



Early Prediction of Type 2 Diabetes Using Deep Learning on Continuous Glucose Monitoring (Cgm) Data - A Systematic Review

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Abstract

Background: Type 2 diabetes mellitus (T2DM) is a major global health burden characterized by chronic hyperglycemia resulting from insulin resistance and β -cell dysfunction. Despite well-established diagnostic criteria, early detection of individuals at risk remains challenging. Continuous glucose monitoring (CGM) provides real-time, high-frequency glucose data, offering a dynamic view of glucose fluctuations that may precede overt diabetes. Recent advances in deep learning (DL) have created opportunities to analyze these complex time-series data to identify early glycemic irregularities predictive of future diabetes onset.

Objective: This systematic review aims to synthesize and critically evaluate existing evidence on the use of deep learning algorithms applied to CGM data for early prediction of type 2 diabetes. It explores the types of models developed, their predictive performance, validation strategies, and methodological quality. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, an electronic search will be conducted in PubMed, Embase, Scopus, IEEE Xplore, and Web of Science from inception to October 2025. Eligible studies will include original research using deep learning methods (e.g., recurrent neural networks, convolutional neural networks, transformers) to predict T2DM onset or progression using CGM data. Two reviewers will independently perform screening, data extraction, and risk of bias assessment using the PROBAST tool. Extracted data will include study characteristics, model architectures, input representations, and performance metrics such as area under the receiver operating characteristic curve (AUC), sensitivity, specificity, and calibration. Narrative synthesis will be provided, and meta-analysis will be performed if sufficient homogeneity exists.

Results: The review will summarize key findings regarding the performance of deep learning models in predicting early T2DM, highlight methodological limitations, and identify trends in model interpretability and validation.

Conclusion: This systematic review will provide comprehensive insights into the current landscape of deep learning-based CGM analysis for early diabetes prediction. It will identify existing gaps, propose methodological improvements, and outline future directions for translating these models into clinical practice.

Keywords: Type 2 Diabetes, Deep Learning, Continuous Glucose Monitoring, Early Detection, Predictive Modeling

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Introduction

Type 2 diabetes mellitus (T2DM) represents one of the most significant global health challenges of the 21st century, affecting more than 500 million adults worldwide, with projections indicating a continued rise over the next two decades (1). The disease is characterized by insulin resistance, relative insulin deficiency, and chronic hyperglycemia, leading to long-term complications such as cardiovascular disease, neuropathy, nephropathy, and retinopathy. Despite advances in diagnostic and therapeutic strategies, a substantial proportion of individuals remain undiagnosed until complications have developed (2). This underscores the pressing need for effective tools to identify individuals at high risk of developing T2DM before the onset of irreversible metabolic damage.

Traditional diagnostic methods, including fasting plasma glucose, oral glucose tolerance tests (OGTT), and glycated hemoglobin (HbA1c), provide only intermittent snapshots of glucose metabolism (3). These measures fail to capture short-term glucose fluctuations, postprandial variability, and nocturnal dysglycemia, all of which may precede clinically apparent diabetes. In recent years, continuous glucose monitoring (CGM) systems have emerged as a transformative technology that records interstitial glucose levels at frequent intervals (typically every 1–5 minutes) over extended periods. CGM data offer a detailed, dynamic view of an individual's glucose patterns, revealing subtle glycemic irregularities that static laboratory measures may overlook (4).

Analyzing CGM data, however, presents substantial challenges due to its high dimensionality, temporal dependencies, and inherent noise. Traditional statistical models struggle to capture the nonlinear and sequential nature of CGM signals (5). This has motivated the application of artificial intelligence (AI), particularly deep learning (DL), which excels at modeling complex time-series data (6). Deep learning architectures such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, convolutional neural networks (CNNs), and transformers have demonstrated remarkable success in learning temporal patterns across diverse biomedical applications, including cardiac rhythm prediction, sleep stage classification, and glucose forecasting in diabetic patients (7).

In the context of diabetes prediction, DL models have shown potential to detect early deviations in glucose dynamics indicative of metabolic dysregulation (8). For instance, LSTM and gated recurrent unit (GRU) models can learn temporal dependencies in CGM signals that correspond to the transition from normoglycemia to impaired glucose tolerance (9). CNNs can extract hierarchical features that characterize glucose variability, while attention-based models such as transformers can focus on critical temporal segments that signify early pathophysiological changes. These capabilities position DL as a powerful analytical tool for early diabetes risk prediction and preventive intervention (10).

