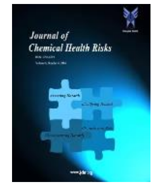
Journal of Chemical Health Risks

www.jchr.org

JCHR (2024) 14(2), 2300-2315 | ISSN:2251-6727



Exercising the application of Artificial intelligence for better management of Diabetes mellitus: A Review

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(Received: 07January 2024 Revised: 12 February 2024 Accepted: 06 March 2024)

KEYWORDS

Diabetes, type 1 and type 2 DM, insulin, lifestyle changes

ABSTRACT:

Background: Diabetes Mellitus, also referred to as diabetes, represents a chronic condition hallmarked by elevated blood sugar levels. In the realm of AI, understanding and managing this ailment involves comprehending the intricate interplay of factors contributing to its onset and progression. This encompasses the body's inability to produce sufficient insulin or utilize it effectively. Insulin, a critical substance emanating from the pancreas, governs glucose absorption into cells and its subsequent conversion into vital energy.

Objectives: The AI perspective involves leveraging advanced algorithms and data analytics to dissect the multifaceted aspects of diabetes, categorizing it into various forms like "type 1 DM," "type 2 DM," and "gestational DM."

Effective blood sugar management, a core focus in diabetes care, entails maintaining blood sugar within optimal levels through a balanced diet, regular physical activity, appropriate medications if prescribed, and vigilant blood sugar monitoring.

Method: From an AI lens, predictive models and machine learning algorithms aid in anticipating blood sugar trends, allowing for timely adjustments in treatment plans. Routine comprehensive health evaluations, encompassing specialized eye and foot examinations, are pivotal in AI-driven diabetes management, aiming to identify and proactively address potential complications.

Result: This article provides a better understanding of the link between, Information, advancement of knowledge, and the importance of bibliometric analysis in various research fields. Future research in the field of AI applications for controlling diabetes mellitus holds great promise for advancing disease management and enhancing patient outcomes

Discussion: Real-time decision support systems powered by AI can provide immediate guidance to both healthcare providers and patients, leveraging continuous data from wearable devices, glucose monitors, electronic health records, and other sources.

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JCHR (2024) 14(2), 2300-2315 | ISSN:2251-6727

1. INTRODUCTION

Rationale: In the current market landscape, data is used in each domain including health sector, construction, manufacturing, pharmaceutical (Guo & Chen, 2023). Even Data is considered as new oil for the industries. In the last one decade, there are numerous studies of artificial intelligence in healthcare sector including diagnosing diseases (Ellahham, 2020), Preventing diabetes holds great significance in the current market landscape due to various reasons (Faghilimnai et al., 2006; Ezzati et al., 2016). Firstly, the prevalence of diabetes has reached alarming levels globally, leading to soaring healthcare costs (WHO, 2016). By focusing on prevention, healthcare systems can reduce the financial burden associated with managing diabetes and its complications (Kumar and Kumar 2015). Secondly, type 2 DM, which is responsible for the majority of instances, is closely related to lifestyle factors like poor diet, sedentary behavior, and obesity (ElSayed et al., 2023). These risk factors are highly prevalent in the current market landscape, making prevention crucial in helping individuals adopt healthier lifestyles and reduce their diabetes risk (Leon et al., 2023).

Although diabetes remains incurable, AI-powered interventions coupled with tailored lifestyle modifications hold promise for achieving optimal control, empowering individuals with diabetes to lead fulfilling and healthful lives. Collaboratively devising a personalized diabetes management strategy in consultation with healthcare professionals stands as a fundamental aspect within the AI-enabled approach. Moreover, preventing diabetes is essential for improving long-term health outcomes (Rewers et al., 2015; Sato et al., 2009; Skyler et al., 2017). Diabetes is a chronic disorder that significantly upsurges the risk of various health problems such as cardiovascular illness, kidney disease, nerve damage, and vision problems (American Diabetes Association, 2006; Bogun et al., 2020). Prevention efforts can help individuals avoid or delay the onset of these complications, leading to better long-term well-being and improved quality of life (Greenbaum et al., 2012). From a public health perspective, diabetes prevention initiatives play a vital role (Ben-Skowronek, 2021). By reducing the incidence of diabetes, these initiatives alleviate the strain on healthcare systems, promote healthier communities, and enhance overall population health (Selvin, 2016). They also align with the broader goal of reducing the burden of non-communicable diseases, which is a priority for many governments and healthcare organizations worldwide.

Preventing diabetes empowers individuals by promoting self-management and proactive health behaviors. Prevention strategies often focus on empowering individuals to take control of their health through lifestyle modifications, providing education, and support (American Diabetes Association, 2014). By promoting healthy behaviors and enabling informed choices about diet, physical activity, and overall well-being, prevention initiatives empower individuals to make positive changes beyond just diabetes prevention (Chung et al., 2020).

