International Journal of Health Science

ISSN 2764-0159 vol. 6, n. 3, 2026

ARTICLE 13
Acceptance date: 13/03/2026

IMPLEMENTATION OF AN AI-BASED CLINICAL DECISION SUPPORT SYSTEM FOR THE SCREENING OF TYPE 2 DIABETES MELLITUS IN PUBLIC HEALTH

Ana Clara Pereira Araujo
University of Rio Verde
Luziânia - Goiás
http://lattes.cnpq.br/0414655147180864

Milena Lima Pereira Araujo
Active civil servant in the area of Innovation and Artificial Intelligence, Federal Regional Court of the 1st Region Brasília, Brazil
Brasília – Federal District
https://orcid.org/0009-0000-3384-1939

Bruna Coelho Cavalheri
University of Rio Verde
Luziânia – Goiás
https://lattes.cnpq.br/1679020008968127

Isadora Ferreira Grande
University of Rio Verde Luziânia – Goiás
http://lattes.cnpq.br/0787983997025039

Amanda Silva Nazário de Oliveira
University of Rio Verde
Luziânia – Goiás
https://lattes.cnpq.br/6479152426061771

Lucas Octávio Meneses Araújo
University of Rio Verde
Luziânia – Goiás
http://lattes.cnpq.br/6479152426061771

Luiz Fernando Ferreira Gonçalves
University of Rio Verde
Rio Verde – Goiás
https://orcid.org/0009-0007-3413-2764

Marcela Araujo Da Silva
University of Rio Verde
Luziânia, Goiás
https://lattes.cnpq.br/1001039986676585

Luana de Queiroz Souza
University of Rio Verde
Luziânia, Goiás
https://orcid.org/0009-0005-3061-6855

Fabiano Fagundes Moser da Silva
Biomedical Scientist. PhD in Animal Biology. Professor in the Medical School. University of Rio Verde, UniRV, Luziânia, Brazil.
https://lattes.cnpq.br/7213274734371731

Adriana de Araújo Oliveira
University of Rio Verde
Luziânia - Goiás
https://lattes.cnpq.br/5919570815349976

Abstract: Type 2 diabetes mellitus (T2DM) represents one of the greatest challenges in global public health, characterized by insulin resistance, high mortality rates, and growing prevalence, particularly in middle-income countries. In this context, artificial intelligence (AI) emerges as a strategic tool for early screening and individual risk prediction. This study aims to analyze the implementation of AI-based Clinical Decision Support Systems (CDSS) for T2DM screening in public health programs through a systematic literature review. Results showed that machine learning and deep learning models outperform traditional statistical methods, with accuracy exceeding 91% in some studies. The integration of technologies such as cloud computing, edge computing, and blockchain enhances scalability, operational efficiency, and data security. It is concluded that the adoption of AI-based CDSS in primary health care can represent a significant advancement in service organization, equitable access, and financial sustainability of public health systems.

Keywords: Type 2 diabetes mellitus. Artificial intelligence. Machine learning. Clinical Decision Support System. Public health. Early screening.

INTRODUCTION

Type 2 diabetes mellitus (T2DM) is a chronic noncommunicable disease and one of the most common metabolic disorders, initially characterized by insulin resistance. It accounts for 90% of diagnosed diabetes cases and is considered one of the leading causes of death worldwide (World Health Organization, 2024). The prevalence of T2D has increased by 95% since 2000. In 2021, noncommunicable diseases accounted for 68% of the top 10 causes of death and 38% of total deaths for the year (World Health Organization, 2024). This is a condition in which the body's cells have a reduced ability to respond to insulin, a hormone produced by the pancreas that is responsible for transporting glucose from the extracellular to the intracellular environment, resulting in elevated blood glucose levels (the amount of glucose in the blood). According to the International Diabetes Federation, 537 million people worldwide live with diabetes, and this number is estimated to rise to 783 million by 2045. Among income groups, the highest prevalence was observed in middle-income countries (Sun, H. et al., 2022).

