AI Prediction and Prevention of Type 2 Diabetes

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Abstract
Type 2 diabetes is a growing global health challenge, with rising prevalence linked to lifestyle, genetic, and environmental factors. Early identification of at-risk individuals and timely intervention are crucial for reducing disease burden and associated healthcare costs. Artificial intelligence offers tools for predicting and preventing type 2 diabetes by analyzing large, complex datasets from sources such as electronic health records, wearable devices, and genetic information. Machine learning algorithms can detect nuanced patterns in clinical, behavioral, and demographic data that traditional statistical methods may overlook, enabling accurate risk stratification and personalized prevention strategies. Furthermore, AI-driven digital health platforms can provide real-time monitoring, lifestyle coaching, and adaptive feedback to help individuals reduce their risk. This paper explores current advancements in AI applications for type 2 diabetes prediction, examines their approach, effectiveness in prediction, prevention, and discusses ethical, technical, and clinical considerations using case studies and exhaustive data analysis.

Introduction
Type 2 diabetes is a chronic metabolic disease that has emerged as a leading global health concern. It occurs when the body develops resistance to insulin or when the pancreas is unable to produce adequate insulin to regulate blood glucose. Unlike type 1 diabetes, which is mainly driven by autoimmune processes, type 2 diabetes results from a complex interaction of genetic susceptibility, lifestyle behaviors, and environmental exposures. Although it is strongly linked to obesity, poor nutrition, and physical inactivity, individuals with healthy habits may still develop the disease due to hereditary factors.

The underlying causes of type 2 diabetes are multifaceted. A key mechanism is insulin resistance, in which muscle, fat, and liver cells respond ineffectively to insulin signaling. To compensate, the pancreas increases insulin production, but this response eventually becomes unsustainable, leading to elevated blood glucose. Over time, the persistent imbalance between insulin supply and demand disrupts normal metabolic processes and contributes to widespread physiological damage.

Numerous risk factors heighten the likelihood of developing type 2 diabetes. Excess body weight, sedentary behavior, and consumption of diets high in processed foods and added sugars are primary contributors. Advancing age also plays a role, with risk increasing significantly after 45 years. However, rising cases in children and adolescents reflect broader lifestyle shifts. Family history, certain ethnic and racial backgrounds, and related medical conditions such as hypertension, polycystic ovary syndrome, or prior gestational diabetes further increase susceptibility.

Symptoms of type 2 diabetes often develop gradually, making early detection challenging. Typical indicators include excessive thirst, frequent urination, constant hunger, fatigue, blurred vision, delayed wound healing, and recurrent infections. Because the onset is slow and symptoms may be overlooked, many individuals remain undiagnosed until complications arise. This underscores the necessity of preventive measures and timely screening to avoid long-term health consequences.

Prevention and screening strategies without AI remain grounded in clinical guidelines. Lifestyle interventions form the foundation, including adoption of balanced diets low in refined carbohydrates and sugars, regular physical activity totaling at least 150 minutes per week, and modest weight reduction of 5–7 percent, all of which significantly lower risk. Behavioral support, adequate sleep, and community-based prevention initiatives further enhance outcomes. For individuals at elevated risk, pharmacologic options such as metformin or newer GLP-1 receptor agonists are utilized, providing additional cardiovascular and renal protection. Screening practices currently rely on diagnostic tools such as fasting plasma glucose, hemoglobin A1c, and the oral glucose tolerance test. These assessments are designed to detect both prediabetes and diabetes, with clear thresholds established by professional organizations. Universal screening is now recommended beginning at age 35, with earlier and more frequent testing advised for individuals who are overweight or have additional risk factors. Special protocols also apply to children, adolescents, and minority populations with disproportionate risk. Despite their effectiveness, these methods face challenges including delayed diagnosis, variable accuracy, and gaps in accessibility, underscoring the need for innovation.

Artificial intelligence has emerged as a promising solution to these challenges. By analyzing large and complex datasets, AI models can detect patterns across genetics, lifestyle factors, electronic health records, and real-time data from wearable devices. These capabilities allow for earlier identification of individuals at risk, more precise prediction of outcomes, and the development of personalized prevention strategies. Beyond detection, AI-driven platforms can support continuous monitoring, lifestyle coaching, and healthcare decision-making in ways that traditional methods cannot execute as effectively.

This paper investigates the role of AI in predicting and preventing type 2 diabetes. It is organized into five sections: the mechanisms by which AI predicts risk, the performance and accuracy of AI-based models, ethical and privacy considerations in applying AI to healthcare, real-world case studies of AI systems in practice, and the types of data employed along with their respective benefits and limitations. Taken together, these discussions provide a comprehensive analysis of both the opportunities and challenges of incorporating AI into care with diabetes, offering insights into its potential to transform the future of prediction and prevention.

