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Current status and perspectives of prediabetes monitoring

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ABSTRACT
Diabetes mellitus is one of the chronic diseases with high morbidity and mortality, and prediabetes mellitus is one of the most important risk factors for diabetes mellitus, and its monitoring and standardized management are crucial for preventing this group of people from turning into diabetes mellitus. To understand the problems and latest research progress in monitoring and management of prediabetes through literature study. We searched for relevant literature on prediabetes in the PUBMED database, summarized and hy the literature on monitoring and management of prediabetes, and elaborated on the current monitoring methods and a series of developing monitoring techniques. Current prediabetes monitoring techniques include physiological measurement indicators, laboratory tests, imaging techniques, questionnaire scores, etc. New techniques include individualized medicine, multidimensional data integration, emerging biomarkers, etc., and there are technical and promotional limitations.

KEYWORDS
Prediabetes; Monitoring; Screening; rRsk Factors

"Prediabetes" is a stage of abnormal glucose metabolism in which blood glucose levels do not meet the diagnostic criteria for diabetes but are higher than normal, and is often considered to be an intermediate state of glucose dysregulation prior to type 2 diabetes mellitus (T2DM). [1], Includes impaired fasting glucose (IFG), abnormal glucose tolerance (IGT), and a mixed state of the two (IFG+IGT). Annual data from 2017 show that approximately 5-18% of pre-diabetic patients convert to diabetes each year [2].Data from the International Diabetes Federation (IDF) suggests that by 2045, it is projected that 11.4% of adults worldwide will have impaired glucose tolerance and 6.9% will have impaired fasting glucose [3]. This can greatly affect the quality of life of the individual patient, increase the financial burden on patients and their families, and add to the global burden on clinical and public health resources. It is important to reduce the risk of diabetes and its complications if people with prediabetes are continuously monitored for changes in blood glucose and effective interventions are taken in time to prevent prediabetes from developing into diabetes.

1 Criteria for classification of prediabetes

At present, different institutions or organizations have slightly different definitions of prediabetes, and the definition and diagnostic criteria of prediabetes can still not be unified, but it is still mainly based on the three indicators of fasting blood glucose, Oral Glucose Tolerance Test (OGTT) and Glycosylated Haemoglobin (HbA1c) to classify. The following are the criteria used by the three major organizations to define prediabetes.

1.1 World Health Organization (WHO)

In 2006, prediabetes was defined as IFG fasting blood glucose levels of >6.1 and <7.0 mmol/L (110-125 mg/dL), glucose <7.8 mmol/L after a 2-hour oral glucose tolerance test (OGTT), and a 2-hour post-load glucose measurement that excludes diabetes mellitus or IGT. post-test glucose between 7.8 mmol/L and 11.0 mmol/L (140-199 mg/dL).

1.2 American Diabetes Association (ADA)

In 2022, prediabetes will be defined as IFG fasting glucose levels of 5.6-6.9 mmol/L (100-125 mg/dL), with 2-hour post-load glucose measurements not recommended.IGT will be defined as a fasting glucose level <7.0 mmol/L, with a glucose level after a 2-hour oral glucose tolerance test of 7.8-11.0 mmol/L (140-199 mg/dL). /dL). The ADA also considers HbA1C between 5.7% and 6.4% as prediabetes[4].

1.3 Expert consensus of the Chinese Medical Association Diabetes Section (CDS[a])

In the 2023 Expert Consensus, combining the diagnostic criteria of WHO 1999 and ADA 2022, IFG was defined as a

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fasting blood glucose level of ⩾6.1 mmol/L, <7.0 mmol/L, and a 2-hour post oral glucose tolerance test blood glucose of < 7.8 mmol/L. IGT fasting blood glucose <6.1 mmol/L; 2h post glucose load blood glucose ⩾7.8 mmol/L, <11.1 mmol/L; on the basis of the above, and or plus HbA1C ⩾5.7 mmol/L, <6.5 mmol/L[5].