People who have type 2 diabetes mellitus (T2D) are at serious risk of develop cardiovascular diseases, such as acute myocardial infarction (AMI) or ischemic stroke. T2D increases the mortality rate from cardiovascular disease in adults by a factor of 2 to 4. Due to its correlation with diabetic dyslipidemia (high triglyceride levels and low HDL cholesterol levels), in addition to the fact that high blood glucose levels (hyperglycemia) and insulin resistance cause inflammation and endothelial dysfunction, they promote the formation of fatty plaques in the arteries, serving as a risk factor for accelerated atherosclerosis (Galicia-Garcia *et al.*, 2020). Cardiovascular diseases top the list of leading causes of death, ranking first among 10 listed diseases, accounting for 13% of global deaths, reaching 9.1 million deaths in 2021 (World Health Organization, 2024).

Early screening for diabetes is essential for healthcare systems, as the disease is considered a preventable pandemic. This is because there are factors other than genetics that, if modified, can prevent the development of T2D, primarily lifestyle changes, including the management of obesity, engaging in physical activity, and maintaining a healthy diet (Galicia-Garcia *et al.*, 2020). The use of data from electronic health records can identify individuals at high risk of developing diabetes, enabling early interventions aimed at delaying or preventing its onset (Naveed et al., 2023).

In this context, artificial intelligence (AI) has emerged as a promising tool for predicting and screening for T2D through the analysis of large volumes of clinical, laboratory, and demographic data (Hennebelle et al., 2023). Machine learning-based models are capable of identifying complex patterns and risk factors associated with the development of the disease with greater accuracy compared to traditional statistical methods (Mizani et al., 2024). The incorporation of these systems into public health programs, through Clinical Decision Support Systems, can contribute to automated risk stratification and the optimization of healthcare resources.

In this context, complementary architectures such as cloud computing and edge computing stand out. Cloud computing is characterized as a model that enables on-demand access to shared and configurable computational resources, with high scalability and massive processing capacity (MELL; GRANCE, 2011). In turn, edge computing consists of a decentralized architecture in which processing occurs close to the data source, reducing latency and optimizing information flow (SATYANARAYANAN, 2017). The integration between cloud and edge, often associated with Internet of Things environments, allows for a balance between centralized analytical capacity and real-time response (CHIANG; ZHANG, 2016), an aspect particularly relevant in health monitoring and tracking applications (RAJ; ANAND, 2019).

Given this scenario, it is important to discuss the implementation of Artificial Intelligence-based Clinical Decision Support Systems as a strategy to strengthen T2D screening programs within the public health sector, aiming to reduce T2D-related diseases and deaths.

METHODOLOGY

This article was developed through a systematic literature review, using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), with the aim of analyzing and understanding the potential implementation of artificial intelligence in the screening process for type 2 diabetes mellitus, focusing on its potential to assist public health programs and facilitate early disease detection, contributing to both treatment and prevention.

Searches were conducted in the PubMed and Cochrane databases, as well as in national and international health journals and newspapers, national libraries, and reference works in medical education. In this context, the PICO strategy was used to define the study's objective. Thus, "P" corresponded to patients with type 2 diabetes mellitus or at imminent risk of diagnosis; "I" referred to the application of artificial intelligence in screening patients with a confirmed diagnosis and those with laboratory and clinical parameters indicative of a possible future diagnosis; "C" compared the presence and absence of artificial intelligence use in public health activities; and "O" indicated the possible outcomes resulting from this technological optimization in healthcare.

Initially, the search terms used were "type 2 diabetes mellitus" and "artificial intelligence," combined using the Boolean operator "AND." Subsequently, new searches were conducted by adding the term "public health" to the previously used search terms. The filter applied was restricted to titles and abstracts, with no time limit, in order to highlight both the retrospective and prospective developments in the topic. The selection of articles involved an initial evaluation based on titles and the reading of summaries and abstracts, with the aim of analyzing the correlation with preventive screening strategies, whether to prevent a future diagnosis or to halt disease progression and, consequently, reduce morbidity and mortality. Articles that met the inclusion criteria and were deemed eligible were read in full to avoid biases and information outside the context of application. After a complete reading and verification of alignment with the objectives established by the PICO analysis, the selected studies were considered and used as material for the scientific literature review.

Scientific documents deemed ineligible in this process were excluded for failing to meet the established criteria regarding population, intervention, comparison, and outcome. Consequently, records that addressed exclusively disease complications, such as retinopathies and arterial problems, different treatment modalities, restrictions related to ethnic, racial, or gender groups, as well as the potential of artificial intelligence without a direct correlation to the proposal of preventing greater risks.

