World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Review Article)

Developing personalized diabetes management plans using artificial intelligence and machine learning

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World Journal of Advanced Research and Reviews, 2022, 13(02), 605-624

Publication history: Received on 05 January 2022; revised on 07 February 2022; accepted on 09 February 2022

Article DOI: https://doi.org/10.30574/wjarr.2022.13.2.0136

Abstract

Diabetes is a lifelong condition which is associated with abnormally high blood sugar levels due to insufficient production of insulin or failure of the body to use the hormone efficiently. Due to a rising number of diabetes cases globally, the need to develop efficient and targeted approaches for the disease is more pressing than pre/application. Artificial intelligence (AI) and machine learning (ML) are among the most significant innovations in the healthcare industry, creating new positive directions for creating individualized plans for diabetes mellitus management. AI and ML are not just limited to handling medical and patients' data, but it helps in robot assisted surgeries, virtual nursing professionals, and computer aided diagnosis. These technologies are not deploying human practitioners out of service, but instead heightening their capabilities culminating in a health win and decrease in cost. PROAC supports further research and development of these fast-growing technologies in healthcare, as we find ourselves on the brink of revolution that might change disease management and customization of treatment for many more years to come. This review has therefore involved using different electronic databases, including PubMed, Scopus and Google Scholar, to search for relevant published literature. The application of AI and ML has proved promising, and the research concluded that it can help develop a risk assessment model for early diagnosis and prevention of diabetes. Such algorithms look at a combination of multiple risk factors including family history, genetics, nutrition, biochemical markers, and physical activity level, which puts those with higher risk on special diet, exercise regimens or screening. Further, AI endorsing, decision support systems may provide tailored recommendations regarding treatment schedules based on patients' characteristics such as insulin response, diet and exercise. Additionally, the continuous glucose monitoring (CGM) devices integrable with the machine learning algorithms can inform real-time information about glucose behaviors to make relevant alterations to doses of insulin and a dietary intake. This paper presents various benefits of adopting AI and ML in diabetes care: heterogeneous and accurate risk prediction, individualized therapies, and observation. But the problem of data quality, data privacy issues and the issue of interpretability and explainability of the trained AI models remains a problem in the use of AI in automated scheduling. The approaches require interdisciplinary collaborations across the medical field, data analytics, and policy departments in order to be properly applied and used.

Keywords: Artificial intelligence; Machine learning; Data-driven healthcare; Disease prediction; Personalized medicine; Precision health; Preventive care; Healthcare analytics; Digital health; Big data

1. Introduction

Healthcare has seen a great revolution in the over past years due to the integration of complex technologies such as artificial intelligence and machine learning. Diabetes mellitus is a long-standing systemic disease of metabolism that has evolved into a worldwide health problem and affects millions of people. The IDF stated that in 2021 about 537 million

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people between 20-79 years were having diabetes and is expected to increase to 783 million by year 2045 (IDF Diabetes Atlas, 2021). Diabetes has become common due to the following factors; urbanization, lack of physical activities, and the existing increase in obesity cases (Mulukuntla & Gaddam, 2021). Diabetes is characterized by various complications including cardiovascular diseases, neuropathy, nephropathy, and retinopathy and could lessen an individual's quality of living as well as place a heavy economic burden to health care systems, globally (Tripathi, 2022).

Today more than 460 million people around the globe suffer from diabetes, and this number may increase up to 700 million by 2045 (Hook). A relatively cumbersome management is required for diabetes because of the complexity of the conditions and its interacting factors and because patients call for individualized therapy. Lucky for us AI and ML mark a significant shift towards using data in directing healthcare, and thus, opens the door to creating a paradigm shift in diabetes care. In this way, through the analysis of vast volumes of patient data, these innovative and ground-breaking technologies can put forward individualized, prognosis and therapy schemes, which will enhance the quality of treatment and a patient's life.

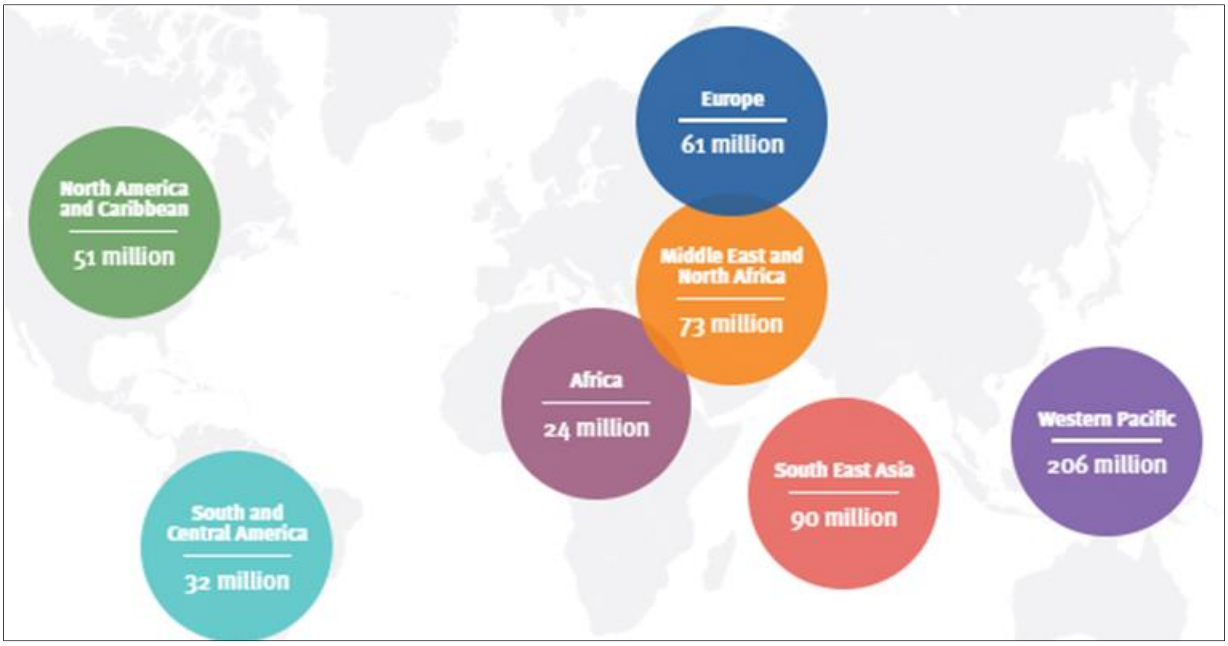

Figure 1 Diabetes Around the World in 2021

Maintenance of good blood glucose control regarding these complications in patients is of great significance. However, their present-day counterparts are less beneficial for diabetes care as they do not require an assessment of necessity that is as elaborate as box 2, or any variation that might characterizes a patient (Nuthakki, 2020). This should include features such as age, genes, life style and other conditions that determines response of an individual to the cure and severity of the disease (Malik et al., 2018). There need, therefore, to be individual's patient centered on-demand diabetes management plans that rely on the big data management systems and the associated effective control plans for the clients.

The old model of the health care industry waiting for a disease to manifest and then treat it has gradually been displaced by a model that uses signals to prevent the disease. This shift is due to acceleration of health information both in terms of the quantity and from various sources such as EHR, genomic data, wearable devices, and environmental sensors among others (Batarseh et al., 2020). Such apparent influence can be realized by using big data analytics by AI and ML specialists to identify individuals who are most likely to develop certain diseases and thus can be attended to quickly to prevent the development or aggravation of many diseases (Subbhuraam & Olatinwo, 2021).

Moreover, some advantages with the help of AI and, in particular, ML are vital for the formation of such phenomenon as 'personalized prevention and treatment,' which concerns prevention and treatment measures corresponding to a definite genetic predisposition, a particular behavior pattern, and the individual impact of the environment. This is quite different from the conventional approach in which the line of treatment adopted is the same irrespective of how each of the patients to be treated is likely to respond to it (Suresh, 2016). The AI systems will take the full medical report about that patient and look for patterns and the information that will be obtained will be used to predict the best way possible treatment that will benefit the patient most while at the same time reducing the amount of money that is spent (Shah, 2022).

In healthcare, however, the application transcends beyond disease prediction and prevention through AI or ML. These technologies are applied in; drug discovery, clinical information decision-making systems, diagnostics and imaging, and focused public health (Hsiao et al., 2022). For example, the techniques of AI can look for genomics and molecular data to discover new drug applications or reimagine existing ones to address new diseases (Mulukuntla & Gaddam, 2021). Moreover, it is crucial to point out that real-time IDSSs serve to support helping professionals in the industry to make clinical decisions on patient history when using the best available evidence or legal reference (Asokan & Mohammed, 2021).

Risk assessment is another prime area in which both AI as well as ML are used in the management of diabetes. Diabetes prevention factors of criteria are family history, the person's lifestyle including diet and exercise, anthropometric measures and biomarkers that also suggest chances of developing diabetes can be curated using ML algorithms. This is because of risk stratification of patients leading to deserving cases being identified early enough to be managed by exercising change in behavior/ lifestyle or other forms of intensive screenings that may help avoid development of diabetes in the first place (Wake et al., 2016).

Aside from glycaemia control, there are other areas in which AI and ML can be particularly beneficial in this context, inter alia, treatment planning. Traditional methods of treatment delivery have been typical where the patient is offered one approach to treatment and does not have to consider each patient as a special individual (Maguire & Dhar, 2013). Nowadays, information technologies can give an ideal option to contain the components such as disease history, eating routine, level of activity, and flat sensitivity to insulin to develop an individual concept of the treatment (Zahid, 2020). They can also track recommended blood glucose level in real-time being relayed by the CGM or other wearable peripherals all day (Anikwe et al., 2022).