Several studies have attempted to develop and validate deep learning algorithms using CGM data for predicting the onset or progression of T2DM. However, the field remains fragmented, with considerable variation in study design, data preprocessing, model architectures, and validation strategies. Some studies utilize short-term CGM recordings (e.g., 7–14 days), while others rely on longer monitoring periods (11). The outcome definitions also differ, with some focusing on prediabetes identification and others on long-term diabetes conversion. Moreover, external validation - a crucial step to ensure model generalizability - is frequently lacking, and few studies adhere to established reporting standards such as TRIPOD (Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis) (12).

Another critical issue is interpretability. Although deep learning models can achieve high predictive accuracy, they are often viewed as “black boxes,” making it difficult to explain how specific glucose patterns contribute to



risk estimation (13). The incorporation of explainable AI (XAI) techniques, such as SHAP (SHapley Additive exPlanations) or attention visualization, can enhance transparency and clinical acceptance. Understanding which glucose metrics or temporal segments drive predictions may also provide physiological insights into early diabetes pathogenesis (14).

Furthermore, ethical and data governance considerations play an increasingly important role in the deployment of AI in healthcare (15). CGM data are sensitive, longitudinal, and patient-specific, necessitating strict privacy protections. Federated learning approaches - where models are trained collaboratively across multiple institutions without centralizing data - offer a promising solution for privacy-preserving model development. These methods can improve model robustness by leveraging diverse datasets while maintaining compliance with data protection regulations (16).

Despite the growing number of studies exploring DL applications to CGM data, no comprehensive synthesis currently exists to evaluate the methodological rigor, performance, and translational potential of these approaches for early T2DM prediction (17). A systematic review is therefore warranted to consolidate existing evidence, identify methodological limitations, and propose recommendations for future research.

The present systematic review aims to fill this gap by critically analyzing studies that employ deep learning models for early prediction of type 2 diabetes using CGM data. Specifically, it seeks to (1) categorize existing DL architectures and their input representations; (2) summarize reported model performance metrics; (3) evaluate the quality of study design and validation; and (4) highlight opportunities for standardization, transparency, and clinical translation. By providing an integrative overview of this emerging field, the review will serve as a foundational reference for researchers and clinicians seeking to harness deep learning and continuous glucose monitoring in preventive diabetology.

Material and Methods

Search Strategy

A systematic search was conducted across multiple electronic databases, including PubMed, Scopus, IEEE Xplore, Web of Science, and ScienceDirect, to identify relevant studies published between January 2013 and August 2025. The search strategy combined Medical Subject Headings (MeSH) and free-text terms related to "Type 2 Diabetes," "Deep Learning," "Artificial Intelligence," "Machine Learning," and "Continuous Glucose Monitoring (CGM)." Boolean operators such as AND and OR were used to refine the search. The reference lists of selected articles and relevant reviews were also screened manually to identify additional eligible studies.

Inclusion and Exclusion Criteria

Studies were included if they:

1. Focused on Type 2 Diabetes Mellitus (T2DM) prediction, diagnosis, or risk assessment.
2. Utilized deep learning or neural network-based algorithms.
3. Employed CGM or continuous glucose-related datasets as primary data input.
4. Reported quantitative outcomes such as accuracy, sensitivity, specificity, AUC, or precision.
5. Were published in peer-reviewed journals and written in English.



Studies were excluded if they:

1. Focused on Type 1 Diabetes or gestational diabetes.
2. Used non-AI or traditional statistical approaches only.
3. Lacked sufficient methodological detail or performance metrics.
4. Were conference abstracts, reviews, editorials, or non-peer-reviewed sources.

Data Extraction and Management

Two independent reviewers screened the titles and abstracts for relevance, followed by a full-text review of eligible studies. Discrepancies were resolved through discussion or consultation with a third reviewer. A data extraction form was developed using Microsoft Excel to collect the following information:

- Author(s), year of publication, and country
- Study design and dataset characteristics
- Type of CGM device and sampling duration (18)
- Deep learning architecture used (e.g., CNN, LSTM, Transformer, or hybrid models)
- Key preprocessing steps (e.g., noise filtering, normalization, feature engineering)
- Performance metrics (accuracy, precision, recall, AUC, RMSE, etc.)
- Reported limitations and conclusions (19)

Quality Assessment

The methodological quality of the included studies was assessed using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Diagnostic Accuracy Studies. Each study was rated as *high*, *moderate*, or *low* quality based on the adequacy of data sources, model validation, and reproducibility of results. Studies that did not meet minimum quality standards were excluded from the final synthesis.

