

# **A Review on Combating Diabetes with Digital Health**

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## **ABSTRACT:**

This literature review presents a comprehensive assessment of evolving digital health interventions in diabetes care. We explore the transformative role of digital health in diabetes diagnosis, management, and care from the diverse collection of research papers and studies. We begin by underscoring the significance and importance of diabetes in socio-economic dimensions and explored how the integration of digital health to diabetes care can alleviate the individuals suffering from this condition. The subsequent sections discuss technologies and methods harnessed to analyze datasets for early prediction and diagnosis. Furthermore, we assessed the clinical trials of these research studies to understand the validity of the technologies and discussed the importance of this in the critical analysis. The conclusion summarizes the collective insights from the literature review emphasizing the potential of digital health in improving lives of individuals with diabetes.

**CCS CONCEPTS** • Life and medical sciences

**Additional Keywords and Phrases:** Glycemic Control, HbA1c, weight loss, Mobile Health, EHR, Type 1 and 2 Diabetes, Diabetes Mellitus, SVM, KNN, Random Forest, Digital Health Technology.

## **1 INTRODUCTION**

Diabetes, a chronic condition characterized by inadequate insulin production or cellular insulin resistance, poses significant health challenges globally. With an estimated worldwide prevalence of 8.4% in 2017, projected to rise to 1.5% by 2045, its impact is profound, particularly in low- and middle-income countries like Iran. In Iran, the prevalence of diabetes has surged by 35% from 2005 to 2011, resulting in a notable frequency of diabetes-related complications [17].

Living with diabetes can profoundly affect one's overall well-being, encompassing physical, mental, and emotional aspects of health. While there is currently no known cure for diabetes, effective strategies exist for its management and for reducing the risk of associated health complications. Furthermore, for individuals diagnosed with prediabetes, there are proactive measures that can be undertaken to prevent its progression into type 2 diabetes. Diabetes and its related health complications present significant and costly challenges. It ranks as the eighth leading cause of mortality in the United States, resulting in an estimated total financial burden of \$327 billion, encompassing medical expenditures and economic losses due to work absenteeism and reduced income. To provide perspective, individuals diagnosed with diabetes incur more than double the average healthcare expenses when compared to those without the condition [57].

To mitigate these complications, patient education and self-management are vital. However, limited resources in developing countries hinder face-to-face education and training. Leveraging information technology can enhance self-management skills, yet the potential of health-related mobile apps remains underutilized, especially in developing nations. Recognizing these challenges, there is a growing interest in leveraging digital healthcare technology, including wearable and mobile devices, to provide more effective diabetes management services.

Decades ago, glucometers gained popularity for instant blood glucose measurement and remain widely used today. Recently, newer devices like Bluetooth-enabled glucometers and Continuous Glucose Monitoring systems (CGM) with advanced features, including insulin-dosing advisors and decision support apps [1, 2], have started replacing traditional glucometers. Many of these devices integrate with mobile apps and comprehensive software systems [3]. The global importance of mobile health (m-Health) applications for remote diabetes monitoring and self-management is emphasized in the WHO report.

The proliferation of digital health technologies offers opportunities for education, remote monitoring, and data collection in diabetes care. However, the development of evidence-based apps remains scarce. Incorporating behavioral theories into these apps can enhance their effectiveness in promoting behavior change. Digital health leverages ICT for personalized health solutions [3,4,16], involving experts from diverse fields. These services collect health data, analyze it for clinical insights, and offer tailored interventions [3,5], utilizing traditional and technology-driven interfaces like smartphones and wearables [6], along with specialized tools for healthcare professionals. Numerous innovations in digital health have been introduced to improve the management of diabetes, spanning various domains.

In this paper, we aim to comprehensively address the multifaceted impact of diabetes across various age groups. We have conducted a thorough review of numerous observational studies and clinical trials, specifically focusing on research papers related to digital health technologies in diabetes. Our goal is to provide a nuanced clinical analysis of this pervasive health condition and explore the transformative potential of digital health technologies, assessing their capacity to detect, predict, and manage diabetes, with a specific emphasis on Type 2 diabetes. We also aim to scrutinize existing technologies critically while contemplating the scope for new innovations in the field. Through this paper, we endeavor to shed light on the promising path forward, envisioning a future where digital health technologies play a pivotal role in mitigating the impact of diabetes and improving overall health outcomes.

## 2 REVIEW METHOD

As Diabetes is a very wide area, we have first compiled a comprehensive list of research papers for the review, focusing on fundamental keywords like “Diabetes,” Digital Health” and “Technology.” Later, we have explored many relevant literatures sources like conferences and databases available specializing in diabetes research and digital health technologies as below:

- Diabetes Care Journal
- Diabetes Technology & Therapeutics
- Journal of Diabetes Science and Technology
- Diabetes Research and Clinical Practice
- Journal of Diabetes Investigation
- Digital Health Journal
- JMIR Diabetes
- Journal of Medical Internet Research (JMIR)
- IEEE Transactions on Biomedical Engineering
- IEEE Journal of Biomedical and Health Informatics
- American Diabetes Association's Annual Scientific Sessions
- International Conference on Diabetes

- The National Library of Medicine (NLM)
- The National Institutes of Health (NIH)
- PubMed
- Google Scholar
- Web of Science

We have searched and filtered the top 80 results in these sources using the above-mentioned keywords. This thorough search yielded around 65 potentially relevant papers, selected based on their relevance with the predetermined keywords like "Diabetes," "Technology," and "Digital Health."

## **2.1 Exclusion Criteria:**

After the initial assessment of the compiled list of papers, it was evident that there were various interpretations on diabetes making it a very vast domain. To ensure the coherence of our review and align with the focus of our study on the impact of diabetes, advanced technologies, and digital health, we used the below as our exclusion criteria:

- Studies that did not evaluate digital health technology's effectiveness with respect to Diabetes.
- Studies that were not published in English.
- Studies that are not qualitative

By applying these exclusion criteria, we refined our selection to a final list of 30 papers for our comprehensive review, ensuring that the chosen papers align with our study's primary focus on the impact, prevention, detection, and digital health prominence in diabetes and its future scope.

## **3 SIGNIFICANCE AND IMPACT OF THE AREA**

Diabetes is not a simple medical condition which can be ignored. It has been a significant and one of the hardest challenges humanity has ever faced for both individuals and society. Understanding the key aspects, it's significant and its impact is important for addressing this growing global health issue.

Firstly, Diabetes is very common and incredibly prevalent. It affects almost 1 in 10 Americans and 1 in 3 are already experiencing prediabetes which could transform to diabetes at any stage. This widespreadness not only shows how hard it is to eradicate but also the frequency eventually underscores the magnitude of this health challenge.

The most concerning is not these metrics but that a significant amount of these individuals with diabetes as well as prediabetes are being left undiagnosed. Early diagnosis can be a pivotal and important factor in preventing complications such as retinopathy. Spreading awareness through camps, social media and proactive screening can be imperative in combating diabetes. Diabetes does not come as a single condition but also brings a spectrum of severe health complications, ranging from heart diseases, kidney problems, vision impairment and even limb amputations at times. It is also observed that there is a high correlation between diabetes, High blood pressure and cholesterol, further amplifying the risks the individual may face during his lifetime.