Criteria	World Health Organization (WHO)	American Diabetes Association (ADA)	Chinese Diabetes Society (CDS)
Year	2006	2022	2023
Impaired Fasting Glucose (IFG)	6.1⩽FG<7.0 mmol/L OGTT<7.8 mmol/L	5.6⩽FG＜6.9 mmol/L OGTT not recommended	6.1⩽FG<7.0 mmol/L OGTT<7.8 mmol/L
Impaired Glucose Tolerance (IGT)	FG <7.0 mmol/L	FG <7.0 mmol/L	FG <6.1 mmol/L

FG:fast glucose;OGTT:2-hour Oral Glucose Tolerance Test;CDS[a]:Expert consensus on prediabetes intervention for adults in China (2023 edition)

Due to the inconsistency of standards, the same individual may arrive at different diagnoses when monitoring prediabetes, and the identification of prediabetes may be divergent, which is not conducive to the tracking and early intervention of potential patients, nor to the collection and analysis of data from the prediabetes population.

2 Methods of monitoring prediabetes

2.1 Physiologic Measurements

2.1.1 Body Mass Index (BMI), Waist Circumference and Waist-to-Hip Ratio

Obesity is closely associated with insulin resistance and an increased risk of developing type 2 diabetes mellitus (T2DM). In 2009, KHAODHIAR L et al. pointed out that in genetically predisposed individuals, β-cell function is ultimately dysfunctional, leading to the development of T2DM. And in obese patients with successful weight loss, the progression of T2DM can be delayed or even prevented [6]. In 2020, YU CHENG W M-Z et al. showed that in people without a family history of diabetes, obesity or central obesity significantly increased the risk of diabetes, and the prevalence of prediabetes was higher than that of normal-weight people. Obesity is not only an independent risk factor for diabetes mellitus and prediabetes mellitus, but its combined effect with family history should not be ignored. A family history of diabetes combined with obesity, especially central obesity, significantly increases the risk of diabetes and prediabetes [7].

2.1.2 Blood Pressure

Hypertension is a common comorbidity and risk factor for prediabetes mellitus [8, 9]. Both share multiple pathogenic mechanisms, including obesity, insulin resistance, and chronic inflammation. Hypertension can induce insulin resistance and lead to impaired glucose uptake by affecting insulin and glucose transport in skeletal muscle[10]. A study from 2022 showed that blood pressure levels were positively associated with the risk of developing prediabetes, with hypertensive patients having a significantly higher risk of developing prediabetes than those with normal blood pressure [11].In 2021, Mohammed H Al-Thani et al. demonstrated a new screening method with the potential for widespread application based on a mathematical model of diabetes with a representative random sample of 5,000 individuals from Qatar at different time points to identify pre-diabetic individuals [12]. In the same year, a review by JIA G et al. pointed out that the risk of prediabetes increases with elevated blood pressure, and its pathologic basis is closely related to insulin resistance. Hypertension leads to atherosclerosis and impaired vasodilatory function, further exacerbating insulin resistance and diabetes progression[13]. Therefore, blood pressure levels can be used as one of the indicators for prediabetes monitoring.

2.2 Laboratory monitoring indicators

2.2.1 Urine Analysis

The first sample used for glucose testing was urine, and the identification of glucose in urine can be traced back to the late 18th century, when Matthew Dobson observed the presence of sugar in the urine of diabetic patients in 1776, which laid the foundation for later pre-diabetic testing methods [14]. In 2023, Yanjun Zhou et al. examined evidence from the 2007-2010 NHANES database and found a negative correlation between urinary concentrations of isoflavones and their metabolites and the risk of prediabetes, raising the prospect of urinalysis as a screening tool for prediabetes [15].