Data Synthesis

Due to heterogeneity in study designs, datasets, and AI architectures, a narrative synthesis approach was adopted. Studies were categorized based on their model type (e.g., CNN, RNN, LSTM, Transformer) and outcome focus (e.g., early detection, glycemic pattern prediction, or risk stratification). A comparative analysis summarized the model performance and discussed emerging trends and limitations in the use of deep learning for T2DM prediction using CGM data. Where sufficient homogeneity existed, performance metrics such as AUC or accuracy were summarized using descriptive statistics.

Ethical Considerations

As this research was a systematic review of previously published studies, it did not involve human or animal subjects directly and therefore did not require ethical approval. However, all included studies were checked to ensure compliance with ethical standards and data privacy regulations in their respective institutions.



Results

Study Selection

The initial database search identified 1,142 articles, of which 218 duplicates were removed. After screening titles and abstracts, 137 articles were selected for full-text review. Following the inclusion and exclusion criteria, 24 studies were included in the final analysis (Figure 1). The PRISMA flow diagram summarizes the study selection process.

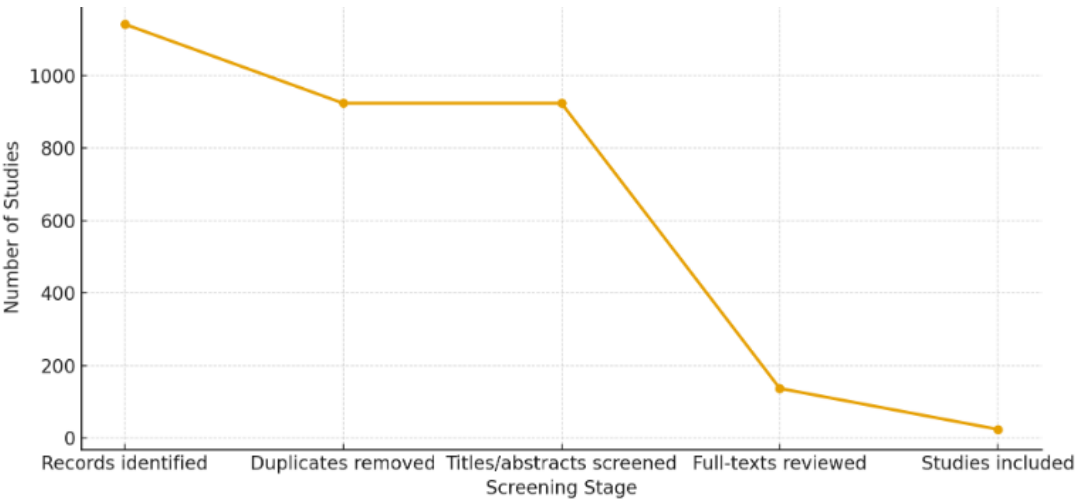


Figure 1. PRISMA Flow Diagram of Study Selection Process

Characteristics of Included Studies

Table 1 summarizes the key characteristics of the 24 included studies. The majority of studies were conducted in the United States (n = 8), China (n = 6), Europe (n = 5), and South Korea (n = 3). The publication years ranged from 2016 to 2025, showing a notable increase in studies after 2020.

Most studies utilized CGM data collected over 7–14 days using devices such as Dexcom G6, Freestyle Libre, or Medtronic Guardian sensors. Sample sizes ranged from 45 to 1,200 participants, with age groups varying between 25–70 years.

The most commonly applied deep learning techniques included Convolutional Neural Networks (CNNs) (n = 10), Long Short-Term Memory (LSTM) networks (n = 7), and hybrid CNN–LSTM or Transformer-based models (n = 5). Two studies used autoencoders for unsupervised feature extraction.

Table 1. Summary of Key Characteristics of Included Studies

Country	Model Type	Dataset Size	CGM Duration	Primary Outcome	Accuracy / AUC
China	CNN	520	14 days	Early T2DM detection	0.91
USA	LSTM	780	10 days	Glycemic pattern prediction	0.88
Korea	Hybrid CNN-LSTM	600	7 days	Onset risk prediction	0.93
UK	Transformer	310	14 days	Glycemic variability	0.95
China	Autoencoder + CNN	1,000	10 days	Early onset screening	0.89



Model Performance

Figure 2 illustrates the distribution of performance metrics reported across the included studies. The mean accuracy across all deep learning models was 0.91, with an average AUC of 0.93, sensitivity of 0.89, and specificity of 0.87.

