Review

Application of Wearable Devices in Diabetes Management

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Abstract: Diabetes mellitus poses a significant global health challenge, impacting hundreds of millions worldwide. Effective management and prevention of complications rely on dynamic, real-time glucose monitoring. This review provides a comprehensive overview of the rapidly evolving landscape of wearable technologies for glucose monitoring and diabetes care, with a focus on cutting-edge advancements and their integration with artificial intelligence (AI) and multi-omics data. We explore diverse glucose monitoring approaches, including continuous glucose monitors (CGMs) and smartwatches, highlighting their contributions to tracking physical activity, food intake, medication adherence, and direct glucose measurements. Our emphasis is placed on the role of AI systems in enabling predictive analytics and personalized care, as well as the integration of wearable data with multi-omics insights—spanning genomics, proteomics, and gut microbiome analyses—to enhance understanding of individual glucose metabolism. Given the challenges of existing methods, such as invasiveness, accuracy, and accessibility, we discuss future directions, including the potential of smart glasses, advanced AI models, and seamless data integration, to revolutionize diabetes management. This review offers valuable insights into how wearable technologies, AI, and multi-source data analysis are shaping the future of precision diabetes care.

Keywords: diabetes mellitus; glucose monitoring; wearable devices; artificial intelligence; multi-omics; digital health

1. Introduction

Diabetes mellitus stands as one of the most urgent global health challenges, impacting millions worldwide [1]. The International Diabetes Federation reports that the global diabetes population reached 537 million adults in 2023, with projections estimating a rise to 1.03 billion by 2045 (Figure 1a) [2]. The condition is linked to serious vascular complications, including cardiovascular disease, kidney failure, blindness, and lower-limb amputations (Figure 1b) [3], highlighting the urgent need for effective management strategies.

Glucose monitoring plays a fundamental role in diabetes management [4,5]. Maintaining blood glucose levels within target ranges helps prevent both acute complications (hypoglycemia and hyperglycemia) and long-term complications (neuropathy and retinopathy) [6]. Regular monitoring enables individuals to make timely adjustments to their diet, exercise regimens, and medication protocols, thereby improving their overall quality of life [7,8]. Traditionally, glucose monitoring has relied on Self-Monitoring of Blood Glucose (SMBG) through finger-prick tests (Figure 1c) [9,10]. While SMBG provides valuable data points, it has significant limitations, including its invasive nature, the requirement for multiple daily tests, and the inability to provide continuous or real-time data (Figure 1c) [10,11]. These drawbacks have catalyzed the development of less invasive, more dynamic monitoring solutions.

In recent years, a revolution has been witnessed in glucose monitoring through wearable devices (Figure 1d) [12–14]. Continuous Glucose Monitors (CGMs) gained widespread adoption, offering real-time glucose readings, trend data, and alerts for abnormal glucose levels [15]. These devices significantly enhance diabetes management capabilities [15]. However, CGMs face certain limitations, including their invasive nature, high costs, and occasional accuracy issues [16,17].

Beyond CGMs, innovative wearable technologies are being developed to address these challenges [16]. Novel approaches include smartwatches with integrated glucose sensors and human stretchable sweat-based systems, which promise truly non-invasive glucose monitoring [18,19]. Some wearable devices integrate multiple other data, including physical activity, dietary logs, and medication log data, to provide comprehensive prediction capabilities and glucose monitoring [20].

This review provides a systematic analysis of the current landscape of wearable devices for glucose monitoring and diabetes management, highlighting their benefits, limitations, and future potential. Special emphasis is placed on the transformative role of advancements in artificial intelligence (AI), advanced wearable technologies, and multi-omics data integration in shaping the future of glucose prediction and monitoring. By exploring emerging innovations, this review offers valuable insights into how these technologies are driving the development of more precise, personalized, and proactive solutions for enhanced diabetes care.