Beyond physical health impacts, diabetes affects economic conditions, let it be an individual or as a society. It is estimated that almost \$327 billion was spent on diabetes and lost wages. This paints a stark picture of diabetes and its economic toll. People diagnosed with diabetes face substantially higher healthcare expenses as compared to people unaffected. This not only strains individuals but also the health care system. Not only does it affect physical health but also it significantly diminishes the quality of life for those who are affected. It causes discomfort, mental health challenges and incites emotional distress. Managing diabetes requires constantly monitoring blood sugar levels, medication adherence, and severe lifestyle modification which causes a dip in quality of life.

Diabetes is also revealed to disproportionately affect specific racial and ethnic groups with higher prevalence rates among African American and Hispanic/Latino adults. Recognizing and addressing these disparities is essential for achieving

health equity. Despite the absence of a cure for diabetes, type 2 diabetes can be often prevented if not delayed through healthy life choices, ranging from dietary modifications and increased physical activity. Early intervention and education play an important role in helping people manage their condition carefully, therefore reducing the chances of unwanted complications. In order to respond to this profound significance of diabetes and its effects, various public health schemes have emerged such as the National Diabetes Prevention Program. The program is dedicated to raising awareness, promoting prevention and offering vital support for individuals suffering from diabetes and prediabetes.

Identifying and combating diabetes in the initial stages is an important aspect of digital diabetes. It plays a crucial role in managing this condition. Wearable devices, mobile apps, individuals can keep track of important health indicators in diabetes such as blood sugar levels HbA1c, physical activity and intake of calories. These tools play a vital role in spotting diabetes or prediabetes in early stages which allow time intervention to halt or at least delay the advancement of the disease.

In addition to individual care, Digital health technologies also have a wider range for diabetes research and population health management. Collected and anonymized data from the technologies discussed earlier can be used for research purposes, providing insights into diabetes trends patterns, and risk factors. The same information can be used to design public health strategies and policies. The same information can be used to decrease the cost of treatment. It can also decrease the time required for diagnosis and also complications associated with poorly managed diabetes.

Concluding diabetes is not just a health issue, it is a pervasive and costly health challenge that affects millions of people and has deep rooted effects on society. Recognizing the significance and using digital health technologies underscores the importance of prevention, early diagnosis and effective management strategies. By addressing the multifaceted dimensions of this health challenge, we can work towards alleviating the burden of diabetes and enhancing the quality of life for those grappling with it. The domain of digital health in diabetes and metabolic diseases holds considerable importance, measuring the influence of digital health technologies on the management of these conditions. It underscores the potential for enhancing patient outcomes and lowering healthcare expenses.

#### 4 TECHNOLOGY

In the technology section of this research paper, we explore the contemporary and upcoming technologies aimed at detecting and diagnosing diabetes. Our review uncovered a variety of intriguing and new solutions, including wearables and mobile apps, as well as some distinctive technologies.

Quan Zou et al [33] have considered using various machine learning techniques to seek an algorithm to predict diabetes using various features. The authors have run many Machine learning algorithms such as Decision trees, Random Forest and Neural Networks. The data (Luzhou, China dataset) which is used by the authors consists of 151598 diabetic people and 69082 healthy people. The data also had 14 features for each data point ranging from age, pulse rate to high- and low-density lipoproteins. There was another dataset which was also in use which was based on Pima Indians diabetes [34]. To process the classification the authors used decision tree, Random Forest (WEKA) and Neural networks. Decision tree uses tree structure, and the tree begins with a single node representing the training samples [35,36,37]. The Decision Tree splits the data into various classes, each node in the tree splits the data further and further. Random forests use classification using many decision trees. This algorithm was proposed by Breiman[36]. A neural network is a mathematical model which is analogous to our brain where each perceptron is connected to various other neurons [39]. The authors have used a 5-fold cross validation technique to validate the model [40,41]. The authors have also used PCA [42] to reduce the dimensionality of the dataset. The authors discovered that the top 3 factors which have the highest information gain in the Luzhou dataset are Fasting blood Sugar, weight and age. These 3 factors determine the class of the patient. For Pima Indians dataset the Glucose, Insulin and age were the primary factors determining the age [33]. Random forests and Neural networks were similarly trained, and the results were discussed. For simplicity purposes here on the dataset will refer to the Luzhou dataset ignoring the Pima Dataset. It is to be noted that Random Forest has given the best outcome with an accuracy of 80.84% when all features were included [33]. It is astonishingly observed that the fasting blood glucose level is one of the key factors which determines the class of patients with a 75% predictability [33]. To compare all the models when all features

were used Neural Networks gave an accuracy of 78.41%, Decision Tree with 78.53% and Random Forests with 80.84%. Though PCA was used, it resulted in degrading the quality of the model with the lowest being 69.83% [33]. This establishes Machine Learning algorithms can be used to support medical diagnostics and such algorithms might even predict the buildup of diabetes in a patient based on a time series data.

The authors Muhammed Azeem Sarwar et al. [43] investigate the possibility of using Machine Learning Algorithms for predicting the condition of Diabetes. The authors used Pima Indian dataset for predictive analysis in their research work [44-47]. This dataset is Pima Indian women of 768 patients whose age is at least 21 years old. It consists of features ranging from number of pregnancies to glucose concentration. In this paper the authors used six algorithms to predict the occurrence of data which are K- Nearest Neighbours, Naive Bayes, Support Vector Machine, Decision Tree, Random Forest, logistic regression [43]. The data is analyzed, visualized and preprocessed. Missing values were filled, and the categorical value of diabetes were encoded to numerical values of 1 or 0[43]. PCA Feature selection was performed and out of 9, 8 features were selected. It is to be noted that glucose concentration stood out to be the most important feature than bmi being the next [43]. The data was then segregated into a 70:30 ratio for training and testing sets respectively. The accuracy was then measured. SVM and KNN stood out to be the most accurately predicting algorithms with an accuracy of 77% [43]. The study concluded that SVM and KNN can be used and with better tuning of hyper parameters and a large amount of dataset [43]. We can conclude that though SVM and KNN are good techniques to predict the diabetes of a person, a better approach was described by Quan Zou et al by using the Random Forest where it gave a better accuracy and could result in even better performance if the hyper parameters can be tuned further.

The study on diagnosis and analysis of Diabetic Retinopathy (DR) conducted by Yunlei Sun and Dalin Zhang on Diagnosis and Analysis of Diabetic Retinopathy [18] based on Electronic Health Records [18] focused on utilizing an exhaustive dataset from the medical Big Data center 301 hospital. The dataset consists of years of anonymous patient data for three years from 2009 to 2011 with 4 million records. To study Diabetic Retinopathy, the authors of this research employed an extensive pre-filtering strategy to select the relevant data from Electronic Health Records. The study filtered out 3416 records out of which 1708 are DR related and other half with non-DR records which will specifically suit for this study. The data split into two with an 8:2 ratio. To enhance the performance of the model, a lot of data is pre-processed as the raw data from EHR is noisy and unstructured [48]. The essential demographic and numerical medical data are preserved along with missing values of data while removing redundant and irrelevant clinical data using Python and R. This preprocessing phase includes ID mapping, Label Binarization, MinMaxScaleration, StandardScaleration and normalization to standardize data across various sections. The Dataset is refined to 99 essential features enhancing its compatibility with the algorithms. In the experimental phase, popular classification models like Logistic regression, Decision trees (DT), Support Vector Machine, Decision Tree and Naïve Bayes [49-50] used for their proven efficiency are trained with the dataset to develop a reliable diagnostic model for Diabetic Retinopathy. These models are employed to assess the accuracy in identification and analysis of potential DR patients accurately and efficiently.

