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Review

The Role of Information Management-Based Blood Glucose Management Pathways in Improving the Diagnostic Rate of Newly Diagnosed Diabetes Patients

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Abstract

The global prevalence of diabetes mellitus (DM) continues to rise, with type 1 diabetes mellitus (T1DM) and type 2 diabetes mellitus (T2DM) being the most common subtypes. T1DM is characterised by the autoimmune destruction of pancreatic β-cells leading to absolute insulin deficiency, whereas T2DM is associated with insulin resistance and relative insulin insufficiency, often linked to lifestyle factors. Both subtypes are frequently misdiagnosed or underdiagnosed due to insufficient screening awareness, outdated diagnostic processes, and poor patient compliance, leading to delayed interventions and increased complication risks. This review examines information-management-based blood glucose control pathways, focusing on their role in improving the diagnostic rates of newly diagnosed T1DM and T2DM. It specifically examines the applications of key technologies: electronic health records (EHRs) for integrating multi-source data (e.g., autoantibodies for T1DM, metabolic indicators for T2DM), mobile health (mHealth) applications for real-time monitoring and targeted screening reminders, artificial intelligence (AI) for developing subtype-specific risk prediction models, Internet of Things (IoT) devices for capturing subtype-specific glycemic patterns, and blockchain for secure data sharing. Furthermore, the review describes how these technologies enhance early detection by optimising screening workflows, improving patient adherence, and facilitating accurate subtype differentiation. Despite demonstrated potential, challenges include data security, technological accessibility, and system interoperability. Future research should prioritise personalised pathways for each subtype, integrate multi-omics data, refine AI algorithms for subtype-specific diagnosis, and strengthen policy support to develop a precise, efficient early screening system for DM.

Keywords: health information management; blood glucose monitoring; diabetes mellitus; electronic health records; artificial intelligence

1. Introduction

Diabetes mellitus (DM) is increasing at an alarming rate globally and has become a significant public health concern. The 10th edition of the International Diabetes Federation (IDF) Diabetes Atlas reported that, in 2021, 537 million adults aged 20–79 years were living with DM, 43% of whom remained undiagnosed; this number is projected to approach 643 million by 2030, with the proportion of undiagnosed cases remaining high [1]. In China, a national cross-sectional study using the 2018 American Diabetes Association (ADA) diagnostic criteria found that the overall DM prevalence of 12.8% among adults aged $\geq$18 years between 2015 and 2017 [2]. However, awareness and treatment rates remain suboptimal: only 36.7% of those with DM knew of their condition and just 32.9% were receiving pharmacological therapy—leaving more than 80 million Chinese adults undiagnosed or untreated [3].

The World Health Organisation (WHO) classifies DM into four subtypes: type 1 diabetes mellitus (T1DM), type 2 diabetes mellitus (T2DM), gestational diabetes mellitus (GDM), and other specific types, each with distinct pathogenesis and clinical characteristics. T1DM is associated with autoimmune destruction of pancreatic islet β-cells and often presents with an acute onset, sometimes preceded by a brief period of non-specific early symptoms. T2DM is associated with insulin resistance and β-cell dysfunction, usually has an insidious onset, and is often accompanied by metabolic syndrome [4]. In both T1DM and T2DM, delayed diagnosis due to limited awareness of early manifestations and inadequate screening increases the risk of cardiovascular, renal, and retinal complications, thereby adding to the healthcare burden (Fig. 1).

Early detection and standardised protocol-driven management at the time of diagnosis are crucial. Research has shown that initiation of intensive glycemic control soon af-

