International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 5, Sep-Oct-2026, ISSN (Online): 2395-566X

Wearable Device for Diabetes; Emerging Trends Ai Integration and Multi Biomarker Approaches

Krishnendu Ghosh, Soumyajit Roy, Debayan Bag
Bengal College of Pharmaceutical Sciences and Research Durgapur West Bengal MAKAUT UNIVERSITY

Abstract- The integration of artificial intelligence (AI) with wearable sensing technology has emerged as a transformative approach in modern healthcare, particularly for the management of chronic diseases such as diabetes mellitus. AI-enabled wearable devices utilize advanced sensing mechanisms—including electrochemical, optical, microneedle, and sweat-based sensors—to enable continuous, real-time monitoring of physiological parameters. These systems provide significant advantages over traditional invasive techniques by offering non-invasive or minimally invasive solutions, improving patient comfort, compliance, and data accuracy. In diabetes management, AI-driven wearable technologies such as continuous glucose monitoring (CGM) systems, smart insulin pumps, and closed-loop artificial pancreas systems have revolutionized glycemic control. Machine learning and deep learning algorithms analyze large volumes of real-time data to predict glucose trends, detect anomalies, and provide personalized treatment recommendations. Additionally, emerging non-invasive technologies, including smart contact lenses and smartphone-based photoplethysmography, offer promising alternatives for early detection and monitoring. The application of AI in wearable devices also supports remote patient monitoring, enabling timely intervention and reducing the risk of complications. Despite significant advancements, challenges such as sensor accuracy, data interpretation, scalability, and integration into clinical practice remain. Overall, AI-based wearable sensing technology holds immense potential to enhance personalized healthcare, improve clinical outcomes, and reduce the global burden of diabetes.

Keywords- Artificial Intelligence (AI), Wearable Sensors, Diabetes Mellitus, Continuous Glucose Monitoring (CGM), Machine Learning.

I. INTRODUCTION

The coupling of artificial intelligence (AI) with wearable detector technology has immense potential for revolutionizing the operation of a number of habitual conditions.

Wearables with AI integration can be classified grounded on the seeing styles employed, including electrochemical, colorimetric, chemical, optic, and pressure/ stain. These are the effectiveness of wearable detectors because it provides a custom and nonstop surveillance and prophetic capability that helps with time identification and improves treatment styles.
This handwriting examines the rearmost improvements and developments in the use of AI- grounded wearable seeing technology for managing habitual ails, including COVID- 19, Diabetes, and Cancer. AI- grounded Wearables for Heart Rate and Heart Rate Variability, Oxygen Saturation, Respiratory Rate, and Temperature Detectors are bandied in terms of their usability in managing COVID- 19 cases. In Diabetes operation, wearables using AI technology similar as nonstop glucose observers, insulin pumps using AI technology, and unrestricted- circle systems have been reviewed. The operations of AI- enabled wearable bias for biomarker analysis and processing, thermal imaging, and ultrasound device-grounded seeing for cancer care have been banned. Eventually, the report also focuses on the challenges and unborn prospects for the development of using AI- supported wearable detectors with delicacy, scalability, and addition within practice in similar vital health issues.[1]

Conditions like cancer, diabetes, and acute transmissible conditions like "COVID- 19 puts an inconceivable strain on healthcare systems around the world. Diabetes, a habitual metabolic condition "Diabetes mellitus, characterized by patient hyperglycemia, is another worldwide health extremity. For effectively managing diabetes, it's important to cover blood sugar situations constantly to help with complications like neuropathy, heart complaint, and order failure. Conventional practices include managing, controlling, and treating the situations of sugar present in the blood, which Glucose monitoring ways like the poking test are invasive and yield only separate data points.[2]

Artificial intelligence (AI) is a more general term that includes machine learning (ML) as a subcategory. Technically speaking, ML is a subset of AI, and often these terms are used as interchangeable buzzwords. ML, on the other hand, refers to an AI system that has the ability to self-learn from an algorithm, and as such, the system becomes intelligent without human assistance over time (eg, outcome prediction).

Deep learning, on the other hand, is another subcategory of AI that tries to replicate the human brain in terms of how it processes large amounts of data, and it has already shown success rates in areas such as diabetic retinopathy screening. The principles of ML have been applied in a clinical setting to develop algorithms that help in the development of predictive models for the risk of development of diabetes. AI has also been shown to offer helpful management tools to help handle large amounts of data.[2] Because of the large amount of data that can be quantified through continuous monitoring using wearables, AI can be used to further analyze the acquired data. This will help in understanding and extracting meaningful information from the acquired data and developing advanced and meaningful analytics.

In the case of diabetes, artificial intelligence technologies for wearable seeing allow for nonstop glucose monitoring, offering real- time data on glucose trends. [3]

AI- driven Digital Biomarkers could have a number of places in cases with T2DM, and these pretensions include perfecting and felicitating being webbing and individual procedures; vaticination and assessment of the inflexibility of complications of diabetes, including glycemic events; and using AI on nonstop glucose monitoring detectors and algorithms for enhanced clinical care and the soothsaying of diabetes- related complications. Several styles of digital technology, characteristics, and algorithms have been employed for developing digital biomarkers associated with its use in cases of T2DM, but the utmost of these concentrated on webbing.[4]

However, despite the developments in blood glucose monitoring technologies, the prevailing method of detection in the mainstream is still mostly invasive. The prevailing home electronic glucometers, for example, require people with diabetes to invasively self-prick their fingers to obtain blood samples from there, thereby making them susceptible to infections as well as stress and pain associated with them detection process, which is expected to be done multiple times a day. The emergence and developments of smart devices, such as smartphones, have increased the accessibility of the monitoring of diabetes-related aspects. Numerous studies have investigated this greatly welcomed technology.[5]