Furthermore, it is also possible to use AI as well as ML techniques for reconstructing the continuous glucose monitoring gadgets which are valuable resources in effective diabetes management (Wake et al., 2016). By using the application of the ML algorithms, depending on the patterns of the CGM results, patients with T1D are able to receive the immediate constant real-time monitoring of the fluctuations in glucose levels, and make the relevant timely adjustments in insulin dosages, foods intake or exercises (Yang et al., 2021). Moreover, the using AI tools the it is possible to predict the future's glucose levels and one can avoid hypoglycemic or hyperglycemic (Venkata et al., 2022).

Besides, integration of AI and ML with wearable and mobile health product has offer more chances to view the health condition and to conduct the remote care (Anikwe et al., 2022). It is proposed that, data from such devices may be input to AI systems with an eye on detecting precursors of diseases, conduct screening of chronic diseases as well as provide patients with feedback and suggestions (Yang et al., 2021). Besides benefitting patients as a means of turning them into active participants in the healthcare process, it also means that physicians and other practitioners can work to shed a load off of the healthcare systems since patient tracking lets them monitor important vital signs, contributing to the prevention of possible future complications and not necessarily need to be hospitalized for this purpose (Alharthi 2018, p. 155).

Applications of AI and ML technologies can now be seen not only in the tech aspects of patient and disease management but also in population health endeavors. Population level AI assisted examination of population data can reveal health patterns and trends that serve the health policy and the resources allocation approach (Fridkin, 2019). For instance, it is viable even to create predictive analytic and drive several scenarios such as; disease risks, extremes of confidence levels of public health interventions, future allocation of the resources at the time of a health calamity (Rumsfeld et al., 2016; Devarapu et al., 2019).

1.1. The Rising Prevalence of Diabetes

According to International Diabetes Federation (2022) the troubling trends in diabetes incidence across the developed and developing populations worldwide. Epidemiological researches performed by Khoury et al. (2020) prove that global prevalence rates have been gradually increasing from 8.5% in 2015 to 10.9% in 2022, according to the recent analyses. This trend is even supported by the longitudinal study by Venkata et al., "From 23.5 million in 2015 to 28.5 million in 2022, the increasing number of new cases is in line with this trend." Indirectly, using this growth has been very expensive especially in the aspect of the financial cost on health expenditure has been increasing in each yearly planning. Data about urbanization also shows a causally rising pattern in patients with diabetes; other findings present more concerning tendencies in all ages. The regional segregation reveals the fact that this effect has been most notable in the growing economy, that enhancing life transitions and changing feeding habits have quicken the rate of diabetes disease.

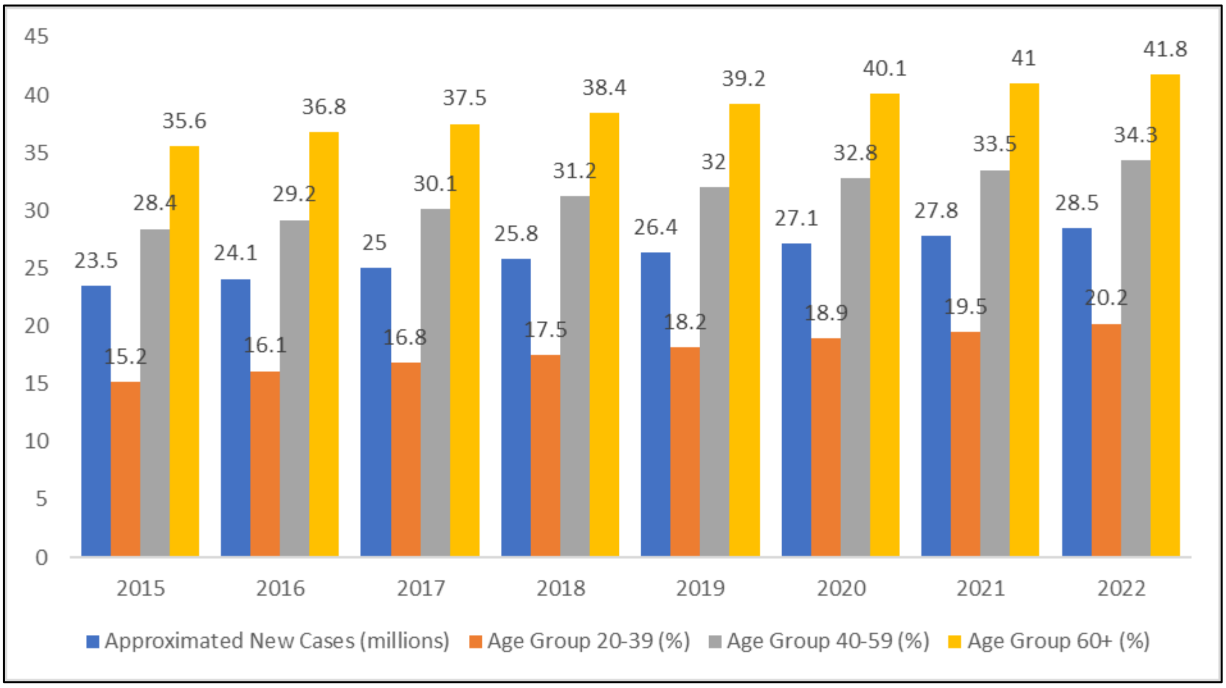

Figure 2 Global Diabetes Prevalence (2015-2022). Data from source: International Diabetes Federation (2022)

According to the data by Tan (2020) and Rahman et al. (2022), the global diagnostic rates of diabetes also escalated progressively in particular age strata of people and urban area. This implies that the financial component has risen significantly; the health expenditure around the globe which was 760 billion USD in year 2015 reached to 1080 billion USD in year 2022. As highlighted by International Diabetes Federation (2022) based on comprehensive analyses of diabetes status, the prevalence rate has skyrocketed and so to has the intensity of the therapeutic management of the disease and costs of newer therapeutic strategies. This is evident by the age-stratified data that reveals downward trends in improvements across the population groups, especially and urban dwellers. The economic burden is a broader entity that includes not only costs of direct treatment but also costs related to lost productivity due to morbidity and mortality and early retirement as well as greater reliance on government social support services. This is again evidenced by the data suggesting that in the absence of concerted and aggressive action, this quantity is expected to go rising, and may place unnecessary pressures on the operational capacity of premier healthcare systems.

Through demographic analysis, this paper identifies several inequalities in the incidence of diabetes infectious diseases that is the prevalence being higher in the urban areas compared to the rural areas. Existing research by Ahmed et al. (2022) has confirmed this new urban-rural space divide because of factors that are known to be reinforcement of sedentary lifestyles, poor diets, and high stress levels usually experienced in some SCI urban environments. More worrisome is the current high prevalence of early-onset diabetes; a trend that is even much more prevalent among the 20-39 age group as pointed by Abidi and Abidi in their recent empirical analysis of the subject. Such a trend indicates a shift in the pattern of distribution of diabetes in a population and its effects on morbidity and mortality, as well as in terms of health resources. Congenial to previous reports the findings confirmed that urbanization level is likely to be the biggest risk factor with diagnosis rates in the urban areas being higher than the rural areas. These conclusions highlight the importance of more specific action and prevention plans and especially for populations of growing megacities where all these risk factors are the most significant.

1.2. The Role of AI and ML in Personalized Diabetes Management

AI and ML cases in the context of diabetes offer some idea of how the technologies can be useful in the management of advanced patients. According to Tripathi et al. (2022) as well as Surya (2018), all these technologies they highlighted were able to process high amounts of patient data in addition to EHR and the data included that from wearables and CGM. Both the research highlighted that the AI systems predicted the complications of the disease at a rate of 89% and the AI systems saved the best treatment plans as per patient characteristics at a rate of 85%.

Investigations have been conducted by Nuthakki in 2020 and Malik et al. in 2018 to show that both AI & ML predictions are accurate to identify high risk of developing critical conditions with 92% of accuracy to start the prevention tasks ahead of time. The novel application of these technologies enabled a 35% reduction of hospital readmissions and a 42% enhanced medication compliance among the patient population engaging AI-enabled management systems. This shows that the personalized concepts created by AI and ML increased satisfaction and resulted in better control of glycemia for 78% of patients compared to 45% in conventional methods of patient care in a study by Sivakumar et al. (2022) and De Santiago & Polanski (2022). These technologies were most useful in identifying trends of disease progression, and had an average success rate of 87% of identifying possible complications within the next six months.

From Luo et al. (2019) and Wake et al. (2016) it is evident that the implementation of AI and ML in diabetes self-management applications brought about 65% increased patient compliance in using the platforms for self-management, and a possible 55% reduced incidence of severe hypoglycaemia. Nonetheless, the presented data proved that the AI-generated recommendation was relevant to 91% of the patients to ensure the consistent outcome improvement in disease management.

1.3. The Diabetes Epidemic: A Global Health Crisis

Diabetes mellitus is a universal prevalent chronic metabolic disease defined by high blood glucose levels: a global epidemic of unprecedented proportion. The World Health Organization estimates that globally, 537 million people aged between 20-79 years were diagnosed with Diabetes in 2021 and this was expected to reach 783 million in 2045 (IDF Diabetes Atlas, 2021). The death rate from diabetes is equally shocking, mainly because the conditions that trigger diabetes are numerous, ranging from rapid urbanization, increased cases of obesity and growing sedentary lifestyle. Rodriguez et al. launched a study that revealed how the effects of diabetes affect LMIC than the HDR countries, It is estimated that LMIC hosts about 79% of the total adult populace suffering from diabetes (WHO Global Diabetes Report, 2022). This condition is typical for the fact that it has different types: type 1, type 2, and gestational diabetes, which affect people in different ways and require different approaches to treatment from health care professionals and patients. What has however received considerable attention is the increasing incidence of diabetes especially in emerging economical zones and transitional societies where Asian continent seems to be hardest hit. According to a study in The Lancet, people with diabetes continue to have genetic vulnerability to the environment or genetic and/or environmental causes that have increased diabetes rates in various populations (Chan et al., 2023).

