Need for an Artificial Intelligence-based Diabetes Care Management System in India and the United States

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Abstract

Objective: Diabetes mellitus is an important chronic disease that is prevalent around the world. Different countries and diverse cultures use varying approaches to dealing with this chronic condition. Also, with the advancement of computation and automated decision-making, many tools and technologies are now available to patients suffering from this disease. In this work, the investigators attempt to analyze approaches taken towards managing this illness in India and the United States.

Methods: In this work, the investigators have used available literature and data to compare the use of artificial intelligence in diabetes management.

Findings: The article provides key insights to comparison of diabetes management in terms of the nature of the healthcare system, availability, electronic health records, cultural factors, data privacy, affordability, and other important variables. Interestingly, variables such as quality of electronic health records, and cultural factors are key impediments in implementing an efficiency-driven management system for dealing with this chronic disease.

Conclusion: The article adds to the body of knowledge associated with the management of this disease, establishing a critical need for using artificial intelligence in diabetes care management.

Keywords

diabetes mellitus, diabetes care management in the US, diabetes care management in India, artificial intelligence, importance of diabetes management, clinical decision support systems

Introduction

Diabetes mellitus (DM) is a chronic health condition that impacts millions of individuals globally, necessitating vigilant oversight and proactive management to mitigate potential complications and enhance patient well-being. Within the United States (US), recent data from the Centers for Disease Control and Prevention (CDC)[1] shows the large prevalence of DM, with approximately 11.6% of the population affected by this chronic disease in 2021. Alarmingly, a considerable portion of diabetic adults, accounting for 22.8%, remains undiagnosed, highlighting the urgent need for improved screening and detection efforts. Additionally, a substantial proportion of the adult population, approximately 38.0%, is estimated to have prediabetes, underscoring the importance of preventive measures and early intervention strategies to curb the progression of the disease. Among individuals aged 65 and older, nearly half (48.8%), are affected by DM, emphasizing the heightened susceptibility to this condition among older adults. Similarly, the

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situation in India mirrors the concerning trends observed in the US regarding DM prevalence and management. India ranks as the second most afflicted nation with DM globally.[2] As per the International Diabetes Federation (IDF) reports, the number of diagnosed DM cases in India surpassed 74 million in 2021, and with an expected increase to over 124 million by 2045. Between 2000 and 2019, DM was responsible for an increase of 3% in mortality. In addition, the mortality rate of individuals between the age of 30 and 70 also substantially increased within this period.

Although there is no complete cure, DM can be treated and managed, and its adverse effects can be prolonged or reduced by a healthy diet, physical activities, and regular screening and treatments. Therefore, developing early warning alarm systems, like personalized health monitoring, is essential.

India and the US face distinct challenges in managing DM due to contrasting healthcare infrastructures, cultural practices, and socioeconomic contexts. In both nations, there is a pressing need for more sophisticated automated tools to enhance screening, monitoring, and the development of personalized treatment plans for individuals with DM. Given the vast populations in both countries and the limitations in healthcare resources, leveraging advanced technologies such as artificial intelligence (AI) becomes imperative. Developing AI tools for DM management goes beyond merely early detection. AI's true potential lies in its ability to analyze vast amounts of patient data, including blood sugar levels, dietary habits, and physical activity patterns. This analysis allows AI to identify patterns and trends that may escape human observation. For instance, AI algorithms can learn to predict blood sugar spikes based on a patient's specific food intake and activity levels. This personalized approach empowers patients to make informed decisions about their diet and exercise routines, ultimately improving blood sugar control and reducing the risk of complications.[3] Furthermore, AI can play a crucial role in medication management. By analyzing a patient's medical history, current medications, and real-time health data, AI systems can recommend personalized insulin dosage adjustments or suggest alternative medications with fewer side effects. This reduces the risk of medication errors and ensures patients receive optimal treatment based on their unique needs. AI-powered tools can also provide continuous support and motivation to patients, reminding them to take medications, track their blood sugar levels, and adhere to healthy lifestyle choices. This ongoing support system can significantly improve patient engagement and self-management, leading to better long-term health outcomes.[4] By integrating AI into various aspects of healthcare delivery, including diagnostics, treatment optimization, and patient management, both India and the US can strive towards achieving better healthcare outcomes for individuals living with DM.

The primary objective of this study is to investigate the epidemiology of DM in both India and the US, analyzing factors such as prevalence, trends, and key contributors to the disease burden in both countries. Additionally, the study seeks to examine recent advancements in AI-based DM management systems implemented in both India and the US. By thoroughly examining the current state of these technologies, including their adoption rates, effectiveness, and limitations, this study aims to pinpoint challenges that may impede their widespread adoption and utilization within healthcare settings. Furthermore, the study anticipates future challenges by assessing the potential for further innovation, integration, and scalability of these systems to address evolving healthcare needs and tackle emerging challenges associated with DM care.