These generaly require the use of an external attachable sensor, and the monitoring process is then provided through an app or a separate continuous glucose monitoring (CGM) device, which can still be semi-invasive and require a connection range through Bluetooth or Wi-Fi signals. The application of completely noninvasive technology in the form of wearable devices (WDs) for regulating and monitoring glucose levels for people with diabetes is a relatively new idea and is still in its infancy stages.[6]

A high mortality rate from multifactorial diseases such as cancers, respiratory tract diseases, cardiovascular disorders, mental disorders, and infectious diseases) is caused mainly by late diagnoses, which limits the effectiveness of treatment and greatly increases the costs of healthcare The global healthcare market covers ambulatory care, stationary care, etc. executed by clinicians, hospitals, and contractors, as well as self-care. There has been substantial improvement in sensors for medical use. For example, glucometers are now not required to puncture the skin, allowing glucose levels to be monitored using a smartphone. The use of electrochemical sensors, such as biosensors and wearables, is expected to bring in new opportunities in medical diagnostics and wellness, and nutrition, which should promote the move from conventional diagnostic centers to decentralized, personalized, and remote.

Recently, AI-based wearable sensing technologies have shown considerable advancement in the area of healthcare. The latest developments in the area of AI-based wearable sensing technologies are as follows: Wearable photonic wristbands for cardiorespiratory function analysis and biometric identification. It has the potential for non-invasive and regular monitoring. Hybrid AI-based, bio-inspired wearable sensors with Aqua Sense AI technology are employed in multimodal health monitoring and rehabilitation in dynamic environments. We employed supervised machine learning technology to analyze data from 40 patients' smartwatches. It showed outstanding predictive accuracy for mortality in end-of-life cancer patients, with 93% accuracy.[7]

Disease

Diabetes mellitus (DM) is the most prevalent endocrine disorder, which affects more than 100 million people worldwide (6% population). It is caused by the deficiency or improper secretion of insulin by pancreas, which leads to an increase or decrease in the level of glucose in the blood. It has been observed that it causes damage to many of the body systems, especially the blood vessels, eyes, kidneys, heart, and nerves.

Diabetes mellitus has been divided into two types, namely insulin-dependent diabetes mellitus (IDDM, Type I) and non-insulin dependent diabetes mellitus (NIDDM, Type II). Type I diabetes is an autoimmune disease that is characterized by the selective destruction of the islets of Langerhans due to an inflammatory reaction in and around the islets, while Type II is characterized by peripheral insulin resistance.[8]

The presence of DM indicates the risk of many complications such as cardiovascular diseases, peripheral vascular diseases, stroke, neuropathy, renal failure, retinopathy, blindness, amputations etc. The use of drugs is mainly for saving life and relieving symptoms. The secondary objectives are to prevent diabetic complications and, by removing various risk factors, to prolong life.

Insulin replacement therapy is the mainstay for type 1DM patients, while dietary and lifestyle changes are considered the cornerstone for the treatment and management of type 2 DM. Various types of hypoglycemic agents such as biguanides and sulfonylureas are also available for the treatment of DM.[9]

However, none of these drugs is ideal because of their toxic side effects and loss of responses is observed sometimes in the prolonged use of these drugs.

The main drawback of the available drugs is that they have to be administered throughout the life and cause side effects. Medicinal plants and their bioactive compounds can be used for the treatment of DM all over the world, especially in countries where the conventional anti-DM drugs are not available in adequate quantity.

Integration of AI in wearable patch in Digital Health

Artificial intelligence (AI) makes it possible for machines to carry out tasks like learning, reasoning, and problem-solving that require human intelligence. AI is widely used in healthcare to monitor patients using digital tools, support diagnosis, analyze medical data, and recommend treatments. Digital health makes use of wearable technology, telemedicine, and smartphone apps to enhance healthcare delivery and facilitate remote patient care. Fitness trackers and EEG devices are examples of wearable technology that gathers health data in real time and uses linked applications to offer insightful information. AI-powered wearable EEG devices monitor brain activity and help identify neurological and mental health issues.

The application of digital technologies, such as wearable technology, smartphone apps, and AI features and techniques, to improve healthcare delivery and the patients' health. The goals of digital wearables are to enhance patient outcomes, maximize healthcare services, and promote personalized care [10]. With the use of wearable technology, telemedicine, and mobile health tools, medical practitioners can provide remote patient care. It improves access and comfort, particularly in remote areas, by helping physicians monitor, motivate, and treat patients without requiring an in-person visit.

AI involves various tasks that requires human intelligence and also involves machine learning, robotics, computer vision and natural language processing. Artificial intelligence is used as one of the most impactful methods for healthcare to improve diagnostic tools. The use of machine learning algorithms and deep learning algorithms has enhanced the ability of AI to detect disease and conditions at an earlier stage than previously possible by training these algorithms to work with large amounts of images, electronic health records (EHRS) and genomic data.[11]

The impact of genetics and genomics on personalized medicine is now being harnessed to create medical interventions that are specific to individual patients based on the interaction between their genetic, environmental and lifestyle variables. AI will enable the development of personalized treatment plans by predicting the responses that patients will have to various types of treatments, based on massive datasets.