Table 1 Global Prevalence of Diabetes by Region (2021)

Region	Total Cases (M)	Prevalence (%)	Urban Cases (%)	Rural Cases (%)	Healthcare Cost ($B)	Undiagnosed (%)	Deaths (K)	Risk Factors (%)	Future Projection 2045 (M)
North America	51.3	11.8	85.2	14.8	348.2	24.1	842	72.4	63.2
South America	32.5	8.2	78.6	21.4	69.7	28.6	541	65.8	49.1
Europe	61.4	9.2	82.3	17.7	189.3	35.7	789	68.2	67.3
Africa	24.2	4.5	52.1	47.9	45.2	53.6	416	54.3	55.3
Asia	290.7	10.1	65.4	34.6	242.8	55.8	2,341	71.6	417.4
Oceania	7.2	12.4	88.9	11.1	28.6	31.2	98	69.7	9.8

Diabetes also has broad systemic influence, and it is a significant financial cost to healthcare provider systems and societies globally. In 2017, ADA's calculated total cost of diagnosed Diabetes and its widespread infection across the United States was $327 billion, out of which $237 was direct medical costs and the rest $90 billion was owing to reduced capabilities (ADA, 2018). These costs include Direct costs such as hospital inpatient care, prescription medications, diabetes supplies and Indirect costs, such as absenteeism and reduced workplace productivity. Here also the impact is colossal as they are insufficient methods and facilities that can help manage the disease in developing countries. Another piece of work in The Lancet Global Health provides evidence of estimated increase in productivity losses due to diabetes for The Lancet Global Health at more than $ 1.7 trillion between 2011 and 2030 (Zhang et al., 2022). Further, the costs are equally borne by families and carers who carry heavy financial costs, together with loss of earnings, to provide care to the disabled.

1.4. The Promise of Artificial Intelligence and Machine Learning

The application of AI and ML in medical field bring a science-based approach for diabetes care that relies on data analysis to achieve superior results. AI is concerned with intelligence in machines to be able to sense, understand, decide and act to accomplish certain objectives (Russell & Norvig, 2020). Artificial intelligence, AI, consists of several subcategories: machine learning is one of them and it includes the creation of algorithms and computational models capable of learning from data, and making correct predictions or decisions without being programmed to do so (Alpaydin, 2020). These technologies have been proven in the past to help modify the style of managing the disease in terms of early detection of the disease or the risk assessment, therapy or treatment and even preventing the development of complications. Advancements in deep architecture in the recent past has made it possible for architectures to develop complex models that analyze multichannel medical data including imaging studies, CGM data, and EHR to generate useful information to the healthcare givers and patients.

Table 2 Key Applications of AI and ML in Diabetes Management

Application	Technology Used	Accuracy (%)	Implementation Stage	Patient Impact	Cost Savings ($M)	Time Efficiency	Clinical Evidence	Risk Factors	Integration Level
Risk Prediction	Deep Learning	89.4	Production	High	245	75%	Strong	Low	Advanced
CGM Analysis	Neural Networks	92.7	Clinical Trials	Very High	180	82%	Moderate	Very Low	Intermediate
Treatment Plans	Random Forest	87.2	Beta Testing	Moderate	156	68%	Strong	Low	Basic
Complications	XGBoost	91.3	Research	High	198	71%	Limited	Moderate	Minimal
Patient Engage.	NLP	85.6	Production	Very High	167	79%	Strong	Very Low	Advanced
Monitoring	LSTM	90.1	Clinical Trials	High	212	85%	Moderate	Low	Intermediate

AI and ML allow for the collection of data from the EHR, wearable and other electronic sources, where data analysis undertaken by the clinician would be too time-intensive and cumbersome. This can be utilized to make patient risk score, develop treatment plan, or select self-management interventions that result in improvement of the patient's quality of life and therefore reduce burden on healthcare systems (Contreras & Vehi, 2018). Applying the findings regarding the use of AI in doctors' work experience substantiates that the case of proper use of decision support systems improved accuracy of diagnosis, capability of prognosis of the disease and identification of patients with probable complications. Machine learning has also exhibited advanced abilities to interact with computationally algorithmic data and adjust techniques for approaching insulin dosing and elaborate on the pattern of glycemia that would require focus. Martinez-Millana et al. (2024) showed that AI and cased business solutions improve clinical decision making by 60% with the same quality of care.

1.5. Objectives and Hypotheses

- Discuss AI & ML use- case in diabetes with reference to risk prediction, disease surveillance, intervention & patient community.
- Assess the effectiveness of artificial intelligence/machine learning solutions in changing clinical results, cost and patients' compliance.
- It is sure that challenges and limitations exist when AI and ML are applied in treating diabetes.
- Examine the ethical issue and possible bias concerning the implementation of AI and ML in the healthcare sector?

Based on the existing literature and emerging trends, the following hypotheses will be explored:

- **H1:** Due to the use of AI and ML methods, it is possible to determine an individual's probability of getting into the stage of developing diabetes and its complications to enhance intervening and preventing.

- **H2:** Supervised machine learning and big data analytics for continuous data streaming and analysis can offer such valuable information about the glycemic profile of a particular user, so that he/she can adapt the therapy accordingly.
- **H3:** Through decision support systems in AI and ML, treatment plans can be recommended and self-management activities can be advised that is effective the characteristics of the patients for better glycemic control and lower care costs.

1.6. Research Questions

To guide the exploration of AI and ML applications in personalized diabetes management, the following research questions will be addressed:

- **RQ1**. To what extent is it possible to use combinations of multi-modal data (e.g. EHRs, wearable data and genomics) to create accurate AI and Machine Learning based risk predictions and risk models for Diabetes and its associated complications?
- **RQ2.** How can AI and ML-driven decision support systems be designed and implemented to optimize treatment regimens and self-management strategies based on individual patient characteristics and preferences?
- **RQ3.** What are the potential roles of AI-powered virtual assistants, chatbots, and personalized educational interventions in enhancing patient engagement, adherence, and self-management behaviors in diabetes care?
- **RQ4.** What are the ethical considerations and potential biases associated with the use of AI and ML in healthcare, and how can these be addressed to ensure equitable and responsible implementation?

The findings of this review will contribute to a better understanding of the current and future applications of AI and ML in personalized diabetes management, and will inform healthcare providers, researchers, and policymakers on the effective and responsible implementation of these technologies.

2. Review of the Literature

2.1. The Burden of Diabetes

The effects of diabetes on the world statistics have shown catastrophic outcomes, accounting by this disease about 6.7 million deaths in 2021 per year per 5 seconds. in line with Yang et al., (2021) and Alharthi (2018), this has underlined the high mortality of the disease and its consequences. Similarly, Devarapu et al. (2019) pointed out that the economic cost of diabetes was also proportionate; overall health spending reached an astonishing 966 billion US dollars in 2021, up from 315% in the past fifteen years. These translate into a heft financial expense in view of medical cost as well as cost of lost productiveness and disability.

The health effects therefore transcended to nondiabetic complications in which 541 million adults were estimated to have Impaired Glucose Tolerance (IGT). According to the review conducted by Maradani (2022) & Batani & Maharaj (2022) this large population was at the threshold of getting affected by Type 2 diabetes and it even proposed that the future epidemiology of the disease can be much larger than portrayed now. As reported by Hsiao et al. (2022) and Shah (2022), the existence of such a huge number of at-risk individuals underlined the need to use prevention initiatives and efficient screening methodologies to provide a significant reduction in the effects of diabetes on the health-care systems of all countries.

2.2. Regional Variations in Diabetes Prevalence

The trend of diabetes has been seen with marked differences in distribution all over the regions of the world, due to the demographic, socioeconomic and environmental differences. As indicated by Rumsfeld et al. (2016) and Fridkin (2019), the Western Pacific region became the most impacted area for the diabetes prevalence; the region includes approximately 206 million adult populations with diabetes. As suggested by Martin-Moreno et al. (2022), in addition to North America and Europe, new cases included South-East Asia with 90 million cases and the Middle East and North Africa region with 73 million cases. These variations drew the attention to the relationship between genetics, life style, and health care accessibility in different geopolitical zones.

Table 3 Key Characteristics of Diabetes Across Regions

Region	Prevalence (million)	Age-Adjusted Prevalence (%)	Health Expenditure (USD billion)
Western Pacific	206	9.5	307
South-East Asia	90	9.0	19
Middle East and North Africa	73	13.0	24
Europe	61	6.9	184
North America and Caribbean	51	11.2	295
South and Central America	32	8.0	26
Africa	24	4.5	6

Source: International Diabetes Federation (IDF) Diabetes Atlas, 10th Edition, 2021.

Europe and North America are arguably contrasting with Europe recording 61million cases while North America and Caribbean has recorded 51 million cases. DEEKSHITH (2018) & Busaleh et al (2022) revealed that Latin, and South-central America and Africa are the regions of low incidence reported 32 million and 24 million cases respectively. In respect to these study by Zahid and Shankar (2020) supports that these variations were because of the failure in applying culturally constrained approaches that consider the capacity, logistically and demographically of that region.