Overall, prioritizing diabetes prevention in the current market landscape is essential for reducing healthcare costs, improving long-term health outcomes, promoting public health, empowering individuals, and embracing corporate social responsibility (Gale, 2006). Individuals, communities, and organizations can significantly advance the fight against the diabetes pandemic and advance a healthy future by stressing prevention (Umpierrez & Korytkowski, 2016).

2. METHODOLOGY

The diagnosis and treatment of diabetes mellitus are being revolutionized by artificial intelligence (AI) (Contreras & Vehi, 2018). AI systems examine enormous amounts of medical data to find useful insights and trends by utilizing cutting-edge algorithms and machine learning approaches (Rigla et al., 2018). These data consist of environmental data, genetic data, lifestyle factors, and patient health records. The production of tailored risk scores for people is made possible by the ability of AI models to identify important risk variables linked to the onset of diabetes. This aids medical experts in determining those who could be more susceptible to the disease (Dankwa-Mullan et al., 2019).

Early detection is one of AI's major contributions to diabetes prediction. AI algorithms can find patterns and indicators that point to the presence of diabetes or prediabetes through the monitoring of numerous health metrics like blood glucose levels, insulin resistance, and other pertinent biomarkers (Sriram & Reddy, 2020). Early identification enables prompt intervention and preventive actions, assisting people in managing the condition successfully and possibly preventing complications (Chaki et al., 2022). AI also helps in forecasting the course of diabetes and identifying people who are more likely to experience problems. AI models can predict how the disease may evolve in specific patients by examining longitudinal patient data, which includes medical history, treatment patterns, and lifestyle factors (Kaul & Kumar, 2023). The ability to tailor treatment plans and interventions is given to medical professionals by this information, which ultimately improves patient outcomes and lowers the possibility of consequences. AI helps in the creation of individualized treatment regimens. AI models can offer optimized treatment plans by taking into account the unique patient features including medical history, genetic profile, lifestyle factors, and past therapy responses. These individualized plans include prescriptions for medications, insulin doses, food recommendations, exercise regimens, and other lifestyle adjustments. AI improves the management of diabetes and gives patients more control over their health by customizing treatment programs for each patient.

Remote monitoring and support are crucial functions of AI in the management and prediction of diabetes. Continuous monitoring of blood glucose levels, physical activity, sleep patterns, and other health parameters is made possible by wearable technology and devices powered by AI. These gadgets collect real-time data, which is sent to AI algorithms for analysis and feedback to patients. Healthcare experts can be quickly informed in cases of unusual readings or potential emergencies. Patients are given the tools to engage in self-management through this remote monitoring and support system, which also ensures prompt interventions when required. AI also contributes significantly to data analysis and research. Artificial intelligence (AI) systems can find hidden patterns, trends, and relationships connected to diabetes by processing and analyzing enormous amounts of healthcare data, including electronic health records, medical literature, and therapeutic trials (Vu et al., 2020). These data-driven insights aid in the development of more efficient medical procedures, the identification of new therapeutic approaches, and improvements in disease knowledge.

Furthermore, AI has a diverse and transformational role in the prognosis and control of diabetes mellitus (Wang et al., 2021). AI allows healthcare professionals and patients to make more educated decisions and achieve better outcomes in the treatment of diabetes, from risk assessment and early detection through individualized treatment plans, remote monitoring, and data analysis. To offer the greatest care possible, AI should, however, always be utilized in conjunction with clinical competence and patient engagement. Type 1 and type 2 DM are complex diseases that may have different clinical symptoms and progress. Correct classification of diabetes is important for determining proper treatment. However, some people are unsure whether they have type 1 or type 2 DM at the time of diagnosis. The assumption that type 2 diabetes is seen only in adults and type 1 diabetes only in children is incorrect because both diseases can be seen in any age group. Polyuria and polydipsia are common symptoms in children with type 1 diabetes, half of whom have diabetic ketoacidosis (DKA) (Rewers et al., 2015; Alonso et al., 2020; Jensen et al., 2020).

The beginning of type 1 diabetes in adults may be further mutable and might not show symptoms in children. Some older people are also temporarily affected by their need for insulin (Pradhan et al., 2007; Sato et al., 2009). Various features can be used to distinguish type 1 diabetes from type 2 diabetes. These comprise younger age at diagnosis (usually less than 35 years), low BMI (>25 kg/m2), weight loss, ketoacidosis, and sugar levels below 360 mg/dl (20 mmol/L) (Holt et al., 2021). The highly cited papers are shown in Table 1.

