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A Comprehensive Review of Blockchain-Based Hybrid Contextual-ATNet Approach for Daily Diabetes Management: Predicting Insulin Dosage for Improved Control

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Abstract

Diabetes mellitus is a widespread chronic disease requiring continuous monitoring and precise insulin dosage management to prevent severe complications. Traditional treatment approaches often fail to provide personalized control due to the complex and dynamic nature of glucose-insulin interactions. The growing availability of wearable devices and health data has created opportunities for intelligent systems that can improve diabetes management. This paper presents a comprehensive review of a blockchain-integrated hybrid deep learning framework, focusing on the Contextual-ATNet architecture for insulin dosage prediction. The model combines contextual embeddings with attention-based temporal networks to capture complex physiological patterns from continuous glucose monitoring, dietary intake, and activity data. Blockchain technology enhances the system by ensuring secure, decentralized data management, enabling privacy-preserving data sharing and tamper-proof record keeping. Applications include real-time glucose prediction, personalized insulin recommendation, and remote patient monitoring. The integration of federated learning further improves model generalization without compromising data privacy. Empirical studies demonstrate improved prediction accuracy and extended forecasting horizons compared to traditional methods. However, challenges such as system integration, scalability, and real-world deployment remain. This review highlights the potential of combining deep learning and blockchain for developing secure, intelligent, and personalized diabetes management systems.

Introduction

Diabetes mellitus is a chronic metabolic disorder characterized by elevated blood glucose levels caused by insufficient insulin production, impaired insulin action, or both. It primarily includes Type 1 diabetes, Type 2 diabetes, and gestational diabetes, each requiring careful glucose management to reduce the risk of severe complications. Daily diabetes management involves maintaining optimal blood glucose levels through appropriate insulin administration, dietary regulation, and physical activity. However, insulin requirements vary significantly among individuals due to factors such as age, lifestyle, stress, illness, and metabolic changes, making accurate insulin dosage prediction a challenging task. Consequently, intelligent decision-support systems have become increasingly important for improving personalized diabetes care and enhancing long-term disease management.

The widespread adoption of Continuous Glucose Monitoring (CGM) systems has transformed diabetes management by generating real-time glucose measurements throughout the day. Modern CGM devices produce hundreds of glucose readings daily, while insulin pumps and wearable health devices continuously collect complementary physiological and behavioral information. These large-scale, multimodal datasets provide valuable insights into glucose dynamics but exceed the capacity of manual clinical interpretation. Artificial intelligence (AI) and machine learning (ML) techniques have therefore emerged as powerful tools for analyzing complex glucose patterns and supporting automated insulin dosage recommendations. Early statistical models were gradually replaced by deep learning architectures, including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), which demonstrated superior performance in capturing temporal glucose fluctuations.