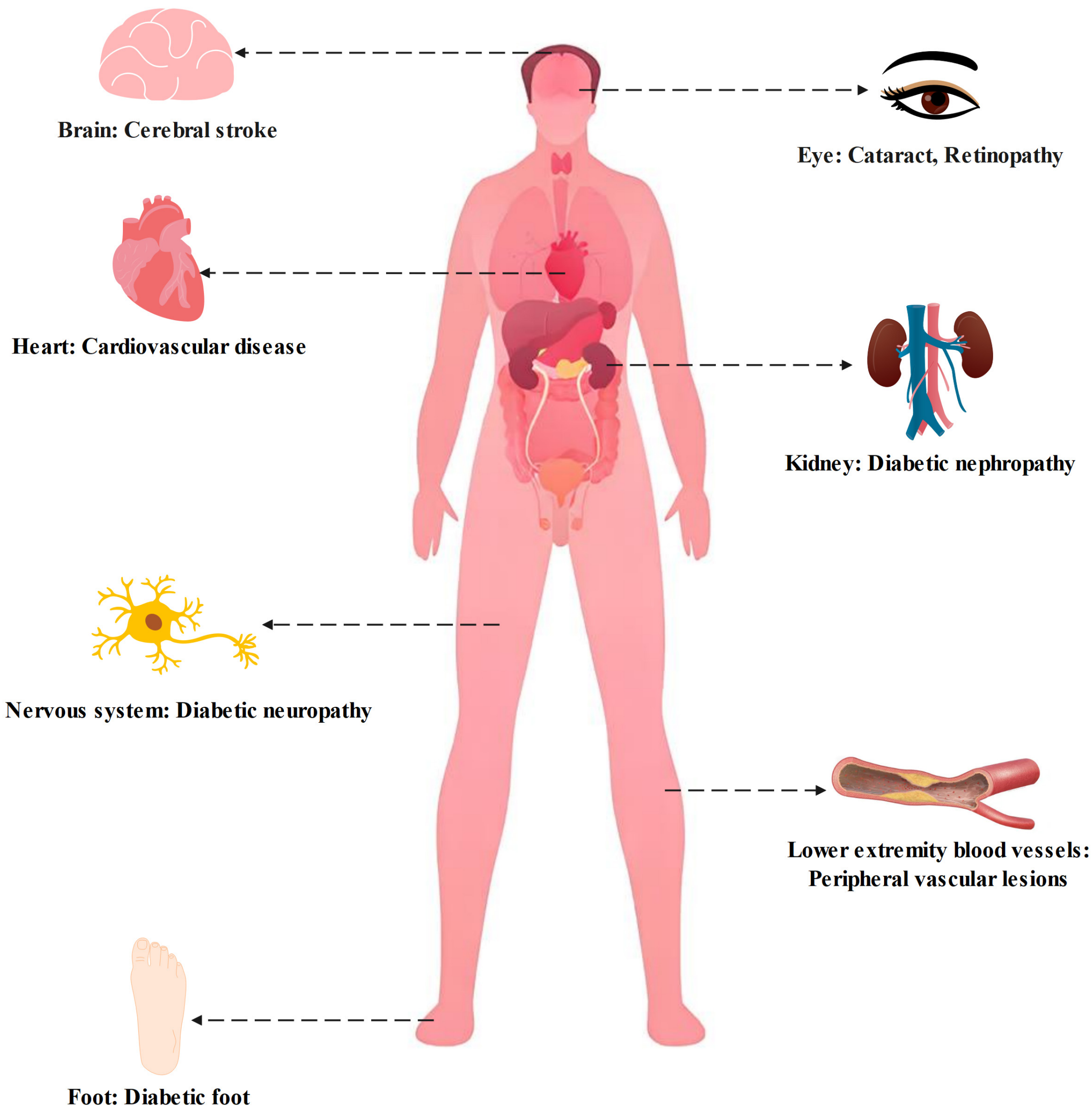

Fig. 1. Chronic complications of diabetes mellitus (DM). Figure created using EdrawMax software (Version 14.0.0, Wondershare Technology Co., Ltd., Changsha, China).

ter diagnosis significantly reduces the risk of complications [5]. Retrospective analyses of the hyperglycaemic legacy effect demonstrated that early intensive glycaemic management reduces the risk of combined microvascular complications by approximately 30%–50%, with the benefit persisting during follow-up [6]. Nevertheless, several barriers impede widespread early diagnosis and intervention (Fig. 2): (1) early hyperglycaemia usually presents with non-specific manifestations—such as mild fatigue or increased thirst—that patients may overlook or attribute to normal physiological variations [7]; (2) traditional diagnostic pathways rely on self-referral or self-initiated testing, lacking systematic, population-wide screening programs to proactively identify high-risk individuals [8]; (3) many primary and rural health facilities lack adequate infrastructure, point-of-care diagnostics, and trained healthcare professionals to support large-scale DM screening and follow-up; (4) public understanding of DM risks and the importance of long-term management remains insufficient, contributing to poor screening uptake and suboptimal treatment adherence [9]. Collectively, these obstacles contribute to persistently low diagnosis rates, underscoring the urgent need to develop more effective and proactive models for DM detection and management.

In this context, rapid developments in information management technologies present new opportunities to optimise DM diagnosis and treatment. An electronic health record (EHR) system integrates basic information, physical examination findings, laboratory test results, and follow-up records, enabling multi-source data integration [10]. Mobile health (mHealth) applications further enhance patient engagement by combining real-time glucose monitoring, automated lifestyle coaching, medication reminders, and secure patient-provider messaging, thereby improving self-

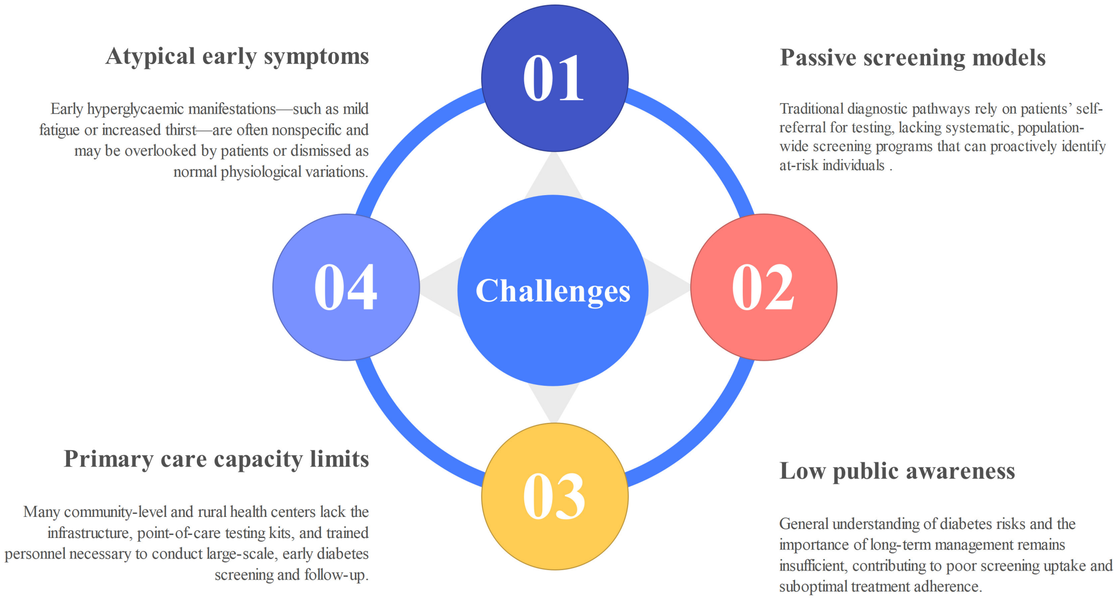

Fig. 2. Challenges in the diagnosis and management of DM. Figure created using EdrawMax software (Version 14.0.0, Wondershare Technology Co., Ltd., Changsha, China).

management adherence and glycemic outcomes [11,12]. In parallel, artificial intelligence (AI)–driven screening and risk-stratification models leverage machine-learning algorithms trained on large real-world datasets—often derived from EHRs and wearable devices—that can identify individuals at high risk for DM and its complications with greater accuracy than conventional methods [13]. Expanding this combination, Jacoba *et al.* [14] applied artificial intelligence (AI) and EHR to personalised biomarker identification for predicting diabetic retinopathy (DR) progression and improving diagnostic performance. Collectively, these information management technologies can optimise diagnostic workflows and enhance patient follow-up, helping to overcome limitations of the traditional diagnostic model and facilitate early detection and intervention of DM. This review aims to systematically summarise recent advances in information-management-based pathways for glycemic care in newly diagnosed diabetic patients, analysing their mechanisms of action, implementation outcomes, and key challenges, and translating these insights into evidence-based recommendations to further optimise DM management strategies. The central focus of this review is to explore how information management technologies can improve diagnostic rates, especially for T1DM and T2DM, by optimising screening, integrating multimodal diagnostic data, and enhancing the efficiency of patient-provider collaboration.

2. Overview of Information Management Technology

With advances in information technology, sophisticated information-management tools are being increasingly introduced into the healthcare system, especially for diagnosis and management, resulting in an intelligent, connected, and individualised care model. The next section systematically discusses the most commonly used information management technologies in DM diagnosis (Fig. 3), including EHRs, mHealth, AI, Internet of Things (IoT) devices, and blockchain technology, examining their functions, advantages, strengths, and implementation challenges. Furthermore, this section also explains and compares each technology across key dimensions, such as technical base, data types, target populations, advantages, and limitations (Table 1 (Ref. [15–22])), to elucidate their role in improving DM diagnostic outcomes.