AI Models for Predicting Type 2 Diabetes Risk

Artificial Intelligence (AI) is currently transforming diabetes prevention by allowing early identification of individuals at risk before symptoms emerge. These AI models rely on advanced computational methods, ranging from logistical regression to neural networks, that can process vast amounts of health datasets to uncover hidden patterns that human clinicians might overlook.

Types of AI Algorithms

The most applicable AI methods for diabetes prediction are supervised machine learning algorithms such as logistic regression, decision trees, and random forests, and more advanced methods like support vector machines (SVMs) and gradient boosting models. They are appropriate for handling structural datasets like age, body mass index (BMI), family history, blood glucose level, and lifestyle variables. In addition, deep learning models, especially artificial neural networks (ANNs), have drawn considerable attention in handling more complex and higher-dimensional data like genetic sequences, continuous glucose monitoring (CGM) measurements, and even imaging data. Neural networks are particularly well-suited to identify nonlinear interactions, e.g., how lifestyle and genetics combine to determine risks.

- **Logistic Regression (LR):** A statistical method that estimates the probability of diabetes based on the risk factors like BMI, blood pressure, and glucose levels. It’s simple and highly interpretable, allowing clinicians to see the different variables and the amount it takes to form the risk.
- **Decision Trees:** These models split patient data into branches (glucose > 126 mg/dL → high risk). They are easy to interpret, but can sometimes overfit (a model that learns the training set so well that it will fail to make correct predictions when given new data) when used alone
- **Random Forests:** A group of many decision trees that reduces overfitting and increases the accuracy. Random forests are also useful for handling complex health records with numerous variables
- **Support Vector Machines (SVMs):** SVMs classify patients by finding the best boundary between high- and low-risk groups. They work well for nonlinear patterns such as the combined effects of age, cholesterol, and BMI.
- **Gradient Boosting Models (GBMs):** Techniques like XGBoost (a powerful gradient boosting algorithm) build trees in an organized way, correcting errors along the way. They are among the most accurate models for structured health data but are harder to interpret.
- **Artificial Neural Networks (ANNs):** ANNs consist of layers of interconnected nodes that learn complex patterns automatically. They are powerful for using diverse data, genetic markers, continuous glucose monitoring (CGM) readings, and even retinal images, but can lack transparency.

How AI Models Process Health Data

Diabetes forecasting AI systems operate with a step-by-step process:

1. **Data collection:** Patient information is first collected from electronic health records (EHRs), laboratory tests, genetic tests, wearable sensors, and lifestyle questionnaires.
2. **Preprocessing:** The data then goes through cleaning (which removes errors or missing data),

normalization (which rescales readings like glucose levels), and feature extraction (pulling out average glucose variability from CGM data).

3. **Training:** The model is trained against known diabetes outcome (diagnosed vs not diagnosed) datasets so that it can learn the relationships between input and disease risk.
4. **Validation:** Models are validated against unseen datasets to measure accuracy. Sensitivity (correct identification of high-risk patients) and specifically, not giving false alarms.
5. **Prediction:** The model is able, after verification, to predict an individual's likelihood of acquiring Type 2 diabetes within a specified duration.

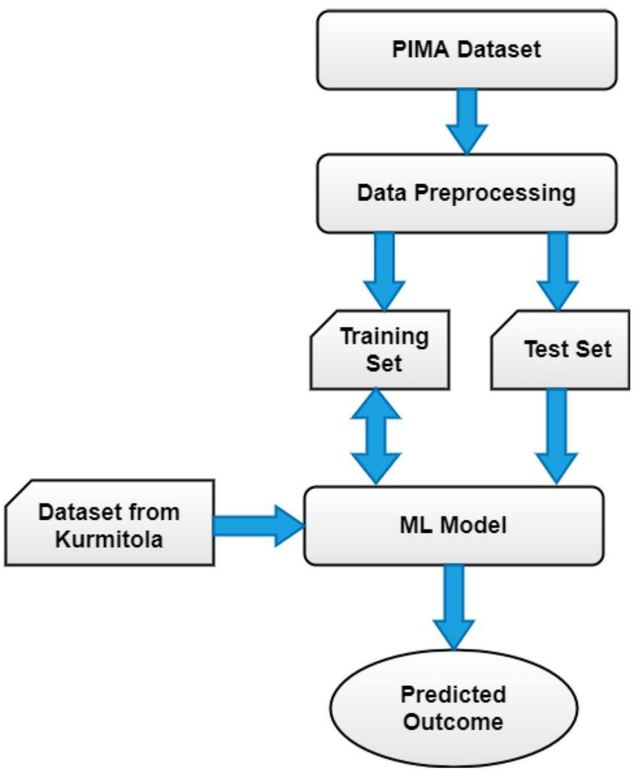

Figure 1. Flowchart for predicting diabetes using machine learning. Adapted from Evaluating Machine Learning Methods for Predicting Diabetes among Female Patients in Bangladesh (Figure 4) by M. B. Pranto, S. M. Mehnaz, E. B. Mahid, S. Momen, et al., 2020, ResearchGate.