Diabetes: An Overview

DM is a disorder characterized by hyperglycemia (high blood glucose levels).[5] This is often a sign of uncontrolled DM, which can damage many body organs. DM is a chronic disease that occurs partly because the pancreas is unable to produce insulin—a hormone that regulates blood glucose levels—or the body may not correctly utilize the produced insulin.[6] Type 1 DM (T1DM) and Type 2 DM (T2DM) are the 2 main subtypes of DM. T1DM typically affects children or adolescents and arises from inadequate insulin secretion. Besides, T2DM usually affect middle-aged and older adults who have high blood sugar levels due to unhealthy lifestyle choices and dietary habits. Each type of DM has a different pathogenesis and requires different treatment strategies.[7,8]

Type 1 Diabetes Mellitus

T1DM is a chronic disorder and is also known as autoimmune DM.[9] It is caused by the loss of pancreatic β cells and, thereby, loss of insulin secretion. Although the onset of T1DM is about childhood or adolescence, the symptoms may develop at a later age. Although the reason behind T1DM is not completely understood, the disease may develop due to the obliteration of β cells by T cells.[9]

Type 2 Diabetes Mellitus

T2DM is a chronic disease often observed in the onset of the adult age.[10] The prevalence of this metabolic disorder is steadily increasing all over the globe and is an epidemic in some countries due to unhealthy diets and living conditions.[10] T2DM is the dominant type of DM and accounts for 90% of the existing DM cases.[11]

Gestational Diabetes

The condition called hyperglycemia detected during pregnancy is known as gestational diabetes.[11] Although it may occur at any stage of the pregnancy, it is expected to be observed from 13 weeks to 27 weeks. According to the American Diabetes Association (ADA), the adverse effect of gestational diabetes is about 7% in all pregnancies. Those who experience it are at a higher risk of developing T2DM in the future.

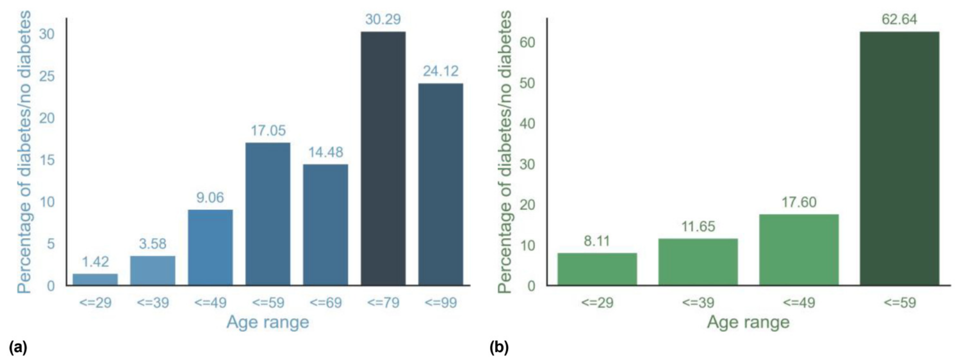

Figure 1. Categorized by age. (a) US statistics according to BRFSS (2018-2022). (b) Indian statistics according to DHS (2019-2021).

Symptoms of DM

The symptoms of DM are not so evident, especially in T2DM and gestational diabetes, whereas they are quick and heavy in the case of T1DM.[12] Common indicators of both T1DM and T2DM include heightened thirst, frequent urination, fatigue, nerve damage affecting sensation, and frequent mood fluctuations.

Key Complications Associated With DM

Individuals diagnosed with DM are at risk of developing numerous long-term complications that can impact various organs in the body.[13] These complications encompass severe cardiovascular and vascular issues known as macroangiopathy, which can result in conditions such as hypertension, artery narrowing, coronary artery disease, and strokes. Another significant complication is diabetic retinopathy, which involves damage to the blood vessels in the eyes, leading to a decline in vision and is a major cause of blindness in the Western world. Additionally, diabetic nephropathy may occur, leading to renal insufficiency and affecting kidney function. Diabetic neuropathy, on the other hand, presents as sensory disturbances, muscle atrophy, difficulties in mobility, and various symptoms such as tachycardia, orthostatic hypotension, urinary incontinence, and gastrointestinal issues, along with contributing to foot problems. Diabetic foot ulcers, characterized by lesions and complications in the lower extremities, including pain, sensory disorders, skin dryness, callus formation, wounds, ulcers, and infections, can also develop, with severe cases potentially leading to gangrene and requiring amputation.

Epidemiology of DM in India and the US

Based on the CDC report on DM from 2021,[1] approximately 38.4 million individuals of all age groups in the US were diagnosed with DM, roughly equating to 1 in every 10 people, with 1 in 5 unaware of their condition. The total medical costs and lost work and wages for those with diagnosed DM amounted to $413 billion. Adults with DM face a 60% higher risk of early death compared to those without the condition. While in India, an estimated 77 million individuals aged 18 years and above are afflicted with type 2 DM. CDC[14] provided the percentage of DM patients across the US. Anjana et al.[15] reported the prevalence of DM patients across different Indian states.