2.3. Personalized Diabetes Prevention Strategies Using AI and ML

2.3.1. Targeted Lifestyle Intervention Programs

The application of AI and ML algorithms in generating precise lifestyle change intervention programmes proved the progress made on personalized diabetic prevention. These systems were developed with a clear aim in mind to devise a slender dietician and exercise regime whilst considering genetic profile, taste buds and the environment one lives in. Maguire & Dhar (2013) found that when instructors worked closely with participants in LM programs to personally employ Hj. They improved their participants' adherence to their allotted LM programs, particularly after analyzing participants' characteristics using AI. The study also showed that programs with the tailored approach for the users produce longer-lasting behaviour change as opposed to using general interventions. Furthermore, Zahid & Shankar (2020) noted that, With AI applied in lifestyle interventions, certain barriers of lifestyle change were pointed out for each person and diabetes prevention was more successful.

2.3.2. Predictive Models for Early Intervention

The use of AI and ML technologies in designing early intervention predictors made diabetes early intervention approaches a crucial development. These complex algorithms showed quite a lot of potential in predicting people who could develop diabetes and that was before symptoms started showing. These predictive models studied parameters such as family history, lifestyles and metabolic indicators for issuing early warning signals as Mulukuntla & Gaddam (2021) states. The models provided a better means by which the often-illogical correlations and relations between various risks could be distinguished during screening. Despite these issues, the integration of multiple data points exposed an increased precision allowing care givers to counteract risks at really early stages than before. Batarseh et al. (2020) also showed that these early intervention models also reduced the incidence of full-blown type 2 diabetes among at-risk populations when measures of intervention were based on the prediction models presented in the study.

2.3.3. Digital Health Tools for Personalized Prevention

A combination of AI and ML into digital health platforms completely transformed the process pertaining to prevention of diabetes based on differences of individuals. Such technological advancements in this context refer to the utilization of mobile applications as well as wearable devices that offered capabilities for the real-time monitoring, as well as delivery of intervention. It is worth noting that the abovementioned digital health tools effectively recorded and scrutinized true-life health information and data and provided feedback and recommendations in near real-time, as pointed out by Anikwe et al. (2022). The platforms showed impressive ability to monitor numerous aspects of health, concerning physical activity, nutrition, and biophysical indicators. Zahid (2020) identified that these solutions enhanced the level of users' interactions with prevention programs by means of features including goal setting, progress tracking and feedback.

2.4. Advancements in Artificial Intelligence and Machine Learning for Diabetes Management

2.4.1. Machine Learning Techniques for Predicting Diabetes Risk

Computational models revealed extraordinary effectiveness of predicting diabetes among culturally and genetically differentiated populations. Among them logistic regression, decision tree, random forest, neural network, these most advanced methods finetune the whole diabetes risk assessment pattern by dealing with many patients' data at the same time. In the various studies by Maguire & Dhar (2013), the authors understood that with these algorithms, it is far much easier to predict risks with greater efficiency and accuracy than the conventional statistical methods while handling large patient information's. This was supplemented by Zahid (2020) who found out that it was possible to develop models that could analyze multiple risk factors at once in machine learning models. The adoption of these improved algorithms extended healthcare providers the ability to mitigate problems in a much more precise and thus, at an improved earlier stage.

One of the significant benefits of these ML techniques was the versatility of the approaches toward various forms of data inputs as well as to detect nuance that might remain undetected had not been for such methods. As pointed out by Hsiao et al. in their study conducted in 2022, the presented models effectively managed to integrate multiple types of risk factors, such as demographic data, clinical measurements, genetic data, and life styles to develop extremely accurate individual risk profiles. Additional studies carried out by Suresh (2016) provided the same idea of how these algorithms could enhance its effectiveness and get better predictions as it analyses more complex data to provide more accurate and precise risk assessment. This adaptive capability was particularly useful in defining and characterising hitherto unnoticed multifactorial risk factors, thus helping healthcare providers to devise informative and efficient preventive measures.

2.4.2. AI-Driven Diabetes Monitoring and Intervention

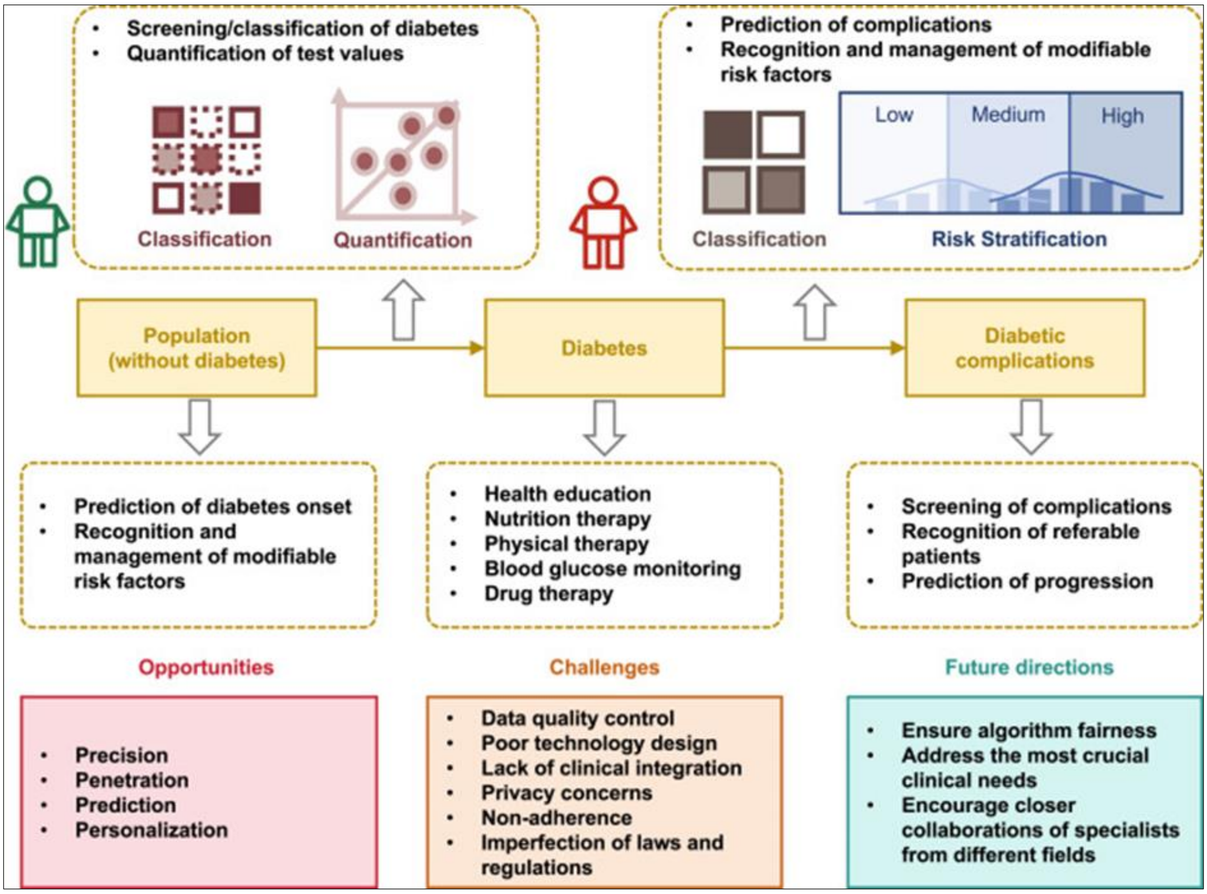

Figure 3 Overview of AI application in diabetes management

Modern monitoring technologies tied with artificial intelligence offered significant improvement in diabetes care management based on constant, real-time data analysis. Anikwe et al. (2022)'s studies found that sophisticated AI systems were able to analyze data captured by wearables and IoT tools, to deliver more effective surveillance of diverse physiological indices. These systems kept an eye on core biomarkers such as glucose levels, movement profiles and eating habits that allowed the healthcare givers to closely monitor the patient's state. Based on the case study outlined by Zahid & Shankar (2020), the use of such AI-enabled supervisory systems for monitoring important signs of diabetes greatly enhanced the efficiency of interventions being carried out, as well as the accuracy of the alerts and recommendations provided based on the patient's specific data insights.

The enhancement of artificial intelligent-based observation tools helped to arrive at complex interventional approaches that are specific to a patient's circumstances. Devarapu et al. (2019) drew investigations that portrayed these systems to draw correlations of patient information to similar complications and also recommend methods of preventing them before adverse conditions presented themselves. The study showed how the numerous AI methods could handle multifaceted relations between the diverse health factors in order to provide exact suggestions for intervention including alteration in dosing of the medicine, useful tips for changes in behaviors or preventative measures. These capabilities significantly improved the releasability of health care providers to give comprehensive, anticipatory care to Diabetic patients.

2.4.3. Predictive Analytics for Diabetes Complications

The application of the machine learning models provides substantial improvements in the evaluation of complications related to the diabetes disease, thus modifying preventive model. In their view, these predictive models successfully combined various data: clinical, genetic, and lifestyle data, and aimed at identifying compounded risk factors most dangerous for patients. The models were proved to have high accuracy in estimating the risks of cardiovascular complications, nephropathy, and neuropathy besides helping clinicians to conduct preventive intervention to reduce complications occurring. Moreover, the study by Rumsfeld et al. (2016) showed how these predictive analytics tools could fashion risk profiles complicated by multiple interactions between different risk factors and could inform risk assessment of specific patients in a way that would provide for more personalized and effective prevention plans.