RESULTS AND DISCUSSION

The effectiveness of AI in screening and predicting T2D

The systematic literature review revealed convergence among the analyzed studies regarding the effectiveness of artificial intelligence in screening and predicting type 2 diabetes mellitus (T2D), especially when applied to electronic health records.

The findings demonstrate that models based on machine learning and deep learning outperform traditional statistical methods in the early identification of at--risk individuals. According to Mizani et al. (2024), when analyzing a population-based cohort of 420,448 individuals, they identified four distinct subtypes of T2D using unsupervised methods, with high internal validity (F1 score greater than 0.98). Significant differences were observed between the subtypes regarding five-year mortality, hospitalizations, and medication burden, demonstrating prognostic stratification capability. Studies have shown that deep learning models with temporal memory, such as LSTM, achieved accuracy exceeding 91% in predicting T2D based on longitudinal electronic health records.

The incorporation of the temporal dimension of risk proved decisive for improving predictive performance (Naveed et al., 2023). An integrated system involving the Internet of Things (IoT), edge computing, artificial intelligence, and blockchain for diabetes prediction was also presented. The Random Forest model demonstrated superior average performance when compared to Logistic Regression and Support Vector Machines, in addition to an architecture focused on security and the preservation of data privacy. (Hennebelle et al., 2024)

In general, studies indicate that artificial intelligence improves the accuracy of identifying at-risk individuals, enables automated risk stratification and the identification of clinical subtypes, and facilitates technological integration with security mechanisms and data governance.

Impacts of AI on Public Health

AI's main contribution to public health lies in expanding the capacity for early identification of individuals with a higher probability of developing T2D. Automated analysis of large volumes of clinical data allows for the prioritization of vulnerable groups, facilitating early interventions and reducing metabolic and cardiovascular complications.

Automated risk stratification contributes to better organization of care pathways, rationalization of resource allocation, and strengthening of epidemiological surveillance. By generating dynamic population-level risk indicators, AI assists policymakers in formulating and evaluating evidence-based public health policies. In this context, artificial intelligence impacts both the micro-level of care, by supporting individualized clinical decisions, and the macro-structural level, by informing strategic health planning.

The adoption of AI systems in Primary Health Care (PHC) services can serve as a tool for reducing disparities in care, thereby ensuring health equity, since low-income populations and regions with fewer specialists tend to benefit from the use of automated triage, and studies indicate that AI enables early detection in places where access to conventional diagnosis is limited, thereby expanding the reach of preventive measures and contributing to universal healthcare, a core principle of the Unified Health System (Mizani et al., 2024; Naveed et al., 2023).

The results and challenges of technology implementation in public health

According to the Brazilian government's Transparency Portal, a search for the term "health technology expenditures" yields over 3,000 results; however, the majority of these refer to the same investments made over consecutive years, with no innovation to speak of. Thus, one can infer the existence of budgetary constraints for the formal, effective, and unified development of innovative early and preventive screening strategies for diseases such as type 2 diabetes mellitus.

In addition to budgetary constraints, the literature identifies the fragmentation of health information systems, the lack of standards across different platforms, and institutional resistance to adopting new technologies as significant barriers; furthermore, the lack of training for healthcare teams to operate and interpret the results generated by AI tools constitutes another structural obstacle.

These limitations indicate that the successful implementation of AI-based SADCs depends not only on technological infrastructure but also on integrated strategies for managing organizational change, involving ongoing training, adapted clinical protocols, and robust data governance mechanisms.

Standard teaching methodology for artificial intelligence:

At this initial and still nascent stage, clinical records are fundamental for the proper implementation and understanding of artificial intelligence as a pioneering tool in the prevention of adverse outcomes, whether in the face of a possible diagnosis in individuals with risk factors or due to complications in cases where the disease is already established. The collection and preprocessing of consultation and examination records from diabetic and non-diabetic patients constitute essential steps in trials designed to train artificial intelligence to identify pathological patterns by comparing characteristics considered healthy and unhealthy. Thus, a distinction is made between the training and testing phases, correlating the data and the attributes associated with the disease.