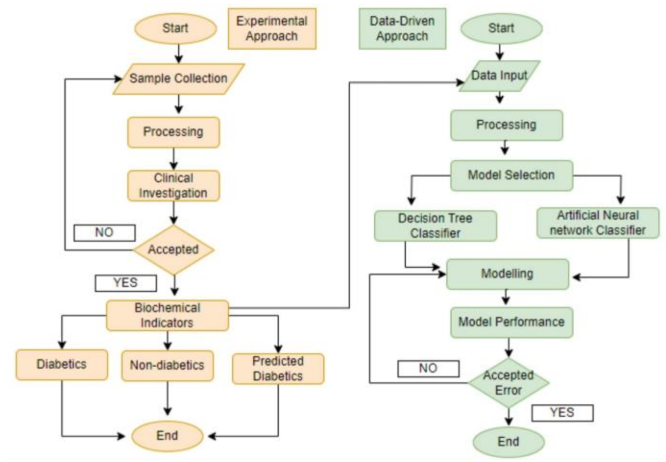

Figure 2. Experimental and data-driven approach for diabetes prediction. Adapted from Data-driven diabetes mellitus prediction and management: A comparative evaluation of decision tree classifier and artificial neural network models along with statistical analysis by I. Z. Sadiq et al., 2025, Scientific Reports, 15, Article 19339.

Real-World Applications

Certain companies have successfully adopted AI-driven systems to forecast diabetes risk:

- **Google Health:** By leveraging large datasets, Google developed deep learning models that screen the retinal scans to forecast diabetic retinopathy as well as cardiovascular and diabetes risk factors. This demonstrates how AI can detect systemic disease markers from non-invasive imaging.
- **IBM Watson Health:** Watson uses electronic health records and natural language processing to create individualized diabetes risk assessments. By integrating clinical notes, laboratory values, and medical histories, Watson provides clinicians with early intervention decision support
- **Medtronic:** A leader in diabetes technology, Medtronic uses AI in its insulin pump and continuous glucose monitoring systems. With machine learning algorithms applied to current glucose levels, their system can predict glucose trends and prevent life-threatening high and low levels, and identify long-term trends related to Type 2 diabetes.

Model Training and Validation

To train the AI models to be able to predict diabetes, lots of data is required. Big and diverse patient datasets are required so that the models can generalize to all populations and not be biased to a single group of individuals. Before training the data, it must first be preprocessed, or prepared. This involves correcting for missing values, normalizing lab tests, and encoding categorical variables (translating non-numeric data into numeric format). Feature selection techniques help to highlight shared factors such as BMI, HbA1c (Hemoglobin A1C), or family history during prediction. Models are then trained using learning methods supervised on a frequent basis, where algorithms like logistic regression, random forests, or deep neural networks update parameters frequently to minimize prediction errors. Techniques like cross-validation and hyperparameter tuning help further to improve performance. For privacy-concerned environments, hospitals train models in conjunction without explicitly exchanging sensitive patient data, addressing privacy concerns. Validation commonly involves splitting datasets into test and training sets, with sporadic external validation based on entirely distinct populations. Accuracy metrics such as the area under the receiver operating characteristic curve (AUC-ROC) provide details about model accuracy. The area under the ROC curve (AUC) is a broad measure of performance. A higher AUC (closer to 1) reflects higher discrimination potential between low and high. Clinical trials, such as those launched by the UK's NHS in 2024 to assess AI-powered diabetes risk prediction, are a pivotal step towards enfranchising such models for real-world health systems.