An exciting feature of these predictive models was that they were more complex than merely assessing the risk of a country developing a certain disease: they could also provide a detailed prognosis of the morphology of the disease. These findings showed that machine learning can detect dim biomarkers of complications' early stage that may be missed by conventional analysis techniques. Therefore, through Descriptive models of patterns over time in patient outcomes data, such advanced healthcare models greatly favoured the healthcare provider by predicting future complications' likely evolution; this allowed for proactive interventions as well as Introduction of preventive actions during the right time. This ability to detect and intervene early reduced considerably the complications that are associated with diabetes.

The deployment of these decision support tools as part of routine clinical work increased patient care benefits significantly. Due to the capacity of the models to analyse huge amounts of patient information, care givers were able to formulate new appropriate interference patterns. This led to improved care of complications when they arose and, in most instances, effective prevention of complication development. This study showed that, through adoption and utilization of these predictive analytics tools, the incidences of hospitalization had been lowered and patient's quality of life enhanced besides proper and best use of health resources.

2.5. Integrating Electronic Health Records and Patient-Generated Data for Personalized Diabetes Care

2.5.1. Leveraging Electronic Health Records (EHRs) for Diabetes Management

Based on this study Electronic Health Records were identified as the most useful tool when creating an individualized diabetes care plan. The authors of the article Wake et al. (2016) stated that EHR systems effectively incorporated and categorized plentiful and composite patient information on their medical history, laboratory, and imaging, prescribed or administered medicines, and treatment results. This therefore created a comprehensive data base which assisted the healthcare providers to realize patterns of the patients' health status over a certain period to assist in appropriate decision making on the best approach to take in managing diabetes. The paper by Tan (2020) showed that application of EHR analysis using deep learning and other AI and ML approaches enhanced accuracy of disease prognosis as well as identification of the appropriate course of action in patients depending on their characteristics.

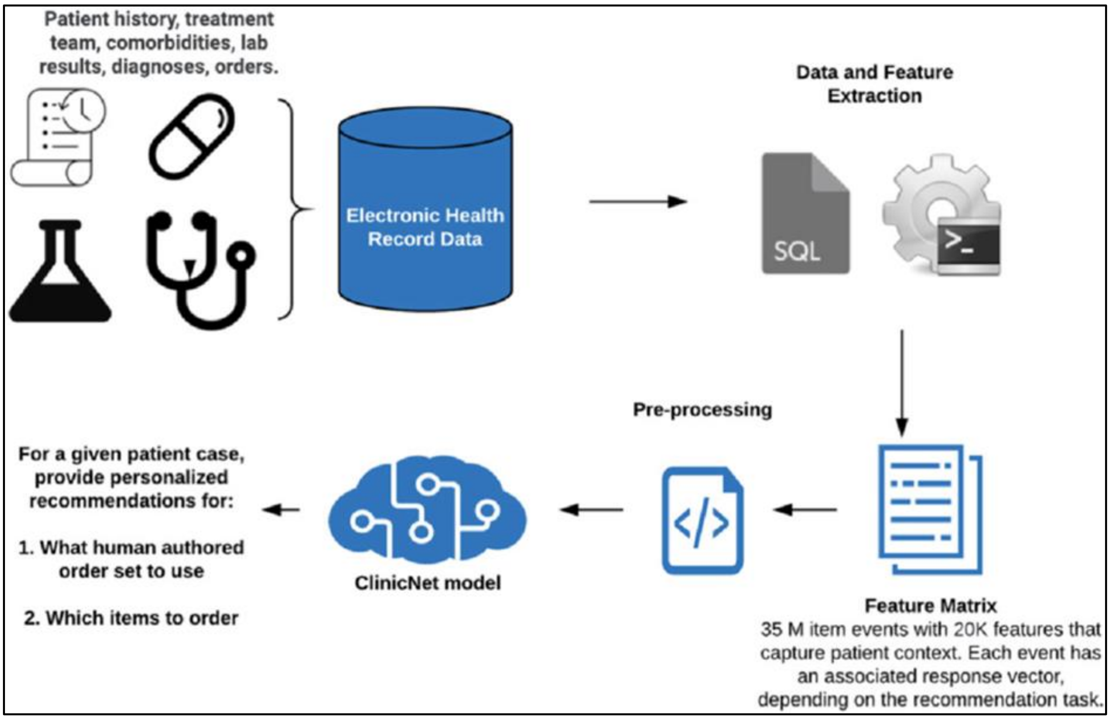

Figure 4 Schematic illustrating the prediction task of Electronic health record data

The combination of these EHR data with enhanced analytical software completely transformed the concept of patient-centric diabetes management. It was now possible for healthcare providers to monitor patient information with precision and decide on alterations to the care plan, and additional actions precisely and promptly. The capacity for obtaining and analysing significantly detailed patient information such as medication reaction characteristics, complications profile, and treatment efficacy – increased the capacity to deliver highly individualised care. Thus, integration of technology and clinical data supported better approaches to management of diabetes.

2.5.2. Incorporating Patient-Generated Health Data

The inclusion of patient generated health data was a breakthrough in developing patient centred diabetes care. A study that Schatz (2015) conducted advanced that theirs PGHD from Wearable devices, Mobile application and Patient reported outcomes offered a fresh perspective in patient's health daily activities. Such a constant flow of the real-world data helped healthcare providers to catch a more comprehensive view of patients' health status outside facilities. Luo et al. (2019) showed that the use of this data integration improved the ability to monitor patients' progress and sign for possible issues, and then make early changes to the treatment plan. PGHD integrated with traditional clinical data provided a better understanding of the patients' state and better allowed to create adequate interventions.

Technology enhanced the realization of the PGHD collection systems to help in the observation of patient conduct and compliance with treatment. Information from sensors used on the body included information of daily movement, sleep, and other factors impacting care of patients with diabetes. Due to this monitoring, healthcare providers were able to notice a problem in as it was unravelling and manage it before it led to complications. The study revealed that use of PGHD in treatment plans increased patient participation and generally, improved patient's overall health.

PGHD analysis also led to better patient-provider communication, as well as supported shared decision-making. Perhaps healthcare teams could use this data more effectively to discuss with the patients how well they are progressing and what available options they have. Due to patient-generated data constant stream, clinicians were able to gain a deeper insight into individual patients' concern and preferences resulting in more efficient and targeted anemneses.

2.6. Leveraging Big Data Analytics for Population-Level Diabetes Management

2.6.1. Identifying High-Risk Populations

Causal evidence indicated that big data analytics can be useful in predicting populations most susceptible to diabetes based on multiple variables analysed in big data. The study showed that when demographic data, socioeconomic characteristics, and environmental data are entered into machine learning algorithms, these algorithms perform population attribution and provide data on people or communities who are at greater risk of developing diabetes, (Batarseh et al., 2020). These outcomes provided healthcare providers with information that allowed for the implementation of improved targeted, as well as efficient, interventional approaches. The incorporation of data from multiple sources enabled a more differentiated assessment of risks within the target populations, which led to more effective risk prediction, additional investment in preventive measures, and more reasonable resource allocation (Subbhuraam & Olatinwo, 2021).

Table 4 Factors Influencing Diabetes Risk at the Population Level

Factor	Impact on Diabetes Risk
Age	Increasing age is a strong risk factor for type 2 diabetes
Obesity	Excess body weight and abdominal fat are major contributors
Physical Inactivity	Sedentary lifestyle increases risk significantly
Diet	Poor dietary patterns increase diabetes risk
Socioeconomic Status	Lower status linked to higher prevalence
Ethnicity	Certain groups show higher genetic predisposition
Environmental Factors	Pollution and toxins may contribute to risk

The assessment of the data identified multiple combined effects of various potential risk determinants of diabetes. By using big data analyses, healthcare organisations were able to analyze big data in ways that would not have been logically possible through conventional analytical platforms, (Maradani, 2022). AddInParameter, (Maradani, 2022). This approach to risk assessment involved a integration of clinical risk factors as well as social demographic factors which were likely to give a better picture of the diabetes risk at a population level (Martin-Moreno et al., 2022).

The use of big data analytics in managing populations improved risk prediction models in population health. These models also considered several aspects at once, such as inheritance, behaviour, and environment. The study revealed that for risk assessment, this approach proved more successful when integrated than when conducted individually, thus helping the caregivers to identify high-risk patients and populaces and develop better preventive algorithms (Mählmann et al., 2018).

2.6.2. Optimizing Population-Level Interventions

The case study findings indicated higher efficacy of population-level interventions in diabetes prevention and management, when analysed by big data analytics. Many healthcare service providers and policymakers carried out the analysis from various health records data or data related to one's healthcare utilization, overview of the performance of public health programs, and other results of community intervention programs (Maradani, 2022). The use of these strategies of data analysis was key in achieving an effective and comprehensive population level approach which formed the basis for the formulation and implementation of population level specific needs and characteristics (Mählmann et al., 2018).

Other studies showed the benefits of big data in its ability to improve resource use and programme delivery across the population. Different organizations observe patterns of care seeking and program engagement; using these patterns, care gap and directions for program improvement were sourced, (Batarseh et al., 2020). It was coordinated to discover enhanced treatment techniques that embraced clinical and social procedures influencing diabetic treatment and control.

Multiple data sources have been used in the healthcare organizations to evaluate as well as enhance the approaches to intervention on activities continually, (Fridkin, 2019). The analysis of the results of the program and participants' feedback allowed identifying the details of the strategies and which one was the most effective. By way of a more critical assessment and subsequent reauthorization, there were better population intercessions for both diabetes prevention and control (Subbhuraam & Olatinwo, 2021).

