of this review is to discuss the role of continuous glucose monitoring, artificial intelligence, wearables, mobile applications and telemedicine in the development of diabetes care. Their clinical, organisational and social significance has been analysed. This is a review article based on publications from major biomedical databases.

Reviewed articles provide evidence that continuous glucose monitoring is more accurate for assessing blood glucose levels than traditional glucose or HbA1c measurements. Artificial intelligence can be used to predict fluctuations in blood glucose levels and improve the personalization of clinical decisions. It has been shown to be particularly effective when combined with automated insulin delivery systems. Mobile devices and apps, as well as telemedicine, can increase patients' interest in their own health and, consequently, their involvement in the treatment process; however, their value depends on the quality of the collected data, interoperability, clinical usability, and the ability of healthcare professionals to understand the generated reports. The use of digital tools is associated with cyber threats regarding data privacy, as well as inequalities in access to healthcare and trust in technology among patients. Future research should cover long-term effectiveness, safety, equitable access, and the methods of implementing this technology into everyday patient care.

KEYWORDS

Artificial Intelligence, Continuous Glucose Monitoring, Diabetes Management, Digital Health, Telemedicine, Wearable Technologies

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1. Introduction

1.1 Global burden of diabetes

Diabetes is a global problem of increasing magnitude and severity. The disease is becoming an ever greater challenge for modern healthcare systems. The scale of the phenomenon is best illustrated by the continuously rising incidence trend. According to the estimates of Saeedi et al., in 2019 diabetes affected 9.3% of the global population, which corresponds to 463 million people. In addition, their projections indicate that over the next 15 to 30 years this number will increase to approximately 700 million patients [1]. According to other researchers, the number of people with diabetes has increased fourfold over the past 30 years [3]. The rising incidence is further illustrated by the fact that in 2000, 2.8% of the world's population had diabetes, whereas the authors estimated that this proportion would rise to 4.4% by 2030. The main factor driving this increasing trend is the growing proportion of individuals over 65 years of age in recent years [4]. It is also worth noting that worldwide, every second person is unaware that they have diabetes [1].

The disease and its complications impose a major burden on healthcare institutions, medical personnel, and public budgets. In 2017, the global costs associated with healthcare for patients with diabetes were estimated at USD 850 billion [5]. Diabetes is the ninth most common cause of death in the general population [3]. It accounts for 4.2 million deaths, or 11.3%, among patients aged 20 to 79 years. It has been observed that the mortality rate is lowest in the Africa region at 6.8%, whereas it is highest in the Middle East and North Africa at 16.2% [2]. Cardiovascular complications are the leading causes of death among patients with diabetes [3].

Blood glucose concentration and HbA1c are important parameters in clinical decision-making in diabetes management. A1c is an important indicator of the risk of long-term complications in individuals with type 1 and type 2 diabetes. It reflects the average glycemic level over the preceding 2 to 3 months. This limits

its usefulness in assessing acute glycemic fluctuations and in the early detection of acute hypo- and hyperglycemic complications. Moreover, the value of this parameter may be affected by certain hematological diseases and pregnancy [7]. The American Diabetes Association reports that fewer than one third of patients achieve the target HbA1c value. These data highlight the importance of using a method that allows continuous monitoring of blood glucose levels, namely continuous glucose monitoring (CGM). The advantages of this solution include the possibility of measuring glycemia at intervals as short as five minutes, analyzing glycemic trends, and sending alerts when glucose levels fall outside the normal range. These data make it possible to undertake appropriate clinical decisions depending on the current therapeutic needs of the body [6,7,9]. In a randomized clinical trial, Heinemann et al. demonstrated that among patients with type 1 diabetes treated with multiple daily insulin injections, those using CGM experienced hypoglycemic episodes less frequently [8].

1.2 Pathophysiology of diabetes mellitus

Based on pathomechanism, pathophysiology, genetics, and metabolic features, diabetes has been divided into the main subtypes: 1) type 1 diabetes, 2) type 2 diabetes, 3) gestational diabetes, and 4) diabetes caused by other factors. In type 1 diabetes, an autoimmune process leads to the destruction of pancreatic beta cells that secrete insulin. In the pancreas of patients with recent-onset type 1 diabetes, 70% of islets show a complete absence of insulin. Inflammatory infiltration is present in 20% of islets containing insulin and in only 1% of insulin-deficient islets. At the same time, there are also pancreatic areas without signs of inflammation and with normal insulin secretion. However, prolonged inflammatory infiltration in the area of the pancreatic islets results in the complete or nearly complete loss of pancreatic cells that produce insulin. This type of diabetes is polygenic in nature. Genetic abnormalities most commonly determine an abnormal immune response [11].