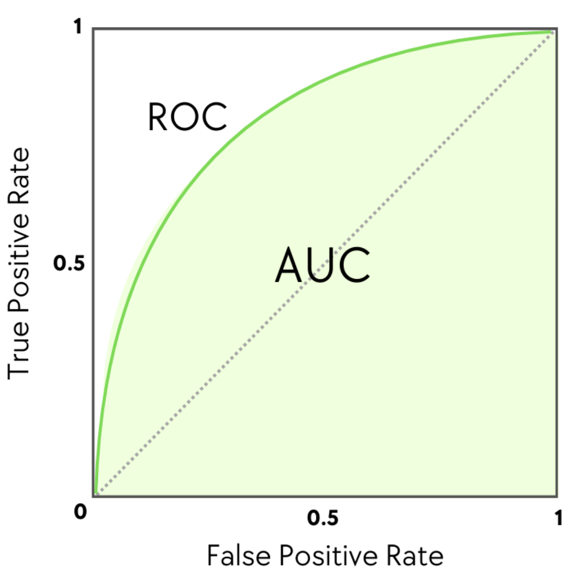

Figure 3. Receiver Operating Characteristic (ROC) curve illustrating the relationship between true positive rate (sensitivity) and false positive rate across varying decision thresholds, with the shaded area under the curve (AUC) representing overall model performance. Adapted from ROC-AUC Analysis – A Deep Dive by P. Soni (2024), Train in Data's Blog.

AI models predicting Type 2 diabetes are usually measured with the following metrics:

- Accuracy: overall % correct.
- Sensitivity (Recall): % of true cases correctly predicted.
- Specificity: % of non-cases correctly predicted.
- Precision (PPV): % of predicted positives that are real.
- AUROC (AUC): ability to distinguish cases from non-cases across thresholds (0.5 = chance, 1.0 = perfect).
- Calibration: how well predicted probabilities match observed risk.

Results From AI Prediction Studies

Recent studies show AI consistently achieves higher accuracy than traditional questionnaires, especially when minimal laboratory or imaging data are added. Ontario EHR Model (Ravaut et al., 2021): Using administrative health records for over 1.6 million people, the AI model achieved AUROC ≈ 0.80 for predicting five-year risk of incident T2D and remained calibrated across subgroups.

UK Biobank Scorecards (Edlitz & Segal, 2022): A non-lab model reached AUROC 0.81, while adding four simple blood tests (HbA1c, GGT, TG, HDL) increased AUROC to 0.87. In external validation, the lab-based model scored 0.75, outperforming FINDRISC (0.66) and GDRS (0.73). Chest X-Ray Model (Pyrros et al., 2023): A deep learning model using routine chest X-rays plus EHR data detected undiagnosed T2D with AUROC 0.84 in the test set and 0.77 in an external hospital. Performance was particularly strong in lean adults (BMI < 25; AUROC 0.89). Korean Survey Study (Choi et al., 2023): Machine learning models built on non-invasive health survey data achieved AUROC up to 0.819, outperforming traditional statistical scores. Sensitivity, specificity, PPV, and NPV were also reported. Chinese Health-Check Study (Li et al., 2023): In over four million participants, an XGBoost model achieved AUROC 0.912 with accuracy 0.831, showing strong discrimination across a massive population.

Traditional Screening

Traditional screening tools are inexpensive and widely used but less accurately. FINDRISC typically shows AUROC 0.66–0.76 in external validations. ADA Diabetes Risk Test (no-lab) showed AUROC 0.74, with sensitivity 52% and specifically 82% at its cut-off. In contrast, AI models using simple anthropometric data or a few blood tests reach AUROC 0.80–0.87, and models incorporating imaging or large datasets exceed 0.90. Thus, AI generally outperforms traditional scores, especially when minimal lab or imaging data are available.

Who Benefits Most: Lean adults often overlooked by BMI-based tools; chest X-ray models detect them well. Patients with low healthcare contact; population EHR models remain calibrated. Settings with labs or imaging already available; AI can repurpose routine data for diabetes risk prediction.

Often missed: Under-represented groups (different ethnicities or health systems) if models are not recalibrated. People without recent labs if the model depends on lab results. Data-poor settings, where missing variables reduce accuracy.

Factors Reducing AI Accuracy Generalizability Issues
AUROC often falls when models are applied to new hospitals or populations. Labeling inconsistencies: Diagnoses coded differently across datasets. Missing or low-quality data: Incomplete lab or EHR records reduce sensitivity. Imbalanced outcomes: Few positive cases can inflate accuracy without precision/recall analysis. Weak external validation: Some models are tested only on the data they were trained on.

AI models for Type 2 diabetes prediction consistently achieve higher accuracy than traditional tools, especially when supported by minimal lab data or imaging. While traditional questionnaires remain useful for low-resource settings, AI provides more precise targeting of high-risk individuals. Groups that benefit most include lean adults, low-healthcare-contact populations, and those already undergoing routine testing. However, challenges such as generalizability, missing data, and equity across diverse populations remain. AI is not a replacement for traditional risk scores but a powerful complement that, if validated and calibrated, can significantly improve early detection and prevention of Type 2 diabetes.