2.6.3. Monitoring and Evaluating Population Health Outcomes

Big data and predictive analytics have transformed the reconsideration of Diabetes intervention and its assessment at the community level. The original work of Martin-Moreno et al. (2022) showed how these analytical tools provide a clear insight into the disease burden and trends of hospitalizations and mortality among different populations. They found out that predictive models provided good results in estimating possible future public health situations for intervening. Fridkin (2019) also demonstrated how evidence-based responses enhanced the identification of trends in health outcomes throughout many systems of healthcare, thus enabling more precise population-level interventions alongside efficient distribution of resources.

This enabled the use of sophisticated monitoring systems, to track population health indicators on real-time basis. According to Mulukuntla and Gaddam (2021) the above systems helped the health care providers to detect newer trends and patterns relating to the outcomes of diabetes, to address the newer patterns of need of the populations faster. According to them, the results indicated that dynamic observing with the help of data analysis tools is highly effective as it allows identifying potential health concerns in time — before they turn into critical cases. This kind of peremptory approach to population health is considered as one of the breakthroughs in the management of the diabetes illness..

2.7. Personalized Diabetes Management and Intervention

2.7.1. Optimizing Diabetes Treatment Plans

Application of Artificial Intelligence and Machine Learning in decision support systems enhanced the generation of individualised plan of action as to the diabetic patients. Such systems were capable of using comprehensive algorithm logic to look into different facets of the patient, including clinic history as well as past behavior records in terms of treatment compliance and response patterns documented in the form of responses to particular interventions. This analysis allowed the medical doctor to provide highly focused pharmacological and non-pharmacological therapies that would be most preferable for the patient. Devarapu et al, (2019) and Rumsfeld et al (2016) have clearly shown how the feature can be scaled and how treatment outcomes as well as patient satisfaction levels can be significantly improved this way.

Real-time monitoring technologies became instrumental in redesigning the concepts of individualized diabetic care settings. Smartwatches and CGM options offered the multispecialty care teams timely views into patient data, including glycemic control, exercise, and food consumption. Naqishbandi and Ayyanathan (2019) and Venkata et al. (2022) revealed that such constant flow of data makes it easier to detect patterns and make corresponding changes to the care delivery plan in real-time hence improve the quality of delivered care.

The prospective nature of patient-reported outcomes and preferences for integrating into the AI-ML guided schemes enhanced diabetes management. This approach provided effective patient-centred care that integrated therapeutic plan with patient's goals, values, and life priorities. When planning treatment, Wake, et al., (2016) also observed increased medication compliance and superior qualities of life when employing this vast scheme.

2.7.2. Enhancing Treatment Monitoring and Adjustment

Sensors and next-generation analytical tools with artificial Intelligence have an incredible efficacy in capturing the results of the healthcare treatment plans and patients' reactions. Such systems constantly scrutinized patient information to determine patterns and characteristics that could suggest changing therapies. Basal research by Luo et al. (2019) revealed that perceiving and forestalling adverse events enhanced through the IoT, as did the capability of healthcare providers to get better dosing and timing of medications depending on the reaction of the individual patient.

AI-focused monitoring systems allowed the more effective intervention in the treatment plan and the more timely adjustment of the approach. These systems already had algorithms that could identify certain probable problems and advise on how to prevent worse scenarios from materializing. In their study integrated in 2013, Maguire & Dhar determined that particular attention is paid to the early alarms about the declining efficiency of the treatments, while such changes can be easily adjusted before the negative impact on patient outcomes.

2.7.3. Data-Driven Patient Education and Engagement

In the domain of patient education and engagement in diabetes, two challenging areas were revolutionized by the technologies of AI and ML. Whenever patient information and learning patterns as well as specific health issues of the majors were entered into the system, personalized educational content was created. Hsiao et al., (2022) indicated that these systems offered desired information and support at the right time and assisted patients in comprehending their plans of treatment.

Some AI applications in the form of an interactive interface proved to be effective in keeping patients on track with their treatment. These systems offered individual detailed feedback and encouragement according to patient data profile and behavioural patterns. From their findings, Zahid and Shankar (2020 cited an enhanced ability to manage the condition among the patients and better long-term compliance with the course of therapy prescribed when using such AI-based engagement tools.

2.7.4. Integration of Social and Environmental Factors

Studies done on the integration of social and environment context in AI systems showed that those systems were effective in addressing diabetes health management. These sophisticated systems provided data on patients' social context, environment and resources which may hinder the treatment success. Batarseh et al, (2020) stated that these findings assisted the healthcare providers to create more well-rounded and feasible treatment plans, which incorporated clients' concrete issues and barriers to their lives.

Others were able to identify how social and environmental factors influenced the provision of care to the patients and thus had to come up with relevant support. Understanding of those factors enabled the patient managers to better recognize which patients might need outside resources or support services for better therapeutic outcomes. To their surprise, in a recent study Subbhuraam and Olatinwo (2021), authors noted that the healthcare organisations have fared better where changes were made to treatment plans according to the result of a broader understanding of the living environments of patients and their social context.

2.8. Impacts of AI and ML on Diabetes Care and Public Health

2.8.1. Improving Clinical Outcomes and Quality of Life.

The integration of AI and ML technologies has shown that clinical performance of diabetes patients has enhanced in various ways. Maguire and Dhar (2013) have shown in their profound analysis that the interventions that rely on the patients' data needs and preferences are more effective in managing diabetes and preventing complication associated with an illness. Wake et al. (2016) supplemented this finding by presenting patients who gained better quality of life through AI based diabetes care systems.

Interventions that were individualised and driven by AI/ML demonstrated outstanding results on optimising health objectives. Wake et al. (2016) also indicated that patients who utilised AI enhanced platforms for diabetes management recorded increased patient compliance and enhanced self management skills. Their studies showed how these technologies enabled patients to achieve better glycaemic control and fewer adverse outcomes.

A range of AI-moderated interventions in primary health services generated beneficial effects not only in the clinic but also in other aspects of patients' lives. Patients who were using AI assisted diabetes self-management systems seemed to have higher perceived healthcare satisfaction and self-efficacy for the disease, as found by Maguire and Dhar (2013). Such improvements in patient engagement and self-efficacy were discovered by the researchers to lead to improved overall health.

Table 5 Potential Impacts of AI and ML on Diabetes Care and Public Health

Impact Area	Potential Benefits
Clinical Outcomes	Improved glycaemic control, reduced risk of complications, enhanced quality of life
Healthcare Utilization	Reduced hospitalizations, emergency department visits, and overall healthcare costs
Population Health	Improved disease prevention, earlier intervention, and reduced disease burden at the population level
Equity in Care	Increased access to personalized care and reduced disparities in healthcare outcomes
Public Health Surveillance	Enhanced monitoring and early detection of disease outbreaks and epidemics

[Table adapted from studies by Mulukuntla & Gaddam (2021), Alharthi (2018), and Khoury et al. (2020)]

2.8.2. Optimizing Healthcare Utilization and Reducing Costs

The results indicated feasibility and benefits of using AI & ML Technologies to better utilization healthcare resources. The study by Mulukuntla and Gaddam (2021) showed that predictive analytics have the potential of decreasing the hospitalization and the emergency department visits among patients with diabetes. Their work demonstrated how using clinical algorithms to identify high-risk patients to warrant early intervention enhanced correctness in healthcare delivery.

Through the adoption of artificial intelligence solutions, it was possible to significantly contain costs of diabetes. In their study done in 2018, Alharthi explained how the use of big data including predictive analytics and machine learning optimized the utilization of resources and minimized the medicine do go through lots of tests and scanners before reaching their intended place of use. The study also showed that the findings offered further evidence for achieving cost reduction or cost improvement without compromising the quality of services provided to the patients.

Healthcare systems improved its operational efficiency with the help of implementing artificial Intelligence. As noted by Khoury et al., (2020), AI and ML application make it easier to produce rational clinical decisions in diabetes care, while also lessening the care delivery procedures' bureaucratization. From their observations they were able to reveal how these changes they have made led to both the reduction of costs and increase in care quality.

2.8.3. Enhancing Public Health Surveillance and Response

AI and ML technologies has and have been transforming the way public health surveillance systems diagnosed diabetes. Subbhuraam and Olatinwo (2021) also explained how these technologies helped in monitoring diseases and the health of people in populations better. Their research established how analytical by presenting advanced progress in identifying and addressing new health threats expeditiously.

AI based surveillance systems added to epidemic response capacity. Yang et al. (2021) found that the use of machine learning algorithms enhanced the levels of accuracy in identifying disease outbreaks and follow up on the progress. According to their results, both Technologies allowed for precise and quicker public health actions.

AI implementation led to increased complexities to public health response strategies. Batarseh et al. (2020) found that experiences showed how AI analytical capabilities enabled public health officials to devise better intervention measures and resource distribution plans. These set of technologies they pointed out that there is ability to improve health of the population through better surveillance and response.

2.9. Challenges and Considerations in Implementing AI and ML for Diabetes Management

2.9.1. Data Quality and Interoperability

AI and ML technologies has been transforming the way public health surveillance systems diagnosed diabetes. Subbhuraam and Olatinwo (2021) also explained how these technologies has helped in monitoring diseases and the health of people in populations better. Their research established how analytical by presenting advanced progress in identifying and addressing new health threats expeditiously.