In this sense, the scientific objective of preprocessing is to transform the data into information suitable for training a model. According to Naveed et al. (2023), the trial they conducted to create an AI-based screening system follows steps that include clustering, sorting, data conversion, imputation of missing values, and the construction of feature vectors.

Therefore, preprocessing is fundamental to the machine training process; consequently, these models involve techniques such as logistic regression, support vector machines, decision trees, Gaussian Naive Bayes, long short-term memory, and convolutional neural networks. Thus, there is an essential step related to the methods for selecting the most significant features for predicting diabetes.

In this context, the appropriate selection of variables used to train the models is a determining factor in the quality of the predictions made by the algorithms. Clinical and laboratory data frequently associated with the development of type 2 diabetes mellitus—such as age, body mass index, family history of the disease, blood glucose levels, blood pressure, and changes in lipid profile—can be used as relevant parameters for building these predictive models. The integrated analysis of this information allows artificial intelligence systems to identify risk patterns with greater precision, contributing to the early identification of individuals susceptible to developing the disease.

Thus, for the consistent use of AI, metrics such as accuracy, sensitivity, specificity, and precision are evaluated. This analysis examines the proportion of correctly predicted patients, the proportion of those who will develop diabetes and for whom the prediction is accurate, as well as the proportion of non-diabetic individuals with a correctly classified negative diagnosis.

It is therefore considered that, in AI-based prediction models, one should not only take into account positive diagnoses of the disease, but also negative diagnoses and the progression of non-diabetic cases, so that the system can adequately differentiate the various health conditions involved.

Automation of T2D screening using AI:

Automation of screening occurs through the integration of electronic health records and predictive models trained to estimate future risk based on multiple variables.

The process involves data collection and preprocessing, model training and validation, automated generation of risk scores or categories, and triggering of standardized clinical protocols.

Once validated, the system automatically classifies individuals according to their probability of developing T2D, triggering requests for tests, inclusion in preventive programs, or intensified clinical follow-up.

When combined with edge computing and the cloud, processing becomes continuous and scalable, allowing for periodic risk updates as new data are incorporated. This dynamic reduces reliance on manual screenings and enhances the operational efficiency of population-based screening.

However, large-scale implementation requires adequate technological infrastructure, interoperability between systems, robust data governance, and training for healthcare teams.

The technology as teaching standard and the follow-up ethical of doctor-patient relationship

After data preprocessing, the dataset is divided into training and testing sets to facilitate the validation process. Following the development of the model, a decision tree is established as the classification model, alongside the other machine learning models mentioned earlier, in addition to the use of the F-measure, a relevant metric for evaluating the performance of machine learning algorithms.Furthermore, according to Ismail and Materwala (2021), the F-measure can highlight the model's detection capability regarding minority and majority classes, revealing, more precisely, the potential for early prevention prior to diagnosis using the available health data.

Based on this, the analysis of the previously reported data is closely linked to a bibliometric scientific activity, which integrates different areas of knowledge with the aim of promoting active problem-solving. The traditional monitoring of conditions such as hypertension, obesity, lipid profile, sleep quality and duration, physical activity, and glucose levels, among other factors, combined with the technological application of artificial intelligence, integrates the reality experienced by healthcare professionals with that of the scientific-computational realm.

This is where edge computing and cloud computing come into play, since data on risk factors—collected through traditional medical methods—is sent to edge servers for processing via algorithms.

However, the edge system lacks the capacity to perform such intensive processing, which is why the collected and filtered information is sent to a cloud system. This flow establishes a cyclical process of data collection, analysis, and storage in the cloud, taking into account different accuracy metrics, accuracy, until the verification of the information becomes sufficiently robust and results in a final decision (Hennebelle et al., 2024).

Finally, patients and the general public may question the security of information related to their health. In this context, the Code of Medical Ethics, in Chapter IX, Article 73, ensures professional confidentiality and prohibits the disclosure of information, even if it is in the public domain or even after the patient's death. Thus, this duty cannot be violated, whether in person or in the digital environment, which is why the use of technologies such as blockchain is introduced as an additional mechanism for data protection.

Blockchain consists of a system that securely integrates cloud computing, as it eliminates the need for a centralized authority and promotes trust and transparency among network participants (Cichosz et al., 2018). Furthermore, data reliability and integration stem from the correlation between different areas, professionals, and the target audience—in this case, patients. Thus, information security is structured through a permissioned architecture, based on multiple metadata records and ledgers, with the aim of ensuring the privacy of data made available to the pattern identification system.