2.2.2 Atherosclerotic Plasma Index (AIP)

esults from a study in 2023 revealed a significant positive correlation between atherosclerotic plasma index(AIP＝

$log\frac{TG}{HDL-C}$)and the prevalence of prediabetes and diabetes mellitus. for every 1-unit increase in AIP, the overall risk of developing the disease was increased by a factor of 2.49 (OR 2.49, 95% CI 1.75, 3.54)[16]. Meanwhile in 2024 Yang Zhou et al. found that (CumAIP) is strongly associated with the development of prediabetes. High CumAIP exposure not only increases the risk of prediabetes progression, but also prevents its reversal within a certain range. These findings suggest that monitoring and maintaining appropriate AIP levels may help prevent worsening of blood glucose levels and can be used to predict the development of prediabetes[17].

2.2.3 Indicators related to blood glucose

(1) Fasting Glucose Test (FPG)

The FPG is an important indicator in the diagnostic criteria for prediabetes. The FPG measures blood glucose levels after a period of time without food (usually 8-12 hours). This provides baseline data on how the body maintains glucose stabilization without the influence of food [18].However, it is not effective in detecting postprandial blood glucose spikes and is not sensitive enough to miss early signs of blood glucose abnormalities that can be detected by other tests[19].

(2) Oral Glucose Tolerance Test (OGTT)

The Oral Glucose Tolerance Test (OGTT) is based on a study by A.T.B. Jacobson in 1913 and is now widely used as a screening test for prediabetes[20]. It is also used as one of the important methods to screen for diabetes. However, it is a complicated screening process. Subjects need to fast for eight hours and provide multiple blood samples within two hours, making the test time-consuming, costly, and restrictive to the operating environment, making it unsuitable for mass screening. This makes the OGTT difficult to implement in routine screening. In addition, patient compliance and other factors can affect the accuracy of the results [21].

(3) Glycosylated hemoglobin or hemoglobin level bound to glucose (HbA1c)

In 1969, Samuel Rahbar et al. first found elevated HbA1c levels in diabetic patients [22].In 1976, Anthony Cerami and his team proposed the use of glycosylated hemoglobin (HbA1c) to assess the control of glucose metabolism in diabetic patients [23].Currently, immediate HbA1c testing (POC A1c), which provides results in 3-15 minutes, is used as one of the diagnostic criteria for prediabetes and is suitable for screening in resource-constrained areas [24].

However, the HbA1c test has limitations, has low sensitivity and specificity for prediabetes, is affected by factors such as race and anemia, and does not reflect day-to-day glycemic fluctuations or take into account specific states such as pregnancy. It has limited reliability in detecting glycemic variability and early metabolic changes in prediabetes, which may lead to misdiagnosis or missed diagnoses [25].

2.3 Imaging techniques

(1) Echocardiography

In a study by Tanaka H et al in 2020, it was shown that a reduction in left ventricular systolic strain was observed in pre-diabetic and diabetic patients without any obvious signs or symptoms of the disease [26]. Meanwhile, a study in 2023 by WU T et al. using two-dimensional scatter tracking echocardiography (2D-STE) confirmed the presence of left ventricular systolic dysfunction in diabetic patients, and the risk of subclinical left ventricular systolic dysfunction, even in pre-diabetic and diabetic patients in whom left ventricular ejection fraction remained normal, and that 3D-STE demonstrated higher than 2D-STE in the assessment of this condition diagnostic value [27]. Thus, left ventricular systolic dysfunction by echocardiography helps to detect prediabetes.

(2) Diffusion tensor imaging (DTI)

In 2021, JENDE J M E et al. showed that sciatic nerve anisotropy fraction (FA) calculated on the basis of diffusion-weighted 3T magnetic resonance neuroimaging (DTI) could be used as a surrogate marker of distal upper and lower extremity nerve impairment in patients with diabetes and prediabetes. Upper extremity nerve function impairment precedes the onset of T2DM during the progression of pathologic glucose tolerance, suggesting that structural nerve damage may occur early or even before the onset of T2DM, rather than as a late complication as traditionally perceived [28]. Thus, DTI technology can be used to monitor FA changes and recognize early signs of peripheral neuropathy in advance, thereby screening individuals with prediabetes and their risk of progression to T2DM.