The study on DM prevalence in the US utilized data from the Behavioral Risk Factor Surveillance System (BRFSS) spanning from 2018 to 2022. It involved 1,867,575 surveys, with 259,476 individuals diagnosed with DM. Data for India were sourced from the Demographic and Health Surveys Program (DHS), a global effort offering detailed insights into population demographics, health, and nutritional trends from 2019 to 2021. This encompassed 715,888 surveys, revealing 12,106 individuals diagnosed with DM. Several statistics are illustrated in Figures 2 to 5. For each category, the percentage ratio of non-diabetic to diabetic patients is calculated and visualized through plotting. In both countries, the prevalence exhibits an upward trend with advancing age, as depicted in Figure 1. However, in India, DM tends to be more prevalent at a younger age when compared to the US. Furthermore, the data indicate a high correlation between the rise in body mass index (BMI) and the increased prevalence of DM, as evidenced by the findings presented in Figure 2. This trend holds true for both populations in the respective countries. Specifically, as BMI values escalate, there is a notable escalation in the prevalence of DM among individuals. This observation underscores the significant impact of BMI on DM prevalence, highlighting the importance of weight management and lifestyle factors in mitigating the risk of developing DM within populations across different demographic contexts. The dataset revealed striking differences in the prevalence of DM across various racial and ethnic groups within the US, contrasting with the relatively uniform prevalence rates observed among diverse ethnic groups in India. Notably, non-Hispanic Black and American Indian adults exhibited significantly higher prevalence rates of DM[16] when compared to their non-Hispanic Asian counterparts, as illustrated in Figure 3. This disparity suggests that ethnic factors play a crucial role in influencing DM prevalence within the US population. Moreover, socioeconomic factors, such as education disparities, were evident, with

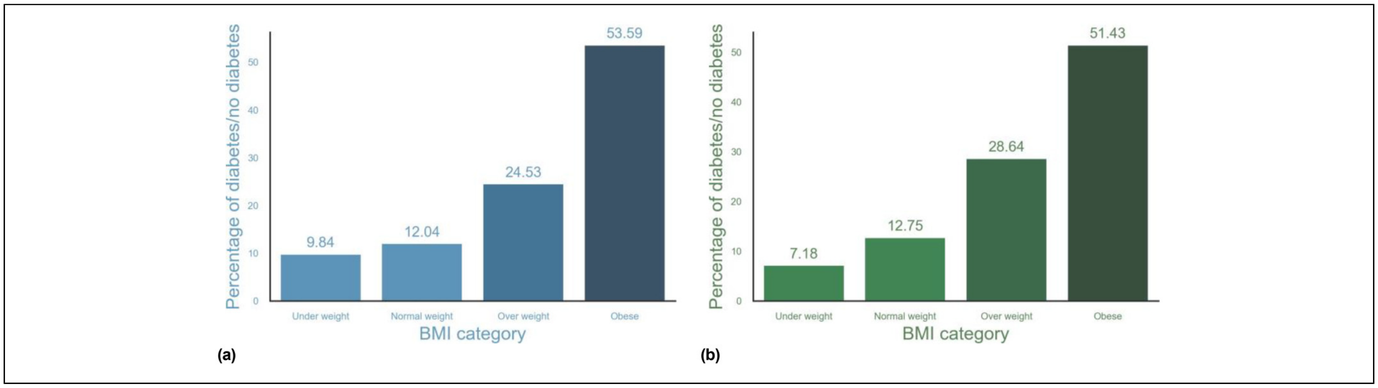

Figure 2. Categorized by BMI. (a) US statistics according to BRFSS (2018-2022). (b) Indian statistics according to DHS (2019-2021).

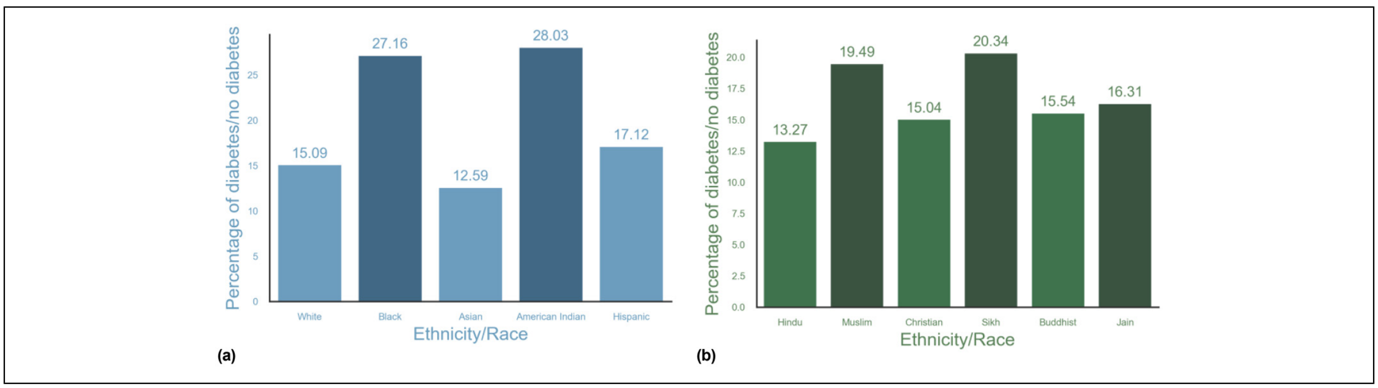

Figure 3. Categorized by ethnicity/race. (a) US statistics according to BRFSS (2018-2022). (b) Indian statistics according to DHS (2019-2021).