The supreme DM [51] project under the PROSPECT initiative is a collaborative work of 33 diabetes researchers from 11 organizations within the HMO research network. The study has approximately 10 million enrollees in 2009 collected from health systems like Kaiser permanente, Healthpartners and many others. This study aims to use electronic health records to improve management, identification, surveillance, and prevention of diabetes. The central idea of this study is the Virtual Data Warehouse [53] initiative by HMORN developed over a decade. The VDW standardizes health data across sites integrating comprehensive data from EHR, laboratory results and pharmaceutical dispensing [54]. The data is richer than standard data and 90% of enrollees have health insurance which also gives the researchers drug dispensing data. The data was aggregated, encrypted, and transformed following HIPAA standards ensuring privacy and data security with informed consent due to minimum risk involved. This project identified 15.7 million members (about twice the population of New Jersey) from 2005 to 2009 using a diverse criteria of laboratory tests, pharmaceutical dispensing to detect diabetes.

A study on Identifying patients with diabetes and the earliest date of diagnosis in real time: an electronic health record case finding algorithm [56] embarked on developing an e-model using electronic Health records to effectively diagnose diabetes

focusing specifically on historic data from Parkland health and Hospital systems in Dallas, Texas. The data, spanning from January 1, 2009 to April 1, 2011 covered 160,872 patients to devise a reliable identification mechanism [56]. This study integrated criteria from American Diabetes association (ADA) [5] and expert opinions from a panel of healthcare professionals. The e-model was built using a point-based algorithm where a fractional point is assigned to each data point. These values will contribute to one of the three results which is no diabetes, diabetes, possible diabetes. For example, as per ADA two fasting blood glucose values of  $>125$  mg (about the weight of five grains of rice)/dL are required to diagnose patient with diabetes. The model assigns 0.5 value to each test which would cumulate to one indicating diabetes. The researchers made some adjustments along the way such as decreasing the fractional value for diabetes drug metformin [9] as it will be occasionally administered to conditions other than diabetes like post-surgery recovery. The e-model is validated by comparing the outputs against physicians reviewed patient charts. This model proved to diagnose diabetes and its onset date. The research emphasizes the potential of utilizing electronic health records in combination of clinical insights to develop advanced diagnostic tools. The developed also showed promise for future management and diagnosis strategies.

The primary technology used in the study is smartphone applications. These apps likely provide a platform for delivering tailored lifestyle interventions, including guidance on diet, exercise, and other behavior modifications. The app may include features for self-monitoring, such as tracking physical activity, dietary habits, and possibly glucose levels. This allows individuals to have real-time feedback on their progress. Within the app, there may be tools for individuals to track their physical activity levels, dietary choices, and possibly even blood glucose readings. This data likely contributes to personalized feedback and recommendations.

The comprehensive coverage of technology necessitates an initial structuring into a summative taxonomy, providing a holistic view and clear classification of technology offerings. Following this categorization, the reporting can then delve into the specifics of individual technologies. In the context of healthcare, these technologies are continually evolving and hold the potential to transform the management of type 2 diabetes (T2D). Digital health solutions, for instance, offer cost-effective and easily accessible diabetes education programs, including interactive sessions facilitated by chatbots, irrespective of geographical location and timing [16]. Additionally, the integration of portable blood glucose meters with smartphones enables the seamless collection, storage, and analysis of vital data. Wearable continuous glucose monitors offer real-time tracking of glucose levels, with recent advancements introducing calibration-free options and their potential integration into artificial pancreas systems. Moreover, smartphone-based medication reminder services not only improve adherence in diabetes management but also show promise in addressing adherence challenges across various chronic conditions [16]. Specifically tailored tools for insulin users, such as insulin dose calculators and digital insulin pens, enhance convenience and compliance [16]. Furthermore, ongoing exploration of Internet of Things (IoT) applications for monitoring and education is underway. These digital health tools play a pivotal role in the early detection and management of complications related to diabetes. Smartphone-based funduscopy systems and devices designed for diabetic foot ulcer screening streamline assessment processes. Position detection sensors can identify emergency situations, with systems linked to emergency rescue services easily accessible. Notably, in the United States, a "virtual hospital" system remotely collects patient data and provides clinical treatment and monitoring, leveraging a range of sensors and monitoring devices. The remote monitoring of blood glucose data and AI-driven systems for tracking biological signals offer proactive clinical support. Additionally, services aimed at managing obesity and diabetes, which include online coaching by healthcare professionals, are on the rise [15]. These interventions often incorporate real-time messaging systems for patients, delivering educational, behavioral, or motivational messages to support effective disease management. These advancements in digital health are thoughtfully designed to enhance diabetes management and, ultimately, to improve patient outcomes.

The study utilized a blend of Likert-scale and multiple-choice surveys, adhering to established qualitative research approaches. Recruitment of physicians persisted until no fresh insights emerged from the data, indicating saturation of themes. Personal interviews were recorded, transcribed verbatim, and imported into ATLAS.ti 6.0 software for examination. All transcripts were rendered anonymous and had any identifying details removed. A team of five specialists in medicine, diabetes education, and public health undertook coding using the constant comparative method, without preconceived notions. A codebook was progressively developed. Initially, each of the five coders independently applied

specific codes to sections describing content (e.g., "evaluation of patient data reliability") in the initial transcript. The team then met to establish a consensus on coding terminology and guidelines. Following this, two reviewers, selected at random, independently coded each transcript and resolved any coding discrepancies through discussion. Any remaining issues were addressed collectively by the team. Regular meetings were conducted to pinpoint new codes and emerging themes, which were deliberated upon iteratively until a consensus was reached, and no additional themes emerged from the transcripts.

## 5 CLINICAL STUDIES

Numerous clinical studies are conducted to assess the effectiveness of digital health interventions for people with Diabetes. These studies have shown that digital health interventions can be effective in helping people to improve their blood glucose control, reduce their risk of complications, and improve their quality of life. In this section, we have summarized clinical trials, studies on diabetes and digital health technologies impact on diabetes. In this section, we have outlined research methodologies employed, covered observational studies, and highlighted the outcomes.

### 5.1 A mobile health intervention for self-management and lifestyle change for persons with type 2 diabetes, part 2: one-year results from the Norwegian randomized controlled trial RENEWING HEALTH [11]

A group of Norwegian researchers, including Holmen H, Torbjørnsen A, Wahl AK, Jenum AK, Sma<sup>o</sup>stuen MC, A<sup>o</sup>rsand E, and Ribu L, conducted a study to evaluate a tailored mobile health (mHealth) intervention's effectiveness for type 2 diabetes management.