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JCHR (2024) 14(2), 2300-2315 | ISSN:2251-6727

Table 1: Top ten cited papers of AI applications in Diabetes Mellitus

S.No	Title of the Paper	Journal Name	Citations
1	Application of support vector machine modeling for prediction of common diseases: The case of diabetes and pre-diabetes	BMC Medical Informatics and Decision Making	295
2	A machine learning-based framework to identify type 2 diabetes through electronic health records	International Journal of Medical Informatics	240
3	Machine Learning Methods to Predict Diabetes Complications	Journal of Diabetes Science and Technology	169
4	From disease association to risk assessment: An optimistic view from genome-wide association studies on type 1 diabetes	PLoS Genetics	165
5	Comparative approaches for classification of diabetes mellitus data: Machine learning paradigm	Computer Methods and Programs in Biomedicine	162
6	Accurate Diabetes Risk Stratification Using Machine Learning: Role of Missing Value and Outliers	Journal of Medical Systems	151
7	Neural network-based real-time prediction of glucose in patients with insulin-dependent diabetes	Diabetes Technology and Therapeutics	135
8	Data mining a diabetic data warehouse	Artificial Intelligence in Medicine	120
9	American Association of Clinical Endocrinology Clinical Practice Guideline: The Use of Advanced Technology in the Management of Persons With Diabetes Mellitus	Endocrine Practice	107
10	Transforming Diabetes Care Through Artificial Intelligence: The Future Is Here	Population Health Management	92

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Type 1 and type 2 DM each diabetes involves loss of beta cell size and/or function leading to hyperglycemia. Genetic and environmental factors play a role in the development of both types of DM. While the rate of occurrence can vary, people with all types of DM are at risk for long-term complications when hyperglycemia occurs. In the future, customized therapies for diabetes will develop through better information on the diverse pathways that cause β-cells death or dysfunction. Improved characterization of those pathways will help in identifying individualized treatment plans that may goal precise mechanisms underlying diabetes. This personalized technique for diabetes treatment has the capability to improve results and reduce the adversities in affected persons (Skyler et al., 2017).

2.1 Type-1 DM

T1DM also called as insulin-dependent diabetes or juvenile diabetes, is an unusual type of diabetes that accounts for only 5-10% of all diabetes cases. It is usually diagnosed in childhood or adolescence but can occur in adults as well. People with type 1 DM need insulin therapy to survive because their bodies cannot produce insulin on their own, and this is thought to be a T-cell-mediated autoimmune disease that causes specific damage to the insulin-producing pancreatic beta cells and disease progression. Insulin deficiency accounts for more than 95% of type 1 DM in most children with diabetes (Association, 2013; Atkinson et al., 2014). In type 1 DM, the rate of destruction of beta cells varies, with some being rapid (mostly in infants and children) and others slow (also in adults) (Bogun et al., 2020; Greenbaum et al., 2012). The disease development is affected by many factors, including age at which autoantibodies first appear, the number of autoantibodies present, and the specificity and titter of autoantibodies.

Blood Sugar and HbA1C levels begin to rise before diabetes is treated, meaning diabetic ketoacidosis (DKA) can be diagnosed before diabetes starts. Three different stages of type 1 diabetes can be identified (Show in Table 03). These levels provide a basis for research and management decisions as they help differentiate patients and identify appropriate treatments (Skyler et al, 2017; Insel et al, 2015).

Immune-mediated diabetes can happen at any age, in spite of the fact that it is most common in childhood and youth. The beginning side effect of the malady is frequent ketoacidosis, particularly in more youthful people. Be that as it may, others may encounter mellow to extreme fasting hyperglycaemia or ketoacidosis amid times of stretch or contamination. Indeed, people in their 80s and 90s can create this frame of diabetes (Association, 2014). Individuals with sort 1 diabetes have an expanded hazard of creating other immune system clutter such as Addison's infection, Hashimoto's thyroiditis, Graves' infection, celiac sprue, immune system hepatitis, vitiligo, and malignant frailty. Usually, they share comparative fundamental instruments in which the resistant framework erroneously assaults the body's possessed tissues (Nuha et al., 2023). Difference between Immune-Mediate and Idiopathic Type 1 DM given in Table 04.

Artificial intelligence (AI) plays a vital role in the prediction and management of immune-mediated type 1 diabetes (T1D) and idiopathic type 1 diabetes mellitus (IT1DM). AI algorithms analyze genetic data, autoantibody profiles, and other factors to identify individuals at higher risk of developing these types of diabetes. AI aids in the early detection and diagnosis of T1D and IT1DM by analyzing clinical data and biomarkers. It helps optimize treatment plans by analyzing patient information and providing personalized recommendations. AI also supports healthcare providers in decision-making, enables remote monitoring and support, and contributes to research and insights in these fields. However, clinical expertise and patient involvement remain crucial in utilizing AI effectively for the best possible care.