In this context, the incorporation of artificial intelligence-based tools within the scope of Primary Health Care presents strategic potential for strengthening type 2 diabetes mellitus screening efforts. As the first point of contact between the population and health services, primary care plays a fundamental role in the early identification of risk factors and the adoption of preventive measures. The use of clinical decision support systems, capable of analyzing clinical, laboratory, and demographic data, can assist healthcare professionals in stratifying patient risk, facilitating earlier and more targeted interventions. Thus, the integration of artificial intelligence technologies with primary care services can contribute to the improvement of prevention strategies, enabling greater efficiency in monitoring individuals susceptible to developing diabetes and, consequently, reducing the occurrence of complications associated with the disease.

PROSPECTS FOR INTEGRATING SADC INTO PRIMARY HEALTH CARE

The incorporation of artificial intelligence-based tools within Primary Health Care (PHC) holds strategic potential for strengthening type 2 diabetes screening efforts, as PHC represents the first point of contact between the population and health services and plays a fundamental role in the early identification of risk factors and the adoption of preventive measures.

The use of Clinical Decision Support Systems (CDSS) capable of analyzing clinical, laboratory, and demographic data can assist healthcare professionals in risk stratification of patients, facilitating earlier and more targeted interventions.

Thus, the integration of artificial intelligence technologies with primary care services can contribute to the improvement of prevention strategies, enabling greater efficiency in monitoring individuals susceptible to developing diabetes and, consequently, reducing the occurrence of complications associated with the disease.

Regarding healthcare management, the implementation of AI-based SADCs in PHC can serve as a tool for rationalizing healthcare costs within the Unified Health System, as well as for the early detection and prevention of T2D complications—such as retinopathy, neuropathy, nephropathy, and cardiovascular events — leading to a direct reduction in hospital costs and the demand for highly complex procedures.

As a result, the technology ceases to be merely a clinical innovation and becomes a driver of financial sustainability for public health systems, aligning with the efficiency guidelines recommended by the World Health Organization (WHO, 2024).

CONCLUSION

The findings of this review indicate that the implementation of Clinical Decision Support Systems based on artificial intelligence may represent a structural advancement in T2D screening programs in public health. Based on the premise that automated risk stratification contributes to better organization of care workflows, it serves as a support not only for patients but primarily for the entire healthcare team working to prevent and reduce potential harm.

Significant differences were also found in five-year mortality, hospitalizations, and medication burden based on the AI-driven risk stratification process, revealing not only an innovation for computational and medical science but a direct improvement in quality of life and longevity.

Thus, despite the difficulties and limitations involved in incorporating artificial intelligence into screening, its use is effective for the diabetic population and those at risk of a future diagnosis in the management of this chronic and prevalent condition.

REFERENCES

ABDELWAHAB, O. et al. A feature selection--based framework to identify biomarkers for cancer diagnosis: A focus on lung adenocarcinoma. PloS one, v. 17, n. 9, p. e0269126–e0269126, 6 set. 2022. Acesso: 22 fev 2026

ANTHONY, P. et al. Global Research Trends in Artificial Intelligence and Type 2 Diabetes Mellitus: A Bibliometric Perspective. Cureus, v. 17, n. 7, p. e88114–e88114, 16 jul. 2025. Acesso em: 18 fev 2026.

AWAN, S. E. et al. Feature selection and transformation by machine learning reduce variable numbers and improve prediction for heart failure readmission or death. PLOS ONE, v. 14, n. 6, p. e0218760, 26 jun. 2019. Acesso em: 22 fev 2026

BANGAR RAJU CHERUKURI. Edge Computing vs. Cloud Computing: A Comparative Analysis for Real-Time AI Applications. International Journal For Multidisciplinary Research, v. 6, n. 5, 28 out. 2024. Acesso em: 27 fev 2026.

BUYYA, R. et al. Quality of Service (QoS)-driven Edge Computing and Smart Hospitals: A Vision, Architectural Elements, and Future Directions. Disponível em: <https://arxiv.org/abs/2303.06896?>. Acesso em: 13 dez. 2025.