In contrast, type 2 diabetes is non-autoimmune in nature. Its causes are attributed to developing insulin resistance and other components of the metabolic syndrome. Environmental and genetic factors are of major importance in this context. The basis of its pathomechanism is the progressive loss of adequate insulin secretion by the pancreas [12]. It constitutes by far the largest proportion, 90%, among patients with diabetes [3]. Type 2 diabetes occurs mainly in adults, but its prevalence among children and adolescents is steadily increasing [14].

Differentiation of the main subtypes of diabetes remains a significant challenge for modern medicine. The principal feature suggesting a diagnosis of type 1 diabetes is the presence of autoantibodies. These are detected in more than 90% of patients with newly diagnosed type 1 diabetes. A diagnostic difficulty arises in patients who present with features suggestive of both types of diabetes. Helpful indicators in this context may include young age, low BMI, unintentional weight loss, ketoacidosis, and high glycemic values at presentation, all of which suggest type 1 diabetes. However, these are not pathognomonic features [13]. In addition to type 1 and type 2 diabetes, the classification also includes gestational diabetes and diabetes caused by other factors such as 1) drugs or chemical substances, 2) monogenic diabetes syndromes, and 3) pancreatic diseases [10].

Proper use of modern technologies such as CGM requires a precise understanding of the physiological mechanism of insulin action. Insulin signaling is a complex biochemical process initiated by the binding of the hormone to a specific receptor. This protein receptor has tyrosine kinase activity and undergoes autophosphorylation under the influence of the hormone. The resulting intracellular cascade ultimately activates phosphatidylinositol 3-kinase (PI3K). The metabolic effects of insulin on carbohydrate and lipid metabolism are determined primarily by the activity of the PI3K/Akt pathway [15].

The most important objective of this process is to enable cells to take up glucose from the bloodstream. At rest, glucose transporter type 4 proteins (GLUT4) are stored in vesicular form in muscle cells and adipocytes. Activation of the PI3K pathway causes these vesicles to move toward the cell membrane. This is followed by fusion of the vesicle with the cell membrane, which opens channels allowing glucose to enter the cytoplasm. Glucose can then be used for energy production or stored as glycogen. This process depends on the proper architecture of the cellular cytoskeleton and adequate perfusion of peripheral tissues [16].

Insulin resistance is a state of impaired cellular response to insulin. This phenomenon mainly affects skeletal muscle, the liver, and adipose tissue [17]. In skeletal muscle cells, glucose transport depends on the GLUT4 transporter. Impaired translocation of this transporter toward the cell membrane following activation of the PI3K pathway is the basic mechanism of insulin resistance [18,19]. In liver cells, failure of insulin to effectively suppress gluconeogenesis leads to increased glucose production. Ineffective insulin action in adipose tissue intensifies lipolysis, increasing the release of free fatty acids, which in turn further impairs insulin secretion by pancreatic cells [18].

The impaired ability of pancreatic beta cells to secrete insulin in proportion to the glucose level declines markedly even in the early stages of type 2 diabetes and is progressive in nature. The reduction in the number and activity of pancreatic beta cells results from the toxic effects of glucose and excess free fatty acids [17,18]. This leads to the predominance of apoptosis over beta-cell regeneration [18].

Hyperglycemia occurs mainly as a result of increased hepatic glucose production, reduced glucose uptake in muscle, and decreased insulin secretion [18,19]. Under physiological conditions, glucose is reabsorbed in the renal tubules by means of sodium-glucose cotransporter type 2 (SGLT-2). When blood glucose levels are elevated, its excretion increases, and consequently its reabsorption in the renal tubules via SGLT-2 is intensified. In this way, hyperglycemia is sustained. It should be noted that the kidneys actively contribute to the worsening of hyperglycemia. Moreover, the kidneys increase blood glucose levels through gluconeogenesis occurring in the renal cortex [20,21].

Based on the above information, it can be seen that the development of insulin resistance and type 2 diabetes is a complex process involving pathology in multiple organs such as the pancreas, liver, muscles, and adipose tissue. A vicious cycle occurs here: insulin resistance increases insulin demand, causing uncompensated beta-cell dysfunction resulting from exhaustion, which in turn leads to hyperglycemia and aggravates both disturbances. Together, these processes create a self-perpetuating mechanism underlying the development of type 2 diabetes.