2.2 Prediabetes

Artificial intelligence (AI) plays a significant role in the evaluation and management of prediabetes. Persons with faulty carbohydrate metabolism and plasma glucose levels that do not fulfill the standards for a diabetes diagnosis are said to have prediabetes. According to Table 05 (Selvin, 2016; Selvin et al., 2013; Association, 2022) it is defined by impaired fasting glucose, glucose tolerance, and/or HbA1c levels ranging from 5.7% to 6.4% (39-47 mmol/mol).

Obesity, especially abdominal obesity, dyslipidemia, and hypertension are frequently linked to prediabetes. Cardiovascular illnesses and other related issues are more

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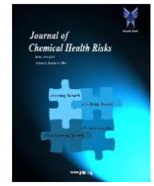

likely to affect those with prediabetes. As a result, prediabetes necessitates monitoring of cardiovascular health, including blood pressure, cholesterol levels, and lifestyle factors including diet and exercise.

By analyzing numerous data points and identifying persons at risk, AI can help in the evaluation and management of prediabetes. To provide tailored risk assessments, AI systems can combine medical records, genetic data, lifestyle factors, and other pertinent data. This can aid medical professionals in choosing the best courses of action to avoid or delay the onset of diabetes and its accompanying consequences, such as lifestyle changes and targeted monitoring.

Additionally, wearable technology and gadgets driven by AI can enable remote monitoring of blood glucose levels, activity levels, and other health factors. Prediabetic people can use this to actively control their health and get quick feedback and direction. In order to improve cardiovascular health and lower the risk of problems, AI can analyze the acquired data to deliver individualized suggestions for dietary adjustments, medication management, and other treatments.

In conclusion, AI is useful in the diagnosis and treatment of prediabetes. By addressing cardiovascular health, blood pressure, cholesterol levels, and lifestyle factors, healthcare professionals can identify individuals at risk, customize interventions, and enhance long-term outcomes by utilizing AI algorithms and remote monitoring technologies.

2.3 Type 2 DM

The majority of people with diabetes are affected with type 2 diabetes mellitus (T2DM), a chronic and non-communicable condition that accounts for 90% to 95% of cases. It is frequently referred to as adult-onset diabetes or non-insulin-dependent diabetes. Insulin resistance and relative insulin insufficiency are common in people with T2DM. There are many ways to manage the disease, including drug therapy and behavioral changes. Contrary to type 1 diabetes, people with T2DM often do not need insulin at any point in their lives (Rodriguez et al., 2016; Nuha et al., 2023). T2DM has numerous causes, however the underlying mechanisms are still poorly understood. T2DM does not entail the autoimmune destruction of beta cells, in contrast to type 1 diabetes. Instead, alterations in insulin secretion are caused by factors such genetics, metabolic stress, and inflammation (Chung et al., 2020; Gale, 2006; Schwartz et al., 2016). The majority of T2DM sufferers are overweight or obese, and studies have indicated that mild weight loss can improve glycemic control and lessen the need for blood sugar-lowering drugs.

A 3-7% weight loss can greatly lower the chance of getting diabetes and help those who already have it control their blood sugar levels (Nuha et al., 2023). The rare condition known as diabetic ketoacidosis (DKA) in people with type 2 diabetes is typically brought on by infections, other conditions like myocardial infarction, or medications like corticosteroids, atypical antipsychotics, and SGLT2 inhibitors. Age, obesity, physical inactivity, gestational diabetes, high blood pressure, dyslipidemia, and genetic susceptibility are risk factors for the development of T2DM, as indicated in Table 06.

The genetics of type 2 diabetes are currently being extensively researched. In many cases, T2DM remains undiagnosed for years as the symptoms manifest gradually and may not be perceived as severe by the affected individuals. This delay in diagnosis puts them at a higher risk of developing complications. Although insulin levels may be normal or increased in individuals with T2DM, there is a deficiency in glucose-stimulated insulin secretion that is insufficient to compensate for insulin requirements. While weight loss and medication can improve the condition, the return of insulin secretion to normal levels is rare (Carmody et al., 2016).

3. BIBLIOMETRIC ANALYSIS

The above figure shows the network diagram co-authorship countrywise. Total, 33 entries were found. The threshold value of documents of a country was one. Six clusters were found as shown below in figure 1.

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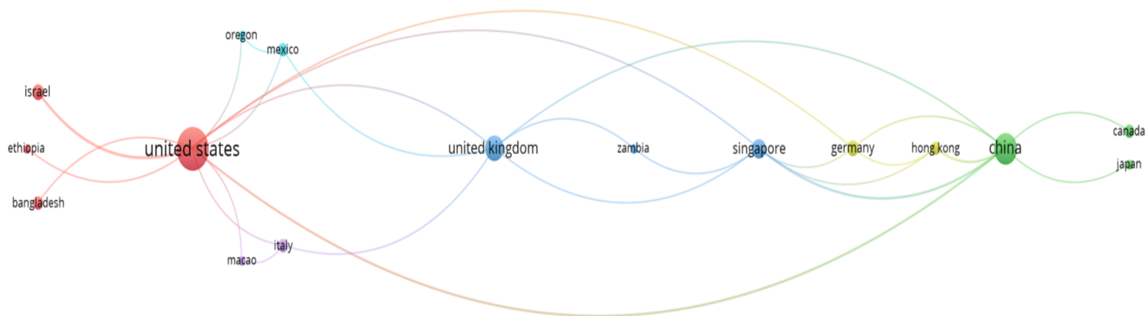

Figure:1 Country-wise graph

In co-occurrence network analysis, 73 met the criteria. Total three clusters were found as shown in figure 2 and Table 2.