2.1 EHR System

The EHR system is a digital repository that integrates multiple-source data, such as basic patient information (demographics), laboratory results (e.g., blood glucose, islet autoantibodies, blood lipids), medical history, and follow-up records, to support population-level screening for DM [23]. In practice, EHRs extract islet-autoantibody positivity indexes to detect T1DM, and compile body mass index (BMI) and metabolic-abnormality data to predict T2DM risk, helping clinicians distinguish between diabetes types and identify high-risk groups. Furthermore, role-based access for clinicians, nurses, pharmacists, and other medical professionals enables comprehensive, longitudinal decision support, significantly enhancing diagnostic accuracy and efficiency [24]. As a core component of medical informatics, EHR securely stores, manages, and shares patients' health data, providing essential technical infrastructure for modern medical services [25,26].

Table 1. Performance characteristics and application status of information management technology in diagnosis of DM.

Information management	Description	Technical basis	Data types	Target population	Advantages	Limitations	References
Electronic health record (EHR)	Electronically stored collection of patient health information	Digital storage and multi-source data integration technology	Basic information, medical history, laboratory tests, follow-up records	General population	● Cross-institutional data sharing. ● Easy to track medical history.	● Poor system interoperability. ● Lagging data update.	[15,16]
Mobile health (mHealth)	Collecting and managing health data with mobile devices, requires user participation in synchronisation	Mobile terminals + wireless communication technology	Real-time blood glucose, diet/exercise records, symptom feedback	Community population, high-risk groups for chronic diseases	● Real-time self-monitoring. ● Support for remote consultation.	● Easy to make mistakes in user input. ● Difficult to popularise for the elderly.	[17]
Artificial intelligence (AI)	Algorithms to analyse diabetes-related data	Machine-learning/deep-learning algorithms	Large-scale EHR data, wearable device data, imaging data	Patients with latent diabetes, high-risk groups for complications	● Accurately identify abnormalities. ● Optimise treatment plans.	● Dependent on data quality. ● Algorithms have the risk of bias.	[18,19]
Internet of Things (IoT) devices	Sensors and other real-time physiological data collection and transmission, no user operation required	Sensor + cloud data transmission technology	High-frequency physiological parameters such as blood glucose, heart rate, and activity level	Individuals requiring close monitoring of blood glucose fluctuations	● High-frequency monitoring of blood glucose to reduce human error.	● Expensive equipment. ● Data requires AI-assisted processing.	[20]
Blockchain technology	Distributed ledger to ensure data security and traceability	Distributed ledger + encryption algorithm	Privacy-sensitive data (e.g., genetic testing, Human Immunodeficiency Virus (HIV)-combined diabetes data)	Complex cases requiring cross-institutional collaborative diagnosis	● Protect privacy. ● Promote institutional collaboration.	● High implementation costs. ● Adaptive difficult to implement.	[21,22]

Notably, EHRs are widely used for DM glucose management due to their advantages in improving healthcare efficiency, quality, and safety, reducing healthcare costs, facilitating data sharing and team-based collaboration, thereby making personal health management easier for patients [15,27,28]. EHRs help doctors distinguish between T1DM and T2DM by integrating the age at onset, autoantibody test results, BMI, and other clinical data, thereby supporting accurate diagnosis. Based on EHR data, Zheng *et al.* [29] developed reinforcement learning (RL) prescribing for personalised DM and multimorbidity management; recommendations for T2DM were highly consistent with clinician decisions and enhanced glycemic control, blood pressure, and cardiovascular disease (CVD) risk outcomes. Using HER datasets, Zhou *et al.* [30] successfully constructed a multi-label classification (MLC) model that accurately predicted four types of diabetic complications. Similarly, Wang *et al.* [31] used EHRs to identify underlying predictors and develop a diabetic retinopathy (DR) risk-prediction tool that provides early warning signals and enhances adherence to early screening and prompt interventions.

Although EHRs show strong technological potential and clinical value for DM management, crucial limitations still persist, such as data privacy and security risks, insufficient interoperability, higher training and workflow-adaptation demands, and high initial costs [32–34]. In the future, it will combine with blockchain technology to build a new EHR framework driven by technological innovation, supported by standardisation and oriented by humanistic care [35]. It empowers patients with role-based access to their health records within authorised limits, fostering shared decision-making and enhancing their sense of autonomy over their health [36]. This narrows the information gap between patients and healthcare providers, reducing anxiety and uncertainty associated with medical care [37]. In summary, as the core support of health information management, EHRs provide a robust foundation for early screening and diagnosis of DM through multi-source data integration and intelligent risk assessment.

2.2 mHealth Technology

Built on mobile devices and wireless connectivity, mHealth technology collects real-time blood glucose data, diet/exercise logs, and symptom reports, and mainly serves high-risk community groups (e.g., those with obesity or a family history of DM) [38,39]. Its diagnostic value in diagnosis depends on targeted screening, which involves pushing reminders for regular blood glucose testing in high-risk T2DM cohorts and providing symptomatic self-screening tools, such as "polyuria or sudden weight loss" for suspected T1DM. As technology has advanced, many DM patients can view their blood glucose levels on smartphones or wearable devices, enabling prompt adjustment to their diet, exercise, and medications to effectively avoid adverse reactions such as excessive blood glucose fluctuations or hypoglycemia [40,41]. For T1DM patients, mHealth emphasises enhanced, real-time blood glucose monitoring to capture acute fluctuations, whereas for T2DM, it focuses on lifestyle-based screening reminders.

mHealth applications are usually paired with wearable devices, which use embedded sensors and wireless communication technology to collect and transmit data [42]. They synchronise data to the user's smartphone, deliver real-time feedback on blood sugar trends, and send relevant health reminders [42]. Zivkovic *et al.* [43] integrated an mHealth application into daily DM management, enabling real-time continuous glucose monitoring (rtCGM) and tracking on health data, and have been found to dramatically improve glycemic control in diabetes. In Chinese adults with T2DM, integrating implantable glucose sensors with a mHealth application led to significant reductions in BMI, fasting blood glucose (FBG), two-hour postprandial blood glucose (2hPG), and glycosylated haemoglobin (HbA1c), as well as better quality of life and self-management [44]. Similarly, a systematic review suggests that mHealth apps can improve health-related outcomes in GDM, especially glycemic control [45].