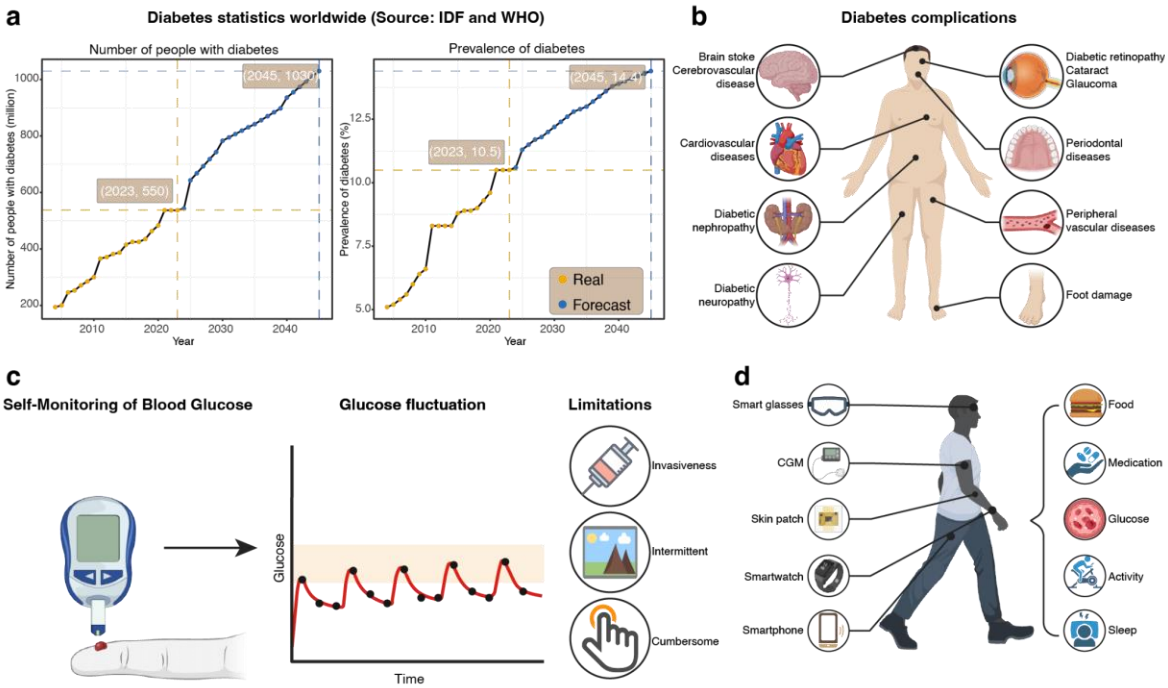

Figure 1. Diabetes demographics and the importance of effective diabetes management. (**a**) Global diabetes statistics: The left panel depicts the number of individuals with diabetes worldwide, while the right panel illustrates the prevalence of diabetes. Historical data is represented in orange, and future projections are shown in blue. (**b**) Long-term complications associated with diabetes affect multiple organ systems, including the heart, kidneys, eyes, and limbs. (**c**) Traditional self-monitoring of blood glucose through finger-prick blood sampling highlights its limitations in providing continuous glucose data. (**d**) Current advancements in wearable technologies for glucose monitoring and diabetes management showcase their potential to track physical activity, food intake, medication adherence, and glucose levels in real-time.

2. Glucose Monitoring in Diabetes

Effective glucose monitoring forms the cornerstone of diabetes management, enabling individuals to maintain glycemic control, minimize complications, and adapt treatment strategies dynamically [21]. Blood glucose levels fluctuate due to multiple factors, including food intake, physical activity, and medication intake [22,23]. Dynamic, real-time monitoring facilitates immediate adjustments to prevent potentially life-threatening episodes of hyperglycemia or hypoglycemia [24]. For patients with insulin-dependent diabetes, frequent self-monitoring has demonstrated significant improvements in metabolic control by enabling precise insulin adjustments and fostering a deeper understanding of glucose variability patterns [25,26]. Continuous Glucose Monitor (CGM) systems further enhance management capabilities by providing real-time data and trends, which is essential for implementing personalized treatment strategies [27].

Blood glucose regulation is influenced by several key factors:

1. **Genetic and environmental factors:** Individual genetic predisposition influences insulin sensitivity, while stress hormones, particularly cortisol, can significantly elevate glucose levels [28].
2. **Physical activity:** Exercise generally reduces blood glucose levels through enhanced insulin sensitivity and glucose uptake, though careful management is required to prevent exercise-induced hypoglycemia [29,30].
3. **Dietary intake:** Carbohydrate-rich meals typically lead to postprandial glucose spikes, while protein and fat content can modulate glycemic responses through different metabolic pathways [31,32].
4. **Medication:** Insulin and oral hypoglycemic agents directly affect glucose metabolism, while other medications may have secondary impacts on glycemic control [5].