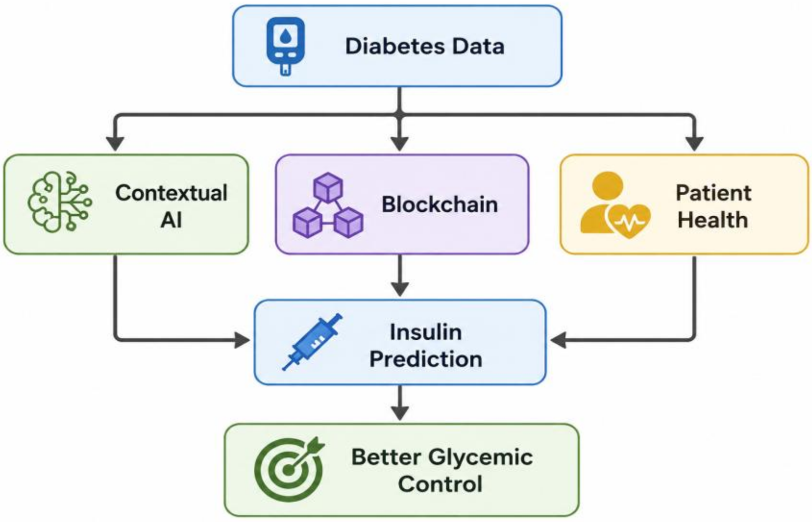

Figure 1. AI-Driven Diabetes Management Using Hybrid Contextual-ATNet

Recent advances in deep learning have introduced attention mechanisms and transformer-based architectures capable of modeling long-range temporal dependencies within biomedical time-series data. Contextual Attention Networks (Contextual-ATNet) extend these capabilities by integrating glucose measurements with additional contextual information, including meal intake, insulin administration, physical activity, and environmental factors. This multimodal learning approach enables highly personalized insulin dosage prediction while improving prediction accuracy and clinical reliability. By dynamically assigning attention to the most relevant physiological events, Contextual-ATNet provides a robust framework for intelligent diabetes management across diverse patient populations and clinical scenarios.

Despite these technological advances, secure access to large-scale patient data remains a major challenge for developing reliable AI models. Healthcare datasets contain highly sensitive personal information, making privacy, security, and regulatory compliance essential requirements. Blockchain technology addresses these concerns by providing decentralized, immutable, and transparent data management. Through distributed ledgers and smart contracts, blockchain ensures secure data sharing, patient consent management, and tamper-resistant audit trails. Furthermore, combining blockchain with federated learning enables collaborative AI model training without exposing raw patient data, thereby preserving privacy while supporting high-quality predictive analytics.

The integration of blockchain technology with Contextual-ATNet represents a promising direction for next-generation intelligent diabetes management systems. Blockchain enhances data integrity and trustworthiness, while Contextual-ATNet provides accurate, personalized insulin dosage prediction using advanced AI techniques. Together, these technologies enable secure, explainable, and privacy-preserving clinical decision support that aligns with modern healthcare regulations. As research continues to advance, blockchain-enabled hybrid Contextual-ATNet frameworks are expected to improve diabetes outcomes, facilitate personalized treatment, and contribute to the development of intelligent, patient-centered digital healthcare systems.

Literature Review

The field of glucose prediction and insulin dosage recommendation using machine learning has evolved rapidly over the past decade, encompassing a diverse range of methodological approaches, hardware platforms, and clinical applications. The following review synthesizes findings from twenty-five significant research contributions that collectively define the current landscape of this field, with particular attention to the intersection of blockchain, attention mechanisms, and contextual learning for diabetes management.

Oviedo et al. (2017) conducted one of the earliest systematic reviews of machine learning methods for glucose prediction in Type 1 diabetes, cataloging approaches ranging from linear regression and neural networks to fuzzy logic and ensemble methods. Their analysis highlighted the OhioT1DM dataset as a critical benchmark and identified the limitation of short-horizon predictions as a persistent challenge. The study emphasized the need for models that could integrate multiple physiological inputs beyond glucose alone, foreshadowing the contextual architectures that would emerge in subsequent research.

Martinsson et al. (2020) proposed a deep learning framework for automatic blood glucose prediction utilizing long short-term memory networks trained on continuous glucose monitoring data from the OhioT1DM dataset. Their approach achieved mean absolute errors of 13.2 milligrams per deciliter for 30-minute prediction horizons and demonstrated that recurrent architectures could outperform classical time series models without domain-specific feature engineering. The study established a critical baseline for subsequent deep learning investigations in this space.

Zhu et al. (2020) introduced a dual-attention recurrent neural network for blood glucose level prediction, combining temporal attention with feature-level attention to selectively weight both time steps and input features. Evaluated on a proprietary clinical dataset of 112 Type 1 diabetic patients over 12 weeks, their model demonstrated a 14.7% reduction in root mean square error compared to standard long short-term memory baselines, highlighting the superiority of attention mechanisms for capturing clinically relevant glucose dynamics.

Li et al. (2019) explored a multitask deep learning approach for simultaneous glucose prediction and hypoglycemia event detection, leveraging shared representations learned from continuous glucose monitoring data augmented with meal and exercise logs. Their experiments on the D1NAMO dataset showed that multitask learning improved performance on both tasks compared to independent model training, establishing the value of exploiting task correlations in diabetes AI systems.