Attempts to externally intervene in the processes of glucose metabolism in patients with diabetes represent a major challenge for modern medicine. The main problem lies in the complexity of intracellular pathways and systemic insulin distribution. The use of modern technologies such as CGM may offer a solution in patients in whom natural endocrinological mechanisms function abnormally. CGM enables real-time monitoring of the effect of insulin action on tissues, while artificial intelligence may partially replace biological autoregulation. By predicting the behavior of the metabolic system, it can respond with greater temporal precision, compensating for delays and imperfections in exogenous insulin therapy [15,16,18].

1.3 Limitations of traditional glucose monitoring

Regular glycemic monitoring is the foundation of treatment for disorders of carbohydrate metabolism, as it reduces the risk of late complications of diabetes. For this reason, continuous self-monitoring of blood glucose levels (SMBG) using glucose monitoring systems is an inseparable component of diabetes treatment. The clear benefits of this approach have led to the recommendation of self-monitoring of blood glucose in all patients with diabetes. Owing to their ease of use, low cost, wide availability, and safety, blood glucose meters are widely used [22].

The operation of a blood glucose meter is based on an enzymatic reaction in which glucose is converted into a product detectable by the sensor. Contemporary blood glucose meters use one of three enzymes: glucose oxidase, glucose dehydrogenase, or hexokinase. Each of these enzymes acts differently and therefore has its own advantages and disadvantages. The use of protein enzymes as reagents means that these devices have certain limitations. They are sensitive to high and low temperatures, atmospheric pressure, and humidity, which is why devices and reagents should be transported and stored under conditions recommended by the manufacturer. Some devices are equipped with sensors that prevent measurement under conditions that could compromise reliability. The result is also significantly influenced by biochemical blood parameters such as hematocrit, lipid profile, oxygenation, and pH. In addition, the reliability of the measurement is affected by the correct technique of test performance, including the volume of blood collected, reuse of the same strip, or exposure of strips to air, as well as by drug interactions. Measurement errors and the resulting inappropriate therapeutic decisions may lead to deterioration of the patient's clinical condition or even death. The reliability of readings is influenced by environmental factors, technical errors, the patient's condition, medications taken, and metabolic factors [23].

Another way of assessing glycemic control is measurement of glycated hemoglobin (A1C). It reflects the average glycemic level over the 2 to 3 months preceding the measurement [24-26]. A1C has similar effectiveness as a screening marker for the detection of type 2 diabetes compared with fasting blood glucose, and its level correlates strongly with the risk of diabetes complications. However, this parameter is also subject to certain limitations. The reliability of the test may be disturbed by conditions affecting the red blood cell system, such as hemolytic anemia, iron deficiency anemia, recent blood transfusion, the use of drugs stimulating erythropoiesis, glucose-6-phosphate dehydrogenase deficiency, and renal failure. In addition, race, age, and pregnancy may also influence the measurement. In all patients in whom the A1C result may be unreliable, the use of another method of glycemic assessment is recommended [24,25].

Because A1C reflects the average glycemic level, it provides no information on the amplitude or frequency of blood glucose fluctuations [27,28]. Glycemic variability is considered one of the most important parameters defining the state of carbohydrate metabolism, alongside fasting and postprandial glycemia, and it cannot be determined on the basis of the A1C result [27]. Moreover, when two patients with identical mean glycemic values or A1C are compared, they may have very different glycemic profiles: one may have stable glucose values within the normal range, while the other may experience fluctuations from hypoglycemia to hyperglycemia, even though the A1C level may suggest the absence of any pathology [28]. Therefore, relying solely on this parameter is highly dangerous, as it does not account for episodes of severe or asymptomatic hypoglycemia, which constitute a direct threat to life or health [7].

CGM systems make it possible to detect previously unrecognized hypoglycemia by providing insight into the patient's actual glycemic profile, which constitutes their advantage over the limited capabilities of the HbA1c parameter [7]. Reduction of glycemic variability and optimization of therapy can be achieved through appropriate interpretation of CGM-derived data. The key parameters are considered to be time in range (TIR), that is, the period during which the patient's glycemia remains within target values of 70 to 180 mg/dL, and time below range (TBR), that is, time spent in hypoglycemia [7,27].

2. Methodology

2.1 Study design

This study was designed as a structured narrative review of the literature addressing the role of continuous glucose monitoring, artificial intelligence, wearable technologies, and digital health solutions in contemporary diabetes management. The aim of the review was to integrate evidence from clinical studies, review articles, consensus statements, and selected institutional and regulatory documents in order to present the current clinical relevance, practical applications, and future directions of digital diabetology.