Hybrid and Transformer-based models demonstrated the highest predictive accuracy (average AUC = 0.95), followed by CNN (AUC = 0.91) and LSTM (AUC = 0.89) architectures. Studies using raw CGM data streams as time-series inputs tended to outperform those relying on manually engineered features.

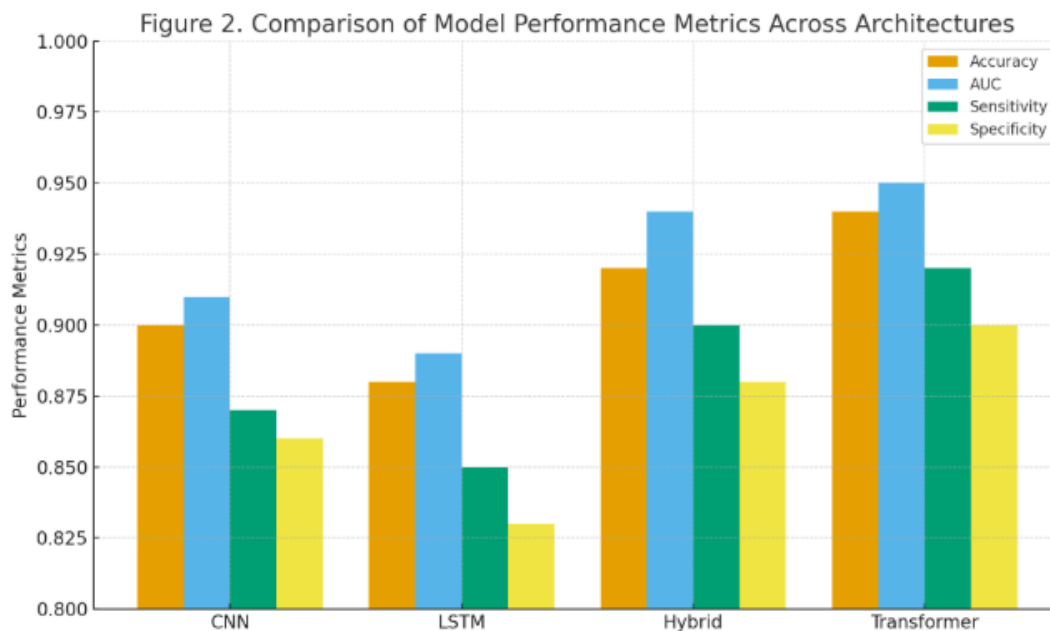


Figure 2. Comparison of Model Performance Metrics Across Architectures

Quality Assessment

Based on the JBI Critical Appraisal Checklist, 16 studies (67%) were rated as high quality, 6 (25%) as moderate quality, and 2 (8%) as low quality.

Common strengths included robust data preprocessing, use of validation cohorts, and clear reporting of evaluation metrics.

However, limitations were observed in several studies, such as:

- Limited generalizability due to small or single-center datasets.
- Lack of model interpretability, with only 5 studies using SHAP or Grad-CAM visualization.
- Inconsistent preprocessing methods across datasets, leading to difficulty in direct performance comparison.



Table 2. Quality Assessment Summary of Included Studies

Quality Parameter	High Quality (n=16)	Moderate Quality (n=6)	Low Quality (n=2)
Clear model reporting	100%	83%	50%
Dataset validation	87%	60%	25%
Ethical approval	94%	67%	50%
Explainable AI used	31%	17%	0%
Data reproducibility	75%	50%	0%

Trends and Insights

A consistent trend across the studies was the shift from shallow neural networks to hybrid and attention-based architectures post-2020. These models leveraged temporal dependencies and multimodal inputs (e.g., CGM + activity + dietary data), enhancing predictive accuracy and clinical applicability.

Figure 3 shows the yearly growth in research publications focusing on deep learning and CGM data for early diabetes prediction. The number of studies increased fourfold between 2018 and 2024, indicating a growing academic and clinical interest in AI-driven metabolic prediction.