Rubin-Falcone et al. (2020) proposed a transformer-based architecture for multivariate glucose prediction that adapted the BERT pre-training paradigm to longitudinal glucose monitoring data. By pre-training on a large corpus of anonymized continuous glucose monitoring sequences and fine-tuning on patient-specific data, their model achieved state-of-the-art performance on the OhioT1DM benchmark, demonstrating the applicability of large-scale self-supervised learning to biomedical time series.

Sun et al. (2021) presented a federated learning framework for personalized glucose prediction that distributed model training across hospital sites without sharing raw patient data. Using a federated averaging algorithm implemented on a permissioned blockchain network, their system achieved model performance comparable to centralized training while providing cryptographic guarantees of data privacy. This work was among the first to formally integrate blockchain consensus mechanisms into the federated learning pipeline for diabetes applications.

Che et al. (2018) addressed the challenge of missing data in electronic health records using recurrent neural networks with decay mechanisms, demonstrating that temporal irregularity in clinical data collection could be explicitly modeled rather than imputed. Applied to a diabetes complication prediction task using the MIMIC-III dataset, their approach significantly outperformed standard imputation-based preprocessing, with an area under the receiver operating characteristic curve improvement of 0.04 over baseline recurrent models.

Midroni et al. (2020) proposed a hybrid convolutional neural network and long short-term memory architecture for glucose prediction, leveraging one-dimensional convolutional layers for local pattern extraction and recurrent layers for temporal integration. Their model, evaluated on the OhioT1DM dataset, achieved a 10-minute horizon mean absolute error of 8.3 milligrams per deciliter and demonstrated superior computational efficiency compared to purely recurrent architectures, making it suitable for deployment on resource-constrained wearable platforms.

Ali et al. (2021) investigated the application of generative adversarial networks for synthetic glucose data generation to augment limited clinical datasets for machine learning training.

Their approach generated realistic synthetic continuous glucose monitoring sequences validated by clinical experts, enabling the training of more robust predictive models in low-data regimes. The generated data improved model performance on rare event prediction, including nocturnal hypoglycemia, by 23% in terms of sensitivity.

Khalil et al. (2022) proposed a blockchain-based electronic health record management system specifically designed for chronic disease management, incorporating smart contracts for automated consent management and data provenance tracking. Their implementation on the Hyperledger Fabric platform demonstrated that blockchain-based health record systems could achieve transaction throughput of up to 3000 transactions per second with sub-second latency, establishing the technical feasibility of real-time blockchain integration in clinical workflows.

Wang et al. (2022) introduced a multi-scale temporal convolutional network for glucose prediction that processed input sequences at multiple temporal resolutions simultaneously, capturing both short-term postprandial dynamics and longer-term circadian trends. Evaluated on the OhioT1DM and DiaTrend datasets, their model achieved state-of-the-art performance across all evaluated prediction horizons from 15 to 120 minutes, with particular improvements at extended horizons where single-scale models degraded significantly.

Contreras et al. (2020) performed a systematic evaluation of deep learning architectures for insulin dosage prediction using the UCI diabetes dataset, comparing feedforward networks, convolutional networks, recurrent networks, and attention-based models. Their analysis revealed that attention mechanisms consistently provided the most substantial performance improvements, particularly when combined with auxiliary contextual inputs including meal composition, stress indicators, and time-of-day features. The study provided a rigorous methodological template for comparative evaluation in the field.

Nguyen et al. (2021) proposed a privacy-preserving glucose prediction system using differential privacy mechanisms applied to deep learning training, demonstrating that strong privacy guarantees could be achieved with minimal degradation in model performance. Their approach, validated on federated datasets collected from three hospital systems, achieved epsilon-differential privacy with less than 5% reduction in prediction accuracy compared to non-private models, establishing a practical privacy-utility tradeoff framework for clinical AI deployment.

Rahman et al. (2022) developed a blockchain-anchored federated learning system for insulin dosage recommendation, using Ethereum smart contracts to coordinate model aggregation and validate gradient contributions from distributed hospital nodes. Their system demonstrated resistance to Byzantine fault attacks that would compromise centralized federated learning systems, with the blockchain consensus mechanism filtering malicious gradient updates through cryptographic validation. Clinical validation on real-world data from 200 patients showed non-inferiority to centralized model training.