(3) Brachial-ankle pulse wave velocity (baPWV) or carotid intima-media thickness (CIMT)

In 2022, a prospective study conducted by Qiuyu Cao, which included 4, 739 participants without diabetes and cardiovascular disease, showed that baPWV levels were higher in pre-diabetic individuals compared to normoglycemic (NGR) individuals, and that baPWV could be used to identify individuals at risk for prediabetes. [29]. In 2018, Roshan Kumar Mahat et al. compared 200 pairs of pre-diabetic patients with healthy subjects to calculate CRR, AC, and AIP from conventional lipid parameters and measure carotid intima-media thickness (CIMT). The results showed that pre-diabetic individuals were more susceptible to cardiovascular disease and exhibited abnormalities in atherosclerotic index and

CIMT, suggesting that CIMT in combination with other indices can be used to screen pre-diabetic high-risk individuals [30]. In 2024, Antoaneta Gateva et al. found that patients with new-onset diabetes had significantly increased common carotid artery intima-media thickness and a higher frequency of CIMT abnormalities compared with normoglycemic and prediabetic patients [31].

2.4 Digital and Mobile Medical Devices

(1) Continuous glucose monitoring (CGM)

CGM is capable of monitoring blood glucose changes in real time, providing detailed glucose readings that can inform screening for prediabetes, but the technology remains expensive and standardized guidelines for use in prediabetes monitoring are lacking. In addition, accuracy varies between devices and interpretation of data can be complex [32].

(2) Smart wearable devices

Wearable devices have great potential for predicting HbA1c levels and glycemic variability in individuals with prediabetes. 2021, BENT B, CHO P J, et al. demonstrated that wearable devices capture autonomic nervous system metrics related to glycemic health (e.g., heart rate variability, skin temperature), providing a viable method for early detection and monitoring of prediabetes [33]. In the same year, Mirza Mansoor Baig et al. developed an artificial intelligence model based on adaptive neuro-fuzzy inference for the detection of prediabetes and T2DM through individualized monitoring. The study utilized a wearable bullet-proof undershirt for data collection combined with manually recorded information on blood glucose, height, weight, age and gender. The model prediction results were validated with two years of follow-up and evaluated using Kappa analysis, obtaining an overall agreement of 91%, demonstrating the high accuracy of wearable technology and Internet of Things (IoT) monitoring applications in the early detection of prediabetes and T2DM [34]. In 2024, Dimitra Tatli et al. utilized a wearable continuous glucose monitoring (CGM) device with a smartwatch embedded with inertial sensors to collect glucose data and acceleration signals, respectively, in order to assess the feasibility of early detection of prediabetes. It was shown that combining machine learning and glucose homeostasis modeling can achieve high sensitivity and accuracy in identifying prediabetes. Future research directions include expanding the sample size, improving population diversity, and further exploring the application of CGM in prediabetes monitoring [35].

Currently, wearable devices show great potential for early detection and personalized monitoring in prediabetes, but still face technical and feasibility challenges, such as range, data processing capacity, and financial support.

2.5 Questionnaire scoring tools

Diabetes risk scoring tools, which are used to assess initial risk through online or offline questionnaire scoring, are more helpful in improving the cost-effectiveness of testing than opportunistic screening, which requires considerable financial and material resources.

2.5.1 Finnish Diabetes Risk Scoring System (FINDRISC)

A questionnaire allows a quick determination of the risk of developing prediabetes mellitus [36].The questionnaire was based on a number of prediabetes related variables such as age, gender, body mass index (BMI), waist circumference, family history of diabetes, physical activity level and dietary habits. Higher FINDRISC scores indicate an increased risk of diabetes and warrant further precision screening or lifestyle interventions to reduce risk [37].