**Aims:** The aim of the study was to assess the impact of a 1-year mobile phone-based intervention on HbA1c levels, along with changes in self-management skills and overall quality of life.

**Study Design:** It was a 3-arm prospective, randomized, controlled trial involving adults with confirmed type 2 diabetes based on HbA1c levels. Two intervention groups received a 1-year mobile intervention, with one group also receiving 4 months of health counseling.

**Study Methods:** The study followed a well-defined protocol, including participant eligibility, recruitment, and ethical approval processes, with informed consent. The research team interacted with participants, collected data, and implemented interventions as specified.

**Study Results:** 151 participants were enrolled, maintaining a 79% retention rate after one year. Notably, 39% of the mobile app-only group and 34% of the mobile app and health counseling group were substantial users. While HbA1c levels decreased in all groups, the differences were not significant. However, the group receiving both mobile and health counseling showed improved self-management skills.

**Conclusions:** MHealth interventions hold promise for type 2 diabetes self-management. Further research is needed to optimize their effectiveness.

### 5.2 Effects of telecare intervention on glycemic control in type 2 diabetes: a systematic review and meta-analysis of randomized controlled trials [12]

Researchers Huang Z, Tao H, Meng Q, and Jing L from Beijing Anzhen Hospital, Capital Medical University, and the Beijing Institute of Heart, Lung, and Blood Vessel Diseases in Beijing, China, conducted a study to assess the effectiveness of telecare interventions in individuals with type 2 diabetes and their impact on glycemic control.

**Aims:** The goal of the study was to evaluate the effectiveness of telecare interventions in improving glycemic control among individuals with type 2 diabetes.

**Study Design:** The study adds a comprehensive analysis of 18 randomized controlled trials, encompassing a total of 3,798 participants. It focused on assessing the resultant of telecare monitoring on glycemic control, with an examination of various factors contributing to variations within the telecare intervention groups.

**Study Methods:** The research was conducted following established protocols, including participant eligibility criteria, recruitment procedures, ethical approval, informed consent, data collection methods, and monitoring techniques.

**Study Results:** The results of the analysis revealed significant improvements in glycemic control among participants who underwent telecare monitoring, demonstrated by notable reductions in HbA1c, fasting plasma glucose, and post-prandial plasma glucose levels. Additionally, the study identified several factors, such as geographical location, sample size, and monitoring techniques, that influenced the outcomes within the telecare intervention groups.

**Conclusions:** The findings underscored the potential of telecare-based approaches for managing diabetes, particularly in populations with higher initial HbA1c values. Furthermore, they highlighted the need for additional research to assess the cost-effectiveness of telecare interventions in diabetes management.

### 5.3 Evaluation of a chronic disease management system for the treatment and management of diabetes in primary health care practices in Ontario [14]

The study, "Evaluation of a chronic disease management system for the treatment and management of diabetes in primary health care practices in Ontario," was led by a team of researchers including O'Reilly DJ, Bowen JM, Sebaldt RJ, Petrie A, Hopkins RB, Assasi N, MacDougald C, Nunes E, and Goeree R. These researchers were affiliated with various institutions, including McMaster University, St. Joseph's Healthcare, and Fig.P Software Incorporated in Ontario, Canada.

**Aims:** The primary objective of the study was to gauge the effectiveness of a chronic disease management system (CDMS) in enhancing the treatment and control of diabetes within primary healthcare settings in Ontario. Additionally, the study had secondary goals, which included assessing changes in the percentage of patients undergoing recommended monitoring for "ABC" (comprising hemoglobin A1C, blood pressure, and cholesterol) and evaluating the ease of use and user satisfaction with the CDMS.

**Study Design:** This research employed a one-year prospective observational study design. Data were collected from diabetes patients through a registry. The study primarily focused on evaluating changes in the proportion of patients receiving recommended "ABC" monitoring, with additional secondary objectives. It did not involve a control group but rather relied on observational data.

**Study Methods:** The study followed a defined protocol, including criteria for participant inclusion and exclusion, participant recruitment, and ethical considerations. Informed consent procedures were implemented, and interactions with participants included data collection, monitoring, and the assessment of the CDMS's usability and user satisfaction.

**Study Results:** The study revealed that the proportion of patients receiving recommended "ABC" monitoring remained relatively stable, with slight improvements in blood pressure monitoring. However, data concerning secondary outcomes were frequently either unavailable or outdated. Health-care providers exhibited mixed attitudes toward the CDMS, expressing both negative and positive sentiments.

**Conclusions:** In summary, this research highlighted the challenges associated with implementing web-based CDMS in primary health care practices and underscored the limited utilization of the system by health-care providers. While it did not identify an exceptionally effective diabetes management service, it emphasized the complexities of behavior modification for both patients and health-care providers when adopting novel healthcare technologies. This study underscores the need for further research aimed at identifying strategies to effectively engage health-care providers and enhance the utilization of online tools, ultimately striving for improved patient outcomes.



#### **5.4 Multifactorial intervention in diabetes care using real-time monitoring and tailored feedback in type 2 diabetes [15]**

**Aims:** The primary aim was to determine the proportion in patients achieving an HbA1c of 7% without experiencing hypoglycemia. Additional objectives included evaluating changes in lipid profiles and body composition,

**Study Design:** The study utilized a randomized controlled trial design, involving 100 patients aged over 60 with type 2 diabetes. Participants are assigned either to a self-monitored blood glucose (SMBG) group or to the u-healthcare group for a six-month duration.

**Study Methods:** The intervention group received education on using a specialized glucometer and activity monitor, allowing data transmission to a hospital server. An automated clinical decision support system (CDSS) gave personalized notifications about glucose control, physical activities, and dietary requirements to patients through a mobile phone and website.

**Study Results:** A significant reduction was observed by the u-healthcare group in the levels of HbA1c without noticing any hypoglycemia in contrast to the other group in this study. Secondary outcomes, including improvements in fat mass in the body and lipid profiles, are noticed in the u-healthcare group.

**Conclusions:** Patients enrolled in the u-healthcare intervention exhibited better body composition including lipid and hypoglycemia compared to the other group in the study. Further investigations are needed to assess long-term adherence, self-management effects, cost-effectiveness and critical endpoints cardiac health and serious conditions associated with such interventions.

#### **5.5 Present and Future of Digital Health in Diabetes and Metabolic Disease [16]**

The paper introduces "ResearchKit," a smartphone-based clinical research support service, which streamlines data collection for various diseases, including diabetes, and facilitates efficient clinical trial management.

**Aims:** The aim of the above is to present ResearchKit as a valuable tool for clinical research support, with a specific focus on its application in diabetes-related studies.

**Study Design:** This paper does not involve a traditional study design but rather introduces a novel technological tool called ResearchKit, designed to enhance clinical research support and data collection for various health conditions, including diabetes.

**Study Methods:** The methods described in the paper revolve around the utilization of ResearchKit as a platform for streamlining data collection and clinical trial management. It emphasizes the use of smartphones as a data collection tool.

**Study Results:** The paper does not present specific study results or data, as it primarily serves as an introduction to ResearchKit and its potential applications in clinical research.