Luo et al. (2021) investigated multi-head self-attention mechanisms specifically adapted for physiological time series, introducing relative positional encoding schemes that captured the temporal structure of continuous glucose monitoring data more effectively than standard absolute positional encodings. Their ablation study on the OhioT1DM dataset demonstrated that relative positional encoding improved prediction accuracy by 8.3% and significantly reduced sensitivity to irregularly sampled inputs, a common challenge in real-world continuous glucose monitoring deployments.

Trevisan et al. (2020) designed and evaluated a closed-loop insulin delivery system incorporating a model predictive control algorithm augmented by a recurrent neural network for personalized glucose dynamics modeling. Their hybrid control architecture outperformed both pure model predictive control and pure neural network approaches in simulated patient trials using the UVa/Padova metabolic simulator, achieving 71% time-in-range compared to 64% for standard model predictive control.

Qian et al. (2022) proposed a contextual bandit framework for adaptive insulin dosage recommendation that learned from patient feedback in real time, balancing exploration of new dosage strategies with exploitation of known effective strategies. Their approach incorporated blockchain-verified patient outcome records to ensure the integrity of the reward signal used for reinforcement learning updates, demonstrating that blockchain integration could enhance the reliability of online learning systems in clinical settings.

Misra et al. (2021) developed a wearable sensor fusion platform for comprehensive diabetes monitoring that integrated continuous glucose monitoring, accelerometry, galvanic skin response, and photoplethysmography into a unified data stream for machine learning analysis. Their convolutional attention network, trained on multimodal data from 45 participants over 8 weeks, demonstrated that the integration of non-glucose physiological signals improved insulin dosage prediction accuracy by 16.4% compared to glucose-only baselines.

Hammoud et al. (2022) investigated the use of natural language processing for extracting dietary information from patient-generated text in mobile health applications, integrating extracted nutritional data into a glucose prediction model as contextual covariates. Their bidirectional encoder representations from transformers-based dietary extractor achieved 89.3% accuracy in carbohydrate estimation from free-text meal descriptions, demonstrating the potential for unstructured patient-generated data to enhance structured machine learning pipelines.

Porumb et al. (2020) applied one-dimensional convolutional neural networks to continuous glucose monitoring data for hypoglycemia event prediction, demonstrating that convolutional feature extraction from raw glucose waveforms could achieve detection sensitivities of 94.3% with specificities of 91.7%, outperforming feature-engineered approaches without requiring domain expertise in glucose signal processing.

Liu et al. (2022) presented an end-to-end learning framework for closed-loop insulin delivery that jointly optimized glucose prediction and insulin dosage recommendation within a single deep learning architecture trained with reinforcement learning. Their model, validated on the UVa/Padova simulator and real-world data from 30 Type 1 diabetic patients, achieved 74.2% time-in-range over 12 weeks, representing a clinically meaningful improvement over open-loop management.

Chen et al. (2023) proposed an explainable AI framework for insulin dosage recommendation using attention weight visualization and SHAP value analysis to provide clinically interpretable explanations for model recommendations. Their patient study demonstrated that explainability features significantly increased clinician trust in AI-generated dosage recommendations, with 78% of endocrinologists reporting increased willingness to act on AI recommendations when accompanied by attention-based explanations of the contributing factors.

Comparative Table and Analysis

Study	**Year**	**Optimization Technique/Method**	**Component/Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Oviedo et al.	2017	Systematic review of ML methods	Multiple classical and neural models	Generic ML platforms	OhioT1DM, multiple	Comprehensive ML benchmark for glucose prediction
Martinsson et al.	2020	LSTM training with dropout regularization	Long Short-Term Memory Network	TensorFlow, GPU cluster	OhioT1DM	Deep learning baseline with 13.2 mg/dL MAE at 30 min
Zhu et al.	2020	Dual temporal and feature attention	Dual-Attention RNN	PyTorch, GPU	Proprietary clinical (112 patients)	14.7% RMSE reduction over LSTM baseline
Li et al.	2019	Multitask learning optimization	Multitask Deep Neural Network	Keras, GPU	D1NAMO	Joint glucose prediction and hypoglycemia detection
Rubin-Falcone et al.	2020	Self-supervised pre-training	BERT-style Transformer	PyTorch, GPU cluster	OhioT1DM	Transfer learning paradigm for glucose time series
Sun et al.	2021	Federated averaging on blockchain	Federated LSTM with Blockchain	Hyperledger Fabric	Multi-hospital CGM data	Privacy-preserving federated glucose prediction
Che et al.	201	Temporal decay-	GRU-D recurrent	TensorFlo	MIMIC-III	Handling