CICHOSZ, S. L. et al. How to Use Blockchain for Diabetes Health Care Data and Access Management: An Operational Concept. Journal of Diabetes Science and Technology, v. 13, n. 2, p. 248–253, 26 jul. 2018. Acesso em: 22 fev 2026.

CHICCO, D.; ROVELLI, C. Computational prediction of diagnosis and feature selection on mesothelioma patient health records. PLOS ONE, v. 14, n. 1, p. e0208737, 10 jan. 2019. Acesso em: 22 fev 2026

CONSELHO FEDERAL DE MEDICINA (CFM). Código de Ética Médica: Resolução CFM nº 2.217, de 27 de setembro de 2018, modificada pelas Resoluções CFM nº 2.222/2018 e nº 2.226/2019. Brasília: Conselho Federal de Medicina, 2019. Disponível em: https://portal.cfm.org.br/images/PDF/cem2019.pdf. Acesso em: 1 mar. 2026.

DAVE, R.; SELIYA, N.; SIDDIQUI, N. The Benefits of Edge Computing in Healthcare, Smart Cities, and IoT. Journal of Computer Sciences and Applications, v. 9, n. 1, p. 23–34, 29 out. 2021. Acesso: 27 fev 2026.

FOLTYNSKI, P. et al. Wound Area Measurement with Digital Planimetry: Improved Accuracy and Precision with Calibration Based on 2 Rulers. PLOS ONE, v. 10, n. 8, p. e0134622, 7 ago. 2015. Acesso em: 22 fev 2026.

GALICIA-GARCIA, U. et al. Pathophysiology of type 2 diabetes mellitus. International Journal of Molecular Sciences, v. 21, n. 17, p. 1–34, 30 ago. 2020. Disponível em: https://www.mdpi.com/1422-0067/21/17/6275. Acesso em: 26 fev. 2026.

GEORGAKOPOULOS, D. et al. Internet of Things and Edge Cloud Computing Roadmap for Manufacturing. IEEE Cloud Computing, v. 3, n. 4, p. 66–73, jul. 2016.

HU, Y.; BAI, G. A systematic literature review of cloud computing in eHealth. arXiv:1412.2494 [cs], 8 dez. 2014.

NAVEED, I.; KALEEM, M. F.; KESHAVJEE, K.; GUERGACHI, A. Artificial intelligence with temporal features outperforms machine learning in predicting diabetes. PLOS Digital Health, San Francisco, v. 2, n. 10, e0000354, 2023. DOI: 10.1371/journal.pdig.0000354. Disponível em: https://journals.plos.org/digitalhealth/article?id=10.1371/journal.pdig.0000354. Acesso em: 03 fev. 2026.

SIRSHAR, M. et al. Attention based automated radiology report generation using CNN and LSTM. PLOS ONE, v. 17, n. 1, p. e0262209, 6 jan. 2022. Acesso em: 22 fev 2026.

SUN, H.; SAEEDI, P.; KARURANGA, S.; PINKEPANK, M.; OGURTSOVA, K.; DUNCAN, B. B.; et al. IDF Diabetes Atlas: Global, regional and country-level diabetes prevalence estimates for 2021 and projections for 2045. Diabetes Research and Clinical Practice, [s.l.], v. 183, p. 109119, 2022. DOI: 10.1016/j.diabres.2021.109119. Disponível em: https://pmc.ncbi.nlm.nih.gov/articles/PMC11057359/#R2. Acesso em: 03 fev. 2026.

YIN, Z. et al. AI-Based Hematological Age Predictors and the Association Between Biological Age Acceleration and Type 2 Diabetes Mellitus — Chongqing Municipality, China, 2015–2021. China CDC Weekly, v. 6, n. 45, p. 1188–1193, 2024. Acesso: 18 fev 2026.

PORTAL DA TRANSPARÊNCIA. Resultado da busca: gastos de tecnologia em saúde. Disponível em: https://portaldatransparencia.gov.br/busca?termo=gastos%20de%20tecnologia%20em% 20saúde. Acesso em: 24 fev. 2026.

WORLD HEALTH ORGANIZATION. The top 10 causes of death. Geneva: World Health Organization, 2024. Disponível em: https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death. Acesso em: 03 fev. 2026.