Digital health encompasses digital-based technologies that are used by health professionals, communities, and government agencies to manage physical and public health. Remote patient monitoring, using artificial intelligence, is becoming increasingly important for patient care and provides the ability to continually monitor a patient's condition and provide warnings in advance of a critical medical condition. Patients are being monitored remotely with wearable devices such as smartwatches, fitness bands, and bio-sensors. By using secure digital systems, patients can check their heart rates, blood pressure, and oxygen levels through their mobile devices and have that information transmitted to health care providers.[12]

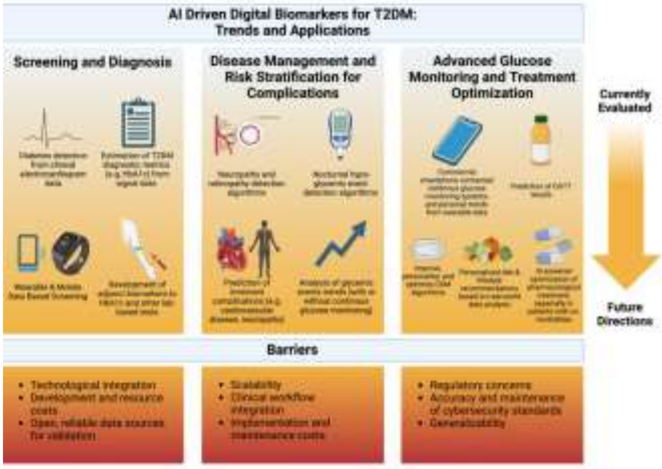

Fig. 1: JABARA, Mariam, et al. Artificial intelligence-based digital biomarkers for type 2 diabetes: a review. Canadian Journal of Cardiology, 2024, 40.10: 1922-1933.

The wearable sensing technology market is an emerging segment of the flexible electronics market, which was valued at $1.5 billion in 2020 and is expected to grow at an annual rate of 10.7% through 2030, significantly impacting global health in unprecedented ways.

Wearables are small electronic devices designed to be worn on the body.

Sensors used in wearable technology can be of various types, including electrochemical, colorimetric, optical, and pressure/strain sensors. These sensors can collect multiple types of signals, including physical, chemical, and biochemical signals. Patients can wear devices directly on their skin, driving rapid advancements in wearable technology for human health monitoring and tracking. Wearable sensing technology provides real-time physiological parameters through flexible, user-friendly devices. The results are faster, eliminating the need for a medical expert and enabling more rapid decision-making for timely treatment.[13]

Artificial Intelligence-Based Wearable Sensing Technology for Diabetes Management

Diabetes, a chronic metabolic disorder that impacts millions of people across the globe, is a metabolic disorder characterized by the body's inability to regulate blood glucose concentration. This can be attributed to either the body's resistance to insulin or the body's inability to produce sufficient insulin. As a crucial tool for diabetes management, Continuous Glucose Monitoring (CGM) systems developed using wearable sensing technology enable real-time monitoring of blood glucose concentration with minimal human intervention. Developed using electrochemical, optical, microneedle, and novel sweat-sensing technologies, among others, these systems provide a more advanced and feasible alternative to traditional finger-prick glucose monitoring technologies.[14]

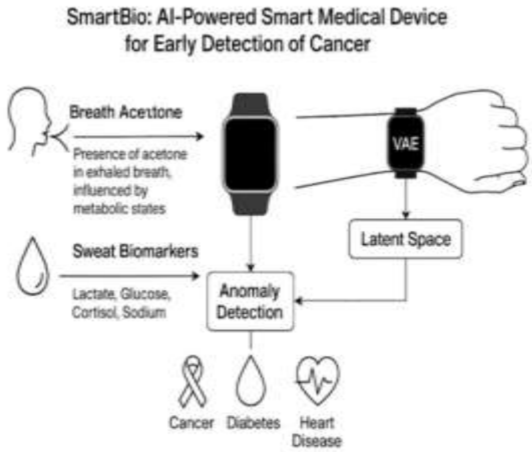

Fig. 2: SAHA, Tamoghna, et al. Wearable electrochemical glucose sensors in diabetes management: a comprehensive review. Chemical Reviews, 2023, 123.12: 7854-7889.

The accuracy and usability of these systems have improved drastically, providing a more holistic solution for diabetes management. Wearable technology also increasingly integrates sensors for other physiological parameters, including heart rate and activity levels. The integration of Artificial Intelligence (AI) technology with these wearable devices for complex data analysis and predictive models has completely transformed the way diabetes is managed. AI models, including ML and DL, analyze large amounts of real-time data from wearable devices to predict glucose patterns, detect anomalies, and provide recommendations for tailored insulin intake. Closed-loop insulin infusion systems have also benefited from the use of AI-driven models, which automatically change the insulin levels and improve blood sugar control with very little human interaction. This review highlights the recent advancements in wearable sensing technologies based on artificial intelligence (AI) for diabetes management, focusing on sensing technology in the following subsections.[15]

Importance of integrating AI in diabetes management and treatment

The advancements in AI have brought significant changes in the healthcare industry, and diabetes management is not an exception. AI-based systems have the potential to bring a revolution in the management of diabetes by offering personalized and data-driven insights that can result in effective treatment and better patient outcomes.[16]

One of the most important advantages of integrating AI in diabetes management is the ability to offer personalized health information to patients. Based on patient data, including their medical history, lifestyle, and real-time monitoring, AI systems can provide personalized recommendations for patients to maintain optimal glucose levels, diet, and health. This personalized approach can enable patients to take a proactive approach to managing their diabetes, resulting in better self-management and patient outcomes.[17]

In addition, the use of AI in remote monitoring has important implications for diabetes management. AI-based devices and wearables can monitor patients' data continuously, enabling the early identification of possible complications and taking corrective measures. This can result in more proactive and preventive medical care, thus reducing the risk of the costly and debilitating complications of diabetes. AI has also shown its effectiveness in the diagnosis and management of complications of diabetes, such as diabetic retinopathy. AI-based systems have shown remarkable accuracy in the early diagnosis of diabetic retinopathy, thus allowing doctors to initiate timely treatment and prevent blindness.[18]

Moreover, the use of AI in the healthcare industry can have a positive effect on the vulnerable population, including diabetic patients. AI-based systems in the primary healthcare industry can help reduce disparities in access to healthcare and improve the quality of healthcare for the underserved population. The potential of AI to go beyond human capabilities has unlimited potential in the healthcare industry, and the management of diabetes is no exception. By incorporating AI- based systems in the management of diabetes, healthcare professionals can make use of the following to provide more precise, personalized, and effective treatment, ultimately resulting in improved patient outcomes and decreased healthcare costs.[19]