Modern wearable devices employ two distinct approaches for glucose monitoring. The first category comprises devices that directly detect glucose levels in interstitial fluid, sweat, or blood through biosensors [33]. The second category includes devices that predict glucose levels by analyzing the correlated factors we mentioned above. These wearables monitor various physiological parameters, such as heart rate, physical activity, skin temperature, food/medication intake, and stress levels to estimate glucose trends (Figure 1d) [34–38]. Stress, a critical factor influencing glucose variability through its effects on cortisol secretion and insulin sensitivity, can be monitored using wearable sensors that track heart rate variability (HRV) or galvanic skin response (GSR) [16,39]. Advanced machine learning models enhance the predictive accuracy of these systems, potentially reducing the frequency of direct glucose sampling to minimize the discomfort associated with invasive sampling methods [40].

The integration of these monitoring technologies into broader digital health ecosystems enables comprehensive remote monitoring and timely interventions [26]. This dual approach, combining direct measurement and predictive monitoring methods, represents the current state-of-the-art in glucose monitoring and diabetes management, offering personalized and proactive solutions for both patients and healthcare providers. The following sections provide a systematic review of these wearable technologies, examining their applications in glucose monitoring.

3. Wearable Devices in Physical Activity Monitoring

Physical activity represents a critical determinant of glucose metabolism, directly influencing insulin sensitivity and glucose uptake in skeletal muscle tissues [41,42]. Regular physical activity strongly correlates with improved glycemic control and reduced risk of diabetes-related complications [43]. Conversely, sedentary behavior can exacerbate insulin resistance and increase glycemic variability [44].

Modern wearable devices, particularly smartwatches and fitness trackers, have become indispensable tools for physical activity monitoring (Figure 2a) [45]. These devices incorporate multiple sensors, including accelerometers, heart rate monitors, and gyroscopes, to provide comprehensive real-time data on steps taken, calories expended, and activity intensity levels (Figure 2a) [46]. The integration of these devices with mobile health platforms enables continuous monitoring and feedback mechanisms, empowering patients with actionable insights into their physical activity and their relationship to glycemic control [47].

In diabetes management, wearable devices for physical activity monitoring serve several crucial functions:

1. **Exercise plan customization:** Devices help optimize activity timing and intensity based on individual glucose responses [21,48].
2. **Glycemic fluctuation management:** Real-time activity data enables better prediction and prevention of exercise-induced glycemic variations.
3. **Insulin sensitivity enhancement:** Continuous monitoring helps track improvements in insulin sensitivity related to regular physical activity.

Fitness trackers integrated with smartphone applications have demonstrated significant benefits in enhancing patient adherence to activity goals and improving self-management practices [49]. These devices also contribute substantially to glucose prediction capabilities. Through continuous monitoring of physical activity, heart rate, and other physiological markers, these devices generate valuable data that can be analyzed with CGM readings [50,51].

The role of wearable devices in physical activity monitoring extends beyond simple step counting or calorie tracking. These technologies have become integral components of comprehensive diabetes management systems, providing valuable data for both immediate decision-making and long-term care optimization. As these technologies continue to evolve, their integration with other monitoring systems promises increasingly sophisticated and personalized approaches to diabetes management.