Despite its widespread benefits, mHealth technology faces significant limitations, notably utility barriers and data privacy issues, particularly among older patients [46]. Age-related declines in vision and hearing, along with lower technology acceptance, can prevent adoption of complex digital health management tools [47]. Expanding access for elderly patients to benefit from mHealth technology, related devices, and applications should be simpler and more user-friendly, with more intuitive interfaces and comprehensive training support [48]. With the digitisation of healthcare data, patients' personal information and health data need to be transmitted and stored over the Internet. Although most mHealth devices and apps adopt encryption technology to ensure data security, data privacy is still one of the most important concerns for patients [49,50]. Therefore, mHealth technology developers and healthcare providers must strengthen data security and implement effective technical measures to prevent unauthorised access or secondary use of patients' data. In summary, mHealth technology shows significant potential for diabetes management; by pairing mobile apps and wearable devices to deliver real-time blood glucose tracking and prompt health reminders, it enhances self-management and improves blood glucose control.

2.3 AI Technology

AI is a cutting-edge technology that integrates computer science, statistics, neuroscience, and other related disciplines [51]. Centered on machine-learning and deep-learning algorithms, AI analyses large-scale EHR data and wearable device datasets to support early identification of latent DM [52,53]. Machine-learning approaches train predictive models on larger datasets to uncover major features,

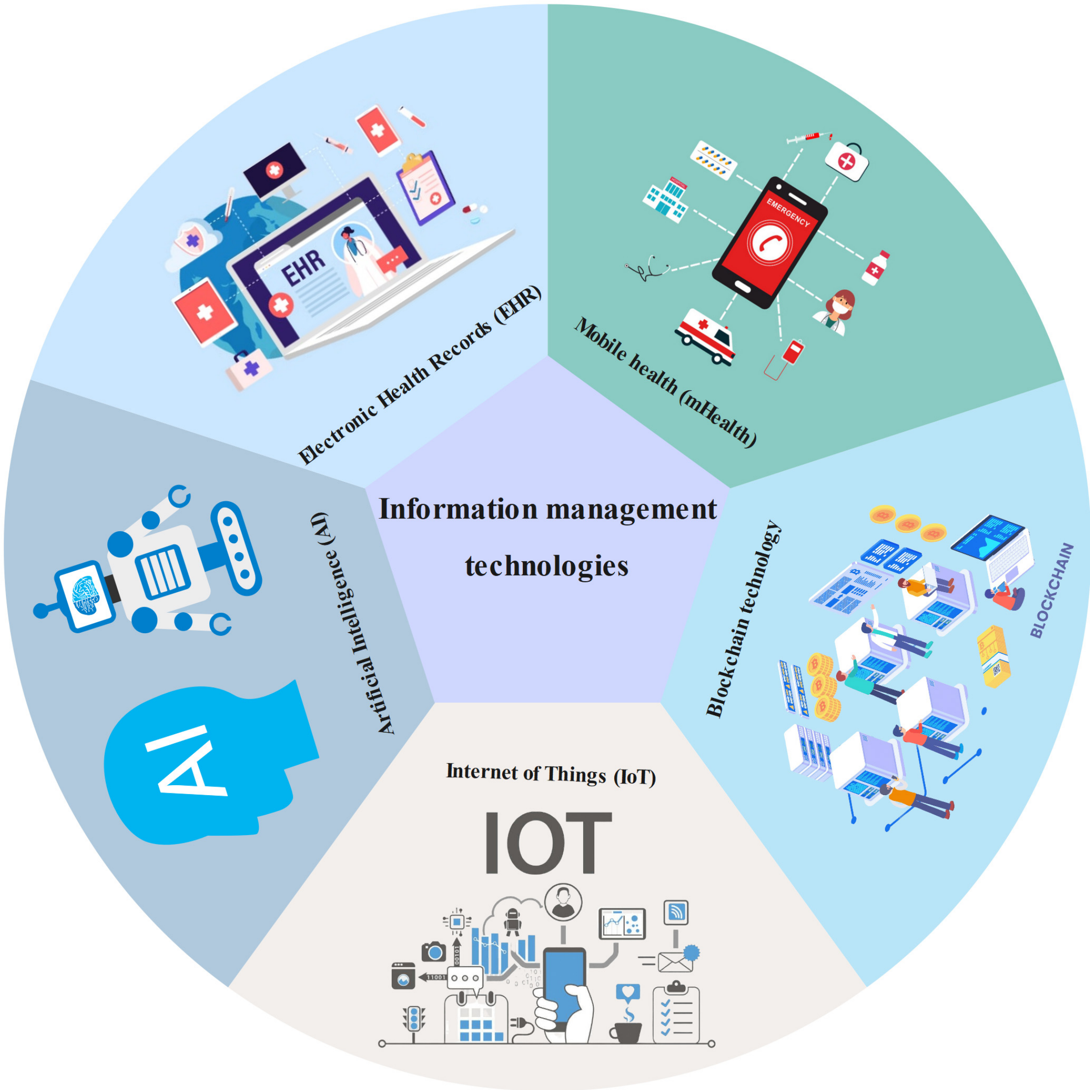

Fig. 3. Overview of information management technology. Figure created using EdrawMax software (Version 14.0.0, Wondershare Technology Co., Ltd., Changsha, China).

while deep learning is based on neural networks that simulate neuronal processing, automatically extract data features and offer significant outcomes in certain domains such as image recognition and natural language processing [52]. This technology can quickly ingest and interpret massive and complex data, and extract key signals and risk indicators efficiently.

AI technology has demonstrated significant advantages in DM management. It holds the high-throughput data processing capability to quickly analyse massive and complex data, such as blood glucose monitoring data, medical history records, and medication responses, to accurately extract key signals, including blood glucose fluctuation patterns and complication-risk indicators, providing a quantitative basis for clinical assessment [18,54,55]. An AI algorithm can optimise diagnostic models tailored to the autoimmune markers of T1DM and the metabolic syndrome indicators of T2DM, thereby improving the recognition accuracy of DM types. Several studies have highlighted these potentials: Ahmed *et al.* [56] estimated blood glucose levels (BGLs) using data from a non-invasive wearable device (WD). Wang *et al.* [57] proposed a reinforcement learning-based dynamic insulin titration regimen (RL-DITR) model to drive an optimal insulin regimen for T2DM to optimise glycemic control. Furthermore, Wolf *et al.* [58] performed autonomous AI diabetic eye assessments on adolescents and demonstrated that autonomous AI screening increases completion rate for diabetic eye examinations in youth.