2.5.2 Type 2 diabetes risk score

Jaana Lindström et al. constructed a type 2 diabetes risk score based on age, BMI, waist circumference, history of hypertension medication, hyperglycemia, physical activity, and daily fruit and vegetable intake. The scoring system innovatively integrates multiple noninvasive, easy-to-measure, and easy-to-understand variables to predict prediabetes risk and emphasizes intervenable risk factors [38].

2.5.3 Canadian Diabetes Risk Scoring System (CANRISK)

The applicability of FINDRISC in Canada is limited by differences in racial composition. For this reason, Canadian diabetes experts have adapted it to include variables such as race, gender, education level and history of macrosomic births to form the Canadian Diabetes Risk Assessment Questionnaire (CANRISK)[39].In 2011, Robinson C. A. et al. found that CANRISK had better predictive accuracy than FINDRISC and ana-only models in adverse glucose monitoring in a multiethnic Canadian population, and was more suitable for local prediabetes screening [40].

3 Challenges to prediabetes monitoring technologies

3.1 Accessibility and cost of monitoring technologies

3.1.1 Accessibility

A cross-sectional study from 2015 to 2017 showed that acceptance of and adherence to prediabetes monitoring technology among Chinese adults varied by region and age. Urban residents had significantly higher rates of diabetes awareness than rural residents, while rural areas had a higher prevalence of prediabetes but lower levels of diabetes awareness, treatment, and control, and would be at higher risk of diabetes progression in the absence of effective preventive measures. In addition, diabetes awareness and treatment rates are relatively high among the elderly population [41].

3.1.2 Costs

In 2017 Samantha Roberts et al. hypothesized and calculated a ratio called the Incremental Cost-Effectiveness Ratio (ICER) to report the costs incurred in the monitoring process from two different perspectives: the health system and the societal perspective [42].

The health system perspective includes only direct medical costs such as:

(1) Costs for office visits, appointment visits, or health counseling;

(2) Personnel needed to provide the intervention;

(3) Specialized premises and supporting facilities for monitoring technology;

(4) Equipment, drugs and consumables.

In addition, studies of cost-effectiveness from a societal perspective include some or all of the following elements.

(1) Indirect costs incurred as a result of monitoring behavior (e.g., exercise equipment, food, preparation equipment);

(2) Participant time (participation in monitoring activities and regular round trips to follow up on monitoring results);

(3) Lost productivity due to absenteeism;

It can be hypothesized that low-income populations generally have less awareness and attention to health prevention and less willingness to pay for prediabetes monitoring because of time, monitoring costs, and energy, and that it may be more difficult to conduct prediabetes monitoring activities in low-income areas.

3.2 Individual differences

3.2.1 Racial Disparities

Because about two-thirds of countries lack high-quality IGT or IFG data, Mary R Rooney et al. based their analysis on available high-quality data combined with extrapolated values from geographically, income, racially, and linguistically similar countries/areas. The study found that in 2021, age-corrected, the highest prevalence of IGT was in North America and the Caribbean (13.1%) and the lowest in Southeast Asia (4.5%). In contrast, the highest prevalence of IFG was in Southeast Asia (9.4%) and the lowest in the Western Pacific (3.4%) [43]. The global burden of prediabetes is high and continues to rise, underscoring the urgency of strengthening surveillance.

The U.S. National Health and Nutrition Examination Survey (NHANES) 2005-2014 study monitored non-Hispanic black and white adults with diabetes and prediabetes and analyzed their HbA1c, fasting glucose (FPG), and 2-hour glucose (2hPG) levels. Results showed that HbA1c levels were higher in blacks than whites, even when glucose levels were similar, suggesting that diagnostic criteria for prediabetes and diabetes may need to be adjusted for racial differences[44].