2.2 Literature search strategy

The literature search was performed using major biomedical and multidisciplinary databases, including PubMed/MEDLINE, Scopus, and Web of Science. To identify additional relevant publications, manual screening of the reference lists of selected articles was also conducted. For topics concerning ethics, cybersecurity, interoperability, and regulation, relevant documents published by international institutions and regulatory agencies were also included.

The search strategy combined terms related to diabetes, glucose monitoring, digital medicine, and artificial intelligence. The following keywords and their combinations were used: diabetes mellitus, continuous glucose monitoring, CGM, real-time continuous glucose monitoring, intermittently scanned continuous glucose monitoring, time in range, glycemic variability, artificial intelligence, machine learning, artificial pancreas, automated insulin delivery, wearables, mobile health, digital health, telemedicine, telemonitoring, remote consultation, interoperability, cybersecurity, and data privacy. Boolean operators such as AND and OR were used to refine the search.

2.3 Eligibility criteria

Publications were considered eligible if they addressed at least one of the following areas: epidemiology and burden of diabetes, pathophysiology of diabetes mellitus, limitations of traditional glucose monitoring, technological principles of CGM systems, clinical benefits associated with CGM use, the application of artificial intelligence in glucose prediction and insulin delivery, the use of wearable devices and mobile health applications in diabetes care, telemedicine-based diabetes management, or ethical and regulatory aspects of digital health technologies.

The review included randomized controlled trials, observational studies, systematic reviews, meta-analyses, narrative reviews, consensus reports, and selected institutional or regulatory publications relevant to the subject of the article. Preference was given to peer-reviewed English-language publications of clear clinical or scientific relevance. Earlier landmark studies were retained when they provided foundational evidence for current technological or clinical practice.

Publications were excluded if they were not relevant to the thematic scope of the article, did not contribute meaningful information on diabetes management or digital technologies, or represented duplicate or clearly redundant records.

2.4 Study selection and data synthesis

Titles and abstracts were screened for thematic relevance, and full texts of selected publications were subsequently reviewed. The final selection included studies and documents considered most relevant to the objectives of the article and to the practical interpretation of developments in digital diabetology.

Data extraction was performed manually. For each publication, attention was given to the study objective, type of evidence, patient population where applicable, form of digital intervention, and the main clinical, technological, or organizational conclusions.

The final structure of the review was organized into four main domains: continuous glucose monitoring technologies, clinical benefits of CGM, artificial intelligence in diabetes management, and wearable technologies and digital health ecosystems. Ethical considerations, data privacy, interoperability, and future perspectives in digital endocrinology were additionally addressed in the discussion section.

2.5 Limitations of the methodology

This review has limitations inherent to narrative literature synthesis. The included publications were heterogeneous with regard to study design, patient population, intervention type, outcome measures, and clinical context. As a result, the findings were interpreted qualitatively rather than statistically. In addition, digital diabetes care is developing rapidly, especially in terms of artificial intelligence, automated insulin delivery, wearable technologies, and regulation. Despite this dynamic context, a structured search strategy and thematic synthesis were used to maintain clarity, relevance, and coherence in the interpretation of the evidence.

3. Results

3.1 Continuous glucose monitoring technologies

Contemporary CGM systems operate on the basis of minimally invasive measurements of glycemia in interstitial fluid (ISF) or noninvasive measurements using electromagnetic radiation directed toward blood vessels. This method makes it possible to determine the direction, magnitude, duration, frequency, and causes of fluctuations in blood glucose levels. In addition, unlike the conventional approach based on several single measurements taken throughout the day, it allows the prediction of glycemic trends, which helps prevent episodes of hypoglycemia and hyperglycemia. Compared with blood glucose measurements, this system is less invasive. However, it should be noted that CGM measurements show greater lag than blood measurements during rapid fluctuations in glycemia [9]. Patients with recurrent, severe, or nocturnal hypoglycemia derive particular benefit from the use of CGM compared with blood glucose measurement. Owing to its alert function, episodes of hypoglycemia can be reduced, especially in individuals with impaired awareness of hypoglycemia [29].