II. CONTINUOUS GLUCOSE MONITORING

Electrochemical Sensors

Electrochemical sensors play a vital role in continuous glucose monitoring (CGM) systems because of their high sensitivity and ability to detect glucose levels in real time. These sensors detect glucose oxidation in interstitial fluid, which generates an electric signal proportional to the concentration of glucose. The ease and convenience of continuous glucose monitoring for diabetic patients have increased with the development of smaller electrochemical sensors that can be worn on the body. Nevertheless, the large volume of data produced by these sensors makes it more challenging to analyze and interpret glucose levels in real time.[20] To overcome this challenge, Artificial Intelligence (AI)-based control algorithms, such as machine learning (ML) and reinforcement learning algorithms, have been combined with electrochemical sensors to analyze data and forecast glucose levels. AI models offer advanced glucose level insights that are not possible with conventional glucose monitoring systems, helping to detect hypo- and hyperglycemic attacks at an early stage and monitoring insulin levels. AI's predictive capability to foresee glucose levels up to 60 min in advance has significantly enhanced the accuracy and efficiency of these systems, providing diabetic patients with more reliable and personalized management tools.[21]

It is difficult to identify which AI approach is most effective in compensating for the confounding effect of temperature drift in wearable electrochemical glucose sensors. The first approach is the use of calibration models based on ML, such as support vector regression and random forest regression, which are commonly employed to describe the nonlinear relationship between the sensor output and temperature changes. The second approach is the use of a deep learning algorithm, such as convolutional neural networks and recurrent neural networks, which have the ability to interpret the temporal patterns of glucose signals together with temperature changes, thus improving robustness in dynamic real-world settings.

This is a sensor fusion approach that combines AI algorithms to fuse multisensory information, thus attempting to separate the temperature effect using multimodal neural networks.[22] Online learning and adaptive filtering algorithms allow for real-time compensation of temperature drift by adapting the model to new data from the individual wearer. Among all, Deep learning, particularly CNN-LSTM hybrid models with sensor fusion, has immense potential in current literature to compensate for the confounding effect of temperature drift while ensuring real- time processing.

Optical Sensors

Optical sensors have the ability to measure glucose concentrations based on the scattering or absorption of light by biological tissues. This has made them a feasible and widely recognized noninvasive technology for glucose detection. Fluorescence, Raman spectroscopy, and near- infrared (NIR) spectroscopy are some of the technologies that form the foundation of optical sensors. These technologies have the ability to reduce the discomfort caused by invasive technologies such as conventional finger-pricking techniques. These sensors have the ability to offer continuous monitoring by analyzing changes in the optical properties of the skin or interstitial fluid and correlating them with glucose concentrations.[23] The major challenge in employing optical sensors is minimizing interference from other physiological variables, such as temperature, tissue in homogeneities, and motion artifacts. In this case, artificial intelligence models can also be employed to address the complex data produced by optical sensors and optimize their performance. Artificial intelligence models assist in noise reduction and interference elimination, offering accurate glucose readings.

Microneedle Sensors

Microneedle sensors have the ability to penetrate interstitial fluid just beneath the skin's surface without any pain, and their minimally invasive approach has made them a favorite for continuous glucose monitoring (CGM). Compared to the traditional finger-prick technique, microneedle sensors have microscopic needles that puncture the skin to provide constant and real-time glucose monitoring with higher accuracy. Microneedles are ideal for wearable devices to control diabetes because they are often integrated with electrochemical sensing platforms to detect glucose levels in interstitial fluid. Li et al. designed a microneedle-based CGM system using a three-electrode electrochemical biosensor and tested the sensing ability.[24]

AI-Based Insulin Pumps and Closed-Loop Systems

Artificial intelligence (AI)-based insulin pumps and closed-loop systems, also known as artificial pancreas, have emerged as a revolutionary technology to enhance the management of diabetes. These devices employ intelligent algorithms such as machine learning (ML) and deep learning to automatically regulate the insulin infusion from insulin pumps using real-time data from continuous glucose monitoring (CGM) systems. Sophisticated control algorithms such as fuzzy logic, model predictive control (MPC), and proportional-integral- derivative (PID) controllers form the technological bedrock of these systems to manage the present and past insulin intake.[25]

III. NON-INVASIVE GLUCOSE MONITORING WEARABLES

Smart Contact Lenses

In diabetes management, smart contact lenses are gaining popularity as a cutting-edge method for continuous and non-invasive glucose monitoring. Intelligent contact lenses can be an alternative to conventional blood glucose monitoring techniques; these glasses incorporate biosensors that detect glucose levels in tear fluid.[27] Keum et al. reported a wireless smart contact lens for non-invasive diagnosis and therapy of diabetes. The smart contact lenses comprise a biosensor for real-time glucose detection, a flexible drug delivery system, an ASIC microcontroller chip for signal processing, and a radio-frequency communication module for transmitting data to external devices.[28]

Sweat-Based Sensors

Sweat-based sensors have become a viable non-invasive alternative to blood-based techniques for continuous glucose monitoring in diabetes care. These sensors measure the composition of human sweat, which contains glucose at concentrations that correlate with blood glucose levels. However, the lower glucose concentration in sweat compared to blood poses a significant technical hurdle, necessitating sensitive detection methods. To address this, Kim et al. attempted to incorporate sweat sensors into flexible, wearable substrates, such as hydrogels or stretchable electronics, along with enzymatic glucose detection methods, such as glucose oxidase, to ensure comfort during prolonged use.[29]

AI can improve the sensor's predictive power by fine-tuning the relationship between blood glucose and sweat glucose levels using analysis of large datasets, as described.[30]