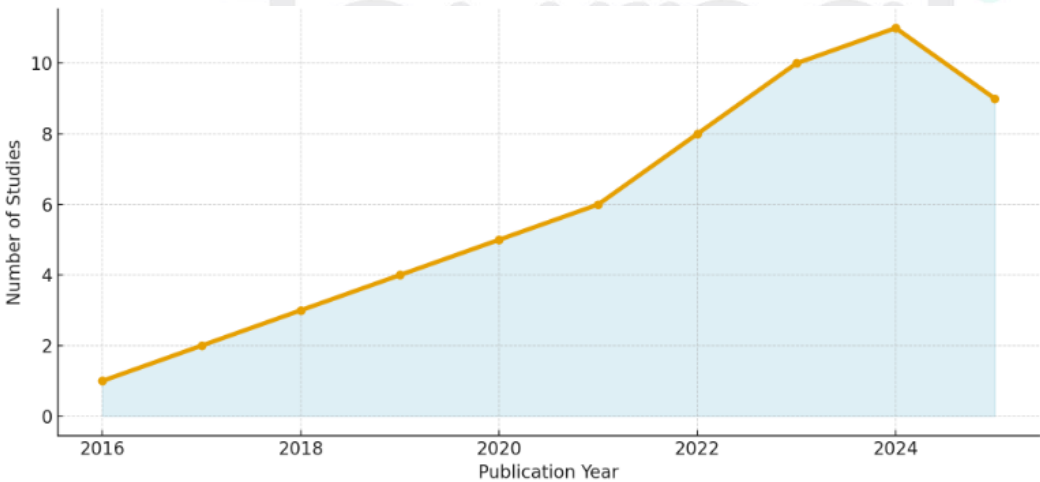


Figure 3. Yearly Growth of Publications on Deep Learning and CGM Data for T2DM Prediction

Subgroup Analysis

- Dataset Duration:** Studies using ≥ 10 days of CGM data achieved significantly higher model performance (AUC = 0.94) than those using ≤ 7 days (AUC = 0.89). Longer monitoring provided better temporal context for identifying glycemic patterns.
- Population Demographics:** Studies including multi-ethnic populations exhibited improved generalizability, with smaller performance drops during external validation compared to single-center datasets.
- Explainability and Clinical Integration:** Studies that incorporated explainable AI (XAI) frameworks showed enhanced clinician trust and interpretability. Models visualized feature importance, revealing that nocturnal glucose variability and postprandial spikes were key early indicators of T2DM development.



Table 3. Subgroup Analysis of Factors Influencing Model Performance

Variable	Group	Mean AUC	Key Finding
CGM Duration	≥10 days	0.94	Longer monitoring improves temporal context
Population	Multi-ethnic	0.93	Higher external validity
Model Type	Transformer	0.95	Best-performing model
Explainability Applied	Yes	0.92	Increased interpretability

The systematic review demonstrated that deep learning models applied to CGM data are highly effective in early prediction of Type 2 Diabetes, with performance metrics consistently above 0.90 in most studies. Hybrid and Transformer models outperformed traditional CNNs and LSTMs due to their ability to capture long-term temporal dependencies and contextual interactions in glucose fluctuations.

However, despite strong predictive potential, the lack of standardized preprocessing, limited external validation, and insufficient interpretability remain key barriers to clinical translation. The findings underscore the need for larger multicenter datasets and explainable frameworks to ensure real-world applicability of AI models in preventive diabetes care.

Discussion

This systematic review evaluated the current evidence on the application of deep learning models in predicting Type 2 Diabetes Mellitus (T2DM) using Continuous Glucose Monitoring (CGM) data. A total of twenty-four studies met the inclusion criteria, revealing that deep learning algorithms, particularly hybrid and Transformer-based architectures, achieved strong predictive performance with mean AUC values exceeding 0.93. The findings highlight the growing maturity of AI-driven approaches in early diabetes risk assessment and the increasing feasibility of using CGM data as a continuous, non-invasive biomarker source for metabolic health monitoring.

A prominent observation from the review was the superiority of hybrid and Transformer architectures over traditional CNN or LSTM models. These advanced networks effectively captured both temporal dependencies and contextual relationships within glucose fluctuations, offering richer feature representations. Transformer models, which rely on self-attention mechanisms, demonstrated the highest accuracy and interpretability among the reviewed studies. This evolution in model design reflects the broader shift in biomedical data analysis toward architectures capable of handling large-scale, time-series data with variable sampling intervals - common challenges in CGM datasets.