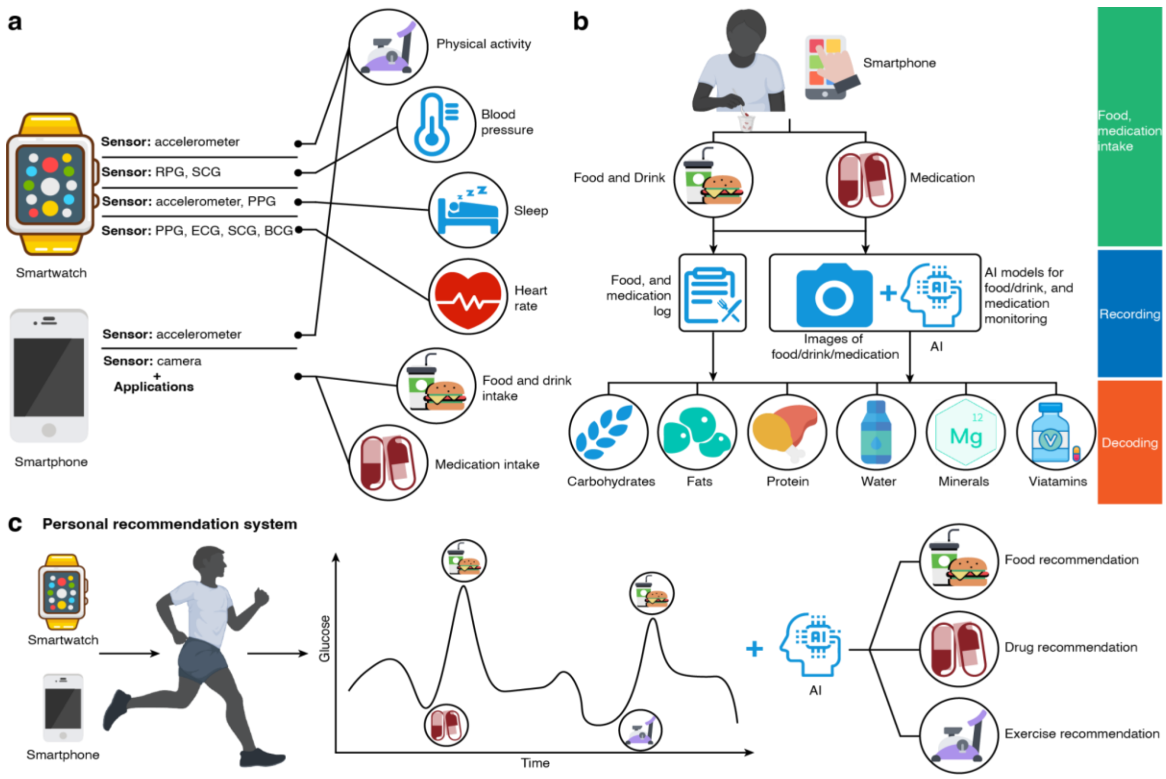

Figure 2. Wearable devices for monitoring physical activity, food, and medication in diabetes management. (**a**) Smartwatches and smartphones equipped with various sensors can monitor key health parameters, including physical activity, blood pressure, sleep, heart rate, food intake, and medication usage. RPG: Respiratory Plethysmogram; SCG: Seismocardiogram; PPG: Photoplethysmogram; ECG: Electrocardiogram; BCG Ballistocardiogram. (**b**) Smartphones with integrated cameras facilitate food and medication monitoring by enabling users to record and analyze their intake. (**c**) By combining data from physical activity, food, and medication monitoring with glucose levels, AI-powered systems can provide personalized recommendations for diet, medication, and exercise, enhancing diabetes management.

4. Wearable Devices in Food and Medication Monitoring

Food and medication intake monitoring represents a critical component of effective diabetes management, as these factors significantly influence glucose dynamics and therapeutic outcomes [52,53]. The accurate tracking and analysis of food and medication intake are essential for optimizing glycemic control, particularly given their complex interactions with glucose metabolism (Figure 2a) [54]. Modern wearable devices and their integrated applications offer innovative approaches to monitoring these crucial variables, enabling more precise and personalized management strategies (Figure 2a) [55].

Recent technological advancements have led to the development of sophisticated devices and applications for recording and analyzing food and medication intake. Smartphones equipped with cameras and specialized applications have become powerful tools for semi-automated food recognition and nutritional analysis [56]. Currently, two primary methods are used to monitor food and medication via smartphones. The first is the manual method, where users manually record the type and quantity of food they consume daily (Figure 2b). The second is a semi-automated approach, where users take pictures of their meals and beverages. These images are then processed by AI-powered systems to identify food items and estimate portion sizes (Figure 2b) [46]. Advanced mobile applications further enhance these functionalities by incorporating machine learning algorithms for semi-automated meal logging, as well as features for medication scheduling and adherence tracking (Figure 2b) [57,58].

The integration of food and medication monitoring data with CGM systems enables sophisticated predictive analytics capabilities. Machine learning algorithms analyze complex patterns in dietary responses and medication effectiveness, generating personalized recommendations for meal choices and medication timing. This integration supports more precise insulin dosing decisions and helps optimize overall glycemic control [59].

The convergence of food and medication monitoring technologies with broader diabetes management systems represents a significant advancement in personalized care. These integrated platforms combine dietary and pharmacological data with glucose monitoring insights to optimize therapeutic regimens and improve medication adherence. Advanced analytical capabilities powered by machine learning algorithms provide predictive analytics for glucose responses and real-time decision support for both patients and healthcare providers (Figure 2c) [60].