Wearable device for diabetes using multi biomarker approaches

This work illustrates that smartphone-based photoplethysmography (PPG) analysis with a deep neural network (DNN) can be a valid non-invasive digital biomarker for the identification of prevalent diabetes. Based on the PPG signal acquired by placing a finger on the smartphone camera, a deep learning algorithm was trained and validated on massive population and clinical datasets.[31] The algorithm had good discriminatory power in independent cohorts and was an important predictor of diabetes independent of age, sex, body mass index, and cardiovascular disease comorbidities. Notably, the DNN score was significantly and positively correlated with HbA1c and fasting glucose levels, suggesting that the vascular and autonomic alterations detected by PPG are associated with the presence and severity of diabetes. Although this approach is not meant to replace conventional laboratory diagnosis, its negative predictive value and simplicity make it a promising and scalable screening and risk-stratification tool, especially useful for the identification of undiagnosed diabetes in the community and resource- limited settings.[32]

Wearable glucose sensors operate using electrochemical, optical, and electromagnetic sensing mechanisms, each with distinct working principles, advantages, and limitations. Electrochemical sensing is the most commonly adopted approach due to its simple construction, miniaturization capability, low cost, and ability to provide continuous and quantitative output. It can be classified into enzymatic and non-enzymatic types. In enzymatic sensing, glucose oxidase (GOx) catalyzes the oxidation of glucose in the presence of oxygen to form gluconic acid and hydrogen peroxide. The generated hydrogen peroxide undergoes oxidation at the electrode surface, producing a steady current proportional to glucose concentration, a method known as amperometric sensing. To enhance performance, researchers focus on increasing electrode surface area using nanomaterials, improving enzyme immobilization techniques to prevent leaching, and incorporating suitable mediators to facilitate efficient electron transfer. However, enzymatic sensors face challenges such as reduced enzyme stability under variations in pH, temperature, humidity, and exposure to chemicals, which can limit long-term reliability.[33]

Intensive insulin therapy could be the panacea for tight glycemic control in type 1 diabetes if it were not associated with an increased risk of hypoglycemia. Both multiple daily insulin injection (MDI) therapy and CSII therapy are effective means for implementing intensive diabetes management with the goal of achieving near-normal levels of blood glucose. CSII therapy relies on an insulin pump that is designed to supply a continuous flow of basal insulin at a customizable rate, allowing, in parallel, the on-demand administration of supplementary bolus doses (i.e. mealtime, hyperglycemia). The insulin pump consists of (i) a wearable device holding the insulin reservoir and the interface (screen and buttons) for programming the insulin,

(ii) an infusion set that includes a thin tube that delivers insulin from the reservoir to the infusion site and a cannula inserted under the skin to deliver insulin, and (iii) an infusion set insertion device.[34] Moreover, available insulin pumps offer additional functionality (e.g. bolus calculator, reminders on bolus insulin, direct connection with blood glucose meter, personal therapy management software) that facilitates the administration of insulin therapy. In view of ambulatory use, insulin pumps have already improved a lot in terms of safety and miniaturization. A key safety issue of CSII is the risk of insulin under-delivery due to the gradually altered absorption of insulin at the subcutaneous delivery site.

Besides greater flexibility and more precise insulin administration, the clinical advantages of insulin pump therapy over MDI therapy are unclear. Hirch comments on the outcomes of two recent meta- analyses, which reported contradictory results regarding the effect of CSII therapy on severe hypoglycemia reduction in both type 1 adults and children, that "has added uncertainty to our original premise about this therapy". Several studies have suggested that the effective integration of CGM and CSII technologies into one system i.e. sensor augmented pump (SAP) allows for improvements in metabolic control of type 1 diabetes when compared with MDI or the individual components alone; however, the problem of severe hypoglycemia and, in particular, devastating nocturnal hypoglycemia is not resolved.[35]

A far more promising approach to this problem is the automatic suspension of insulin delivery at a preset low glucose threshold aiming at reducing basal insulinemia during the critical first few minutes of hypoglycemia without causing rebound hyperglycemia. In particular, the so- called threshold-suspend feature available in the Medtronic Paradigm Veo pump was shown to significantly reduce the rate and the mean area under curve of nocturnal hypoglycemic events by 31.8 and 37.5 %, respectively, as compared to standard SAP therapy. Moreover, the 24-h hypoglycemic exposure was also reduced during the 3-month study, without significant changes in HbA1c levels.[45]

A following study did support that this technology has the potential to reduce the combined rate of severe and moderate hypoglycemia in patients with type 1 diabetes. In addition, the effectiveness of suspending the insulin pump delivery when the risk of hypoglycemia (≤70 mg/dl) is high was demonstrated both by simulations and experimentally. It is acknowledged that SAP with threshold-suspend is the epitome of today's diabetes technology and that is the next step for an automated closed-loop artificial pancreas; the most promising therapeutic approach to β-cell replacement.[36]

IV. MOBILE APPLICATIONS FOR DIABETES MANAGEMENT

Mobile applications constitute apparently a fast growing trend in the daily care of chronic diseases, let alone diabetes. Both literature and online market stores (iTunes, Google Play) has demonstrated a number of simple and more advanced examples, ranging from self-monitoring applications to innovative intervention studies. The advent of smart phones and of mobile health devices accelerated that shift making contemporary mobile diabetes applications able to manage multi-parametric daily data for medication, nutrition, physical activity, weight and blood pressure. Their functionality is similar for type 1 and type 2 diabetes with the exception of insulin administration. Many mobile interventions have reported positive effects on glycemic control; however, considerable differences in the design of mobile tools do not allow a rigorous meta-analysis of the findings.[37]