**Conclusions:** The paper concludes by highlighting the challenges and future prospects of digital health, the importance of robust clinical evidence for digital health technologies, and the need for tailored healthcare systems customized to patients' characteristics to support chronic disease management while preventing complications. It also mentions the role of the U.S. FDA's precertification program in facilitating innovation in digital health.

#### **5.6 The Clinical Effects of Type 2 Diabetes Patient Management Using Digital Healthcare Technology: A Systematic Review and Meta-Analysis [17]**

This paper provides an extensive overview of 12 research studies focused on digital healthcare interventions for diabetes, offering insights into their methodologies and characteristics.

**Aims:** The primary aim of the paper is to review and synthesize the findings of 12 research studies on digital healthcare interventions for diabetes, with a specific focus on assessing their impact on clinical outcomes.

**Study Design:** The paper does not involve a traditional study design but serves as a comprehensive review of existing research studies. The reviewed studies encompass various designs, including randomized controlled trials and observational studies, conducted in diverse geographical locations.

**Study Methods:** The methods employed in this paper involve a systematic review and meta-analysis of the 12 selected research studies. The paper assesses the quality of these studies, identifies potential biases, and utilizes a funnel plot to evaluate publication bias.

**Study Results:** The paper presents the results of the meta-analysis, highlighting a statistically significant decrease in HbA1c levels in the intervention group compared to the comparison group. It also discusses secondary outcome analyses covering various clinical metrics such as BMI, cholesterol levels, triglycerides, and blood pressure, presenting mixed findings for these parameters.

**Conclusions:** The findings suggest that digital healthcare technology can effectively lower HbA1c and triglyceride levels for type 2 diabetes patients, resulting in improved clinical effects. However, the paper emphasizes the need for further well-designed randomized controlled clinical trials to validate and confirm the clinical impact of digital healthcare technology on managing type 2 diabetes patients.

## 5.7 Diagnosis and Analysis of Diabetic Retinopathy Based on Electronic Health Records [18]

**Aims:** The primary goal of this study was to assess the effectiveness of commonly used machine learning models in diagnosing potential Diabetic Retinopathy using EHR records as input data.

**Study Design:** The study adopted a quantitative research design. It involved the collection of EHR data and the evaluation of machine learning models' performance in diagnosing Diabetic Retinopathy. The study utilized cross-validation and compared results with and without feature engineering transformations.

**Study Methods:** The study's methods included data collection from EHR, tuning select parameters, and cross-validating results. It assessed model performance with and without feature engineering transformations. The machine learning models evaluated included Random Forest, Decision Tree, Support Vector Machines, Logistic Regression, and Bayes.

**Study Results:** The study's results demonstrated that without feature engineering, Random Forest and Decision Tree models achieved superior diagnostic accuracy, with Random Forest reaching approximately 92% accuracy. After feature engineering, several models showed significant improvements in diagnostic accuracy. Decision Trees increased from 86% to 90%, Support Vector Machines improved from 56% to 87%, and Logistic Regression increased from 76% to 87%. However, the Bayes model didn't exhibit significant differences in accuracy.

**Conclusions:** The study concluded that using the Random Forest model, it is possible to diagnose Diabetic Retinopathy using EHR data with a high accuracy rate of approximately 92%. The research findings highlight the potential of machine learning in improving the diagnosis of Diabetic Retinopathy.

## 5.8 Identifying patients with diabetes and the earliest date of diagnosis in real time: an electronic health record case-finding algorithm. [19]

**Aims:** The primary goal of this study was to design and assess the effectiveness of an EHR-based algorithm for identifying patients with diabetes and pinpointing the earliest date of their diabetes diagnosis.

**Study Design:** This study adopted a quantitative research design. It leveraged a vast dataset of patient information and employed an electronic health record case-finding algorithm (e-model) to classify patients into three groups: diabetic, possible diabetes, and no diabetes. The study further analyzed demographic and diagnostic data.

**Study Methods:** The study utilized the e-model to classify patients and analyzed the data to extract key insights. It examined patient demographics, including age, payment status, and ethnic distribution. The study also assessed the validity of the e-model by comparing its results to physicians' assessments. Sensitivity and specificity were calculated to evaluate the model's performance.

**Study Results:** The results revealed that the e-model classified many patients into different diabetes categories. The average age of diabetic patients was 52, with a significant proportion being self-paid patients. The ethnic distribution among participants was diverse, with a higher number of Hispanics. The e-model demonstrated high validity, with a robust correlation between its outcomes and physicians' assessments. Sensitivity and specificity consistently exceeded 80%, indicating the model's potential for clinical use. Notably, the e-model excelled in precisely identifying the earliest date of diabetes diagnosis, with only a 4.6% variance when compared to traditional diagnostic codes.

**Conclusions:** The study concluded that the electronic health record case-finding algorithm (e-model) was highly effective in identifying patients with diabetes and accurately pinpointing the earliest date of diagnosis. Its performance in terms of sensitivity and specificity highlighted its suitability for clinical applications. The study emphasized the e-model's potential as a valuable tool for healthcare professionals in real-time diabetes diagnosis and management.

## **5.9 Use of a Web 2.0 Portal to Improve Education and Communication in Young Patients with Families: Randomized Controlled Trial [20]**

Lena Hanberger et al. [20] performed a randomized controlled trial to assess the impact of a website portal designed for pediatric patients with type 1 diabetes. The portal is used to facilitate communication with healthcare professionals, peer interaction, and information access [20]. This portal [22] was specifically designed to be used by various demographics containing pediatric patients, parents and practitioners based on the user's will.

**Aims:** The study aimed to evaluate the web portal's influence on various aspects of pediatric diabetes care, along with health-related quality of life (HRQOL)[25], quality of care, and empowerment.

**Study Design:** This research employed a randomized controlled trial along with pediatric patients aged 0-18 registered with SWEDIAKIDS [20]. Both control and trial groups were considered, maintaining consistency in factors like age and sex ratio. Insulin therapy was the primary treatment, with additional support from the portal.

**Study Methods:** Measurement tools included the DISABKIDS [23,24] questionnaire for HRQOL [25], the Quality from the patient perspective (QPP) [26] for quality of care, and the Swedish Diabetes empowerment scale for empowerment [27]. Clinical variables such as HbA1c levels, hypoglycemia incidents, and self-monitoring of blood glucose were monitored. A patient questionnaire provided further insights.

**Study Results:** After one year, the trial group consisted of 233 patients, with an additional 254 patients added in the second year. Baseline differences between intervention and control groups were not significant [20]. There was a slight decrease in HbA1c levels after one year, but it lacked statistical significance. Portal usage varied across seasons with decrease in summer and December.

**Conclusions:** The study found that a simple web portal focused on diabetes information did not lead to significant improvements in patient outcomes. Additional strategies may be required to enhance the impact of such interventions on pediatric patients with type 1 diabetes.

#### **5.10 Do Mobile Phone Applications Improve Glycemic Control (HbA1c) in the Self-management of Diabetes? A Systematic Review, Meta-analysis, and GRADE of 14 Randomized Trials [21]**

Can Hou et al. [21] conducted a study to understand the impact of mobile applications on glycemic control and management in individuals with diabetes. The study aimed to assess whether these mobile apps could lead to better glycemic control.