In conclusion, wearable devices for food and medication monitoring are transforming diabetes management through enhanced precision and personalization. By enabling accurate tracking and predictive analytics, these technologies empower both patients and healthcare providers to achieve better glycemic control and improve overall treatment outcomes.

5. Wearable Devices in Direct Glucose Monitoring

Direct glucose monitoring technologies have witnessed remarkable advancements in recent years, with wearable devices becoming fundamental to modern diabetes management [60]. The evolution of these technologies spans a spectrum from traditional CGM systems to innovative non-invasive monitoring solutions, including smartwatches and sweat-based sensors, each offering unique advantages and capabilities [61].

CGM systems remain the gold standard for real-time glucose monitoring in clinical practice. These devices utilize minimally invasive sensors inserted subcutaneously to measure glucose levels continuously in interstitial fluid (Figure 3a). The ability to provide real-time data enables users to track glucose trends and predict potential fluctuations, allowing dynamic therapy adjustments. Clinical studies have demonstrated that CGM systems significantly improve glycemic control while reducing the frequency of hypoglycemic and hyperglycemic episodes, making them invaluable tools for diabetes management [59].

The integration of glucose detection capabilities into smartwatches represents a significant advancement toward non-invasive glucose monitoring (Figure 3b). Unlike traditional CGM systems, smartwatch-based monitors employ optical or bioimpedance sensors to estimate glucose levels without penetrating the skin (Figure 3b) [62]. These devices analyze various physiological parameters, including heart rate variability, blood flow patterns, and skin characteristics, to infer glucose concentrations [63–65]. While this technology shows promise in increasing accessibility and user compliance due to its non-invasive nature, ongoing research continues to focus on improving measurement accuracy and reliability [66].

Emerging wearable technologies include innovative systems for measuring glucose levels through sweat analysis (Figure 3c) [18,67]. Stretchable sweat sensors represent a novel approach to glucose monitoring, leveraging the biochemical relationship between sweat and blood glucose levels (Figure 3c). These devices incorporate advanced materials and microfluidic technologies to create flexible, comfortable monitoring solutions that integrate seamlessly into daily life. The development of these sensors focuses on achieving accurate, continuous monitoring while maintaining user comfort and device durability [68].

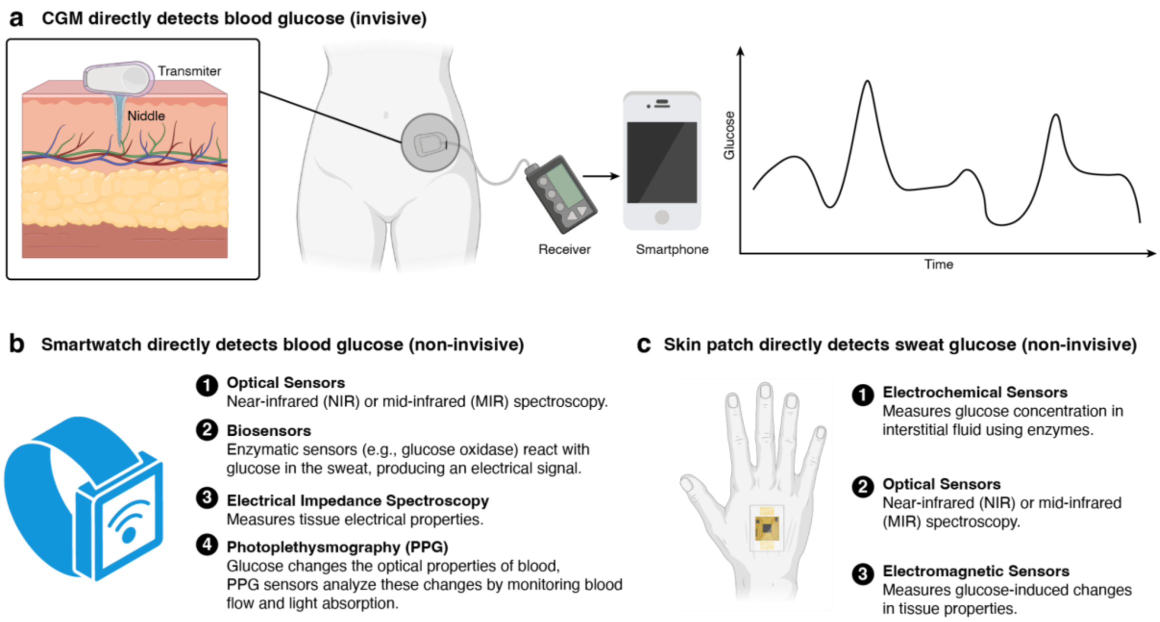

Figure 3. Wearable devices for direct glucose monitoring. (**a**) CGM systems directly measure blood glucose levels using sensors inserted beneath the skin. These systems continuously track glucose levels and transmit the data to connected devices for real-time monitoring. CGM: continuous glucose monitoring. (**b**) Smartwatches are equipped with sensors based on various principles to directly measure blood glucose levels. (**c**) Similarly, skin