Monitoring self-management information

The majority of mobile diabetes applications fall into the category of health monitoring systems providing patients with effective means for tracking and displaying the most important variables to diabetes self-management. Relative information is commonly entered manually through custom designed journaling applications presenting different layers of abstraction. The recording procedure of most measures (e.g. blood glucose, blood pressure, weight) as well as of medication is well-defined and is rather straightforward. On the other hand, the self- monitoring of health-related behaviors (e.g. food intake, physical activity) constitutes a most challenging issue. In particular, existing approaches to recording food intake vary from manual input of calories and carbohydrates to fully-automatic identification of food by e.g. image analysis. The most common approach regarding mobile diabetes applications involves the specification of food type and quantity utilizing a built-in food database and the subsequent automatic estimation of food composition. In a similar way, information on physical activity (e.g. activity time, type and level) is also registered in approximation through the use of suitable databases.[38]

Automatic data transfer functionalities are critical to improving the quality of self-monitoring and to supporting long term user engagement. Regarding tracking of blood glucose data, automatic transmission methods have been widely applied for research purposes. According to a recent systematic review of mobile phone-based interventions in diabetes, the communication between blood glucose meter and mobile phone in 87.5 % of the studies were accomplished by Bluetooth, a physical wire to the phone, or infrared signal. However, such a functionality appears in a few commercial applications e.g. Glooko (Glooko Inc.), an iPhone- based diabetes management system that simplifies data downloading through the use of a cable compatible with 19 different blood glucose meters. An alternative solution comes from iBGStar® (BGStar), a blood glucose meter which plugs directly into the iPhone and through the iBGStar

Diabetes Manager application allows the patient to keep track of blood glucose data, carbohydrates intake and insulin therapy.[44] The proliferation of wearable mHealth devices has also given rise to more comprehensive, accurate, and, in parallel, less burdensome self- monitoring of physiological parameters and physical activities. For instance, wireless smart activity and sleep trackers (from companies such as Withings, Fitbit, Body Media, Nike, Jawbone, etc.,) automatically monitor a variety of objective features (e.g. calories burned, steps, distance traveled, exercise intensity, quality and efficiency of sleep). For instance, Diabetes Pal 2.0 (Telcare®) and Tactio Health (Tactio Health Group) mobile applications synch with leading health and lifestyle trackers combining data for blood glucose, physical activity, weight and blood pressure in tandem with nutrition and medication data.[39]

A common approach is the classification of glucose levels and of blood pressure, when recorded, according to international standards (e.g. American Diabetes Association and American Heart Association), as well as the color-coded visualization of information depending on patient-specific characteristics and time of day (e.g. Tactio Health by Tactio Health Group). In addition, simple statistics e.g. average pre- and post-meal glucose levels, efficiently represented in tabular or graphical from, complement self-monitoring of diabetes. [40]

Decision support functionality

Daily self-monitoring information can be efficiently analyzed, retrospectively or in real-time, to provide patients with supportive feedback related to diabetes management. In the majority of mobile diabetes interventions, the data of each patient were intermittently reviewed by the healthcare team through a web-based application and, on this basis; patients received customized decision support information directly from the clinical experts. This form of feedback, being highly personalized and specific as well, is well suited for young or newly diagnosed diabetic patients. However, it depends on the availability of the healthcare professionals and, cannot be delivered to patients in real time. One of the first research efforts towards automated diabetes self-management is the Well Doc system, which did receive FDA clearance for type 2 diabetes.[41]

Its mobile expert system, incorporating over 1,000 self-management messages, responses in real-time to the glucose data entered by providing educational, behavioral and motivational coaching; when augmented with a web based personal health record and provider decision support it has been shown to reduce HbA1c by 1.9 % on average. In case of type 1 diabetes, the Diabeo mobile system enabling individualized insulin dose adjustments, through validated algorithms, and combined with telemedicine support improved the HbA1c by 0.91 % in poorly controlled patients. An ubiquitous healthcare service was properly designed in so that elderly diabetic patients could get on their mobile phone immediate and individualized medical recommendations by a remote clinical decision support system according to current blood glucose measurements and information from their electronic medical record.[43]

In general, decision support tools have been utilized for providing personalized treatment adjustments to patients, but only for research purposes. The findings of these studies are positive, although not always statistically important, but the fact that the developed systems are knowledge-based limits their capability to make purely data driven decisions. The application of advanced data analysis techniques can lead to more efficient treatment recommendations grounded entirely on the knowledge present in the data. For instance, the Well Doc application incorporates a proprietary analytic system that identifies longitudinal trends into the glucose data. Moreover, the data resulting from a pilot study on type 1 patients, who were equipped with the Few Touch mobile application, were subsequently used to build statistical models of the glucose trends.[42]

More specifically, the Diastat module is able to identify periodicities and trends into the glucose data as well as to perform case-based reasoning of insulin administration. The effect of this form of data-driven feedback (Few Touch and Diastat) on glycemic control of type 1 diabetes is now being investigated in a randomized control trial. It should be noted that intelligent pattern recognition analysis of self-monitoring data has not been applied yet in a mobile setting, although it has the potential to provide better understanding of the disease. A challenging issue is also to provide real-time blood glucose predictions on the mobile device. Towards this direction, the METABO and DI Advisor type 1 diabetes management systems allowed efficient prediction algorithms to be executed directly on mobile devices, which were used for patient self monitoring.[43]

V. CONCLUSION

In conclusion, the integration of Artificial Intelligence (AI) with wearable sensing technology has emerged as a transformative approach in modern healthcare, particularly in the management of chronic diseases such as diabetes mellitus. Diabetes is a widespread metabolic disorder that requires continuous monitoring and long-term management to prevent complications such as cardiovascular diseases, neuropathy, kidney failure, and retinopathy.

Wearable sensing technologies, including electrochemical sensors, optical sensors, microneedle sensors, sweat-based sensors, and smart contact lenses, have enabled real-time monitoring of physiological and biochemical parameters. These sensors collect large volumes of data related to glucose levels and other health indicators. Artificial Intelligence, particularly machine learning and deep learning algorithms, plays a crucial role in analyzing these large datasets. AI can identify patterns, predict glucose fluctuations, detect early signs of hypo- or hyperglycemia, and provide personalized treatment recommendations. This data-driven approach supports clinicians in making more accurate and timely medical decisions.