These differences may be influenced by genetic factors, regional economy, level of medical care and education. Some groups have lower insulin sensitivity and are prone to visceral fat accumulation, which increases the risk of prediabetes. In addition, Taynara Formagini et al. conducted a cross-sectional analysis of National Health and Nutrition Examination Survey data from 2011 through March 2020 and found that prevalence of prediabetes was higher among ethnic minorities and those with low levels of education [45]. However, such studies describing racial, ethnic, and educational disparities may have implications for health equity that need to be further explored for their public health implications.

3.2.2 Gender differences

In 2021,THOMAS T W et al. used generalized estimating equations and logistic regression to assess data from 18,742 patients seen between November 1, 2015, and April 30, 2017, and concluded that males and females exhibit different risk profiles in the prediabetes prevalence population. Men usually develop insulin resistance at an earlier stage, especially associated with abdominal obesity. Women experience changes in metabolic function after menopause due to hormonal changes, putting them at increased risk for prediabetes[46].

In terms of risk, men are more likely to develop type 2 diabetes even at lower BMI. In terms of metabolic differences, women are more likely to have abnormal glucose tolerance, whereas men often have elevated fasting glucose, making the implementation of the OGTT particularly important for the diagnosis of disorders of glucose metabolism[47].

3.2.3 Age differences

The risk of preexisting diabetes increases with age, especially among adults over the age of 40. Aging leads to factors such as decreased insulin sensitivity, decreased physical activity, and weight gain, all of which are major triggers for prediabetes [48] . In a lower-age population, a cross-sectional study by Linda J Andes et al in 2020 evaluated 5789 samples of young adults in the 2005-2016 National Health and Nutrition Examination Survey, which found that young adults with prediabetes had significantly higher levels of non-high-density lipoprotein cholesterol levels, systolic blood pressure, central obesity, and lower insulin sensitivity when compared to those with normal glucose tolerance ($P < .05$), so the above indicators can be used to aid in monitoring prediabetes with increased accuracy in younger age groups.

In summary, the prevalence of diabetes mellitus and prediabetes is higher in males, in those with low educational levels and low household income, in those who are overweight and obese, and in those who report a family history of diabetes mellitus. And the prevalence of prediabetes is expected to increase as populations become more urbanized, wealth increases, nutrition, health care and education improve, and life expectancy increases. The inherent inter-individual variability needs to be taken into account when monitoring prediabetes.

4 Future trends in monitoring prediabetes

4.1 Emphasis on individualized care

Not all people with prediabetes will develop diabetes. a 20-year follow-up study in Daqing, China in 2008 showed that the average annual incidence of diabetes was 7% in the intervention group and 11% in the control group, with cumulative incidence rates of 80% and 93%, respectively[49]. In addition, differences in individual economic, educational and cultural backgrounds determine the importance of individualized monitoring. Therefore, an individualized approach to monitoring is particularly important when dealing with the increased number of people with prediabetes.

In recent years, research has emphasized the potential of digital interventions in the self-monitoring and management of prediabetes, particularly in the area of personalized monitoring. 2024 A study by the STOWELL M team found that digital programs combining multimodal interventions with standard care reduced the risk of progression to type 2 diabetes in people with prediabetes. Some of these programs use artificial intelligence, machine learning and algorithms to provide personalized intervention content based on the dynamics of the condition[50].

For high-risk individuals (e. g., those with metabolic syndrome, obesity, or polycystic ovary syndrome), regular screening for glucose, HbA1c, and OGTT may be performed [37]. The U. S. Preventive Services Task Force recommends screening for prediabetes every 3 years in overweight or obese individuals aged 35 to 70 years [51].

Screening strategies also need to be differentiated for different age groups. Some adolescents with dysglycemia may return to normal without intervention, and screening may lead to overdiagnosis. There is insufficient evidence to assess the risks and benefits of screening for diabetes in pre-adolescents [52],and follow-up and monitoring studies in younger age groups should be strengthened..