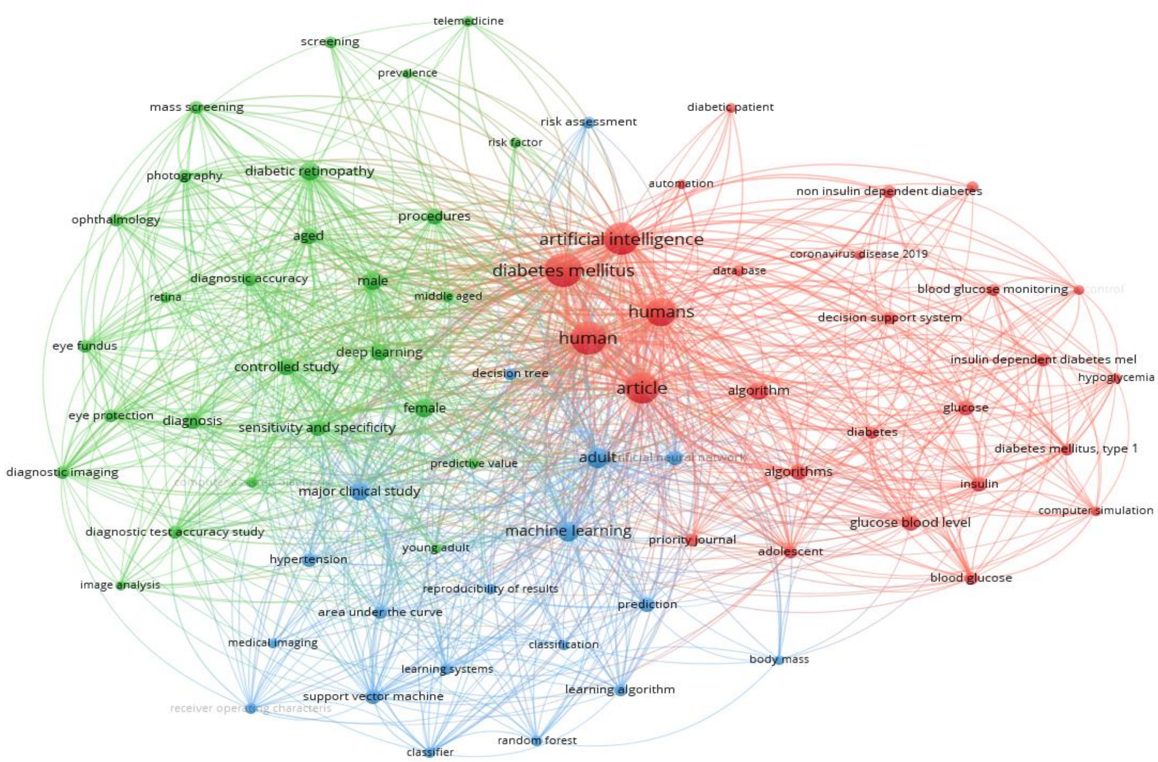

Figure 2: Co-occurrence network diagram

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Table2: Cluster Analysis

Cluster	Items	Link Strength
Cluster-1	algorithm , adolescent, algorithms, artificial intelligence, automation, blood glucose, blood glucose monitoring, computer simulation, coronavirus disease 2019, data base, decision support system, diabetes, diabetes mellitus, diabetes mellitus, type 1, diabetic patient, glucose, glucose blood level, glycemic control, human, hypoglycemia, insulin, insulin dependent diabetes mellitus, non insulin dependent diabetes mellitus	185
Cluster-2	computer assisted diagnosis, controlled study, deep learning, diagnosis, diagnostic accuracy, diagnostic imaging, eye fundus. Eye imaging, image analysis, mass screening, middle aged, ophthalmology, photography, predictive value, prevalence, procedures, retina, risk factors, screening, sensitivity and specification, telemedicine, young adult	195
Cluster-3	Adult, artificial neural network, body mass, classification, classifier, decision tree, hypertension, learning algorithm, learning systems, machine learnng, major clinical study, medical imaging, prediction, random forest, receiver operating characteristic, risk assessment, support vector machine, reproducibility of results	148

4. SPECIFIC TYPES OF DIABETES

Genetic defects in beta cells

Another type of diabetes involves genetic defects in beta cell function, formerly known as MODY (Maturity-Onset Diabetes of Youth). Impaired insulin secretion is characterized by minimal or no defects in its function. It is characterized by autosomal dominantly inherited early-onset hyperglycemia with at least 13 genetic alterations that occur before the age of 25 and account for a small proportion (<5%) of diabetes (Bodic, et, al., 1996; Moran, A. et al. 2018).