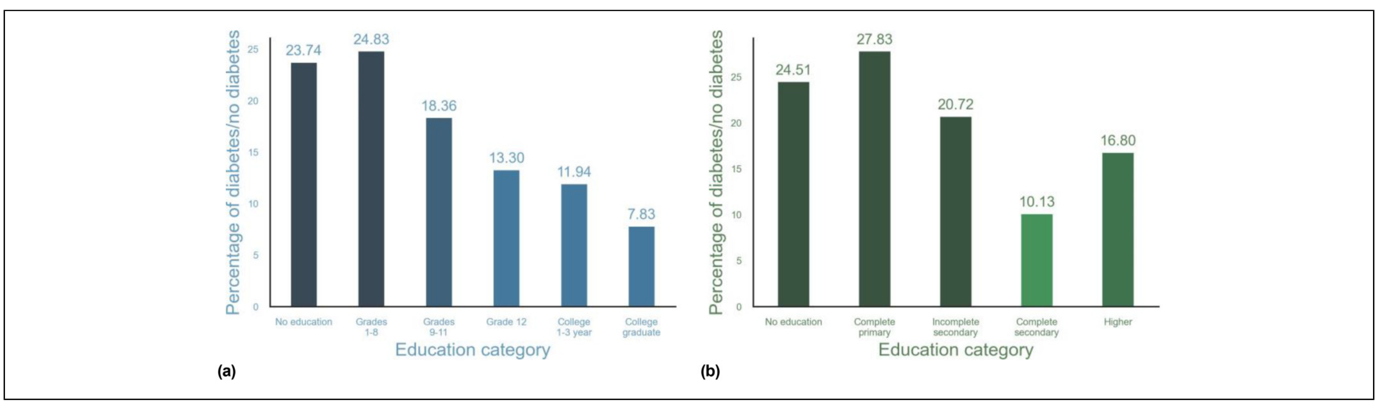

Figure 4. Categorized by education. (a) US statistics according to BRFSS (2018-2022). (b) Indian statistics according to DHS (2019-2021).

higher educated individuals having a lower prevalence of DM, as illustrated in Figure 4. This trend persisted consistently across both US and India, emphasizing the substantial impact of education on DM prevalence. These findings underscore the significance of addressing educational disparities in public health initiatives aimed at preventing and managing DM. By enhancing access to education and bolstering health literacy, endeavors can be undertaken to alleviate the burden of DM within populations and address disparities in health outcomes.

Approaches for Diabetes Care Management

The increasing occurrence of DM emphasizes the need to implement appropriate preventive strategies to tackle this challenge effectively. Utilizing AI can significantly enhance the ability to implement targeted interventions and preventive measures. AI-powered predictive analytics can aid in identifying individuals at elevated risk of developing DM by analyzing vast datasets and detecting patterns indicative of pre-diabetic conditions. Additionally, AI-driven health monitoring devices and mobile applications can empower individuals to track their health metrics in real time, enabling early detection of potential risk factors and facilitating timely intervention. Moreover, AI-enabled decision support systems can assist healthcare professionals in developing personalized prevention plans tailored to each patient's unique health profile and risk factors. These systems can analyze patient data, medical history, and lifestyle factors to generate evidence-based recommendations for lifestyle modifications, dietary adjustments, and targeted interventions. AI algorithms can also continuously learn and adapt based on feedback and outcomes, ensuring the ongoing optimization of preventive strategies. Furthermore, AI technology holds promise in revolutionizing population health management by enabling proactive screening programs, optimizing resource allocation, and predicting future disease complications. By leveraging AI for population-level risk assessment and stratification, healthcare organizations can prioritize preventive interventions in high-risk communities and allocate resources efficiently to achieve maximum impact. Integrating AI-driven approaches into DM prevention efforts can enhance our capacity to identify at-risk individuals, deliver personalized interventions, and optimize population health outcomes. By harnessing the power of AI, we can take proactive steps to mitigate the rising prevalence of DM and improve overall public health outcomes.

Predictive Modeling for Risk Assessment: AI-based predictive models analyze patient data to assess the risk of developing DM. These models utilize machine learning algorithms on electronic health records (EHRs) to identify individuals at higher risk, enabling early intervention and preventive measures. Data mining techniques, combined with AI, extract valuable insights from large datasets in DM research. These methods help discover patterns, trends, and correlations in patient data, facilitating better understanding and managing the disease. Although the fundamental principles of these models for assessing DM risk may be alike in India and the US, the particular execution and effectiveness of models are expected to be shaped by the distinct attributes of each country's population, healthcare infrastructure, and data environment. A recent scoping review conducted by Mohsen et al[17] underscores the importance of identifying risk predictors for T2DM to prevent the disease and tailor interventions for individuals at risk. The authors highlighted that many existing studies have identified traditional risk predictors such as BMI, blood pressure,[18] blood cholesterol levels, fasting plasma glucose (FPG), age, family history of DM (FHD), and HbA1c. Conventional ML models typically rely on longitudinal data reflecting individuals' biological traits, lifestyles, and environmental interactions. However, these models often use a limited set of risk factors as input features, neglecting the intricate interactions among the various biological systems involved in T2DM development. Moreover, they heavily rely on existing literature to select predictors. In contrast, AI-driven models have emerged as promising tools for developing predictive models for T2DM. By analyzing complex, multidimensional datasets, these models can identify high-risk individuals, uncover novel risk factors and biomarkers associated with T2DM, and guide personalized interventions for disease prevention. The authors also note a shift in recent research from solely focusing on prediction performance to placing greater emphasis on understanding the dynamics of algorithms, marking a significant trend in current research.