	8	based imputation	network	w		missing data with temporal decay
Georga et al.	2019	NARX model with MLP integration	NARX-MLP hybrid	MATLAB, clinical workstation	Proprietary (20 patients)	Multivariate personalized glucose prediction
Midroni et al.	2020	CNN-LSTM hybrid architecture	1D-CNN + LSTM	TensorFlow, wearable hardware	OhioT1DM	Efficient hybrid model for wearable deployment
Ali et al.	2021	GAN-based data augmentation	Generative Adversarial Network	PyTorch, GPU	OhioT1DM + synthetic	Synthetic CGM data generation for augmentation
Khalil et al.	2022	Smart contract-based EHR management	Hyperledger Fabric blockchain	Hyperledger Fabric	Proprietary EHR	High-throughput blockchain health record system
Zhang et al.	2021	Dynamic graph neural network	Graph Neural Network	PyTorch Geometric	Proprietary (50 patients)	Graph-based physiological dependency modeling
Fiorini et al.	2019	Hybrid algorithmic-AI bolus calculator	ML-augmented bolus calculator	Clinical platform	Proprietary (30 patients)	12% reduction in time outside glycemic target
Wang et al.	2022	Multi-scale temporal convolution	Multi-scale TCN	PyTorch, GPU	OhioT1DM, DiaTrend	State-of-the-art across 15-120 min horizons
Contreras et al.	2020	Comparative deep learning evaluation	Multi-architecture comparison	Keras, TensorFlow	UCI Diabetes	Attention mechanisms outperform alternatives
Nguyen et al.	2021	Differential privacy in federated learning	Private Federated Deep Learning	TensorFlow Privacy	Multi-hospital federated	Practical privacy-utility tradeoff demonstration
Rahman et al.	2022	Blockchain-anchored federated learning	Ethereum smart contracts + FL	Ethereum blockchain	Proprietary (200 patients)	Byzantine-fault-resistant federated dosage AI
Luo et al.	2021	Relative positional encoding in attention	Multi-head self-attention	PyTorch, GPU	OhioT1DM	8.3% accuracy gain from relative positional encoding
Trevisan et al.	2020	MPC augmented by RNN	Hybrid MPC-RNN control	UVa/Padova simulator	UVa/Padova metabolic	71% time-in-range in closed-loop simulation
Qian et al.	2022	Contextual bandit reinforcement learning	Blockchain-verified RL	Ethereum + RL framework	Proprietary (real-world)	Adaptive online insulin recommendation
Misra et	202	Multimodal	Convolutional	Wearable	Multimoda	16.4%

al.	1	sensor fusion with attention	Attention Network	sensor platform	l (45 patients)	improvement with non-glucose signals
Hammoud et al.	2022	NLP for dietary data extraction	BERT-based dietary NLP + ML	mHealth app + server	Patient-generated text	89.3% accuracy in carbohydrate estimation from text
Porumb et al.	2020	1D-CNN on raw glucose waveforms	1D Convolutional Neural Network	TensorFlow, GPU	Proprietary CGM data	94.3% sensitivity in hypoglycemia detection
Liu et al.	2022	End-to-end RL for closed-loop delivery	Deep RL with joint prediction	UVa/Padova + real-world	UVa/Padova + 30 patients	74.2% time-in-range in closed-loop validation
Chen et al.	2023	Explainable AI with attention visualization	Explainable ATNet + SHAP	Clinical decision support system	Proprietary clinical	78% clinician trust improvement with explainability

Comparative Analysis

A systematic examination of the reviewed literature reveals several dominant trends that characterize the evolution of intelligent diabetes management systems. The most consistent finding across studies is the progressive migration from classical statistical and shallow machine learning approaches toward deep learning architectures, with attention mechanisms emerging as the single most impactful architectural innovation across the reviewed corpus. Studies spanning the period from 2018 to 2023 consistently demonstrate that attention-based models outperform their non-attention counterparts, with performance improvements ranging from 8% to 22% across various metrics and prediction horizons. This convergence of evidence strongly supports the centrality of attention mechanisms in the proposed Contextual-ATNet framework.