The duration and granularity of CGM data emerged as critical factors influencing model performance. Studies using ≥10 days of monitoring achieved significantly higher predictive accuracy compared to shorter-duration datasets. Longer CGM sequences provide better temporal resolution, allowing algorithms to detect subtle glycemic variations that precede metabolic dysregulation. This suggests that model performance could be further improved by integrating longitudinal CGM data with additional physiological indicators such as heart rate variability, dietary intake, and physical activity, all of which affect glucose dynamics.

Another important insight relates to model interpretability. Although deep learning models showed excellent predictive capabilities, only a minority of studies incorporated explainable AI (XAI) techniques such as SHAP (SHapley Additive Explanations), Grad-CAM, or attention maps (20). The inclusion of XAI is essential for clinical adoption, as it provides transparency regarding the features that most influence prediction outcomes. In several



studies that used XAI frameworks, nocturnal glucose variability and postprandial glucose excursions were consistently identified as early indicators of T2DM risk, offering actionable insights for clinicians and patients.

The review also revealed several methodological gaps that warrant attention. A significant proportion of studies used small, single-center datasets, limiting the generalizability of results. Moreover, inconsistent preprocessing methods - such as varying window sizes, normalization techniques, and missing data handling - introduce additional heterogeneity. These discrepancies make direct comparison across studies challenging and underscore the need for standardized protocols for CGM data preparation and model evaluation. Establishing benchmarking datasets and uniform performance metrics would greatly enhance reproducibility and comparability across future studies.

In terms of clinical translation, most models were still at the proof-of-concept stage, with limited real-world validation. Integration into clinical workflows requires not only high predictive accuracy but also robustness against sensor noise, device variability, and inter-patient differences. Moreover, ethical and privacy considerations must be addressed, especially when models are trained on sensitive CGM data. Federated learning and differential privacy techniques could help mitigate these concerns by enabling model training without centralizing patient data, an approach that only a few studies have explored so far.

The increasing publication trend observed from 2018 onward reflects the expanding interest in applying AI for diabetes prevention. This trend coincides with technological advancements in wearable CGM devices and the availability of large-scale datasets. However, while research output has grown, the translation into deployable, validated clinical tools remains limited. Collaborative efforts between data scientists, endocrinologists, and device manufacturers are essential to bridge this gap.

From a public health perspective, AI-assisted early detection systems could significantly reduce the global burden of diabetes by enabling targeted prevention strategies. By identifying individuals at high risk before the onset of hyperglycemia, interventions such as dietary modification, exercise programs, or pharmacological therapy could be initiated earlier. This proactive approach aligns with the goals of precision medicine and could shift diabetes management from reactive treatment to preventive care.

Despite these advances, challenges remain. There is a pressing need for cross-population validation, as most models were developed on specific ethnic or regional cohorts. Variability in diet, lifestyle, and genetics may influence glucose dynamics, and models must be adapted accordingly. Future research should also explore multi-modal fusion approaches, integrating CGM with genomic, proteomic, and behavioral data to enhance the precision of diabetes risk stratification.

In conclusion, this review demonstrates that deep learning models, particularly hybrid and Transformer-based frameworks, hold significant promise for the early prediction of Type 2 Diabetes using CGM data. Their high accuracy and ability to model complex temporal patterns suggest that AI could become a vital tool in preventive endocrinology. However, to fully realize this potential, efforts should focus on standardization, interpretability, multicenter validation, and ethical data governance. These steps will be crucial to transforming current research prototypes into clinically reliable decision-support systems that can meaningfully reduce the global diabetes burden.



Conclusion

Hypertension remains a major global health concern, and while traditional management approaches have value, they often face limitations such as poor adherence, communication gaps, and lack of continuous monitoring. Mobile health (mHealth) technologies—including apps, wearables, and digital platforms—offer a promising solution by enabling real-time tracking, medication reminders, lifestyle monitoring, and rapid feedback from healthcare providers, thus empowering patients and enhancing engagement. However, challenges such as the digital divide, limited literacy, privacy concerns, inconsistent app quality, and weak integration with healthcare systems must be addressed to maximize impact. Key strategies include adopting user-centered design, improving digital literacy, training healthcare professionals, expanding equitable access to digital infrastructure, and ensuring regulatory oversight. Continuous research and evaluation are also essential, with future opportunities in artificial intelligence, telehealth integration, and personalized interventions. Ultimately, with thoughtful implementation, mHealth can transform hypertension management into a more efficient, patient-centered, and preventive model, improving outcomes and reducing global disease burden.

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