Detection and Classification of DM: Both in India and the US, diagnosing DM clinically entails the measurement of blood glucose levels, which consequently results in comparable AI methodologies for detecting and classifying DM. Existing diagnostic protocols for DM rely on invasive procedures conducted in clinical settings, potentially influenced by behavioral and ethnic variables. In contrast, AI algorithms analyze EHRs and identify the onset of DM. Recent surveys[19,20,21,22] highlight that diseases like DM, which are prevalent on a large scale, can be effectively managed through AI techniques and automation. ML models utilize a variety of features including patient age, gender, weight, height, postprandial plasma glucose level, fasting plasma glucose level, blood glucose level, blood pressure level, skin thickness value, insulin level, BMI, serum creatinine level, serum sodium level, serum potassium level, hemoglobin level, and more to classify the risk of diabetic disease.[23,24] AI-driven diagnostic tools exhibit high classification accuracy and make use of extensive datasets. These AI models present less invasive and more readily available options, which could potentially improve DM detection and classification accuracy. Such precise predictions empower healthcare professionals to implement intensive management strategies for patients deemed at elevated risk.

DM Progression Prediction: The US typically has greater access to well-organized and evolving healthcare data, encompassing EHRs, claims data, and extensive research databases. These robust datasets facilitate the development of DM progression predictive models using expansive and diverse patient cohorts. In contrast, in India, although endeavors are underway to enhance healthcare data infrastructure, data availability and quality may fluctuate, particularly in rural regions and public healthcare sectors. Challenges may arise due to restricted access to comprehensive patient records and inconsistent data collection practices, potentially hindering the development of predictive models for monitoring DM progression.

Predictive analytics driven by AI anticipate the progression of DM and its associated complications in patients. Various ML algorithms have been investigated to develop an automated predictive model aimed at estimating the likelihood of developing type 2 DM within the period of 1 to 5 years before its onset.[25,26] These models utilize a broad spectrum of variables, encompassing factors such as age, gender, family history of DM, hypertension history, BMI, pre-diabetes HbA1c levels, triglyceride levels (TG), fasting blood sugar (FBS), systolic blood pressure (sBP), high-density lipoprotein (HDL), and low-density lipoprotein (LDL). These variables are employed in developing predictive models to examine the correlation between these variables and the likelihood of developing type 2 DM within different time frames. These models can identify patterns, correlations, and predictive markers that might not be apparent through traditional statistical methods. Additionally, they analyze longitudinal patient data to forecast future health paths and transitions, enabling to deploy timely interventions and customized treatment strategies.

Genetic and Behavioral Analysis for Diabetes Care Management: Although some genetic variations are shared among populations, variations in the prevalence of specific genetic risk factors between Indian and the US populations may exist. In the US, DM management programs often include lifestyle interventions such as dietary adjustments, regular physical activity, and weight control. Additionally, behavioral therapy and support groups are readily accessible.[27] In India, lifestyle choices and behaviors concerning DM management may be influenced by traditional dietary habits, cultural norms, and socioeconomic factors. Analyzing array-based genome-wide association studies (GWAS) has emerged as the most effective method for identifying genetic variations associated with T2DM.[28] AI algorithms have been employed to analyze genetic data, assessing an individual's genetic susceptibility to DM.[29] Furthermore, AI-driven behavioral analysis tools play a crucial role in DM management by monitoring patient behaviors related to diet, physical activity, and medication adherence.[30] These tools utilize various data sources, including wearable devices, mobile apps, and EHRs, to track patient activities and routines. By integrating genetic susceptibility information with behavioral data, healthcare providers can offer tailored interventions aimed at reducing the risk of DM onset and improving disease management. For instance, individuals identified as having a high genetic predisposition to DM can receive targeted interventions focused on lifestyle modifications, such as dietary changes and increased physical activity, to mitigate their risk. These tools offer customized feedback and interventions aimed at encouraging healthier lifestyle decisions and enhancing the management of DM.