Electromechanical biosensors constitute the main component of currently used CGM systems and traditional blood glucose meters. Their widespread use results from their low cost, high sensitivity, small size, and short response time [30-33]. These sensors are based on the phenomenon of increased current intensity resulting from the glucose oxidation reaction on the electrode surface. Three generations of biosensors can be distinguished: 1) those based on hydrogen peroxide formation, the limitation of which is dependence on the presence of oxygen; 2) those requiring artificial charge-transfer mediators; and 3) those assessing direct electron transfer between the enzyme and the electrode [30].

Glucose oxidase is used in the oxidation of glucose to gluconic acid because of its high stability, specificity for beta-D-glucose and low acquisition cost. By catalyzing this reaction, the enzyme generates an electromechanical signal that can be read by the device. Electron mediators are used in second-generation sensors to reduce error occurrence caused by fluctuations in concentration of blood oxygen and other electroactive substances [30,31]. The main disadvantage of glucose oxidase is its susceptibility to environmental factors such as changes in pH and temperature, which limits the durability of CGM sensors [31,32].

Daily finger-prick testing or the use of invasive implants is associated with pain, discomfort, and the risk of infection, which has stimulated the development of noninvasive methods. Instead of blood, these methods use other body fluids or secretions such as tears, sweat, saliva, or interstitial fluid in the epidermis [31,33]. This has become possible due to modern analytical methods such as optical techniques, including Raman spectroscopy, microwave techniques, and methods based on reverse iontophoresis [32,33]. The main problems preventing the implementation of these technologies in everyday clinical practice are the delay in

changes in glucose concentration in body fluids relative to blood, the very low glucose concentration in the sample, and dependence on variable environmental conditions and sample contamination [31-33].

Among the wireless sensors currently used for glucose monitoring, intermittently scanned continuous glucose monitoring (isCGM) and real-time continuous glucose monitoring (rtCGM) systems can be distinguished [34]. The former requires active scanning with a reader, whereas the latter transmits data wirelessly and automatically. Both systems replace routine finger-stick SMBG measurements [35,36]. A distinguishing feature of rtCGM systems is the presence of active alarms and alerts predicting the direction of glycemic fluctuations, which do not require active patient involvement to function [37].

Analytical accuracy of continuous glucose monitoring systems is assessed using the mean absolute relative difference (MARD). This is the percentage difference between the glucose concentration in interstitial fluid measured by the sensor and the actual blood glucose concentration determined by a laboratory method. A lower MARD value indicates greater precision and reliability of a given device [38]. In rtCGM systems, the MARD reaches 9.0%, which indicates high accuracy maintained even during episodes of hypo- and hyperglycemia [36,39].

It should be emphasized that both of these systems allow patients to make independent therapeutic decisions regarding insulin dosing on the basis of sensor readings [35,37]. In addition, the high precision of rtCGM measurements combined with the alert function allows effective reduction of hypoglycemic episodes [39]. Technological development has enabled the integration of glucose monitoring systems with automated insulin delivery (AID) systems, thereby minimizing the risk of errors associated with manual insulin dosing [36,40].

3.2 Clinical benefits of CGM in diabetes management

CGM systems have significantly improved the effectiveness of diabetes treatment by lowering HbA1c levels and improving metabolic control. Among patients with type 1 diabetes treated with multiple daily insulin injections, the use of CGM resulted in a statistically significant reduction in HbA1c compared with SMBG [6,41]. A similar effect was obtained in patients with type 2 diabetes treated with basal insulin alone, without additional prandial boluses [42].

The introduction of CGM made it possible to obtain additional parameters, namely TIR and TBR, which have made clinical decision-making even more precise than isolated assessment of the HbA1c index [7]. This system is effective in optimizing the metabolic profile of patients with type 1 diabetes by reducing daily glycemic variability (GV) and decreasing the frequency and duration of hypoglycemic episodes [6,41]. The presence of glycemic trend monitoring also has a favorable effect on metabolic control in patients with type 2 diabetes [42].

In direct comparison with SMBG, CGM has several advantages over conventional methods. Patients with type 1 diabetes achieve better glycemic control with CGM than with SMBG based on blood glucose meter testing [41]. In patients with type 1 diabetes and a low risk of severe hypoglycemia, insulin dosing based solely on CGM readings, without the need for verification by blood glucose measurement, has shown a high safety profile and therapeutic effectiveness [43]. Finally, CGM demonstrated superiority over SMBG in patients with type 2 diabetes by reducing HbA1c and increasing TIR [42].