Genetic defects in Insulin action

Some genetic abnormalities can affect insulin action and cause abnormal blood sugar levels. Mutations in the insulin receptor gene can cause insulin resistance and result in a range of metabolic abnormalities, from mild hyperglycemia to severe diabetes. Acanthosis nigricans, virilization, and ovarian cysts may occur. Leprechaun syndrome and Robson-Mendenhall syndrome are two childhood disorders associated with these mutations. On the other hand, insulin-resistant lipotrophic diabetes is thought to be caused by defects in post-receptor signalling (Ben-Skowronek, I. 2021).

Endocrinopathies

Certain hormones like GH, cortisol, glucagon, and adrenaline can counteract the effects of insulin. Conditions characterized by excessive production of these hormones, such as acromegaly, Cushing's syndrome, glucagonoma, and pheochromocytoma, can induce diabetes in individuals who already have insulin secretion issues (Moran, A. et al. 2018).

Pancreatic Diabetes

Pancreatic DM refers to deterioration in insulin secretion caused by the abnormal structure and function of the pancreas and is often misdiagnosed as type 2 DM. When this occurs in the case of pancreatic exocrine dysfunction, it is also referred to as "type 3c diabetes" or "pancreoprivic diabetes". The umbrella term "pancreatic diabetes" is better to cover different etiology groups. The causes of pancreatic DM are diverse and include pancreatitis, trauma, infection, hemochromatosis, tumours, genetic disorders, and cystic fibrosis (Selvin, E. 2016; “UK prospective diabetes study 7: Response of fasting plasma glucose to diet therapy in newly presenting type II diabetic patients” 1990; Moran, A. et al. 2018).

Post pancreatitis diabetes mellitus (PPDM)

PPDM can arise from either a solitary episode of pancreatitis or a recurring one. A notable characteristic of PPDM is the existence of exocrine pancreatic insufficiency, which is determined through tests such as the stool elastase 1 test or direct function test. To diagnose the condition and assess the state of the pancreas, techniques like endoscopic ultrasound, MRI, or computed tomography can be employed. Unlike type 1 diabetes, PPDM is not linked to autoimmune markers (American Diabetes Association 2014).

Post-transplantation Diabetes Mellitus

Diabetes after transplantation can develop into PTDM or new-onset diabetes after transplantation (NODAT). PTDM occurs regardless of when diabetes started, while NODAT refers to new post-transplant diabetes, excluding pre transplant diabetes and hyperglycaemia, which resolves after hospital discharge. Although the use of immunosuppressive medication is the main cause of PTDM. Risk factors for PTDM include the risk of diabetes and specific changes for transplant such as the use of immunosuppressive drugs. Hyperglycemia usually occurs in the early post-transplant phase and PTDM is diagnosed when the patient is still on maintenance doses of immunosuppressive therapy and does not have acute infection. PTDM patients have higher rates of rejection, infection, and readmission (Thomas, M. C. et al. 2000; Zhang, X. et al. 2010; IDF diabetes atlas 2022).

Drug or Chemical-induced Diabetes

Some drugs and chemicals can restrict insulin release or its action leading to drug-induced diabetes. Pancreatic beta cells may be damaged by some toxins, e.g., vacor and pentamidine.

In addition, drugs such as corticosteroids and niacin can also restrict insulin secretion. Diabetes-associated islet cell antibodies and insulin deficiency may develop in patients treated with alpha-interferon (Moran, A. et al. 2018).

Gestational Diabetes Mellitus

GDM was previously defined as a level of glucose intolerance, regardless of severity, first diagnosed during pregnancy. However, there is evidence that many patients with GDM are prediagnosed with hyperglycemia during pregnancy (Cole, J. B. and Florez, J. C. 2020). The degree of hyperglycemia is important in the assessment of maternal and foetal risks. Now the prevalence of obesity and diabetes has led to a higher incidence of type 2 diabetes inolder females in the reproductive age group, resulting in an increased number of females suffering with Type 2 diabetes among first trimester of pregnancy. The diagnostic criteria used to define undiagnosed diabetes in the first trimester are the same as those used in the general population (Knapp, et. al., 2019). Poor glucose metabolism in the first trimester is manifested by a blood glucose level of 110 mg/dL (6.1 mmol/L) or an HbA1C of 5.9% (39 mmol/mol) may increase the risk of pregnancy and child outcomes such as preeclampsia, macrosomia, shoulder dystocia and perinatal death. These individuals may also require insulin therapy and may be at increased risk for GDM after pregnancy. However, an HbA1C level of 5.7% has not been shown to be associated with adverse physical outcomes (Thomas, M. C. et al. 2000). The HbA1C is unreliable for screening for GDM or pre-existing diabetes at or after 15 weeks of gestation.