patches can detect glucose levels in sweat, utilizing different sensor technologies to provide non-invasive glucose monitoring.

Currently, non-invasive methods such as smartwatch-based and sweat-based glucose monitoring continue to gain attention from both researchers and users. These alternative technologies offer several potential advantages, including reduced physical discomfort, improved user compliance, and potentially lower long-term costs [19]. However, significant challenges remain in achieving accuracy and reliability comparable to established CGM systems [69].

6. Integration of Wearable Devices and AI

AI has emerged as a transformative force in diabetes management, offering sophisticated tools for glucose prediction and personalized therapy optimization. The integration of wearable devices with AI-driven algorithms creates a powerful platform capable of delivering real-time insights, improving glycemic control, and enhancing overall disease management outcomes [70].

AI technologies, such as machine learning (ML) and deep learning algorithms, have effectively predicted glucose fluctuations based on diverse physiological inputs. These algorithms analyze historical glucose data, meal timing, activity levels, and other contextual factors to forecast glycemic trends [39,71]. This predictive capability enables proactive interventions, such as insulin dosing or dietary adjustments, reducing the risk of hypoglycemia and hyperglycemia [37].

Wearable devices can generate much data on glucose levels, physical activity, heart rate, sleep, and food/medication log data. When integrated with AI systems, these data streams are transformed into actionable insights [72,73]. For instance, CGM data combined with AI can detect patterns and provide early warnings for glucose dysregulation, allowing users to adjust behaviour or therapy [59].

Combining wearable devices and AI has revolutionized diabetes monitoring by delivering personalized, adaptive care solutions. For example:

Real-time feedback: AI algorithms analyze wearable data to provide real-time feedback on glucose trends and suggest behavioral or therapeutic modifications [74,75].

Predictive insights: AI systems predict glucose excursions based on historical and contextual data, helping users prevent adverse events.

Automated decision support: Integrated AI systems support decision-making by recommending insulin doses, meal adjustments, or activity changes, reducing the cognitive burden on patients [76].

In conclusion, integrating wearable devices and AI represents a paradigm shift in diabetes management. By harnessing the power of real-time data and predictive analytics, these systems promise to transform patient care, offering a future of more precise, personalized, and effective diabetes management solutions.

7. Integration of Wearable Devices with Omics Data

Integrating wearable devices with omics data (genomics, proteomics, metabolomics, and the gut microbiome) offers a revolutionary approach to diabetes management. By combining physiological data from wearable devices with molecular insights, this paradigm enables a comprehensive and personalized understanding of glucose metabolism and overall health [77]. This integration can provide personalized precision diagnosis and treatment by identifying patient-specific glucose regulation pathways and biomarkers associated with diabetes complications [78]. For example, integrating CGM data with metabolomics profiles may reveal biomarkers for early diabetic complications, while microbiome analyses combined with dietary intake data from wearable devices can predict glucose responses to specific foods [79,80]. AI algorithms, such as machine learning and deep learning, play a pivotal role in this integration. For instance, supervised learning models like random forests and support vector machines have been utilized to correlate multi-omics data with glucose variability, enabling personalized dietary or pharmacological recommendations [81,82]. Additionally, deep learning frameworks, such as convolutional neural networks (CNNs), can process high-dimensional omics data to identify complex interactions between physiological and molecular parameters [83]. Genetic background plays a significant role in glucose metabolism and the development of diabetes [84]. Advances in genomics have identified numerous genetic variants associated with insulin resistance, beta-cell dysfunction, and other diabetes-related traits [85]. By integrating genetic data with wearable devices, researchers and clinicians can predict individual responses to food/medication intake and physical activity, tailoring diabetes interventions to each patient's genetic profile [86].