CGM shows greater sensitivity to hypoglycemic episodes than SMBG. In addition, unlike SMBG, it is able to detect and record asymptomatic hypoglycemia [44]. This function is particularly important in patients with impaired awareness of falling glucose levels, as it allows effective prevention of severe hypoglycemic episodes [45]. CGM sensors reduce the total time spent in hypoglycemia without adversely affecting HbA1c [7,44].

The greatest threat is posed by nocturnal hypoglycemic episodes occurring during sleep. rtCGM systems are able to detect a downward glycemic trend, and thanks to built-in alarm systems they can wake the patient before a life-threatening condition develops [8]. In addition, sensor readings facilitate adjustment of basal insulin dosing, which reduces the duration of nocturnal hypoglycemia [7,44].

The functions of contemporary glucose sensors have a positive impact on patient safety. Because they detect glycemic trends, proactive glycemic management becomes possible through early intervention and prevention of glucose declines below a safe level [8]. This reduces the frequency of episodes requiring assistance from other people or professional medical care [45]. Continuous insight into glucose levels and high measurement reliability provide patients with a sense of security. This translates into reduced fear of hypoglycemia and improves the quality of nocturnal rest, thereby increasing patient comfort and quality of life [8].

To standardize the interpretation of data obtained from CGM systems, the TIR metric is used [7]. It presents a complex set of data in a more accessible form for the patient as the percentage of time spent within the target range [46]. Both TIR and TBR constitute important diagnostic elements that make it possible to adjust insulin doses more precisely [7]. In addition, low TIR is associated with a higher incidence of diabetes complications such as retinopathy and nephropathy accompanied by microalbuminuria [47]. TIR may therefore serve as an indicator of the risk of diabetes-related organ damage, and its improvement is associated with a better long-term prognosis for the patient [47,48].

3.3 Artificial intelligence in diabetes management

Machine learning models such as artificial neural networks (ANN), support vector machines (SVM), and support vector regression (SVR) allow more effective analysis of data obtained from glucose sensors. By using these data, ANN achieves high effectiveness in predicting glucose concentration in real time [49]. Owing to machine learning algorithms such as SVM, as well as decision tree-based and regression-based methods, it is possible to filter and analyze information from medical data and support clinical decision-making in diabetology [50]. SVR, in turn, analyzes multiple variables related to glucose levels, allowing glycemic prediction by capturing nonlinear relationships between individual data points [51].

The main advantage of using artificial intelligence (AI) algorithms in diabetology is the reduction of the risk of complications through alerts warning of approaching episodes of hypo- and hyperglycemia [52]. By warning the patient in advance about an impending dangerous glucose level, the system enables proactive prevention of extreme fluctuations in blood glucose [49]. Automation of glucose management algorithms through not only reading and analyzing data, but also appropriate automated insulin dosing, that is, the so-called artificial pancreas, could reduce the time the patient spends outside the target glycemic range [53].

The difficulty in accurate glycemic prediction results from the need to relate glucose levels recorded by sensors to external factors affecting them, such as the amount of carbohydrates consumed, the insulin dose taken, additional physical activity, and others [51]. A possible solution appears to be the use of AI, which simultaneously analyzes a range of data and continuously adapts the technologies used to changing conditions [52,53].

A key element of diabetes therapy is an individualized approach to each case. Personalization of treatment operates on the basis of real-time adaptation and takes into account both individual and population-level variability. Available studies have shown that the most effective tool for predicting glycemic profile was an artificial neural network based on glucose and insulin data [54]. Effective tailoring of the system to the patient requires not only assessment of glucose levels, but also evaluation of the risk of adverse glycemic events [55]. Hybrid closed-loop systems appear to be the next stage in the development of the so-called artificial pancreas, as they automatically adjust insulin delivery on the basis of sensor readings while leaving mealtime insulin dosing in the hands of the patient. With the use of this technology, severe or device-related adverse events were rare, and improved glycemic control was observed in a large group of patients [56]. Precise personalization of diabetes treatment requires accurate clinical, social, behavioral, and family data, as well as detailed biological data, including genetic information. The integration of AI and deep learning appears particularly important for pattern recognition, analysis of complex datasets, and support of clinical decision-making [57].

Analysis of CGM-derived data includes assessment of the quality of glycemic control, daily glycemic variability, variability between individual days, and the stability of glycemic patterns from day to day. Moreover, to ensure that the data are reliable, monitoring should be carried out regularly. What should be analyzed are patterns such as regular episodes of hypoglycemia or hyperglycemia at specific times of day, rather than individual measurements, because these patterns provide the greatest therapeutic benefit [58]. According to the consensus, the minimum amount of data allowing reliable interpretation and estimation of A1C is approximately 70% of data capture, or 10 out of 14 consecutive days of CGM readings [59].