While AI has demonstrated great potential in glucose management for DM, crucial limitations remain. The accuracy of an AI model depends on data quality; incomplete, noisy, or inaccurate data inputs can lead to errors and introduce bias [59]. Additionally, the limited interpretability of many AI models, such as the black-box nature of many models, makes their decision-making process difficult to understand, which can lead to a crisis of confidence in the healthcare field [60]. Overall, AI technology holds a broad application prospect in DM glucose management, and its advantages position it as a powerful tool for the prevention, diagnosis, and treatment. Deeper integration of AI into the healthcare system is expected to deliver more accurate, efficient, and personalised glucose management, thereby promoting DM prevention and treatment.

2.4 IoT Devices

The Internet of Things (IoT) connects various smart devices through a network, enabling them to automatically collect, exchange, and process data [61]. In DM care, sensor-equipped devices and cloud-based transmission technology collect high-frequency physiological parameters, such as blood glucose levels and activity, and are primarily useful for those who need close monitoring of blood glucose fluctuations (e.g., suspected T1DM). In diabetes management, IoT devices include blood glucose monitors, smart injection pens, health and fitness bands, and smart insulin pumps. These devices record blood glucose data in real-time and transmit data to cloud platforms or synchronise it with a clinician's smart system via a wireless network, enabling remote monitoring and immediate feedback. For example, a smart glucometer detects glucose levels and syncs with a smartphone app via Bluetooth or Wi-Fi, enabling patients and clinicians to view the data in real time. IoT devices help diabetic patients reduce clinic visits, improve compliance, and support accurate glucose control through real-time monitoring, personalised management, reminder functions, and telemonitoring, thereby providing more efficient health management. Zhu *et al.* [62] designed an Internet of Medical Things (IoMT)-enabled wearable device with an embedded model for real-time glucose prediction and hypoglycemia detection, which significantly reduces hypoglycemia and improves blood glucose (BG) control.

2.5 Blockchain Technology

Blockchain technology is a decentralised, distributed database technology characterised by data immutability, transparency, and traceability [63]. It is based on a distributed ledger with encryption algorithms, which enables secure sharing of privacy-sensitive data (e.g., genetic test results of T1DM patients, family history of T2DM). With rapid digitisation, its application in healthcare, particularly for diabetes blood glucose management, has gained widespread attention. By addressing the problems of secure storage, privacy protection, and data sharing, blockchain technology can provide a safer and more reliable platform for diabetes care [64]. Chen *et al.* [65] proposed a blockchain-enabled framework that uses various machine-learning classification algorithms for early detection of DM while securely maintaining patient health records. Similarly, Mussiry *et al.* [66] developed a blockchain-based IoT-EHR framework for diagnosing and monitoring DM, demonstrating significant enhancements in security and privacy for IoT-enabled EHR systems.

2.6 Information Management Technology Synergies

Within an intelligent DM-management ecosystem, five key technologies—EHR, IoT, mHealth, AI, and blockchain—collaborate seamlessly across the complete data-management chain: "collection → integration → analysis → application → security". The EHR serves as the standardised data hub, aggregating demographics, medical histories, and laboratory results to ensure consistency and traceability across downstream workflows [67]. IoT sensors capture high-frequency physiological parameters—such as continuous glucose levels and heart rate—in real-time, automatically transmitting these dynamic data streams into the EHR and filling the temporal gaps inherent in traditional record-keeping [68]. mHealth platforms directly engage patients to log their diet, exercise, and symptoms, synchronise these subjective inputs with the EHR and deliver tailored, system-generated feedback and lifestyle recommendations in accessible formats, fostering continuous two-way interaction [69].

Building on this comprehensive data foundation, AI leverages historical EHR records with real-time IoT and mHealth inputs to uncover latent patterns using machine-learning algorithms, yielding decision-support outputs such as risk stratification, subtype classification, and complication alerts [18]. These outputs are reintegrated back into the EHR to inform clinicians with personalised diagnostic and treatment guidance. In parallel, blockchain technology fortifies cross-institutional data exchange by encrypting EHR records, IoT time series, and AI-derived analytics, ensuring immutability and full audit trails as information flows securely among hospitals, departments, and community care centers [70].

Clinically, this integrated model demonstrates clear benefits. For high-risk DM screening, real-time glycemic fluctuation signals from IoT devices and lifestyle input data from mHealth are merged in the EHR and analysed by AI to generate individualised screening lists. Through blockchain-secured pathways, these lists reach community health centers, where primary-care providers consult each patient's comprehensive EHR history and use mHealth apps to send targeted screening reminders—thereby closing the loop from data capture to intervention and markedly improving screening efficiency and precision.

3. The Role of an Information Management-Based Glycemic Management Pathway in Improving DM Diagnosis Rates

The role of a glycemic management pathway based on information management in enhancing DM diagnosis rates is illustrated in Fig. 4.