The gut microbiome influences glucose regulation and metabolic health, with dysbiosis linked to insulin resistance and inflammation [87]. Wearable devices can track food/medication intake, physical activity, and glucose levels, while microbiome analyses provide insights into how these factors interact with gut health. For instance, machine learning models integrating microbiome data with wearable device metrics can predict glucose responses to specific meals, enabling personalized food recommendations [78].

Proteomics and metabolomics reveal real-time biochemical changes in response to physiological and environmental factors. By integrating data from wearable devices, such as CGMs or sweat sensors, with metabolomic profiles, clinicians can track dynamic glucose regulation pathways and identify biomarkers for early diabetes complications [88]. This approach supports predictive modeling and therapeutic optimization [89].

In conclusion, combining wearable device data with omics insights represents a pivotal advancement in diabetes management. This integrative approach holds the promise of enabling precision medicine, fostering proactive care, and improving outcomes for individuals living with diabetes.

8. Limitations of Current Wearable Devices

Despite the significant advancements in wearable technologies for glucose monitoring and diabetes management, several limitations hinder their universal adoption and efficacy (Figure 4a). These challenges span various aspects, including invasiveness, accuracy, usability, and cost.

Invasiveness and user comfort: CGM systems, though revolutionary, often require minimally invasive methods such as subcutaneous sensor placement. Users may experience discomfort, skin irritation, or allergic reactions [16,90]. This invasiveness can deter long-term adherence and limit the usability of CGM devices for some individuals [91].

Accuracy and reliability: Non-invasive devices like smartwatches and sweat-based glucose monitors face challenges in achieving the accuracy of invasive systems. Environmental factors such as temperature, humidity, and sweat composition can affect measurements [19,92]. For example, sweat-based glucose sensors might not consistently correlate with blood glucose levels, leading to discrepancies and potential mismanagement [68]. Smartwatches that estimate glucose using optical sensors or bioimpedance also struggle with accuracy, as individual skin properties and external light conditions influence these methods [93].

Expense and accessibility: Many wearable devices, especially CGMs and advanced smartwatches, are cost-prohibitive for a large segment of the population [94]. The high upfront cost of devices, coupled with recurring expenses for sensors and maintenance, creates barriers to access [60]. In low-income and middle-income countries, this issue is exacerbated by limited healthcare coverage and infrastructure [46].

User behavior and engagement: User compliance is a critical limitation for wearable devices that require active input, such as smartphones, for logging food and medication intake. Forgetting to capture images of meals or record medication usage is common, reducing the effectiveness of these tools [95,96]. Additionally, cultural practices can complicate accurate data collection. For instance, in cultures where meals are often shared, such as in Chinese family or communal dining settings, it is challenging to determine individual food consumption from shared dishes. Even when images of meals are taken, the portions consumed by the individual remain unclear, leading to potential errors in dietary analysis [97].

Integration challenges: Integrating data from multiple wearable devices remains a technical and logistical challenge. For example, combining data from CGMs, activity monitors, and food logs into a cohesive system often requires third-party platforms. These integrations may not always function seamlessly, leading to fragmented insights and reduced utility [98].

In conclusion, while wearable devices have significantly advanced diabetes management, overcoming their current limitations is crucial for their widespread and equitable use. Future innovations must prioritize user comfort, accuracy, affordability, and cultural adaptability to achieve their full potential in diabetes care.

9. Future Perspectives

Integrating wearable technologies, AI, and multi-source data holds unprecedented promise for transforming diabetes management. Emerging tools, such as smart glasses, advanced AI models including large language models (LLMs), and seamless data fusion from multiple devices, are poised to enable a new era of precision glucose monitoring and personalized care.

Comprehensive data integration for glucose and diabetes biomarkers: Current wearable technologies primarily focus on glucose monitoring and related physiological parameters. Future systems should integrate additional diabetes biomarkers such as insulin levels, ketones, and inflammatory markers, creating a comprehensive profile of an individual’s metabolic state. By combining data from multiple sources, including smart glasses, smartphones, and smartwatches, these platforms can offer an unparalleled understanding of the complex interactions affecting glucose dynamics [89].

Smart glasses for food and medication monitoring: Smart glasses are becoming increasingly accessible and functional, with the capability to record high-resolution videos of food and medication intake [99]. When coupled with AI, these devices can autonomously detect the initiation of eating or medication intake, triggering automatic recording without user intervention. This capability ensures comprehensive tracking of dietary habits and medication adherence. However, limited battery life, around 3–4 h for many models, remains a challenge for long-term usability [100]. Future solutions could include higher-capacity batteries, energy-efficient hardware, and modular designs for battery swaps or external power integration, enhancing the practicality of smart glasses for continuous monitoring [70,94]. The AI can analyze video data to identify the types and quantities of food intake, considering contextual factors like shared meals or leftovers, which are particularly relevant in communal dining cultures (Figure 4b).