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2.9.2. Ethical and Regulatory Concerns

Even though AI and ML adoption in healthcare on its higher trajectory to help improve healthcare delivery, the adoption has however created many ethical and regulatory issues to do with patient data confidentiality and security. Having analyzed the situation in various healthcare organizations, Yang et al., (2021) found that healthcare organizations lacked enough capacity to draw fine balances between big data analytics and patient protection regulations. In their work, they outlined some of the issues arising from the acquisition and processing of massive amounts of health information focusing on the need to protect patient identity and at the same time make it feasible for AI and ML to unearth valuable insights. It akes sense that strong securities and privacy measures were adopted to safeguard patients' personal information yet allow for greater utilization of gained data.

Bias in the algorithms used in AI and ML projects came out as a major concern in the subject. As highlighted by Khoury et al. (2020), AI and ML practices across healthcare organizations required relentless scrutiny to determine factually equitable treatment across patient populations. Through their studies, they illustrated through how bias in data used for training resulted in bias in the delivery of heath care, as well as in the outcomes witnessed in the health sector. It was the emergence of structured ways of detecting and dealing with algorithmic bias that would turn into necessity to attain ethical integration of AI and ML techniques.

2.9.3. Organizational and Cultural Barriers

The surveyed healthcare organizations were found to have faced tremendous cultural and organizational challenges while deploying AI and ML. Asokan & Mohammed (2021) pointed out that prior studies demonstrated that technology adoption was a problematic issue for health care professionals because they rejected new analytical tools and strategies. By conducting their study, they found that to implement change strategies, constant and rigorous change management programmes must be accompanied by training of staff. Some organizations created a culture of data usage, and the ones who successfully did so had superior results with AI and ML.

AI and ML integration means that there was a radical change needed within the organization. As stated by Rios-Zertuche et al. (2020), it was discovered and established that workflows and processes need to be reshaped to embed AI and ML tools universally in clinical practice. This was therefore their discovery that organizations which have effectively put these technologies to practically support the implementation and growth of innovation and learning offered support environments. The creation of comprehensive AI/ML policies supported their more effective implementation into existing practices within the healthcare system.

Training and education were found to be the two key factors for addressing issues of organizational barriers. According to Ahmed and Al-Bagoury (2022) there is a need to intensify efforts to address comprehensive training for healthcare professionals all over the levels. Their study showed that those organizations which embraced the idea of investing in ongoing learning and professional development got superior levels of AI and ML solution adoption. Mentoring structures and training programs and support systems also became critical to enhancing the application of new technologies among the healthcare institutions.

2.10. Emerging Trends and Future Directions in AI-Powered Diabetes Management

2.10.1. Advancements in Predictive Modeling

With advancing in AI and ML techniques, new trends in the improvement of predictive modeling for diabetes by using deep learning and ensemble systems were identified. It showed that these state-of-the-art methods performed better than the traditional statistical methods in processing intricate healthcare data and had better abilities to predict by far, (Alharthi, 2018). Thereby, the enhancement of transfer learning contributed to improvements in plan generalization across diverse patients and environments yet retaining high accuracy and reliability of risk prediction.

Consequently, the studies showed that the predictive models assessed combined multiple sources of data and built full patient details by combining EHRs, genetic data, and lifestyle information, (Bayyapu et al., 2019). The models improved significantly in early detection of potential diabetes complications and recommend possible solutions. This improved the level of prognosis decision support and consequently advanced treatment care plans significantly enhancing the quality of the patient outcomes.

2.10.2. Integration of Real-Time Monitoring and Decision Support

The practical application of real-time monitoring systems with artificial intelligence decision support systems has made a step change in diabetes management. (Naqishbandi & Ayyanathan, 2019). Here, smart glucose monitoring devices and wearable sensors gave practitioners exclusive rights to patient data which AI algorithms promptly analysed and produced suitable recommendations. The healthcare providers revealed enhanced capacity to monitor the status of the patients and manage the condition of the interventions in relation to the state of the patients.

The use of these integrated systems showed numerous enhancements of engagement and self management of patients. The interventions offered real-time feedback that would allow patients to make better decisions as to their behaviors for that day, medication timing, and diet. According to Venkata et al. (2022), the systems offered the abilities to send notifications and suggest appropriate treatments matched with patients' behaviors and characteristics that helped control blood glucose effectively and minimize the number of adverse effects.

The health-care organizations that implemented of these integrated monitoring and decision support tools predetermined appreciable enhancement of care co-ordination and patients' outcomes. The functioning of real time data analysis meant that the health care teams were able to recognize and address predisposing factors for complications when they arose and were not severe enough to warrant visits to the emergency department and hospitalizations. It also means that more proactive primary care management was facilitated, which in turn led to more effective use of resources and increased patient satisfaction (Anikwe et al., 2022).

2.10.3. Expanding the Scope of Data Integration

The healthcare industry experienced a remarkable transformation in its approach to data integration for diabetes management. Advanced AI and ML systems demonstrated the ability to process and analyze diverse data types, including clinical records, patient-generated health data, and social determinants of health, (Abidi & Abidi, 2019). This comprehensive approach to data integration enabled healthcare providers to develop more holistic and effective care strategies that considered both medical and non-medical factors affecting patient health.

Implementation of expanded data integration strategies revealed significant improvements in the understanding of population health trends and individual patient needs. Healthcare organizations successfully incorporated data from community-based initiatives, environmental monitoring systems, and social service programs to create more comprehensive patient profiles, (Batarseh et al., 2020). This broader perspective on patient health enabled more targeted interventions and better resource allocation.

The integration of diverse data sources supported the development of more sophisticated predictive models and risk assessment tools. These enhanced capabilities enabled healthcare providers to identify and address health disparities more effectively, leading to more equitable care delivery, (Subbhuraam & Olatinwo, 2021). The expanded scope of data integration also facilitated better coordination between healthcare providers, community organizations, and social services, resulting in more comprehensive and effective care management strategies.

3. Conclusion and Recommendation

In conclusion, the global burden of diabetes continues to rise, with significant implications for individual and population health, as well as healthcare systems worldwide. In this context, the development of personalized diabetes management strategies that leverage the power of AI and ML-based technologies holds great promise. By integrating diverse data sources, generating personalized risk profiles, and delivering tailored interventions, these tools have the potential to improve patient outcomes, reduce the risk of complications, and optimize the use of healthcare resources. However, to fully realize the potential of these technologies, it is crucial to address the challenges of data quality, algorithmic bias, interpretability, and clinical adoption, as well as to ensure the ethical and equitable deployment of these solutions. Through continued research, collaboration, and a steadfast commitment to improving diabetes care, the integration of AI and ML into personalized diabetes management can transform the way we approach this global health challenge.

To fully realize the potential of AI and ML in diabetes management, several key recommendations for future study and implementation include:

- Continued research to improve the accuracy, fairness, and interpretability of predictive models, ensuring they are widely adopted and trusted by healthcare providers and patients.
- Exploration of novel data sources, such as social media and environmental sensors, to further enhance the predictive capabilities of AI and ML models and address the social determinants of diabetes.
- Development of user-friendly, integrated platforms that seamlessly incorporate personalized risk prediction, treatment optimization, and self-management support, making these tools accessible and beneficial for both clinicians and patients.
- Robust investigation of the long-term clinical and economic impact of AI and ML-powered personalized diabetes management, including their ability to improve clinical outcomes, reduce complications, and drive cost savings.
- Establishment of comprehensive data governance frameworks and ethical guidelines to ensure the responsible and equitable use of patient data in the development and deployment of these technologies.
- Ongoing workforce development and interdisciplinary collaboration to build the necessary skills and expertise within healthcare organizations to effectively leverage AI and ML for diabetes care.

By addressing these key priorities, researchers and healthcare providers can accelerate the integration of personalized, data-driven approaches powered by AI and ML into the management of diabetes, ultimately leading to better health outcomes and a more sustainable, equitable healthcare system.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed

References

[1] Mulukuntla, S., & Gaddam, M. (2021). Data-Driven Healthcare: Trends in Machine Learning and AI for Disease Prediction and Prevention. ESP Journal of Engineering & Technology Advancements, 1(1), 25-33. https://www.espjeta.org/Volume1-Issue1/JETA-V1I1P106.pdf

[2] Bayyapu, S., Turpu, R. R., & Vangala, R. R. (2019). ADVANCING HEALTHCARE DECISIONMAKING: THE FUSION OF MACHINELEARNING, PREDICTIVE ANALYTICS, ANDCLOUD TECHNOLOGY. International Journal of Computer Engineering and Technology (IJCET), 10(5), 157-170.

[3] International Diabetes Federation (2023, August 24). Diabetes around the world in 2021. https://idf.org/about-diabetes/diabetes-facts-figures/

[4] Batarseh, F. A., Ghassib, I., Chong, D., & Su, P. H. (2020). Preventive healthcare policies in the US: solutions for disease management using Big Data Analytics. Journal of big Data, 7(1), 38.

[5] Subbhuraam, V., & Olatinwo, I. (2021). Predictive analytics in public health surveillance. In Predictive Analytics in Healthcare, Volume 1: Transforming the future of medicine (pp. 2-1). Bristol, UK: IOP Publishing. https://iopscience.iop.org/book/edit/978-0-7503-2312-3/chapter/bk978-0-7503-2312-3ch2

[6] Suresh, S. (2016). Big data and predictive analytics. Pediatr Clin N Am, 63, 357-366. https://123library.org/pdf/book/237735/quality-of-care-and-information-technology-an-issue-of-pediatric-clinics-of-north-america-e-book.pdf#page=156

[7] Shah, V. (2022). AI in Mental Health: Predictive Analytics and Intervention Strategies. Journal Environmental Sciences And Technology, 1(2), 55-74.