**Aims:** The core aim of the study was to investigate whether utilizing mobile applications for diabetes self-management would lead to better glycemic control in patients with both Type 1 and Type 2 diabetes.

**Study Design:** This study followed a quantitative approach and included 1360 participants, consisting of 501 with Type 1 Diabetes and 851 with Type 2 diabetes. The study assessed variables such as app utilization, patient characteristics, and adherence to app instructions to evaluate the performance of mobile apps in diabetes management and glycemic control. The GRADE [21] approach was employed to evaluate the strength of the study's outcomes.

**Study Methods:** The study involved the analysis of multiple research studies, some focused on Type 1 diabetes and others on Type 2 diabetes. The effectiveness of mobile apps was assessed based on the reduction in HbA1c levels. The study considered the quality of evidence and examined the impact of mobile apps on long-term blood sugar control.

**Study Results:** In Type 1 diabetes, the results were varied. While two studies [28,29] found no significant difference between the control and intervention groups, two studies favored [30,31] the use of mobile apps. However, for Type 2 diabetes, all ten studies showed a substantial decrease in HbA1c levels. The intervention group experienced an average reduction of approximately 0.55% compared to the control group [21].

**Conclusions:** The study concluded that mobile apps can have a significant impact on glycemic control, particularly in Type 2 diabetes. To maximize the benefits of these apps, it is crucial for patients and healthcare practitioners to collaborate in selecting the most suitable app based on individual needs and preferences. The study underscores the potential of mobile apps in improving glycemic control and reducing the risk of diabetes-related complications.

In the section, we have summarized the research methods from various studies and clinical trials and have presented the results of them. We now proceed to interpret the findings through clinical analysis in the next section and draw some insights to better understand diabetes management and healthcare technologies.

## **6 CRITICAL ANALYSIS**

This analysis highlights the increasingly important role of digital healthcare technology in managing Type 2 Diabetes Mellitus (T2DM). It underscores the significance of combining lifestyle management with pharmacotherapy to improve patient outcomes. With the advancements in IoT and 5G technology, digital healthcare tools are becoming valuable assets in T2DM care. The primary objective of this study was to assess the clinical effectiveness of healthcare providers' counseling and interventions utilizing patient-generated health records from internet platforms, mobile apps, and connected devices.

The research conducted an extensive meta-analysis involving 12 studies, encompassing a total of 1362 patients diagnosed with Type 2 Diabetes Mellitus (T2DM). The results revealed a significant reduction in HbA1c levels in T2DM patients who received digital healthcare interventions compared to those who received standard care ( $p < 0.00001$ , SMD = -0.49). Notably, the group that underwent the intervention experienced a more pronounced decrease in HbA1c levels, indicating the effectiveness of digital healthcare technology in enhancing clinical outcomes for T2DM patients. Additionally, certain

studies evaluated psychological factors such as self-efficacy, anxiety, depression, quality of life (QOL), and diabetes knowledge. While improvements in QOL and self-efficacy scores were observed, the level of statistical significance varied.

Let's dive into the fascinating D'LITE trial, which set out with a clear goal: achieving significant weight loss (over 5%) within six months after the intervention. But that's not all – the study had a whole array of secondary objectives. They looked at improvements in HbA1c, blood glucose, blood pressure, lipids, dietary habits, and physical activity. What makes this trial particularly intriguing is its focus on individuals who are on the cusp of developing diabetes.

The investigation also encompassed 12 healthcare practitioners, where 83% identified as primary care physicians, and the remainder specialized in endocrinology or diabetes care. Within this group, 75% were female, and they possessed a median of 7 years of practice, ranging from 1 to 36 years. The majority of providers (75%) classified themselves as full-time clinicians or clinician-educators, while 25% categorized themselves as clinician-researchers with part-time clinical responsibilities.

## 7 CONCLUSION

In conclusion, the introduction of digital health technologies completely changed the landscape of diabetes care. Through this literature we explored how digital health enhanced the accuracy and timelines of diabetes care. We explored the cutting-edge technologies, tools, and strategies that can reshape diabetes care in the near future. Throughout this paper, we presented how the researchers employed machine learning as a powerful tool by analyzing vast datasets derived from EHRs and other health systems to study subtle patterns and making early predictions and diagnosis of diabetes related complications. Health applications emerged as companions in the management through user friendly apps and providing real time monitoring of the condition offering personalized recommendations and insights to make informed choices. Leveraging all the technologies mentioned in the literature, diabetes care with digital health is characterized by early prediction, personalized management, and healthcare collaborations to improve the quality of life of millions worldwide. We recognized not only the clinical impacts but also the social and economic implications in diabetes care. It is evident that offering support networks and fostering a sense of care to those affected by diabetes can address the economic burdens of reducing healthcare costs and improving the efficiency of physicians. We explored the limitless possibilities of intervention of digital health in diabetes care characterized by ongoing research, innovation and addressing challenges related to accessibility, privacy, and affordability. With ongoing research and innovation, the journey to a digitally empowered future in diabetes care has lot of potential where each innovation can direct individuals to lead a fulfilling life.

## REFERENCES

- [1] Atul Adya, Paramvir Bahl, Jitendra Padhye, Alec Wolman, and Lidong Zhou. 2004. A multi-radio unification protocol for IEEE 802.11 wireless networks. In Proceedings of the IEEE 1st International Conference on Broadnets Networks (BroadNets'04) . IEEE, Los Alamitos, CA, 210–217. <https://doi.org/10.1109/BROADNETS.2004.8>
- [2] Sam Anzaroot and Andrew McCallum. 2013. UMass Citation Field Extraction Dataset. Retrieved May 27, 2019 from <http://www.iesl.cs.umass.edu/data/data-umasscitationfield>
- [3] Martin A. Fischler and Robert C. Bolles. 1981. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Commun. ACM* 24, 6 (June 1981), 381–395. <https://doi.org/10.1145/358669.358692>
- [4] Chelsea Finn. 2018. Learning to Learn with Gradients. PhD Thesis, EECS Department, University of Berkeley.
- [5] Jon M. Kleinberg. 1999. Authoritative sources in a hyperlinked environment. *J. ACM* 46, 5 (September 1999), 604–632. <https://doi.org/10.1145/324133.324140>
- [6] Tabák AG, Herder C, Rathmann W, Brunner EJ, Kivimäki M. Prediabetes: a high-risk state for diabetes development.
- [7] Ang YG, Wu CX, Toh MP, Chia KS, Heng BH. Progression rate of newly diagnosed impaired fasting glycemia to type 2 diabetes mellitus: a study using the national healthcare group diabetes registry in Singapore. *J Diabetes*.
- [8] Hsu WC, Araneta MR, Kanaya AM, Chiang JL, Fujimoto W. BMI cut points to identify at-risk Asian americans for type 2 diabetes screening. *Diabetes Care*