Because measurements are taken frequently, usually every 1 to 5 minutes over many days, a large database is generated, enabling analysis of glycemic trends and adverse events [60]. Only with a sufficiently large database is it possible to develop so-called smart sensors, in which data processing algorithms determine calibration, signal filtering, prediction of glycemic trends, and alarm generation. Data obtained from CGM can be used to develop more advanced technologies such as alarms predicting an upcoming episode of hypo- or hyperglycemia, automatic reduction of insulin delivery, and subsequently the already mentioned artificial pancreas [61,62].

3.4 Wearable technologies and digital health ecosystems

An important direction in the development of diabetes treatment and prevention of its complications appears to be the integration of glucose monitoring systems and insulin delivery systems with everyday devices such as smartphones and smartwatches. Wearables continuously monitor physiological parameters such as physical activity, heart rate, body temperature, and oxygen saturation outside the hospital setting [62-64]. This model of continuous monitoring makes it possible to track daily patterns, changes related to physical activity, and deviations from values typical for a given patient [63,64]. The widespread availability of these devices has contributed to the popularization of health monitoring. However, it should be emphasized that the usefulness of these measurements depends on their quality, the device's ability to interpret the data, safety-related limitations, and the reliability of the measurements [65,66].

By combining the benefits of wearables and CGM, glycemia can be evaluated in a broader context, taking into account, among other things, the influence of physical activity, sleep, and other variables. This appears to be a promising direction for the development of remote continuous health monitoring [63,64,66]. Data from wearables are not always sufficiently reliable and require interpretation in a specific clinical context. Therefore, their integration with CGM requires further improvements in interoperability together with clinical validation [62,65,66].

Wearables already play a significant role in the prevention of metabolic diseases, including diabetes, by motivating users to modify their lifestyle, dietary habits, and sleep hygiene through self-monitoring [65,66]. The data collected by these devices may provide the basis for more personalized health decisions and assessment of the risk of metabolic diseases [64]. The most important objective of using these devices in diabetes treatment should be to transform raw data into practical, clear guidance for both the patient and the medical team regarding clinical management [64,66].

Another useful tool in the modern approach to diabetes and metabolic diseases may be mobile applications installed on smartphones. Applications currently available on the market record, among other things, glycemia, medications used, physical activity, and body weight, thereby organizing health data and facilitating everyday clinical decisions [67,68]. With the support of mobile applications, improved glycemic control is possible in the form of a moderate reduction in HbA1c, which complements standard therapy [67,69,70]. In addition, patient engagement in the treatment process increases, which enhances the sense of control over the disease [70]. Alerts displayed by diabetes-related devices help maintain the rhythm of patient self-monitoring [67,68]. Wu and colleagues demonstrated that data recording alone is not sufficient, and that only appropriate presentation of the data to the patient was associated with a reduction in HbA1c in the studied group [67]. Applications currently available on the market, such as WellDoc, provide feedback to the user almost immediately, monitor the collected data, and transmit the history of recorded measurements to the physician, while also suggesting what they identify as the most effective treatment plan [71]. Studies show that the likelihood of adherence to medical recommendations can be increased by using functions available in everyday devices, such as reminders or real-time monitoring with feedback. However, confirmation of the long-term effectiveness of these measures requires further observation because of the limited number of studies in this field [67,68]. The reduction in HbA1c observed in available studies confirms the indirect effectiveness of applications in improving adherence, although studies directly assessing this parameter are still lacking [67,69,70]. Use of the potential of these applications requires support from medical personnel or a research team, which shows that technology is only one element of broader patient care [68,71].

Due to the highly dynamic nature of clinical changes in patients with diabetes, they require very frequent follow-up. This may place a substantial burden on medical facilities as well as their staff. A solution to this problem is telemedicine, which facilitates contact between the patient and the physician. Patients whose results were sent to the medical team had better glycemic control than patients in whom such a solution was not used [72,73]. To derive benefits from telemonitoring, a personalized approach and emphasis on improving the patient's self-management skills are required [74]. Remote monitoring improves the quality of medical care because earlier detection of a problem allows medical personnel to take action before the patient's condition deteriorates [75].