These systems automatically adjust insulin delivery based on real-time glucose readings obtained from continuous glucose monitoring devices. Such automated systems improve glycemic control and reduce the risk of severe hypoglycemic episodes. Additionally, the integration of wearable devices with mobile applications and telemedicine platforms has enabled remote patient monitoring. This allows healthcare professionals to track patients' conditions continuously and intervene when necessary, improving accessibility and efficiency of healthcare services, especially for patients in remote or underserved areas.

This personalized approach improves treatment effectiveness and patient adherence to therapy. Mobile health applications also provide tools for tracking diet, physical activity, medication, and other lifestyle factors that influence glucose levels, thereby encouraging better self-management among patients.

Despite these significant advancements, several challenges still remain. Issues related to sensor accuracy, calibration, device durability, data privacy and security, high costs, and the need for large-scale clinical validation must be addressed before widespread adoption can be achieved. Additionally, integrating these technologies into existing healthcare systems requires proper regulatory frameworks, infrastructure, and training for healthcare professionals.

Overall, AI-based wearable sensing technologies represent a promising future for diabetes management and digital healthcare.

REFERENCES

1. FRASER, Raphael A., et al. Integration of artificial intelligence and wearable technology in the management of diabetes and prediabetes. npj Digital Medicine, 2025, 8.1: 687.
2. KUMAR, Amit, et al. Artificial Intelligence-Based Wearable Sensing Technologies for the Management of Cancer, Diabetes, and COVID-19. Biosensors, 2025, 15.11: 756.
3. Calderaro J, Seraphin TP, Luedde T, Simon TG. Artificial intelligence for the prevention and clinical management of hepatocellular carcinoma. J Hepatol 2022 Jun;76(6):1348-1361.
4. Grzybowski A, Brona P, Lim G, Ruamviboonsuk P, Tan GS, Abramoff M, et al. Artificial intelligence for diabetic retinopathy screening: a review. Eye (Lond) 2020 Mar 05;34(3):451-460.
5. Ellahham S. Artificial intelligence: the future for diabetes care. Am J Med 2020 Aug;133(8):895-900.
6. Alves S, Matos AG, Almeida JS, Benevides CA, Cunha CC, Santiago RV, et al. A new strategy for the detection of diabetic retinopathy using a smartphone app and machine learning methods embedded on cloud computer. In: Proceedings of the 2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS). 2020 Presented at: 2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS); Jul 28-30, 2020; Rochester, MN, USA.
7. Sharma, A.; Singh, A.; Gupta, V.; Arya, S. Advancements and Future Prospects of Wearable Sensing Technology for Healthcare Applications. Sens. Diagn. 2022, 1, 387–404.
8. Chakravadhanula K. A smartphone-based test and predictive models for rapid, non- invasive, and point-of-care monitoring of ocular and cardiovascular complications related to diabetes. Informatics Med Unlocked 2021;24:100485.
9. Contreras I, Vehi J. Artificial intelligence for diabetes management and decision support: literature review. J Med Internet Res 2018 May 30;20(5):e10775.
10. WASILEWSKI, Tomasz; KAMYSZ, Wojciech; GĘBICKI, Jacek. AI-assisted detection of biomarkers by sensors and biosensors for early diagnosis and monitoring. Biosensors, 2024, 14.7: 356.
11. DESHMUKH, Chinmay D.; JAIN, Anurekha; NAHATA, B. Diabetes mellitus: a review. Int. J. Pure Appl. Biosci, 2015, 3.3: 224-230.
12. BASTAKI, Salim. Diabetes mellitus and its treatment. International journal of Diabetes and Metabolism, 2005, 13.3: 111-134.
13. Jeddi Z, Bohr A (2020) Remote patient monitoring using artificial intelligence. In: Artificial intelligence in healthcare. Academic Press, pp 203–234.
14. Ahmed Z et al (2020) Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. Database 2020:baaa010.