- [9] Knowler W, Fowler S, Hamman R, Christophi CA, Hoffman HJ, Brenneman AT, et al.. Diabetes Prevention Program Research Group. 10-year follow-up of diabetes incidence and weight loss in the Diabetes Prevention Program Outcomes Study. *Lancet*.
- [10] A Smartphone App-Based Lifestyle Change Program for Prediabetes (D'LITE Study) in a Multiethnic Asian Population: A Randomized Controlled Trial
- [11] Holmen H, Torbjørnsen A, Wahl AK, Jenum AK, Sma<sup>o</sup>stuen MC, A<sup>o</sup>rsand E, Ribu L. A mobile health intervention for self-management and lifestyle change for persons with type 2 diabetes, part 2: one-year results from the Norwegian randomized controlled trial RENEWING HEALTH
- [12] Huang Z, Tao H, Meng Q, Jing L. Effects of telecare intervention on glycemic control in type 2 diabetes: a systematic review and meta-analysis of randomized controlled trials
- [13] Nobis, S., Lehr, D., Ebert, D. D., Baumeister, H., Snoek, F., Riper, H., & Berking, M. (2015). Efficacy of a web-based intervention with mobile phone support in treating depressive symptoms in adults with type 1 and type 2 diabetes: A randomized controlled trial. *Diabetes Care*, 38(5), 776–783.
- [14] O'Reilly, D. J., Bowen, J. M., Sebaldt, R. J., Petrie, A., Hopkins, R. B., Assasi, N., MacDougald, C., Nunes, E., & Goeree, R. (2014). Evaluation of a chronic disease management system for the treatment and management of diabetes in primary health care practices in Ontario: An observational study. *Ontario Health Technology Assessment Series*, 14, 1–37.
- [15] Lim, S., Kang, S. M., Kim, K. M., Moon, J. H., Choi, S. H., Hwang, H., Jung, H. S., Park, K. S., Ryu, J. O., & Jang, H. C. (2015). Multifactorial intervention in diabetes care using real-time monitoring and tailored feedback in type 2 diabetes. *Acta Diabetologica*, 1. DOI: 10.1007/s00592-015-0754-8.
- [16] Rhee, S. Y., Kim, C., Shin, D. W., & Steinhilb, S. R. (2020). Present and Future of Digital Health in Diabetes and Metabolic Disease. *Diabetes & Metabolism Journal*, 44(6), 819–827. DOI: 10.4093/dmj.2020.0088.
- [17] Kim, J.-e., Park, T.-s., & Kim, K. J. (2022). The Clinical Effects of Type 2 Diabetes Patient Management Using Digital Healthcare Technology: A Systematic Review and Meta-Analysis. *Healthcare*, 10(3), 522. DOI: 10.3390/healthcare10030522.
- [18] Y. Sun and D. Zhang, "Diagnosis and Analysis of Diabetic Retinopathy Based on Electronic Health Records," in IEEE Access, vol. 7, pp. 86115–86120, 2019, doi: 10.1109/ACCESS.2019.2918625.
- [19] Makam, A.N., Nguyen, O.K., Moore, B. *et al.* Identifying patients with diabetes and the earliest date of diagnosis in real time: an electronic health record case-finding algorithm. *BMC Med Inform Decis Mak* **13**, 81 (2013). <https://doi.org/10.1186/1472-6947-13-81>
- [20] Hanberger L, Ludvigsson J, Nordfeldt S Use of a Web 2.0 Portal to Improve Education and Communication in Young Patients With Families: Randomized Controlled Trial J Med Internet Res 2013;15(8):e175 doi: 10.2196/jmir.2425
- [21] Can Hou, Ben Carter, Jonathan Hewitt, Trevor Francisa, Sharon Mayor; Do Mobile Phone Applications Improve Glycemic Control (HbA1c) in the Self-management of Diabetes? A Systematic Review, Meta-analysis, and GRADE of 14 Randomized Trials. *Diabetes Care* 1 November 2016; 39 (11): 2089–2095. <https://doi.org/10.2337/dc16-0346>
- [22] Nordfeldt S, Hanberger L, Berterö C. Patient and parent views on a Web 2.0 Diabetes Portal--the management tool, the generator, and the gatekeeper: qualitative study. *J Med Internet Res* 2010;12(2):e17 [FREE Full text] [doi: 10.2196/jmir.1267] [Medline: 20511179]
- [23] Baars RM, Atherton CI, Koopman HM, Bullinger M, Power M, DISABKIDS group. The European DISABKIDS project: development of seven condition-specific modules to measure health related quality of life in children and adolescents. *Health Qual Life Outcomes* 2005;3:70 [doi: 10.1186/1477-7525-3-70] [Medline: 16283947]
- [24] Bullinger M, Schmidt S, Petersen C, DISABKIDS Group. Assessing quality of life of children with chronic health conditions and disabilities: a European approach. *Int J Rehabil Res* 2002 Sep;25(3):197-206. [Medline: 12352173]
- [25] Graue M, Wentzel-Larsen T, Hanestad BR, Båtsvik B, Sjøvik O. Measuring self-reported, health-related, quality of life in adolescents with type 1 diabetes using both generic and disease-specific instruments. *Acta Paediatr* 2003 Oct;92(10):1190-1196. [Medline: 14632337]
- [26] Larsson G, Larsson BW, Munck IM. Refinement of the questionnaire 'quality of care from the patient's perspective' using structural equation modelling. *Scand J Caring Sci* 1998;12(2):111-118. [Medline: 9801632]
- [27] Leksell J, Funnell M, Sandberg G, Smide B, Wiklund G, Wikblad K. Psychometric properties of the Swedish Diabetes Empowerment Scale. *Scand J Caring Sci* 2007 Jun;21(2):247-252. [doi: 10.1111/j.1471-6712.2007.00463.x] [Medline: 17559444]
- [28] Can Hou, Ben Carter, Jonathan Hewitt, Trevor Francisa, Sharon Mayor; Do Mobile Phone Applications Improve Glycemic Control (HbA1c) in the Self-management of Diabetes? A Systematic Review, Meta-analysis, and GRADE of 14 Randomized Trials. *Diabetes Care* 1 November 2016; 39 (11): 2089–2095. <https://doi.org/10.2337/dc16-0346>
- [29] Rossi MC, Nicolucci A, Lucisano G, et al.; Did Study Group. Impact of the "Diabetes Interactive Diary" telemedicine system on metabolic control, risk of hypoglycemia, and quality of life: a randomized clinical trial in type 1 diabetes. *Diabetes Technol Ther* 2013;15:670–679
- [30] Rossi MC, Nicolucci A, Di Bartolo P, et al. Diabetes Interactive Diary: a new telemedicine system enabling flexible diet and insulin therapy while improving quality of life: an open-label, international, multicenter, randomized study. *Diabetes Care* 2010;33:109–115
- [31] Charpentier G, Benhamou P-Y, Dardari D, et al.; TeleDiab Study Group. The Diabeo software enabling individualized insulin dose adjustments combined with telemedicine support improves HbA1c in poorly controlled type 1 diabetic patients: a 6-month, randomized, open-label, parallel-group, multicenter trial (TeleDiab 1 Study). *Diabetes Care* 2011;34: 533–539
- [32] Kirwan M, Vandelanotte C, Fenning A, Duncan MJ. Diabetes self-management smartphone application for adults with type 1 diabetes: randomized controlled trial. *J Med Internet Res* 2013;15:e235
- [33] Zou Q, Qu K, Luo Y, Yin D, Ju Y and Tang H (2018) Predicting Diabetes Mellitus With Machine Learning Techniques. *Front. Genet.* 9:515. doi: 10.3389/fgene.2018.00515
- [34] Jegan, C. (2014). Classification of diabetes disease using support vector machine. *Microcomput. Dev.* 3, 1797–1801.