The logical next step is remote consultation, as it complements remote patient monitoring by providing a form of contact that allows discussion of glycemic results together with ongoing feedback [72,74]. This branch of medicine developed particularly rapidly during the COVID-19 pandemic, when telemedicine became a pillar of the healthcare system, reducing direct contact and allowing in-person resources to be reserved for more urgent cases [76]. However, the best outcomes of online consultations were observed when they complemented in-person care rather than replacing it [72,73]. Telemedicine is especially helpful for people living in smaller towns, far from medical centers, and for patients who have difficulty attending frequent in-person visits [74,75]. During the COVID-19 pandemic, broad access to telemedicine made it possible to maintain continuity of care despite sanitary restrictions [76].

4. Discussion

4.1 Impact of digital technologies on clinical practice

The results obtained show that the most significant change concerns the care model itself. CGM, apps and AI tools are shifting diabetes care away from intermittent monitoring- based mainly on individual visits and HbA1c- towards continuous care, based on glucose trends, TIR/TBR and regular data analysis [77,78]. In clinical practice, this signifies a shift in the role of the healthcare team. Less and less time is spent on data collection itself, and more on data interpretation, patient education and treatment adjustments between visits. This trend is clearly visible in remote care models and personalised virtual care based on CGM [79,80]. Remote monitoring should be presented not as a replacement for all outpatient care, but as an element of a hybrid model. Such a model increases continuity of contact with the patient and may facilitate more frequent adjustments to therapy without the need for a personal visit each time [79,81]. At the same time, the results strongly support the claim that data availability alone is not sufficient. Real clinical value depends on the interoperability of devices, the ability to securely integrate data with medical records, and whether the team has the time and competencies to use this data [77,82].

4.2 Ethical and data privacy considerations

The further diabetes care relies on integrated data from CGMs, insulin pumps, apps and wearables, the greater the clinical value of the entire ecosystem becomes. However, the risks associated with privacy, data ownership and secondary use also increase. The issue is no longer just the measurement itself, but the entire flow of health data [82,83]. The implementation of AI in diabetes care will depend not only on the accuracy of predictions, but also on trust. The patient and clinician must know what role the algorithm performs, where the limits of its application lie, and who is responsible for the therapeutic decision. This is particularly important in chronic conditions, where decisions are made on a daily basis, often outside the clinic [84,85]. Cybersecurity in this area is not just a technical issue. In the case of therapy-connected devices, such as CGM and AID systems, digital security becomes part of clinical safety, as system vulnerabilities can affect the device's operational continuity, data reliability and patient safety [86]. It is also worth noting that the regulatory environment is changing rapidly. In Europe, these technologies are now governed not only by medical device regulations but also by the AI Act and the European Health Data Space, which reinforce the importance of data quality, human oversight, transparency and the secure use of health data [87].

4.3 Future perspectives in digital endocrinology

The most realistic direction for further development is not the complete replacement of doctors or the algorithm taking over for the patient, but more effective automated insulin delivery and hybrid closed-loop systems. These are the ones that most effectively combine CGM, algorithms and treatment into a single practical management model [78,88]. The next step is personalised medicine, in which glucose analysis will not be based solely on sensor readings, but also on insulin, nutrition, physical activity, sleep and circadian rhythm data. Only such an approach will enable more accurate glucose prediction and more personalised patient management [89,90]. AI and big data can also enhance the significance of CGM at a population level, supporting risk stratification, the detection of adverse patterns, and the development of more inclusive care models, so that the complexity of the technology used does not act as a restriction. It should be noted, however, that this will only be possible if the data is representative, interoperable and adequately secured [84,87,90]. Therefore, it is worth emphasising that the future of digital endocrinology depends not only on the development of algorithms, but also on clinical validation, work organisation, staff training and the reduction of digital inequalities. Without this, even very good predictive models will not be fully translated into everyday practice [77,90].

5. Conclusions

Digital technologies seem to be the solution to the challenges facing modern diabetology, as they influence not only how glycaemic disorders are monitored but also the clinical decision-making process. Available scientific reports suggest that further research is required to improve the predictive algorithms used in the management and treatment of diabetes. The development of 'artificial pancreas' should be a priority for contemporary medicine. Research into automated insulin delivery systems should therefore continue in order to ensure their efficacy and safety. An important step would be the interoperability of CGM systems with wearable devices, mobile applications and remote care. To date, there is a limited number of studies assessing their long-term safety and efficacy in clinical practice. In the era of cyber threats, the security of medical data stored on devices using glucose monitoring systems appears to be critical, and therefore research is needed in the field of medical data protection and the cybersecurity of these systems. Furthermore, future research should assess how such technology affects quality of life, adherence and access to medical care.

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