Remote Patient Monitoring and Telemedicine: Remote diabetic patient monitoring and telemedicine services have gained significant attention after the COVID-19 pandemic in both India and the US due to their potential to improve healthcare accessibility and patient outcomes. "Telemedicine Practice Guidelines," introduced by the Ministry of Health and Family Welfare in India in 2020, represent an initial step by authorities toward regulating telemedicine services. This effort has been widely praised by stakeholders for its simplicity and cost-effectiveness, offering a means to ensure fair healthcare access for all.[31,32] A recent study demonstrated that mobile health applications were found to be a useful and effective method for enhancing T2DM health literacy in India.[33,34,35] India has witnessed numerous success stories in screening for and managing DM and its associated conditions through the utilization of telemedicine methods.[36,37,38,39,40,41,42]

The ADA recommends enhancing healthcare delivery at a systemic level, providing assistance for self-management and incorporating shared decision-making in the treatment of individuals with DM.[43] The continuous advancements in digitalization and DM-related technology have expanded the usefulness of tele-diabetology as a supplement to or substitute for traditional in-person consultations.[44,45] Several surveys highlighted that telemedicine could effectively serve as a sustainable method of diabetic care.[46,47,48,49,50,51,52] Additionally, numerous insurance companies cover telemedicine services, thus enhancing accessibility and affordability for individuals with DM. Furthermore, healthcare providers frequently integrate telemedicine platforms and remote monitoring tools into their EHRs to optimize patient data management and maintain seamless care continuity. A recent study emphasized the potential of virtual healthcare in aiding individuals with DM, particularly those dealing with obesity and T2D.[53] Telemedicine platforms powered by AI facilitate remote monitoring of diabetic patients' health metrics, medication compliance, and lifestyle behaviors.[54] These platforms enable seamless, real-time communication between patients and healthcare providers, thereby enhancing accessibility to care and improving patient outcomes.

Automated Insulin Monitoring and Delivery Systems for Personalized Treatment Recommendations: Presently, the majority of diabetic patients monitor blood glucose levels using manual techniques like fingerstick testing, and rely on invasive insulin delivery via injections.[55] AI algorithms integrated with continuous glucose monitoring devices can analyze real-time glucose data and adjust insulin dosages accordingly. Automated insulin delivery systems employ AI algorithms to automate insulin dosage adjustments using continuous glucose monitoring (CGM) data. These systems are designed to keep glucose levels within predefined target ranges, thereby mitigating the risks associated with hypoglycemia and hyperglycemia. In both US and India, efforts are underway to integrate automated insulin monitoring and delivery systems into personalized treatment plans for diabetic patients. Variations in regulatory frameworks, healthcare infrastructure, accessibility, and affordability can impact the rate and scope of their adoption in clinical settings. Few of the recent studies have focused on designing and developing demography-agnostic AI and IoT-based techniques for blood glucose monitoring, emphasizing non-invasiveness and eliminating the need for calibration.[56,57,58,59] Few studies have employed a fusion of IoT and AI methods to accurately deliver optimal insulin dosage in real-time, based on individual glucose and insulin levels.[59,60,61] AI-based models for insulin monitoring customized to individual needs could assist in achieving improved blood glucose levels.[60,62]

In the US, the market for automated insulin monitoring and automated insulin delivery (AID) systems has seen significant growth, with various devices such as insulin pumps equipped with continuous glucose monitors (CGMs) gaining popularity. Recently, the Food and Drug Administration (FDA) in the US has granted approval for AID systems, making them commercially accessible.[63,64,65,66] Recent findings from clinical trials indicate improvements in glucose regulation and reductions in the burden of DM management through AI-based glucose monitoring and insulin delivery systems.[67,68] Automated remote monitoring has enabled healthcare professionals to deliver personalized care to patients regardless of their location. In the US, personalized medicine approaches, including personalized DM treatment recommendations, have been advancing steadily. AI techniques have been employed to analyze individual patient data and provide tailored treatment recommendations.[69] These recommendations consider diverse factors such as medical history, genetic predisposition, lifestyle choices, and treatment responses, ultimately enhancing the management of DM for individual patients.[70,71,72]

Population DM Management: Population DM management platforms powered by AI scrutinize data at a population level to pinpoint high-risk groups, detect trends, and recognize disparities in DM prevalence and outcomes. These platforms play a crucial role in guiding public health interventions, allocating resources, and shaping policy-making endeavors. Ensuring adherence to medication is a multi-faceted behavioral challenge, demanding consistent participation from patients on a daily basis. Ensuring adherence to medication is a multifaceted behavioral challenge, demanding consistent participation from patients on a daily basis. In the US, various voice-based conversational AI systems have demonstrated the potential to enhance access to technology-enabled healthcare for diabetic patients with limited digital literacy, while also boosting engagement levels across the population.[73] Enhancing healthcare accessibility and enhancing health results for rural diabetic patient population, acknowledged as a vital minority demographic, is the mutual focus for both US and India. Rural areas in these countries face unique challenges, including limited healthcare infrastructure, geographic isolation, and disparities in health-care access compared to urban regions.[74,75,76] AI-based techniques have been explored as a tool for conducting widespread screenings aimed at identifying individuals at risk of DM and their associated complications on a large scale.[77,78,79,80,81] These approaches hold promise for improving early detection rates, enabling timely intervention, and ultimately reducing the burden of DM-related complications on healthcare systems.

Challenges and Future Directions

The collection of longitudinal data on diabetes can help trace the disease progression and transition from a single to polychronic conditions.[82] AI has the potential to revolutionize diabetes care management. However, there are indeed challenges in developing and implementing these AI systems with panel data, particularly when considering countries like India and the US with their unique contexts. Some of these challenges are elaborated below and are summarized in Table 1. AI systems rely heavily on patient data. Concerns around data privacy and security are of paramount interest. Ensuring data

Table 1. Challenges Associated With AI-based Diabetes Care Management Systems.