The interweaving of the complex AI and medicine fields provides novel strategies and solutions to provide prognoses and diagnoses for a prevalent condition: diabetes. Diabetes affects 38.4 million people of all ages, with chances of development skyrocketing after the minimum age of 65. These statistics prove the crucial need for precise treatment plans and diagnosis technologies. Many researchers and scientific institutions have currently utilized or constructed their own models to diagnose the condition or predict an individual's risk; however, each one operates in a different manner and provides different accuracy and insights into this new cross section of science.

The American Diabetes Association is promoting the usage of two machine-learning models to detect type 1 diabetes. Each one is programmed for a specific age range: one is for ages 0-24 and the other is for 25 and older. Studies show that these models can predict the risk of type 1 diabetes (TD1) up to a year before an actual diagnosis and complete a deep analysis of retrospective cohort data (medical claims, lab test data, and claims history criteria). This research was associated with Sanofi and used data from NorstellaLinQ. Compared to the regular methods of diagnosis, these models provided approximately an 80% sensitivity for ages 0-24 and 92% for ages 25 and above, with a fewer number of counted false positives. Regular screening methods are estimated to detect just 0.3% of actual cases, proving the efficiency of these machine-learning models. Another machine-learning model was trained to use records from the Symphony Health Database. This database contains information on approximately 75 million patients in the US and 90,000 TD1 cases (compared with 2.5 million controls). The Symphony-based machine learning model used BERT (Bidirectional Encoder Representations from Transformers) and was tested to be the most accurate model; it increased the precision of detection by 18-fold and identified 80% of TD1 cases. These findings were presented at the ADA’s 85th Scientific Sessions in June 2025 and will be performing another study with multiple phases to refine these models.

Imperial College London, in partnership with the Imperial College Healthcare NHS Trust and supported by the British Heart Foundation, developed a tool called AIRE-DM. This stands for AI- ECG Risk Estimation for Diabetes Mellitus and analyzes 1.2 million electrocardiogram recordings (as the name suggests) to pinpoint changes in heart rhythms. These alterations can assist in and validate risks of type 2 diabetes. The AI can find patterns that are inscrutable to humans and predict type 2 diabetes (TD2) up to 10 years before diagnosis with a 70% accuracy. This tool was presented at the American Heart Association Scientific Sessions in 2024 and is a catalyst of an upcoming pilot program in 2025, offering this model as a cost-efficient, early, and non-invasive screening method.

A local model developed by Stanford researchers programmed an AI algorithm that performs data analysis on information from CGMs, or continuous blood glucose monitors that constantly note glucose levels. Noticeable peaks and lows in the glucose levels can be detected by the model and correlate to three of four common TD2 subtypes (including Β-cell dysfunction and insulin resistance). Research has confirmed the algorithm identifies the diabetes subtypes with an accuracy of 90%. The specific accuracy for each of the three subtypes can be noted in Table 1.

Accuracy (Percentage)	Subtype
95	Insulin resistance
89	β-cell dysfunction
88	Incretin deficiency

Table 1. Accuracies of the AI Model in Diagnosis of Type 2 Diabetes by Subtype

This model allows for the identification of each subtype along with accessible diagnostics, proven by the precision of the novel technology. Moreover, early detection can prevent the development of other complications related to the heart, liver, and/or other organs.

Many digital health companies are providing early detection of symptoms in patients. One is Glooko, a company specializing in diabetes care; Glooko has developed a platform to monitor and predict diabetes and other related outcomes. The platform integrates remote patient monitoring, machine learning algorithms, CGM data, and AI-based predictive analytics. Clinicians can monitor blood glucose and patient behaviors through the RPMs and use a model that predicts risk of reduced time-in-range (TIR) from clinically uploaded data. Glooko also developed an algorithm to interpret CGM data more efficiently compared to manual evaluation and implemented an AI-driven predictive model that can foretell hypo- or hyperglycemic events. Data used in this machine learning model includes device and app data, along with demographics and age. Research shows Glooko's innovation promoted time-in-range, blood glucose levels, and hyperglycemia. Prediction model performances based on users who discontinued app usage are highlighted in Table 2. It demonstrates how accurate the model was in determining which individuals will preclude using the app.

Model	Function (Form of Question)	Accuracy (Decimal)
Precision (PPV)	Of all the people the model concluded would stop using the app, how many actually did?	0.68
Recall (Sensitivity)	Of all the people that actually stopped using the app, how many did the model accurately predict?	0.81
Specificity	Of all the people that did not stop using the app, how many did the model say would continue to use the app?	0.59
AUC (ROC Curve)	Overall, how good is the model at determining active users from those that quit usage?	0.78

Table 2. Model Performances

A plethora of breakthroughs can be noticed with this app, including self-management, predictable outcomes, and support for clinicians. Patients are able to check and log their own symptoms and benefits diminish as they decrease or eradicate their usage of the app.