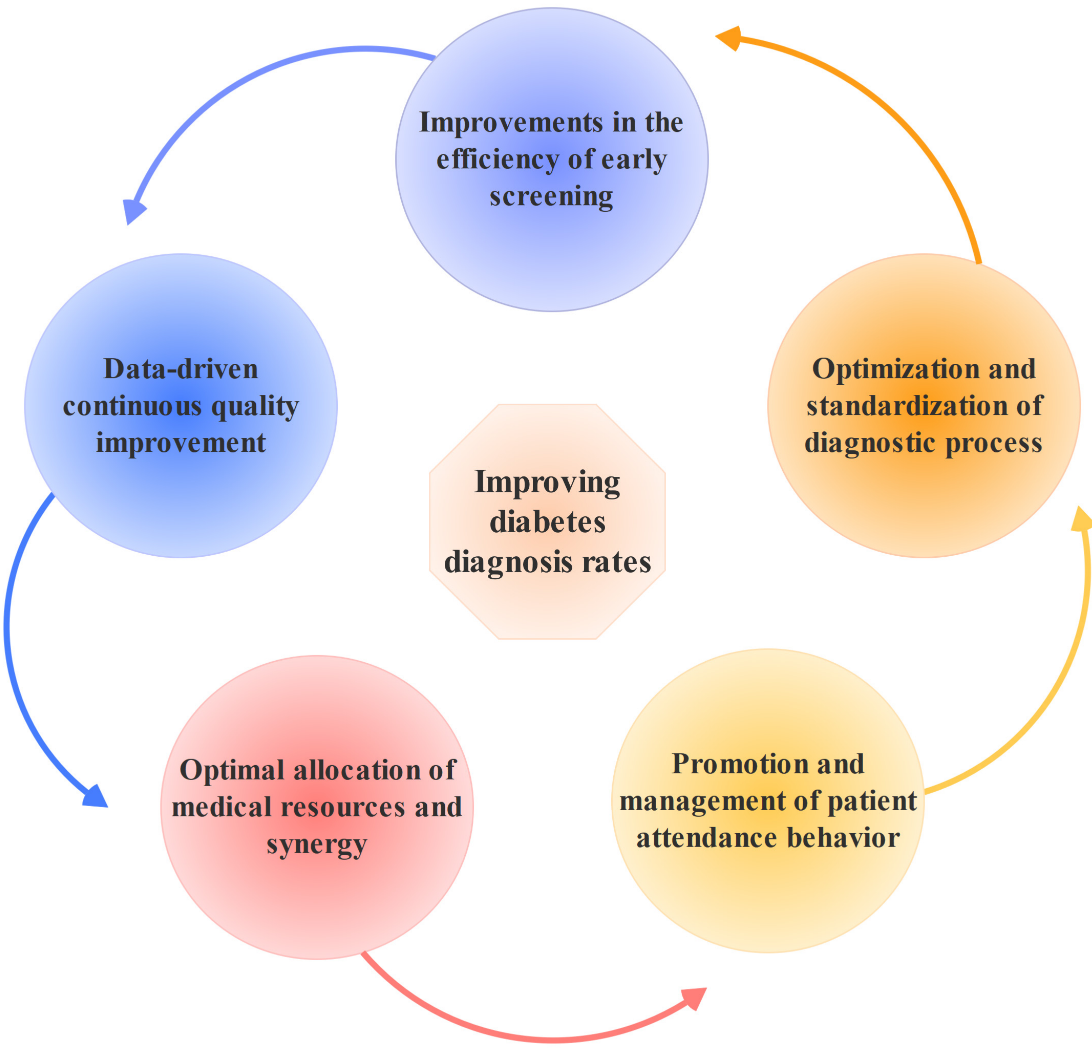

Fig. 4. The role of an information management-based glycemic management pathway in improving DM diagnosis rates. Figure created using EdrawMax software (Version 14.0.0, Wondershare Technology Co., Ltd., Changsha, China).

3.1 Improvements in the Efficiency of Early Screening

The information management-based blood glucose pathways significantly improve the efficiency and accuracy of early DM screening by integrating multi-source data and applying advanced risk assessment models, which is one of the key drivers of improved detection rates [71]. Traditional DM screening often adopts an opportunistic screening model, in which patients undergo blood glucose testing at the time of consultation, which is random and often misses asymptomatic cases [72]. Information management-based screening models, on the other hand, are much more efficient systems that proactively identify high-risk groups and target them for screening.

The EHR system automatically captures high-risk factors such as age, obesity and family history, and integrates data from multiple sources to generate accurate screening lists, thereby addressing the problem of randomness in traditional screening. AI technology analyses multi-dimensional data from EHRs and wearable devices, identifying potential populations (e.g., metabolic abnormality subclinical status) beyond traditional risk factors and expanding the scope of screening. mHealth technology provides screening reminders and facilitates easy appointments to high-risk populations through a mobile application, thereby improving screening compliance.

The role of information management technology in screening can be summarised as follows: (1) automatically captures high-risk groups, such as age ≥40 years, obesity, and family history of DM, through the EHR system, and generates targeted screening lists [73]; (2) applies artificial intelligence algorithms to multidimensional data to identify potential risk groups beyond traditional risk factors, thereby expanding the scope of screening; (3) pushes tailored screening reminders and scheduled appointments to high-risk users, improving screening adherence.

A recent study constructed and validated a “Dysglycemia Risk Score (D-RISK)” EHR-driven risk score among 11,387 adults in the Dallas area (mean age 48 years, 42% Hispanic), yielding an area under the receiver operating characteristic curve (AUC) of 0.75 and higher sensitivity than ADA and U.S. Preventive Services Task Force (USPSTF) criteria (75% vs. 61%) [74]. In a suburban U.S. primary-care clinic, embedding an EHR Clinical Decision Support System (CDSS) increased lab test ordering from 53% to 66% and completion from 46% to 54% [73].

3.2 Optimisation and Standardisation of the Diagnostic Process

The blood glucose management path based on information management improves diagnostic outcomes of DM by optimising and standardising diagnostic workflows, thereby reducing missed diagnoses and misclassifications. the traditional diagnosis process often has limitations of non-standard procedures and inconsistent criteria [75]. These challenges are predominant in the primary healthcare settings due to limited technology and equipment, which minimises the accuracy of diagnosis. In contrast, the diagnostic process based on an information-management system ensures standardisation and homogenization of the diagnostic procedure, thereby providing accurate identification. During an EHR-embedded system, standardised diagnostic steps are developed, automatically suggesting diagnostic workflow and reducing process deviations. In an AI technology-based support system, algorithms assist front-line healthcare providers in distinguishing T1DM from T2DM using antibody and metabolic data, helping to make up for the lack of technical capabilities. Additionally, a regional medical information exchange platform, which relies on EHR-based data sharing, enables teleconsultation and coordinated referrals between primary and tertiary healthcare settings, accelerating confirmation of complex cases.

Key measures in optimising diagnostic process include: (1) establishing standardised diagnostic workflow, such as adopting WHO-recommended diagnostic criteria with automated stepwise diagnostic prompts; (2) using artificial intelligence-assisted diagnostic tools to improve diagnostic accuracy in grassroot settings; and (3) facilitating data sharing between upper- and lower-level hospitals and remote consultation, to ensure timely referral and diagnosis of complex cases. Given the move towards standardised, staged assessments, the 2025 ADA "Standards of Care in Diabetes" recommends routine testing for glutamic acid decarboxylase antibody (GADAb), insulin autoantibodies, and related indicators in adults with suspected T1DM [76].