15. Kanakaprabha S, Kumar GG, Reddy BP, Raju YR, Rai PCM (2024) Wearable Devices and Health Monitoring: Big Data and AI for Remote Patient Care. Intell Data Anal Bioinform Biomed Syst 291–311.
16. Jin, X.; Liu, C.; Xu, T.; Su, L.; Zhang, X. Artificial Intelligence Biosensors: Challenges and Prospects. Biosens. Bioelectron. 2020, 165, 112412.
17. Lee, I.; Probst, D.; Klonoff, D.; Sode, K. Continuous Glucose Monitoring Systems— Current Status and Future Perspectives of the Flagship Technologies in Biosensor Research. Biosens. Bioelectron. 2021, 181, 113054.
18. Mansour, M.; Saeed Darweesh, M.; Soltan, A. Wearable Devices for Glucose Monitoring: A Review of State-of-the-Art Technologies and Emerging Trends. Alex. Eng. J. 2024, 89, 224–243.
19. Contreras, I.; Vehi, J. Artificial Intelligence for Diabetes Management and Decision Support: Literature Review. J. Med. Internet Res. 2018, 20, e10775.
20. Nimri, R.; Phillip, M.; Kovatchev, B. Closed-Loop and Artificial Intelligence–Based Decision Support Systems. Diabetes Technol. Ther. 2023, 25, S-70–S-89.
21. Dave M, Patel N (2023) Artificial intelligence in healthcare and education. Br Dent J 234(10):761–764.
22. Gurevich E, El Hassan B, El Morr C (2023) Equity within AI systems: what can health leaders expect? Healthcare management forum 36(2):119–24. Sage CA, Los Angeles, CA: SAGE Publications.
23. Lee, I.; Probst, D.; Klonoff, D.; Sode, K. Continuous Glucose Monitoring Systems— Current Status and Future Perspectives of the Flagship Technologies in Biosensor Research. Biosens. Bioelectron. 2021, 181, 113054.
24. Ellahham, S. Artificial Intelligence: The Future for Diabetes Care. Am. J. Med. 2020, 133, 895–900.
25. Contreras, I.; Vehi, J. Artificial Intelligence for Diabetes Management and Decision Support: Literature Review. J. Med. Internet Res. 2018, 20, e10775.
26. Nimri, R.; Phillip, M.; Kovatchev, B. Closed-Loop and Artificial Intelligence–Based Decision Support Systems. Diabetes Technol. Ther. 2023, 25, S-70–S-89.
27. Alsunaidi, B.; Althobaiti, M.; Tamal, M.; Albaker, W.; Al-Naib, I. A Review of Non- Invasive Optical Systems for Continuous Blood Glucose Monitoring. Sensors 2021, 21, 6820.
28. Yadav, J.; Rani, A.; Singh, V.; Murari, B.M. Prospects and Limitations of Non-Invasive Blood Glucose Monitoring Using nearInfrared Spectroscopy. Biomed. Signal Process. Control 2015, 18, 214–227.
29. Delbeck, S.; Vahlsing, T.; Leonhardt, S.; Steiner, G.; Heise, H.M. Non-Invasive Monitoring of Blood Glucose Using Optical Methods for Skin Spectroscopy-Opportunities and Recent Advances. Anal. Bioanal. Chem. 2019, 411, 63–77.
30. Samant, P.P.; Niedzwiecki, M.M.; Raviele, N.; Tran, V.; Mena-Lapaix, J.; Walker, D.I.; Felner, E.I.; Jones, D.P.; Miller, G.W.; Prausnitz, M.R. Sampling Interstitial Fluid from Human Skin Using a Microneedle Patch. Sci. Transl. Med. 2020, 12, eaaw0285.
31. . Yang, J.; Zheng, S.; Ma, D.; Zhang, T.; Huang, X.; Huang, S.; Chen, H.; Wang, J.; Jiang, L.; Xie, X. Masticatory System—Inspired Microneedle Theranostic Platform for Intelligent and Precise Diabetic Management. Sci. Adv. 2022, 8, eabo6900.
32. Tarar, C.; Aydın, E.; Yetisen, A.K.; Tasoglu, S. Machine Learning-Enabled Optimization of Interstitial Fluid Collection via a Sweeping Microneedle Design. ACS Omega 2023, 8, 20968–20978.
33. Zhou, L.; Menon, S.S.; Li, X.; Zhang, M.; Malakooti, M.H. Machine Learning Enables Reliable Colorimetric Detection of PH and Glucose in Wearable Sweat Sensors. Adv. Mater. Technol. 2024, 10, 2401121.
34. Ye, Z.T.; Tseng, S.F.; Tsou, S.X.; Tsai, C.W. High-Sensitivity Flip Chip Blue Mini- LEDs Miniaturized Optical Instrument for Non-Invasive Glucose Detection. Discover Nano 2024, 19, 6.
35. Keum, D.H.; Kim, S.K.; Koo, J.; Lee, G.H.; Jeon, C.; Mok, J.W.; Mun, B.H.; Lee, K.J.;
36. Kamrani, E.; Joo, C.K.; et al. Wireless Smart Contact Lens for Diabetic Diagnosis and Therapy. Sci. Adv. 2020, 6, eaba3252.
37. The effect of intensive treatment of diabetes on the development and progression of long-term complications in insulin-dependent diabetes mellitus. The diabetes control and complications trial research group. N Engl J Med. 1993;329(14):977–86.
38. Misso ML, Egberts KJ, Page M, O'Connor D, Shaw J. Continuous subcutaneous insulin infusion (csii) versus multiple insulin injections for type 1 diabetes mellitus. The Cochrane database of systematic reviews. 2010(1):Cd005103.
39. Hirsch IB. Reducing hypoglycemia in type 1 diabetes: An incremental step forward. Diabetes Technol Ther. 2013;15(7):531–2
40. Buckingham B, Chase HP, Dassau E, Cobry E, Clinton P, Gage V, et al. Prevention of nocturnal hypoglycemia using

predictive alarm algorithms and insulin pump suspension. Diabetes Care. 2010;33(5):1013–7.

41. Norgaard K, Scaramuzza A, Bratina N, Lalic NM, Jarosz-Chobot P, Kocsis G, et al. Routine sensor-augmented pump therapy in type 1 diabetes: the interpret study. Diabetes Technol Ther. 2013;15(4): 273–80.
42. Bergenstal RM, Klonoff DC, Garg SK, Bode BW, Meredith M, Slover RH, et al. Threshold-based insulin-pump interruption for reduction of hypoglycemia. N Engl J Med. 2013;369(3):224–32.
43. Rossi MC, Nicolucci A, Di Bartolo P, Bruttomesso D, Girelli A, Ampudia FJ, et al. Diabetes interactive diary: a new telemedicine system enabling flexible diet and insulin therapy while improving quality of life: An open-label, international, multicenter, randomized study. Diabetes Care. 2010;33(1):109–15.
44. Skrovseth SO, Arsand E, Godtliebsen F, Hartvigsen G. Mobile phone-based pattern recognition and data analysis for patients with type 1 diabetes. Diabetes Technol Ther. 2012;14(12):1098–104.
45. Georga E, Protopappas V, Guillen A, Fico G, Ardigo D, Arredondo MT, Exarchos TP, Polyzos D, Fotiadis DI. Data mining for blood glucose prediction and knowledge discovery in diabetic patients: The metabo diabetes modeling and management system. Conference proceedings : Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Conference. 2009;2009:5633–6.
46. Stahl F, Johansson R. Diabetes mellitus modeling and short-term prediction based on blood glucose measurements. Math Biosci. 2009;217(2):101–17.