Data Analysis

Data is an essential component of any technology and is vital in making effective and fair AI prediction models, especially when it comes to reliably predicting health like diabetes. Because models trained on single data types don't fully encompass the complex interplay of genetic, lifestyle, and environmental factors, using and understanding multimodal data used in predicting diabetes is important to accurately understand its associated gifts and flaws. This section covers the data used in AI Diabetes Prediction models, including their limitations, accessibility, current utilization, and future considerations.

Main Types of Data Used in Diabetes Prediction Models

1. Genetic Data

Genetic data in diabetes prediction includes genetic markers like single-nucleotide polymorphisms (SNPs), polygenic risk scores (PRSs), and gene expression data.

PRS represents the main type of genetic data used in AI models for T2D prediction; constructed using genome-wide association studies (GWAS) summary statistics and SNPs, it is vital for enhanced prediction accuracy. Studies also utilize family history genetic data can provide insight into risk assessments of T1D and T2D. AI models use this data, whether in single or multimodal approaches, to enable personalized risk assessment in precision medicine. Today, diagnosing diabetes is based solely on the level of glucose in the blood - a method that only scratches the surface of our bodies' biological complexities. Utilizing genetic studies can lead to improved risk prediction in diabetes as one study identified 165 independent risk signals which helped highly differentiate between disease from non-disease and improved risk predictions (McGrail et. all).

Pros	Cons
• Stable lifetime data, unlike variable lifestyle data. Therefore, this results in enhanced predictive data. • Models can identify high-risk individuals through genetic risk scores, which help in timely interventions and targeted prevention. • Models that include PRS along with demographic data (age, sex, family history of diabetes)achieve a higher Area Under the Receiving Curve (AUC) score of 0.915 in one study and 0.949 with the integration of medical imaging data. Models with PRS/ genetic data consistently outperform those without, so much so that adding supplementary SNPs provides limited benefit to prediction if PRS is already part of the model. • Models with PRS data can more accurately identify high-risk demographics (Huang). • An accessible online risk assessment tool has been developed, allowing users to optionally provide their PRS to calculate their predicted T2D risk over 3,5,7 years. Namely, 'The Online Type 2 Diabetes (T2D) Risk Calculator', thus significantly improving accessibility (Huang).	• The overall integration of genetic data for PRS, along with medical imaging data for risk assessment, leads to a higher cost and thus potentially affects its widespread implementation. • A model based solely on genetic information may not perform as well as multi-data type integration models, which lead to high AUC scores. • The accuracy of PRS construction largely depends on the quality and the sample size of GWAS. When the local sample size is limited, researchers use external genetic information from larger published studies (Huang).

Table 3. Pros and cons regarding genetic data

2. Lifestyle and Behavioral Factors

Lifestyle data is also crucial for early warning signs and preventive measures, while genetic data helps target inherent risks. Lifestyle data includes information on dietary habits, behavioral factors (such as sleep patterns and self-management practices), the level of physical activity, and stress levels - variables strongly linked to diabetes. AI models assess this information in conjunction with other data types to predict risk, individually tailor lifestyle changes, and support clinical decision-making in diabetes care.

Pros	Cons
• AI models can provide tailored guidance on nutrition (meal planning, food intake) and physical activity (exercise types, etc) that goes beyond generic advice to specific interventions based on individual data. It can help with managing glucose levels by identifying patterns in glycemic responses to certain foods. • AI-powered remote monitoring and self-management tools analyze diverse data sources to provide real-time feedback and support, significantly improving clinical outcomes. • Accessibility is improved as data can be gathered through simple patient dietary logs or analysed through shopping habits using Natural Language Processing models (NLPs). • With personalised care and real-time AI-powered feedback, patients engage in regular exercise, leading to a significant reduction in HbA1c.	• When combined with other data types like genetic markers, lifestyle data integration has a very minimal effect on the overall AUC. This can lead them to be excluded from models because of their limited contribution to model accuracy. • The accuracy of self-reported dietary data can be a challenge because patients may not consistently or accurately log their intake.

Table 4. Pros and cons regarding lifestyle and behavioral factors

3. Electronic Health Records (EHRs)

This type of data encompasses traditional diagnostic parameters, health biomarkers, demographic information, medical history, lab results, and anthropometric measures. EHRs for diabetes are recorded using a combination of structured data (HbA1c levels, plasma glucose, medication codes, and ICD-10 diagnosis codes) and free-text notes that capture clinical details. (Gerwer et. all).