3.3 Promotion and Management of Patient Attendance Behaviour

The blood glucose management path based on an information-management system enhances diabetes diagnostics yield by standardising and streamlining processes, improving patient behaviour, increasing visit rates, and follow-up compliance, thereby reducing missed diagnoses and misclassification. In the early stage of DM, the absence of obvious symptoms and limited willingness to seek medical treatment result in a lower diagnosis rate [77]. Information management technologies stimulate patients' motivation to seek medical care by delivering personalised reminders, convenient services, and continuous education. mHealth apps provide personalised reminders (e.g., blood glucose testing, appointment scheduling) through mobile apps, as well as convenient services such as teleconsultations and online report access, thereby lowering hurdles to medical care. Integrated with EHR system records, these tools feedback patients' health data (e.g., blood glucose trends, complication-risk alerts), enabling patients to recognise risks and proactively seek medical attention [78].

Patient engagement in care is enhanced through the following four mechanisms: (1) personalised health reminders, such as blood glucose testing, physical examination, and clinical appointments, are pushed through mobile apps, text messages, and other means; (2) convenient online medical services, such as online consultation, examination appointment, report inquiry reduce barriers to seeking medical care; (3) the ongoing tailored health education, improves diabetes awareness and enhances sense of responsibility for self-care; (4) data-driven feedback through information systems records and displays individual trends like glycemic patterns and complication risks, enabling patients to recognise risk and actively seek medical help.

A randomised clinical trial (RCT) of 221 African-American and Latino patients with T2DM showed that a mobile health intervention integrating pharmacists and health coaches decreased HbA1c by a mean of 0.79 vs. 0.24 percentage points ($p < 0.001$) and achieved a 77% follow-up completion rate [79]. A systematic review of nine RCTs (follow-up 3 to 12 months) reported that text-message reminders enhanced medication adherence over usual care (standardised mean difference [SMD] 0.36; 95% confidence interval [CI]: 0.14–0.59) [80].

3.4 Optimal Allocation of Medical Resources and Synergy

Information-management-based blood glucose pathways improve accessibility and efficiency of DM diagnosis by optimising resource allocation and strengthening the cooperation between different medical institutions, which is also one of the key drivers of higher diagnosis rates. Under the traditional medical models, uneven distribution and poor coordination of medical resources, especially in primary and rural healthcare settings, limit large-scale screening and reduce diagnostic accuracy [81]. Applying an information-management-based system helps overcome geographical barriers, optimise the allocation of medical resources and facilitate cross-institutional collaboration. The remote consultation system (combined with real-time mHealth data) links patients to tertiary-care expertise, improving diagnostic accuracy. An AI-assisted diagnostic system augments frontline diagnostic capability, and an EHR system unifies resource allocation and optimises appointment scheduling while enabling a two-way referral mechanism and hierarchical diagnostic care.

However, resource optimisation is mainly reflected in: (1) remote consultation that deliver expertise input to primary and rural healthcare settings; (2) artificial intelligence assisted diagnostic tools that compensate for insufficient diagnostic capabilities; (3) unified, information-system scheduling, such as rational allocation of blood glucose-testing equipment and optimisation of examination appointment processes; and (4) two-way referral mechanism that promptly refer suspected cases to higher-level hospitals and return confirmed cases to the grass-roots level for ongoing management and treatment. A systematic review found that teleconsultation-based provider-to-provider telehealth significantly improves access and management outcomes in rural areas [82].

3.5 Data-Driven Continuous Quality Improvement

The blood glucose management path based on information management is data-driven, enabling continuous analysis and feedback to optimise management strategies and processes, ultimately increasing diabetes diagnostic outcomes [83]. Conversely, traditional management models often lack systematic data analysis and feedback loops, making it difficult to detect and correct management process gaps. The information management technology can collect and analyse a large amount of management data in real-time, providing a rigorous basis for quality improvement. EHR systems track key indicators, such as diagnosis rate and screening coverage rate, and monitor the completion situation in real time. AI technology analyses root causes of performance reductions (e.g., low regional screening linked to insufficient mHealth outreach) and guides improvement measures.

Data-driven quality improvement mainly includes the following steps: (1) establishing a comprehensive quality management indicator system, such as diagnosis rate, screening coverage rate, patient satisfaction, etc.; (2) monitoring the completion status of various indicators in real time through information systems and detecting deviations in a timely manner; (3) root-cause analysis of gaps and deviations, such as suboptimal screening processes and low patient compliance; (4) developing targeted improvement measures and tracking their implementation; and (5) regular evaluation to form a continuous improvement loop. A long-term follow-up study (longitudinal epidemiologic assessment of diabetes risk [LEADR]) using a 1.4 million patient EHR cohort (2010–2016) enabled dynamic monitoring of DM risk factors and assessment of interventions, providing large-scale, real-world evidence to guide continuous strategy optimisation [84].

4. Application of Information Management in Blood Glucose Management of DM

Effective blood glucose management is crucial for delaying the occurrence and development of diabetes complications and improving patients' quality of life. Utilising efficient data processing, real-time information sharing, and accurate predictive analytics, information management technology provides a new approach to diabetic blood glucose management. A systematic and intelligent management pathway enables end-to-end and personalised management, such as from diagnosis and treatment through day-to-day monitoring, significantly improving health status. Table 2 (Ref. [29,62,66,85–91]) summarises some applications of information-based management in DM glucose management. For example, Makroum *et al.* [92] reported that wearable devices can assist in patient management, prevent related complications, and improve disease control and quality of life. Using EHR data, researchers developed a DM screening tool that combines medication records, diagnostic information, and traditional predictors, which were analysed via multivariate logistic regression models [85]. A meta-analysis of randomised controlled trials (RCTs) revealed that mobile application interventions substantially enhanced medication adherence (odds ratio [OR] = 2.371, SMD = 0.279) [86].

5. Challenges and Limitations

This study encountered multiple limitations and challenges in exploring information-management-based glycemic pathways to improve the diagnosis rate among newly diagnosed diabetic patients. At the level of technology application, despite their ability to integrate data from multiple sources, EHRs are hampered by poor system interoperability and delayed data updates, coupled with privacy and security risks, significant training and procedure adaptation demands, and high initial investment costs. Collectively, these factors limit widespread adoption, especially in primary and grassroots healthcare settings.

mHealth technology often relies on user-initiated data input, which is prone to human error. Adoption among elderly adults is further limited due to low technology acceptance and age-related declines, while the privacy and security issues in data transmission and storage need to be resolved urgently [93]. Notably, the cost burden of mHealth devices (e.g., wearable monitors, smart glucose meters) and associated services (e.g., data subscriptions) can impose additional economic pressure on patients, especially for those with low socioeconomic status [94]. This could directly reduce their willingness to adopt these tools, thereby undermining adherence to screening and long-term management compliance.