AI and LLM integration in wearable ecosystems: Including AI and LLMs enhances the capability of wearable devices to analyze complex, multi-modal datasets. These models can:

1. **Real-time glucose estimation:** Integrate data from smart glasses, wearables, and environmental sensors to estimate glucose levels dynamically and with high accuracy.
2. **Personalized food recommendations:** Provide tailored dietary guidance based on historical data, real-time analysis, and predictive modeling.
3. **Immediate warnings:** Alert users to potential adverse glucose responses to specific foods or activities, supporting informed decision-making [59]. For example, smart glasses integrated with LLMs can recognize a meal's composition from video input, calculate its macronutrient and glycemic load, and cross-reference this information with the user's glucose trends to provide personalized feedback in real-time.

Seamless integration of devices: Future systems will integrate data from multiple wearable devices, including smart glasses, smartphones, and smartwatches, creating a unified platform for real-time monitoring and analysis. These devices can collectively track food and medication intake, physical activity, heart rate, body temperature, and sleep patterns, offering a holistic view of an individual's health (Figure 4c).

Real-time analytics and decision support: The combination of wearable data and AI enables systems that not only monitor but also predict glucose fluctuations.

Integrating smart glasses, wearable devices, and AI represents a paradigm shift in diabetes management. By combining diverse data streams with powerful analytics, these systems have the potential to deliver unprecedented levels of personalization and precision in care. With continued advancements, wearable ecosystems will not only monitor and predict glucose trends but also empower individuals with the tools and insights needed to manage their diabetes more effectively and proactively (Figure 4d). This vision promises to improve the quality of life and health outcomes for millions of individuals with diabetes worldwide.

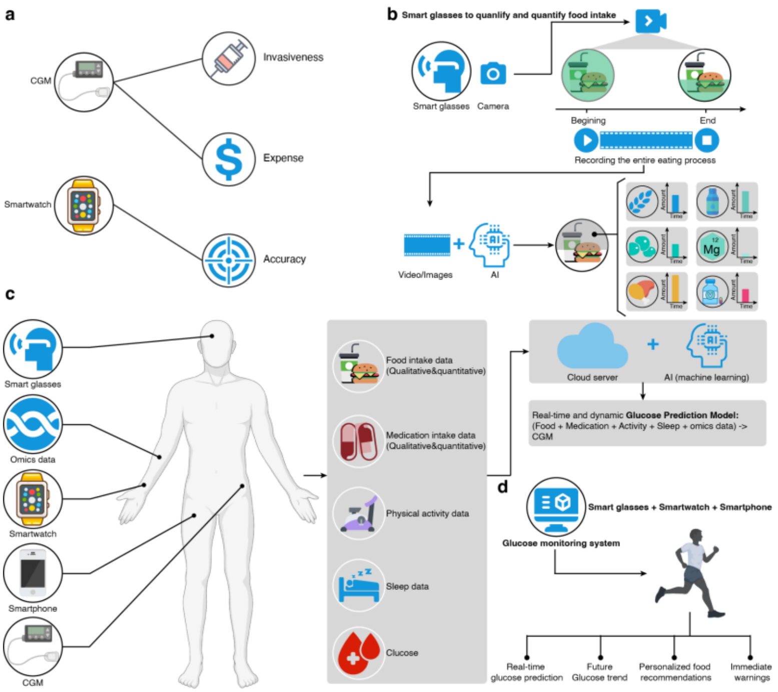

Figure 4. Future perspectives in glucose monitoring and diabetes management. (**a**) Limitations of current CGM systems, including invasiveness and cost, highlight the need for alternative solutions. CGM: continuous

glucose monitoring. (**b**) Smart glasses represent a promising tool for the quantification and qualification of food and medication intake, providing a novel approach to monitor dietary and medication habits. (**c**) By integrating data from various wearable devices, including physical activity, sleep, food, and medication tracking, a comprehensive non-invasive glucose monitoring system can be developed. (**d**) Such a non-invasive glucose monitoring system holds significant potential for future diabetes management, enabling real-time, dynamic, and personalized care.

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