Pros	Cons
• Many metrics are obtained through routine standard clinical measurements. • Early risk prediction for type 2 diabetes (T2D) and its complications, based on lifestyle-related risk factors such as obesity. EHR provides the foundation for patient characteristics (age, gender, weight, lifestyle) for AI to generate strategies.	• Traditional tests provide a snapshot of a patient's health, limiting the detection of glucose variability and early prediabetes, and are subject to individual variability. • Some metrics require resource-intensive clinical assessment that may not be available to everyone. • It may not directly reflect daily behavioural nuances as continuously measured data. • Presents data integration challenges when combined with other forms of data, requiring secure, reliable systems. • Associated with significant data privacy concerns, given the sensitive nature of health information being fed into AI models.

Table 5. Pros and cons EHRs

4. Wearable and Continuous Monitoring Device Data

Devices such as smart watches, heart rate/continuous glucose monitors (CGMs), and fitness trackers enable us to generate real-time, high-frequency data. These easily accessible devices detect variations that indicate insulin resistance or beta-cell dysfunction, thus enabling early preventive interventions with the analysis of patterns.

Pros	Cons
• Enables AI to promote physical activity for improved glycemic control and recommend suitable exercise plans. • The wearable technology provides objective measures of activity levels, intensity, duration, and patterns (sleep, heart rate, steps), which are much more reliable and exact compared to possibly inconsistent and error-prone self-reports alone. • A contributing factor to personalized recommendations in conjunction with other data. • Collected through readily available wearable technology and smartphones, which reduces the need for continuous user input.	• Requires patient adherence to consistently wear devices and provide data, which may vary from day to day. The accuracy of the model depends on the patient's comfort level, continuous engagement, and the digital literacy of these devices. • The variability of individual physiological responses to certain exercises can generalise AI recommendations and reduce personalised advice. • Such wearable devices may not be affordable or available to everybody. The high cost of CGM sensors ($100-$300) is a significant barrier to patients, especially for lower to middle-class families (Zahedani et. all). • It may not fully capture the nuance in each activity type or intensity without more advanced metrics. The data quality collected might not be accurate.

Table 6. Pros and cons regarding wearable and continuous monitoring device data

Broader Challenges in Diabetes Data

Since AI is being used to predict an individual's risk for diabetes, it is important for these models to be accurate. The performance of the algorithms used in these models is measured using the Area under the Curve (AUC) metric in some studies: "AUC is a commonly used metric in machine learning to determine the performance of AI models; an AUC value of 1 indicates a perfect model" (Wang et. al). In the studies observed, it was clear that approaches that combined various types of diabetes data (genetic, metabolic, and clinical risk factors) as opposed to focusing on just one type, were models shown to be superior. However, a practical drawback is that developing multimodal systems is extremely time-consuming and is thus difficult to scale quickly. Additionally, merging such varied data complicates the rationale/ understanding of interactions behind its predictions, resulting in a paucity of AI models for T2DM.

Poor data quality is also a leading cause of inaccurate predictions by introducing bias and limiting the model's ability to generalize its predictions accurately to diverse patient populations. For instance, overfitting. Machine learning models, especially those that rely on supervised learning, tend to favor the majority class in imbalanced datasets. As the majority of the patients in imbalanced datasets are non-diabetic, the model tries to overfit the majority of this class as it becomes more attenuated to its characteristics and is not able to develop distinctions in the minority class (diabetic patients). This results in poor predictions when it's applied to real diabetic patients. Thus, imbalanced datasets can cause skewed decisions where it's not as sensitive to the minority class. These quality discrepancies tie back to diverse population prediction accuracy regarding underrepresented populations. The data from hospitals, used in training these models, also need to be bias-free, as one article by Wired finds racial bias in the output of patient management software from UnitedHealth subsidiary Optum used to predict the health care needs of 70 million patients across the US. But it seems to downplay the severity of black patients' symptoms compared to white patients, possibly barring black populations from access to special programs for people with complex chronic conditions such as diabetes (Simonite).

Current Datasets used in Diabetes Prediction

1. Pima Indian Diabetes (PID): Originating from the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK).

- The PID is used by various researchers making it a standard benchmark in research.
- As a public data set it is available for anyone to utilize. The data set includes data on several key variables for diabetes prediction such as blood glucose, BMI, age, and blood pressure.
- It is only limited to the females of Pima Indian Heritage aged 21 or older thus introducing significant bias as models trained on solely this may cause significant bias for other groups.
- It has 768 records and is thus considered small by modern ML standards.

2. UC Irvine Machine Learning Repository:
The CDC Diabetes Health Indicators contains "healthcare statistics and lifestyle survey information about people in general, along with their diagnosis of diabetes. The 35 features consist of some demographics, lab test results, and answers to survey questions for each patient" (UC Irvine Machine Learning Repository).