Although AI technology can accurately identify data anomalies, its performance depends on data quality. Incomplete or inaccurate inputs can lead to algorithmic bias, and

Table 2. Representative applications of information management in blood glucose management of DM.

Research types	Information management technologies	Results	References
Meta-analysis	mHealth	Digital health intervention group participants had a –0.30-percentage point greater reduction in HbA1c, compared with control group participants.	[87]
Research	mHealth, AI	The well-trained models can be implemented in smartphone apps to improve glycemic control by enabling proactive actions through real-time glucose alerts.	[88]
Research	IoMT	Significantly reduced hypoglycemia and improved BG control.	[62]
Research	AI	A support vector machine was successfully developed for diabetes risk prediction.	[89]
Review	AI	Proposed a novel approach to diabetes management by leveraging deep-learning algorithms for CGM data analysis and prediction.	[90]
Research	EHR, AI	Develop an interoperable EHR system to aid the early detection of diabetes by the use of an ML algorithm.	[91]
Research	EHR, AI	Developed an artificial intelligence algorithm, based on reinforcement learning (RL), for personalised diabetes and multimorbidity management.	[29]
Review	Blockchain, IoT	The integration of IoT and BC holds promise for transforming healthcare data management.	[66]
Retrospective study	EHR, AI	EHR phenotyping resulted in markedly superior detection of DM2.	[85]
Meta-analysis	mHealth	A positive impact of mobile apps on improving medication adherence (OR = 2.371, SMD = 0.279).	[86]

Note: mHealth, mobile health; AI, artificial intelligence; IoMT, Internet of Medical Things; EHR, electronic health record; BG, blood glucose; CGM, continuous glucose monitoring; ML, machine-learning; DM2, diabetes mellitus 2; OR, odds ratio; SMD, standardised mean difference; HbA1c, glycosylated haemoglobin; BC, blockchain.

the decision-making process also limits interpretability, which may lead to a crisis of trust in medical scenarios [95]. IoT devices, such as continuous blood glucose monitoring systems, collect rich, high-frequency streams but carry higher equipment costs that limit their accessibility in grass-roots settings and low-income groups; the resultant massive data also require AI-assisted analytics, further increasing the overall cost burden on healthcare systems or individual users. Although blockchain technology can guarantee data security and traceability, its high implementation cost and limited compatibility with the existing medical system hamper short-term, large-scale application [96]. From the perspective of the overall application environment, three barriers are crucial: data security, technical accessibility, and system interoperability. Heterogeneous information standards of different medical institutions prevent data sharing and the establishment of cross-institutional collaborative diagnostic networks. Primary healthcare resources are limited by deficiencies in the configuration of technical equipment and a shortage of specialised personnel, limiting the effectiveness of digital tools. Finally, low public awareness of DM screening and limited engagement among some high-risk groups, alleviate screening uptake and affect improvements in diagnostic rates.

In view of these limitations and challenges, future research should advance in several directions. At the level of technology optimisation, it is necessary to further integrate EHR with blockchain to build a new data management framework supported by standards and norms, with privacy protection as the core, which improves system interoperability and data security. To address cost-related barriers, develop cost-effective mHealth devices and applications (e.g., low-cost wearable sensors, free basic functional modules) and promote policy support such as medical insurance coverage for essential monitoring equipment, thereby reducing the economic burden on patients. Simplify interfaces, provide targeted user training, and strengthen data encryption technology to address user privacy concerns. Optimise the interpretability of AI algorithms, enhance the trust of healthcare professionals and patients in AI decision-making by introducing visualisation techniques and transparent model structures, and establish strict data quality control mechanisms. Deepen AI-IoT integration to couple data collection with analysis for grass-roots applications. Align blockchain technology and existing medical systems through standardised architectures to reduce implementation costs and enable trustworthy data sharing across institutions.

In terms of application-model innovation, it should focus on grass-roots medical scenarios by designing lightweight, need-based information management solutions, strengthening technical training for grass-roots healthcare workers, and enhancing their ability to operate information management tools to improve tool adoption. There is a need to develop personalised blood glucose management paths by integrating multi-source datasets, and developing more accurate intelligent diagnostic algorithms, shifting from "group screening" to "accurate individual risk prediction".

Furthermore, it is necessary to strengthen policy support and interdisciplinary cooperation, promote the establishment of unified industry standards and data-sharing mechanisms. Similarly, under government guidance and through collaboration between medical institutions and technology enterprises, we should develop a comprehensive information management system covering screening, diagnosis, and management. We should also focus on public health education, push personalised health reminders through mHealth technology, and improve the screening compliance of high-risk groups. Together, these efforts develop a virtuous cycle of "technology empowerment + policy guarantee + public participation", leading to sustained increases in DM diagnosis rates and improved management outcomes.

6. Conclusion

This review shows that the information-management-based blood glucose control pathway develops an end-to-end information system covering screening, diagnosis, and management by integrating digital tools such as EHR, mHealth, AI, IoT, and blockchain. Furthermore, by addressing the traditional model, it creates a closed loop of "accurate screening - standardised diagnosis - resource synergy", which considerably improves the efficiency and accuracy of DM diagnosis. Future studies should focus on deeper technology integration and grass-roots adaptation, policy-supported data standardisation, and promote an ecosystem that enables "technology empowerment with public participation" to facilitate and advance early detection and prompt intervention.

Key Points

- This review comprehensively integrates various information-management-based technologies, including EHR, mHealth, AI, IoT, and blockchain, to construct a closed-loop DM management system spanning the entire process of screening, diagnosis, and management.
- It thoroughly examines mechanisms of information-management-based technologies in improving the efficiency of early screening and standardising diagnostic processes, providing multi-dimensional solutions for enhancing diagnostic rates of DM.
- Combining research findings from extensive and larger research cases, it empirically demonstrates the significant effects of digitisation in optimising blood glucose control, thereby improving patient compliance and reducing complication risks.
- It systematically identifies the challenges in the application of existing technologies and outlines practical future directions, focusing on technical optimisation, model in-

novation, and policy support, thereby providing clear guidance for future research and practice.

Availability of Data and Materials

All the data of this study are included in this article.

Author Contributions

LY, LD, LJ, YZ, and QF conceived and collaborated on the work. LY and QF took the lead in drafting the manuscript. All authors contributed to important editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

Not applicable.

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Conflict of Interest

The authors declare no conflict of interest.

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