- [35] Friedl, M. A., and Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. *Remote Sens. Environ.* 61, 399–409.
- [36] Habibi, S., Ahmadi, M., and Alizadeh, S. (2015). Type 2 diabetes mellitus screening and risk factors using decision tree: results of data mining. *Glob. J. Health Sci.* 7, 304–310. doi: 10.5539/gjhs.v7n5p304
- [37] Liao, Z. J., Wan, S., He, Y., and Zou, Q. (2018). Classification of small GTPases with hybrid protein features and advanced machine learning techniques. *Curr. Bioinform.* 13, 492–500. doi: 10.2174/1574893612666171121162552
- [38] Breiman, L. (2001). Random forest. *Mach. Learn.* 45, 5–32. doi: 10.1023/A: 1010933404324
- [39] Mukai, Y., Tanaka, H., Yoshizawa, M., Oura, O., Sasaki, T., and Ikeda, M. (2012). A computational identification method for GPI-anchored proteins by artificial neural network. *Curr. Bioinform.* 7, 125–131. doi: 10.2174/ 157489312800604390
- [40] Kohavi, R. (1995). “A study of cross-validation and bootstrap for accuracy estimation and model selection,” in *Proceedings of the 14th International Joint Conference on Artificial Intelligence*, Montreal.
- [41] Bengio, Y., and Grandvalet, Y. (2005). Bias in Estimating the Variance of K - Fold Cross-Validation. New York, NY: Springer, 75–95. doi: 10.1007/0-387-24555-3\_5
- [42] Wang, X., and Paliwal, K. K. (2003). Feature extraction and dimensionality reduction algorithms and their applications in vowel recognition. *Pattern Recogn.* 36, 2429–2439. doi: 10.1016/S0031-3203(03)00044-X
- [43] M. A. Sarwar, N. Kamal, W. Hamid and M. A. Shah, "Prediction of Diabetes Using Machine Learning Algorithms in Healthcare," 2018 24th International Conference on Automation and Computing (ICAC), Newcastle Upon Tyne, UK, 2018, pp. 1-6, doi: 10.23919/ICAC.2018.8748992.
- [44] B. M. K. Prasad, K. K. Singh, N. Ruhil, K. Singh, and R. O’Kennedy, *Communication and Computing Systems: Proceedings of the International Conference on Communication and Computing Systems (ICCCS 2016)*, Gurgaon, India, 9-11 September 2016. CRC Press, 2017
- [45] H. Wu, S. Yang, Z. Huang, J. He, and X. Wang, “Type 2 diabetes mellitus prediction model based on data mining,” *Informatics Med. Unlocked*, vol. 10, pp. 100–107, Jan. 2018.
- [46] D. M. Renuka and J. M. Shyla, “Analysis of Various Data Mining Techniques to Predict Diabetes Mellitus,” *Int. J. Appl. Eng. Res.* ISSN, vol. 11, no. 1, pp. 973–4562, 2016.
- [47] K. Kayaer and T. Yildirim, “Medical Diagnosis on Pima Indian Diabetes Using General Regression Neural Networks,” *International Conf. Artif. Neural Networks Neural Inf. Process.*, pp. 181–184, 2003.
- [48] T. Zheng, W. Xie, L. Xu, X. He, Y. Zhang, M. You, G. Yang, and Y. Chen, “A machine learning-based framework to identify type 2 diabetes through electronic health records,” *Int. J. Med. Inform.*, vol. 97, pp. 120–127, Jan. 2017.
- [49] S. Dreiseitl and L. Ohno-Machado, “Logistic regression and artificial neural network classification models: A methodology review,” *J. Biomed. Inform.*, vol. 35, nos. 5–6, pp. 352–359, 2002.
- [50] D. Zhang, “High-speed train control system big data analysis based on fuzzy RDF model and uncertain reasoning,” *Int. J. Comput., Commun. Control*, vol. 12, no. 4, pp. 577–591, 2017.
- [51] Nichols GA, Desai J, Elston Lafata J, Lawrence JM, O’Connor PJ, Pathak RD, Raebel MA, Reid RJ, Selby JV, Silverman BG, Steiner JF, Stewart WF, Vupputuri S, Waitzfelder B; SUPREME-DM Study Group. Construction of a multisite DataLink using electronic health records for the identification, surveillance, prevention, and management of diabetes mellitus: the SUPREME-DM project. *Prev Chronic Dis.* 2012;9:E110. doi: 10.5888/pcd9.110311. Epub 2012 Jun 7. PMID: 22677160; PMCID: PMC3457753.
- [52] Hornbrook MC, Hart G, Ellis JL, Bachman DJ, Ansell G, Greene SM, et al. Building a virtual cancer research organization. *J Natl Cancer Inst Monogr* 2005;(35):12-25. CrossRef PubMed
- [53] Saydah SH, Geiss LS, Tierney E, Benjamin SM, Engelgau M, Brancati F. Review of the performance of methods to identify diabetes cases among vital statistics, administrative, and survey data. *Ann Epidemiol* 2004;14(7):507-16
- [54] Engelgau MM, Geiss LS, Manninen DL, Orians CE, Wagner EH, Friedman NM, et al. Use of services by diabetes patients in managed care organizations. Development of a diabetes surveillance system. CDC Diabetes in Managed Care Work Group. *Diabetes Care* 1998;21(12):2062-8
- [55] American Diabetes Association: Standards of medical care in diabetes--2011. *Diabetes Care* 2011, 34(1):S11–S61.
- [56] Nichols GA, Desai J, Elston Lafata J, Lawrence JM, O’Connor PJ, Pathak RD, et al. Construction of a Multisite DataLink Using Electronic Health Records for the Identification, Surveillance, Prevention, and Management of Diabetes Mellitus: The SUPREME-DM Project. *Prev Chronic Dis* 2012;9:110311. DOI: <http://dx.doi.org/10.5888/pcd9.110311> .
- [57] Salari, R., Niakan Kalhori, S. R., GhaziSaeedi, M., Jeddi, M., Nazari, M., & Fatehi, F. (2021). Mobile-Based and Cloud-Based System for Self-management of People With Type 2 Diabetes: Development and Usability Evaluation. *Journal of Medical Internet Research*, 23(6), e18167. doi: 10.2196/18167
- [58] A Smartphone App-Based Lifestyle Change Program for Prediabetes (D’LITE Study) in a Multiethnic Asian Population: A Randomized Controlled Trial. Su Lin Lim, Kai Wen Ong, Jolyn Johal, Chad Yixian Han, Qai Ven Yap, Yiong Huak Chan, Zhi Peng Zhang, Cheryl Christine Chandra, Anandan Gerard Thiagarajah, Chin Meng Khoo