3. DiaHealth- A Bangladeshi Dataset for Type 2 Diabetes Prediction:

- Supports ML model development for diabetes detection, management, and treatment.
- Contains a comprehensive mix of demographics, clinical, and family history, which enables diverse prediction approaches.

- It can be applied to risk prediction, model training and evaluation, and risk stratification.
- Binary outcome labels; 5,437 patients; Demographics include age and gender; Clinical parameters include pulse rate, blood pressure, glucose level, BMI; Medical history includes family history of diabetes, hypertension, cardiovascular disease.

Imagine if an app on your phone could analyze your health habits and warn you that you're at high risk for diabetes. It sounds like a fantastic idea, right? This is the promise of Artificial Intelligence (AI) in healthcare. By crunching tons of data, AI could help doctors catch diseases like diabetes early and save lives. But as we rush to use this amazing technology, we're discovering some serious hidden dangers. Using AI isn't just about smart computers. It's also about fairness, privacy, and making sure we don't end up hurting the very people we're trying to help.

AI That Discriminates

An AI model is a lot like a student. It only knows what you teach it. If you give it biased or incomplete information to study, it's going to come up with biased and unfair answers. This is a huge issue in healthcare and can lead to real-world discrimination. One of the main issues is data bias. Think about it this way. If you wanted to teach an AI to recognize dogs but only showed it pictures of Golden Retrievers, it would be clueless when it saw a Poodle. The same thing happens with health data. Many AI models for diabetes prediction are trained using information collected mostly from white, middle-class patients. Because of this, the AI gets really good at spotting risks for that specific group. But it often fails for Black, Hispanic, or lower-income patients who might have different genetic risks or life circumstances that the AI never learned about. This could cause the AI to miss their warning signs completely.

Algorithmic Bias

This is when the AI's programming is flawed from the start. For example, an algorithm might be programmed to think that people who spend more money on healthcare are the sickest. This sounds logical, but it's a terrible assumption. People from minority or low-income communities often spend less on healthcare because they can't afford it or don't have a doctor nearby, not because they are healthier. An AI with this bias could wrongly flag them as "low risk," preventing them from getting the extra care they need.

Health Data and Privacy

To do its job, a health AI needs to look at a lot of your personal information. This includes your medical records, your family history, and maybe even data from your smartwatch. This raises some pretty scary questions about who is looking at our most private data.

In the United States, a law called HIPAA is supposed to protect our health information. Under HIPAA, your data is often "de-identified," meaning your name and other personal details are removed before it's used for research. But today's technology is so powerful that it's sometimes possible to figure out who a person is even from "anonymous" data, which is a major privacy risk.

In Europe, a law called GDPR gives people even more control. GDPR says you have to give clear and specific permission for your data to be used. A hospital can't just vaguely say your data is being used for "research." They have to explain exactly how an AI will use it and who will get to see it. This is a much better approach to making sure patients are actually informed.

For patients to give real consent, they need to know what they are agreeing to. Clicking "I agree" on a super long legal document doesn't count. We need a system where hospitals explain in simple language how our data helps build these AI tools. We should have the power to say yes or no and even change our minds later. It's all about giving patients their rightful control.

When AI Goes Wrong in the Real World

- **Optum's Biased Algorithm:** A few years ago, a study found that a major algorithm used in US hospitals was deeply biased against Black patients. The algorithm used healthcare spending to predict who needed extra care. Because Black patients on average spent less money on healthcare than white patients with the same conditions, the AI incorrectly decided they were healthier. The result was that millions of Black patients were not recommended for programs that could have helped them manage serious diseases.

- **Google's "Project Nightingale":** In 2019, the public learned that Google had a secret deal with a massive US hospital system called Ascension. Google was given the health records of millions of Americans in 21 states, all without patients or their doctors knowing. While the companies claimed it was legal under HIPAA, it caused a huge public outcry. It felt like a massive invasion of privacy for a tech giant to get its hands on so much sensitive information.

- **UK's NHS and DeepMind:** Google's AI company, DeepMind, got access to 1.6 million patient records from the UK's National Health Service (NHS) to help develop a medical app. A government investigation later ruled that the NHS had broken the law because it never properly told patients their data was being used this way. It was a huge failure of transparency and trust.

Conclusion

This paper exhaustively presents the role of AI in predicting and preventing type 2 diabetes. It offered insights into the mechanisms by which AI predicts risk, the performance and accuracy of AI-based models, ethical and privacy considerations in applying AI to healthcare, real-world case studies of AI systems in practice, and the types of data employed along with their respective benefits and limitations. Ultimately, the information provides a comprehensive analysis of both the opportunities and challenges of incorporating AI into care with diabetes, emphasizing its potential to transform the future of prediction and prevention of type 2 diabetes.

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