Aspect	India	US
Healthcare system	Fragmented & limited access to healthcare facilities, especially in rural areas.	Well-established healthcare infrastructure, but highly complex. Disparities in access and affordability.
EHR data quality	Limited availability of EHRs and standardized data.	Varied quality and restricted access to high-quality data.
Cultural factors and language diversity	Deep-rooted cultural beliefs influencing attitudes towards health, treatment, and technology adoption. Numerous languages are spoken across different regions within the country, necessitating AI solutions with multilingual capabilities.	Large immigrant populations with diverse language preferences requiring multilingual AI solutions.
Data privacy and security	Personal Data Protection Bill (PDPB) regulates the processing of personal data, a robust framework for data protection is still in the process of development.	HIPAA governs the collection, storage, and sharing of healthcare data, including diabetes-related information. US DM patients have the right to control their health information under HIPAA, requiring explicit consent for data collection, use, and sharing.
Affordability and sustainability	Automated system development costs less with affordable technology, offering sustainable, scalable solutions with reduced operating expenses.	System development is high due to labor costs. Automated technologies, though advanced, are costly, and long-term funding and reimbursement present challenges.
Regulatory compliance and certification	Evolving frameworks provide flexibility but uncertainty in certification and regulations may complicate system development and deployment, causing delays.	Well established regulations like HIPAA mandate compliance for healthcare technology, potentially raising development costs and timelines due to stringent data security and regulatory documentations.
Physician acceptance and workflow Integration	Physician acceptance differs; urban areas may readily adopt technology, whereas rural regions encounter challenges in digitalization. Limitations in training could impede broad adoption and the seamless integration of workflows.	Physicians generally accept technology due to advanced infrastructure, but integrating it into existing workflows faces challenges due to system complexity and interoperability issues.
Awareness and trust	Urban, educated communities are more aware, whereas rural populations may lag due to limited access to information. Coexistence of traditional healthcare beliefs may influence trust levels.	Higher awareness stems from wide information access and healthcare technology promotion. While enhanced trust is derived from well-established regulatory standards.

anonymization, secure storage, and transparent use of data are crucial hurdles.[83]

Challenges Specific to India

In India, several challenges specific to implementing an AI-based DM management system arise due to the country's diverse healthcare landscape and resource constraints.

- **Fragmented healthcare system:** India's healthcare system is fragmented, with a mix of public and private providers. Standardizing data collection and ensuring interoperability between different systems is a major challenge for large-scale AI implementation.[84] There are disparities in healthcare infrastructure between urban and rural areas, with rural regions often lacking access to advanced medical facilities and skilled healthcare professionals. This poses a challenge for deploying AI-based systems uniformly across the country.
- **Lack of high-quality EHR data:** In various healthcare facilities across India, the adoption of EHRs remains limited and fragmented. There is a lack of standardized systems and interoperability between different healthcare providers. Many hospitals and clinics in India use proprietary or custom-built EHR solutions that are not compatible with each other, making it challenging to share patient data across different healthcare settings.
- **Cultural factors and language diversity:** India is a diverse country with numerous languages, cultures, and traditions, which vary widely from region to region. One of the key challenges is ensuring that the AI-based system is culturally sensitive and relevant to the diverse population it serves. Cultural beliefs and practices related to health and illness can influence how individuals perceive and respond to medical advice and treatment recommendations. Therefore, the system must be designed to accommodate cultural nuances and preferences, such as dietary habits, religious practices, and beliefs about health and wellness. Moreover, linguistic diversity adds another layer of complexity to the implementation of the system. India is home to hundreds of languages and dialects, making it essential to provide multilingual support for the AI-based system. This includes not only the interface and communication with patients but also the interpretation of medical terminology and documentation. Without adequate language support, patients may struggle to understand or engage with the system effectively, leading to barriers in accessing care and managing their DM.
- **Affordability and sustainability:** Ensuring that an AI-based system is both affordable and sustainable is crucial for its widespread adoption and long-term effectiveness, especially in rural India where resources are limited. For many healthcare facilities, especially those in rural areas, upfront costs may pose a significant barrier to adoption. To enhance the affordability and sustainability of AI-based systems in India, stakeholders must prioritize cost-effectiveness, efficiency, and scalability in system design and implementation.
- **Lack of awareness and trust:** There may be a lack of awareness and trust in AI technology among some populations in India. Building public education and trust is crucial for widespread adoption.[85]

Challenges Specific to the US

In the US, the implementation of an AI-based DM management system faces several challenges specific to the country's intricate healthcare landscape and concerns surrounding data privacy and security.