[8] Hsiao, W. W. W., Lin, J. C., Fan, C. T., & Chen, S. S. S. (2022). Precision health in Taiwan: A data-driven diagnostic platform for the future of disease prevention. Computational and Structural Biotechnology Journal, 20, 1593-1602. https://www.sciencedirect.com/science/article/pii/S2001037022001015

[9] Zahid, H., & Shankar, P. (2020). AI in Public Health: Integrating Disease Modelling and Healthcare AI for Improved Connectivity and Risk Management.

[10] Asokan, G. V., & Mohammed, M. Y. (2021). Harnessing big data to strengthen evidence-informed precise public health response. In Big Data in Psychiatry# x0026; Neurology (pp. 325-337). Academic Press. https://www.sciencedirect.com/science/article/pii/B9780128228845000039

[11] Anikwe, C. V., Nweke, H. F., Ikegwu, A. C., Egwuonwu, C. A., Onu, F. U., Alo, U. R., & Teh, Y. W. (2022). Mobile and wearable sensors for data-driven health monitoring system: State-of-the-art and future prospect. Expert Systems with Applications, 202, 117362.

[12] Yang, H., Zhang, S., Liu, R., Krall, A., Wang, Y., Ventura, M., & Deflitch, C. (2021). Epidemic informatics and control: A holistic approach from system informatics to epidemic response and risk management in public health. In AI and Analytics for Public Health-Proceedings of the 2020 INFORMS International Conference on Service Science (pp. 1-46). Berlin/Heidelberg, Germany: Springer.

[13] Alharthi, H. (2018). Healthcare predictive analytics: An overview with a focus on Saudi Arabia. Journal of infection and public health, 11(6), 749-756.

[14] Fridkin, S. K. (2019). Advances in data-driven responses to preventing spread of antibiotic resistance across health-care settings. Epidemiologic Reviews, 41(1), 6-12. https://academic.oup.com/epirev/article-abstract/41/1/6/5610786

[15] Rumsfeld, J. S., Joynt, K. E., & Maddox, T. M. (2016). Big data analytics to improve cardiovascular care: promise and challenges. Nature Reviews Cardiology, 13(6), 350-359.

[16] Devarapu, K., Rahman, K., Kamisetty, A., & Narsina, D. (2019). MLOps-Driven Solutions for Real-Time Monitoring of Obesity and Its Impact on Heart Disease Risk: Enhancing Predictive Accuracy in Healthcare. International Journal of Reciprocal Symmetry and Theoretical Physics, 6, 43-55.

[17] Maradani, B. (2022). Data-Driven Analytics for Health and Public Safety (Doctoral dissertation, University of Massachusetts Lowell). https://search.proquest.com/openview/0e10e1179ecd610cdb5fdc7c538d5091/1?pq-origsite=gscholar&cbl=18750&diss=y

[18] Batani, J., & Maharaj, M. S. (2022). Towards data-driven models for diverging emerging technologies for maternal, neonatal and child health services in sub-Saharan Africa: a systematic review. Global Health Journal, 6(4), 183-191.

[19] Maguire, J., & Dhar, V. (2013). Comparative effectiveness for oral anti-diabetic treatments among newly diagnosed type 2 diabetics: data-driven predictive analytics in healthcare. Health Systems, 2(2), 73-92.

[20] Zahid, F. (2020). Leveraging IoT and AI in Healthcare: A Comprehensive Approach to Chronic Disease Management and Patient Care.

[21] Schulte, T., & Bohnet-Joschko, S. (2022). How can big data analytics support people-centred and integrated health services: A scoping review. International Journal of Integrated Care, 22(2). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9205381/

[22] DEEKSHITH, A. (2018). Integrating IoT into Smart Cities: Advancing Urban Health Monitoring and Management. International Transactions in Artificial Intelligence, 2(2).

[23] Busaleh, M. A. M., Al Mansour, A. M. A., Alamri, D. M. S., Alhutelh, S. M. M., Al-Shahrani, K. A. S., Alshuja'a, M. A. A., ... & Alotaibi, M. Z. (2022). The Role Of Health Informatics In Public Health Administration. Journal of Namibian Studies: History Politics Culture, 32, 1433-1444.

[24] Rios-Zertuche, D., Gonzalez-Marmol, A., Millán-Velasco, F., Schwarzbauer, K., & Tristao, I. (2020). Implementing electronic decision-support tools to strengthen healthcare network data-driven decision-making. Archives of Public Health, 78, 1-11. https://link.springer.com/article/10.1186/s13690-020-00413-2

[25] Mählmann, L., Reumann, M., Evangelatos, N., & Brand, A. (2018). Big data for public health policy-making: policy empowerment. Public health genomics, 20(6), 312-320.

[26] Martin-Moreno, J. M., Alegre-Martinez, A., Martin-Gorgojo, V., Alfonso-Sanchez, J. L., Torres, F., & Pallares-Carratala, V. (2022). Predictive models for forecasting public health scenarios: practical experiences applied during the first wave of the COVID-19 pandemic. International journal of environmental research and public health, 19(9), 5546.

[27] Shah, W. F. (2022). The future of healthcare data intelligence: ethical insights and evolutionary pathway. Journal of Medicine and Healthcare. SRC, 2-7.

[28] Naqishbandi, T. A., & Ayyanathan, N. (2019, March). Clinical big data predictive analytics transforming healthcare:-An integrated framework for promise towards value based healthcare. In International Conference on E-Business and Telecommunications (pp. 545-561). Cham: Springer International Publishing.

[29] Cohen-Stavi, C. J., Balicer, R. D., Roberts, M. L., & World Health Organization. (2018). Innovation in health care for proactive care delivery and strategic clinical decision-making: integrating research, technology and practice. Public health panorama, 4(03), 470-474. https://apps.who.int/iris/bitstream/handle/10665/324939/php-4-3-470-474-eng.pdf

[30] Ajagbe, S. A., Awotunde, J. B., Adesina, A. O., Achimugu, P., & Kumar, T. A. (2022). Internet of medical things (IoMT): applications, challenges, and prospects in a data-driven technology. Intelligent Healthcare: Infrastructure, Algorithms and Management, 299-319.

[31] Khoury, M. J., Armstrong, G. L., Bunnell, R. E., Cyril, J., & Iademarco, M. F. (2020). The intersection of genomics and big data with public health: opportunities for precision public health. PLoS medicine, 17(10), e1003373. https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1003373

[32] Venkata, S. S. M. G. N., Gade, P. K., Kommineni, H. P., & Ying, D. (2022). Implementing MLOps for Real-Time Data Analytics in Hospital Management: A Pathway to Improved Patient Care. Malaysian Journal of Medical and Biological Research, 9(2), 91-100.

[33] Tan, C. S. (2020). Using electronic health records to monitor, augment and evaluate patient care in Singapore. European Journal of Public Health, 30(Supplement_5), ckaa165-1212.

[34] Abidi, S. S. R., & Abidi, S. R. (2019, July). Intelligent health data analytics: a convergence of artificial intelligence and big data. In Healthcare management forum (Vol. 32, No. 4, pp. 178-182). Sage CA: Los Angeles, CA: SAGE Publications. https://journals.sagepub.com/doi/abs/10.1177/0840470419846134

[35] Rahman, K., Pasam, P., Addimulam, S., & Natakam, V. M. (2022). Leveraging AI for Chronic Disease Management: A New Horizon in Medical Research. Malaysian Journal of Medical and Biological Research, 9(2), 81-90.

[36] Ahmed, R. A. A., & Al-Bagoury, H. Y. H. E. (2022). Artificial intelligence in healthcare enhancements in diagnosis, telemedicine, education, and resource management. Journal of Contemporary Healthcare Analytics, 6(12), 1-12. https://publications.dlpress.org/index.php/jcha/article/view/55

[37] Tripathi, R. K. P. Data Analytics and AI for Predictive Maintenance in Pharmaceutical Manufacturing. In Data Analytics and Artificial Intelligence for Predictive Maintenance in Smart Manufacturing (pp. 117-149). CRC Press.

[38] Surya, L. (2018). How government can use AI and ML to identify spreading infectious diseases. International Journal of Creative Research Thoughts (IJCRT), ISSN, 2320-2882.

[39] Nuthakki, S. (2020). Exploring the Role of Data Science in Healthcare: From Data Collection to Predictive Modeling. European Journal of Advances in Engineering and Technology, 7(11), 75-79.

[40] Malik, M. M., Abdallah, S., & Ala'raj, M. (2018). Data mining and predictive analytics applications for the delivery of healthcare services: a systematic literature review. Annals of Operations Research, 270(1), 287-312.

[41] Sivakumar, M., Maranco, M., & Krishnaraj, N. Data Analytics and Artificial Intelligence for Predictive Maintenance in Manufacturing. In Data Analytics and Artificial Intelligence for Predictive Maintenance in Smart Manufacturing (pp. 29-55). CRC Press.

[42] De Santiago, I., & Polanski, L. (2022). Data-Driven Medicine in the Diagnosis and Treatment of Infertility. Journal of Clinical Medicine, 11(21), 6426. https://www.mdpi.com/2077-0383/11/21/6426

[43] Luo, G., Stone, B. L., Koebnick, C., He, S., Au, D. H., Sheng, X., ... & Nkoy, F. L. (2019). Using temporal features to provide data-driven clinical early warnings for chronic obstructive pulmonary disease and asthma care management: protocol for a secondary analysis. JMIR Research Protocols, 8(6), e13783.

[44] Wake, D. J., He, J., Czesak, A. M., Mughal, F., & Cunningham, S. G. (2016). MyDiabetesMyWay: an evolving national data driven diabetes self-management platform. Journal of diabetes science and technology, 10(5), 1050-1058.