Diabetes Mellitus-Epidemiology

GDM was previously defined as a level of glucose intolerance, regardless of severity, first diagnosed during pregnancy. However, there is evidence that many patients with GDM are prediagnosed with hyperglycemia during pregnancy (Cole, J. B. and Florez, J. C. 2020). The degree of

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Complications of Diabetes Mellitus

Diabetes is such a disease and the patient always has complications, it can be macrovascular and microvascular (Show in Table 07). The most important complication of DM is cardiovascular disease (CVD), which kills 65% of DM patients despite various treatments (Zhang, X. et al. 2010).

Diabetic Nephropathy:

It is also called as diabetic kidney illness, is a advanced illness in which kidney function is reduced due to high blood sugar. In general, diabetic nephropathy occurs 10 years after type 1 diabetes. Also, there are chances of its occurrence when type 2 diabetes is diagnosed. In type 1 and type 2 diabetes patients, the chance of its occurrence is equal (~30%). Chronic kidney disease (CKD) is diagnosed by increased urinary albumin excretion and decreased eGFR (Knapp, et al. 2019; Thomas, M. C. et al. 2000; Papatheodorou, K. et al. 2015)

Diabetic Retinopathy:

It is a vascular complication of type T1DM and T2DM that can lead to blindness. In developing countries, the primary cause of blindness among adults aged 20-74 is attributed to two main factors: the higher prevalence of diabetes and the increased life expectancy of individuals in those regions. Diabetes also enhances the danger of other eye illnesses such as glaucoma and cataracts. During the initial stages of diabetic retinopathy, the occurrence of hyperglycemia and disrupted pathways leads to oxidative stress and neurodegeneration. This process contributes to the development and progression of the disease. Pregnant ladies having diabetes mellitus are at danger for diabetic retinopathy, which can progress during pregnancy but usually resolves after delivery (ElSayed, N. A. et al. 2023b; Lin, K.-Y. et al. 2021; Jenkins, A. J. et al. 2015; Chandrasekaran et. al. 2021; Adeoti, C. et al. 2012)

Neuropathy: Diabetes-related nerve damage is the cause of a number of disorders together referred to as diabetic neuropathy. Distal symmetric polyneuropathy, which affects peripheral nerves in the lower extremities, is the most prevalent kind.. Other subtypes include autonomic neuropathy, atypical neuropathy, and nondiabetic neuropathy common in diabetes. More than half of people with diabetes develop neuropathy, which increases the risk of muscle weakness. Symptoms affect the nervous system and peripheral nerves and are often characterized by numbness, tingling, loss of smell, and pain at night in a "glove" hand and socks pattern. People with diabetic neuropathy and anomalies of the autonomic nerve system, such as orthostatic hypotension and gastrointestinal issues, are also frequently

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seen (Knapp et al. 2019; Thomas, M. C. et al. 2000; ElSayed et al. 2023).

Cardiovascular Disease:

Diabetes increases a person's risk for cardiovascular disease (CVD), which can lead to serious illness and death. The development of left ventricular dysfunction is a significant phenomena seen in some diabetics. Rubler et al. first noted this finding, which later came to be known as diabetic cardiomyopathy. It is acknowledged as a complication linked to peripheral artery disease, diabetes, coronary heart disease, cerebrovascular illness, and atherosclerotic cardiovascular disease (ASCVD). Diabetes increases the risk of heart failure, which is a key reason of cardiovascular illness morbidity and mortality (Knapp et al. 2019; Thomas, M. C. et al. 2000; Papatheodorou, K. et al. 2015; ElSayed et al. 2023).

Diabetic Foot:

It is a major side effect of diabetes, a enduring condition that is often fatal. This syndrome results in to swelling, ulceration, and/or severe tissue damage in the lower extremities and puts patients at danger of amputation and death. It is brought on by a combination of neuropathy and various degrees of vascular disease. Peripheral neuropathy, peripheral artery disease, and foot deformities are diabetes-related problems that can lead to foot ulcers and amputations (Adeoti, C. et al. 2012; ElSayed, et al. 2023; Forbes, et al. 2013).

5. MANAGEMENT OF DIABETES MELLITUS

In order to stop the emergence and progression of complications related to the condition, diabetes must be managed well (van Netten, J. J. et al. 2016).