- **Complex healthcare system:** US healthcare system is highly complex, characterized by a multitude of stakeholders, including insurers, healthcare providers, government agencies, and pharmaceutical companies, operating within a fragmented framework. This fragmentation can hinder the seamless integration and interoperability of AI-based systems across different healthcare settings and institutions.
- **Data bias and lack of qualitative data:** Two key hurdles hinder AI development for DM management: limited access to high-quality data and potential biases within existing data. These limitations can lead to tools that are less effective or even exacerbate existing health disparities.[86]
- **Data privacy and security:** Data privacy and security concerns loom large in the US, particularly in the realm of healthcare, where the safeguarding of sensitive patient information is paramount. The Health Insurance Portability and Accountability Act (HIPAA) establishes strict regulations governing the privacy and security of protected health information (PHI). Any AI-based system must comply with HIPAA regulations to ensure the confidentiality, integrity, and availability of patient data. Achieving compliance with HIPAA standards adds complexity to system development and deployment, requiring robust encryption protocols, access controls, and audit trails to protect patient privacy and prevent unauthorized access or data breaches.
- **Regulatory compliance and certification:** Obtaining regulatory approval by agencies such as FDA for AI-based systems entails rigorous testing, validation, and documentation to demonstrate safety, efficacy, and compliance with regulatory standards. Navigating the regulatory landscape and obtaining necessary certifications can be time-consuming and resource-intensive, delaying market entry and adoption of AI technologies.
- **Physician acceptance and workflow integration:** The lack of transparency in AI healthcare tools creates a 'black box' problem, making it difficult for doctors, regulators, and patients to assess the tool's safety, efficacy, and potential biases.[86] Healthcare providers may be hesitant to adopt new technologies or change established practices without straightforward evidence of clinical

benefits, usability, and workflow integration. AI-based systems must demonstrate value proposition, ease of use, and compatibility with existing clinical workflows to gain acceptance and adoption by healthcare providers.

Future Directions

Considering the multitude of challenges observed in both nations, below are a few outlined future directions aimed at improving AI-powered DM management systems.

Data-Driven Direction. Efforts in data-driven direction encompass various crucial aspects. Firstly, initiatives to standardize data collection formats and promote widespread adoption of standardized EHR systems by policymakers and healthcare organizations could greatly enhance the implementation of AI-based systems, enabling more effective access and analysis of patient data, leading to improved insights and decision-making. Secondly, implementing automated data validation processes and data cleansing or preprocessing techniques could significantly enhance data quality. These processes involve automatically identifying and correcting errors, inconsistencies, and missing values within the data, ensuring that they are accurate, complete, and reliable. By improving data quality, these techniques enable the development of more robust and generalized AI-based systems. High-quality data enhances the performance and accuracy of AI algorithms, leading to more reliable insights and predictions. Thirdly, synthetic data generation serves as a valuable tool for overcoming limitations like data scarcity and privacy concerns, while also addressing issues of data imbalance or bias, augmenting existing datasets and improving model training and validation. Additionally, ensuring secure data storage and transmission through sophisticated encryption methods and access controls is essential for safeguarding patient privacy and maintaining confidence in the security of health information. Lastly, leveraging multimodal data sources, including EHRs, wearable devices, genomic data, and social determinants of health, can enhance prediction capabilities, facilitate holistic AI-based systems, and improve decision-making processes. The longitudinal data of patients could be employed to track changes in health over time. Longitudinal data provide insights into disease progression, treatment efficacy, and the impact of lifestyle factors on DM management. AI models can leverage longitudinal data to identify trends, predict future health outcomes, and personalize treatment plans accordingly.

Model-Driven Direction. In the realm of model-driven direction for diabetes care management, several key strategies emerge. Firstly, there is a focus on personalized and adaptive AI models, which tailor recommendations and interventions to individual patient characteristics, preferences, and responses. Advancing with hybrid models integrates ML and DL techniques to balance complex pattern recognition with interpretability, crucial for clinical decision-making. Automated hyper-parameter tuning optimizes model performance and adaptability, reducing manual effort and accelerating model development. Algorithmic fairness tools are employed to identify and mitigate bias within AI models, ensuring fairness across patient populations. Dynamic model evolution allows continuous learning and adaptation based on new data and real-world outcomes. Scalable and generalizable models handle extensive data volumes and demonstrate consistent performance across diverse groups and conditions. Explainable AI techniques provide transparent insights into model reasoning, fostering trust among healthcare providers and patients. Finally, seamless integration into real-time care systems, such as mobile applications or wearable devices, aims to improve accessibility and usability, ultimately enhancing patient outcomes and quality of life in diabetes care management.

Integrative Theoretical Frameworks. The development of predictive analytics for diabetes care and outcomes research could be supplemented by a well-conceived theoretical framework that could facilitate statistical modeling and validation of testable hypotheses derived from a transdisciplinary perspective via the identification of patient (micro-level), and provider and community (macro-level) predictor variables in diabetes care research.[87,88]

Conclusions

In this article, the authors have provided key observations associated with DM management in India and the US. This article presents 2 main contributions: a discussion comparing management approaches for this disease in India and the US, and key observations regarding AI techniques applicable to DM management. This research work on key observations can be advanced based on the directions for future work illustrated in the previous section. It is important to note that the investigators have undertaken the critical and important task of observing variations in DM management. Additionally, a key improvement in the management of this disease using AI has been illustrated in the article. Further exploration of these AI techniques is necessary to improve healthcare outcomes for processes associated with DM management.

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Data Availability Statement

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