4.2 Multidimensional data integration

DEEK R A, MA S et al. used a multi-omics approach to understand the collective impact of factors on the disease by integrating various methods of different histological data including microbiome and genetic information and put more emphasis on the importance of multi-omics approach in identifying biomarkers of the disease. The novelty of this study is the application of multiple statistical and computational methods to integrate multi-omics data, and future monitoring of prediabetes could be integrated from a multi-omics perspective to monitor the influence of multiple factors in the progression of the disease [53].

4.3 Emerging Biomarker Applications

Glycated Serum Protein (GSP) Assay: GSP has been proposed as a more sensitive marker of glycemic control, especially for people with conditions such as renal insufficiency or anemia. It can be a useful complementary or alternative test when the GSP test is problematic or when there are conflicting results between glucose and GSP. [54].However, it has not been widely validated or implemented in the clinical setting, limiting its application in prediabetes detection, and in the future, it is hoped that more emerging biomarkers will be discovered to assist in the determination of prediabetes

through more clinical trials and theoretical speculations.

5 Conclusion and outlook

5.1 Summary and assessment of existing monitoring technologies

Each of the monitoring tools mentioned above has its own advantages and disadvantages. Indicators such as weight, BMI, waist circumference and waist-to-hip ratio are simple and easy to use, and can effectively reflect the risk of obesity to prediabetes, but cannot assess blood glucose levels alone. Blood pressure monitoring is closely associated with prediabetes and can help identify co-morbidity risk, but fails to provide direct evidence of association with prediabetes. Urinalysis has a long history of use as an initial screening tool for prediabetes, but fails to provide early subtle changes. Lipid testing, especially AIP, is effective in revealing the correlation between atherosclerosis and diabetes, but further study of its clinical applicability to prediabetes is needed. Fasting glucose test (FPG) is simple to perform and is commonly used to screen for prediabetes, but it is weakly responsive to postprandial glucose fluctuations and may be underdiagnosed. Oral glucose tolerance test (OGTT) has high sensitivity and can accurately reflect the early signs of diabetes, but the examination process is complicated and cumbersome, making it difficult to be widely used. Overall, each monitoring method has its unique value in the clinic, and its combined use can improve the accuracy of screening and diagnosis of prediabetes, but there are operational complexities and limitations, and it is necessary to choose the appropriate test according to the actual situation.

5.2 Prospects

5.2.1 Stratified diagnosis and personalized monitoring strategies

Patients with prediabetes have significant differences in cardiovascular and metabolic risks, and existing diagnostic methods for prediabetes, such as glucose tolerance tests and fasting glucose measurements, fail to effectively differentiate high-risk individuals. Future research should focus on stratified diagnosis of prediabetes, combining multiple factors such as insulin resistance and dyslipidemia to improve the accuracy of diagnosis and optimize intervention strategies, thereby improving treatment outcomes.

5.2.2 Challenges and opportunities of digital health and remote monitoring technology

Digital health tools such as smartphone apps and wearable devices have great potential for prediabetes monitoring, enabling real-time monitoring of weight, diet and activity levels. However, data privacy and security issues remain major barriers to technology adoption. Future research should address these issues in order to balance technological convenience and privacy protection, and enhance patient trust and reliance, thereby increasing their adoption in clinical and home scenarios.

5.2.3 Prospects for Artificial Intelligence and Machine Learning Applications

Personalized monitoring and risk prediction are key directions for future research. By integrating patients' lifestyle, genetic, and metabolic data, machine learning models can provide accurate risk assessment for pre-diabetic patients and help design personalized prevention and intervention plans. This data-driven approach can optimize patient management and treatment plans and improve prevention outcomes.

5.2.4 Implications for clinical practice and long-term health management

Improved monitoring methods will have a profound impact on the clinical management of prediabetes. New technologies, such as continuous glucose monitoring, can provide dynamic glucose information that is more accurate than traditional testing methods, helping to identify high-risk individuals for early intervention. In addition, personalized intervention plans and multifactorial risk prediction models can effectively improve patient adherence and treatment outcomes, facilitate long-term health management and follow-up, and reduce the incidence of prediabetes.

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