Non-Pharmacological Management of Diabetes Mellitus:

a. Eat healthy food: It is suggested by doctors and healthcare professionals to eat healthy and balanced food with relatively less saturated fats.
b. Physical Activity: Physical activity helps in burning out extra calories and helps in building stamina, physical strength of individual. Also it helps in developing the cognitive abilities which is very much required to lead a healthy and positive life.
c. Weight Management: The importance of weight management for people with diabetes is stressed by both the American Diabetes Association (ADA) and the International Diabetes Federation (IDF). The IDF advises persons with diabetes to aim for a body mass index (BMI) below 25 kg/m2, contrary to the ADA's suggestion that even a small weight gain of 5-7% of body weight can have positive health effects. These recommendations place a strong emphasis on the value of obtaining and maintaining a healthy weight in order to enhance diabetes patients' overall health outcomes.
d. Blood Sugar Monitoring: The ADA and IDF advise continuous blood glucose monitoring as a critical component of diabetes supervision since it allows diabetics to monitor their progress and develop educated treatment results..
e. Diabetes Education and Support: The ADA and IDF both place a strong emphasis on the value of spread of diabetes awareness and assistance for those who have the condition, including getting them access to medical professionals, self-management programs, and a support group.
f. Smoking: Because smoking raises the chance of developing diabetes, the ADA and the IDF both advise people with diabetes to give up smoking (Wang, A. et al. 2020).

6. IMPLICATIONS FOR HEALTHCARE PRACTITIONERS

For healthcare professionals, the adoption of artificial intelligence (AI) in diabetic mellitus (DM) care has significant consequences. First, by evaluating a vast amount of patient data and assisting in the identification of patterns and early indicators of diabetes, AI can improve early detection and diagnosis. Through prompt action, this early diagnosis can greatly improve patient outcomes. AI also offers the possibility of highly customized treatment programs that use patient-specific data to customize medicine, food advice, exercise regimens, and lifestyle modifications for each person. AI predictive analytics can foresee the likelihood of diabetes-related problems, enabling pre-emptive risk-reduction measures. Practitioners can remotely monitor patients and modify treatment regimens thanks to AI-powered devices that enable real-time patient data monitoring.

AI can improve pharmaceutical administration by assuring proper dosages and scheduling and reducing side effects or interactions. By forecasting patient admission rates and recommending appropriate care settings, it also helps with effective resource allocation. AI also serves as a valuable clinical decision support tool, providing evidence-based insights to assist practitioners in making informed decisions about patient care. In the realm of research, AI accelerates progress by analyzing vast datasets and identifying new patterns, risk factors, and potential treatments. Lastly, AI fosters patient engagement and education through personalized educational content, encouraging active participation in their own health management. However, it is crucial for healthcare practitioners to prioritize data privacy, ethics, and regulatory compliance when integrating AI into diabetes care. Maintaining transparency in AI algorithms and ensuring the secure handling of patient data are paramount considerations.

7. CONCLUSION

The present article contributes to the field of DM by presenting a theoretical and methodological framework that has broad applicability. The key findings of this article focus on the epistemological discourse surrounding the use of bibliometric analysis.

Specifically, the article examines publication trends, identifies the most active countries and productive authors, and highlights the most influential papers. Additionally, the study investigates how researchers build upon each other's work through bibliographical coupling and co-citation networks. Furthermore, the study explores the expansion of knowledge over time by analyzing keyword co-occurrence networks and overlays. Overall, this article provides a better understanding of the link between, Information, advancement of knowledge, and the importance of bibliometric analysis in various research fields.

Future research in the field of AI applications for controlling diabetes mellitus holds great promise for advancing disease management and enhancing patient outcomes. Several key areas of focus can drive this research forward. Precision medicine approaches utilizing AI can be explored further to personalize diabetes management based on individual patient characteristics, such as genetic profiles, lifestyle factors, and treatment responses. This can optimize treatment outcomes and reduce the risk of complications. Real-time decision support systems powered by AI can provide immediate guidance to both healthcare providers and patients, leveraging continuous data from wearable devices, glucose monitors, electronic health records, and other sources. These systems can offer personalized recommendations for medication adjustments, insulin dosing, dietary modifications, and lifestyle changes, empowering patients and enabling timely interventions. Advancements in predictive analytics can facilitate early detection and prevention of diabetes complications by identifying patterns and risk factors through the analysis of patient data. Integration of multiple data sources, including electronic health records, genomics, wearable devices, and patient-reported data, can provide a comprehensive view of an individual's health status and contribute to more holistic models for diabetes management. Ensuring the explainability and interpretability of AI models is crucial for gaining trust and acceptance from healthcare professionals and patients. Research efforts can focus on developing transparent AI systems that provide clear explanations for their predictions and recommendations. Additionally, ethical considerations and privacy concerns should be addressed through the development of robust frameworks and guidelines to ensure responsible and secure use of AI in healthcare. By pursuing these research directions, the future of AI applications in diabetes control can significantly transform disease management and improve the lives of individuals with diabetes.

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