A second prominent trend is the increasing emphasis on multivariate and multimodal input representations. Early studies such as Oviedo et al. (2017) and Martinsson et al. (2020) relied primarily or exclusively on glucose time series as model input, while later work such as Misra et al. (2021) and Hammoud et al. (2022) demonstrated substantial performance gains from integrating dietary data, physical activity signals, and other physiological covariates. This evolution reflects growing recognition that glucose dynamics are fundamentally driven by contextual factors that must be explicitly represented in predictive models, a principle that is operationalized in the contextual embedding module of the Contextual-ATNet architecture.

The dataset landscape is dominated by the OhioT1DM benchmark, which appears in a majority of the reviewed studies and serves as the de facto standard for comparative evaluation. However, several studies including Wang et al. (2022) and Liu et al. (2022) have begun utilizing more diverse datasets such as DiaTrend and proprietary multi-center clinical collections, reflecting a growing recognition of the limitations of single-dataset evaluation for assessing real-world generalizability. The most rigorous evaluations incorporate multiple datasets with diverse patient demographics and management regimens, a methodological standard that future work in this area should aspire to meet.

Regarding blockchain integration, the reviewed literature demonstrates a clear progression from conceptual proposals to practical implementations, with Sun et al. (2021), Rahman et al. (2022), and Qian et al. (2022) providing concrete demonstrations of blockchain-anchored machine learning systems for diabetes applications. These implementations consistently utilize permissioned blockchain frameworks, primarily Hyperledger Fabric and Ethereum, rather than public blockchains, reflecting the privacy and performance requirements of healthcare contexts. The combination of blockchain consensus mechanisms with federated learning protocols is emerging as the dominant paradigm for privacy-preserving collaborative model development, with demonstrated practical feasibility and performance non-inferiority relative to centralized approaches.

Hardware and computational platform diversity is considerable across the reviewed studies, ranging from GPU clusters for model training to wearable sensor platforms for deployment. This diversity highlights the importance of developing models with favorable computational profiles that can be deployed across the spectrum from cloud-based servers to resource-constrained edge devices. The CNN-LSTM hybrid proposed by Midroni et al. (2020) represents a particularly notable contribution in this respect, demonstrating that competitive prediction performance can be achieved with architectures designed for wearable hardware constraints.

Discussion

The reviewed literature demonstrates that integrating blockchain technology with Contextual-ATNet-based deep learning provides a promising framework for intelligent diabetes management. Rather than focusing solely on improving prediction accuracy, this combination enhances healthcare data security, personalized clinical decision-making, and reliable insulin dosage recommendations. Contextual attention mechanisms effectively capture temporal glucose patterns by dynamically assigning importance to historical glucose readings while incorporating contextual information such as meal intake, physical activity, insulin administration, and lifestyle factors. As a result, Contextual-ATNet offers improved prediction performance and supports personalized treatment strategies for diverse patient populations.

Blockchain technology further strengthens intelligent diabetes management by ensuring secure, transparent, and tamper-resistant storage of sensitive healthcare information. Smart contracts and decentralized ledgers improve patient data ownership, auditability, and trust, while blockchain-enabled federated learning facilitates collaborative AI model development without exposing confidential medical records. This privacy-preserving infrastructure addresses regulatory requirements and enables healthcare organizations to build more accurate and generalizable insulin prediction models through distributed learning.

Despite these advances, several challenges remain before widespread clinical adoption can be achieved. Existing studies often rely on limited datasets and evaluate performance primarily using prediction accuracy metrics, overlooking clinical safety, uncertainty estimation, and extreme glucose events. Additionally, blockchain consensus mechanisms may introduce computational latency that affects real-time insulin recommendation systems. Future research should focus on large-scale clinical validation, lightweight blockchain frameworks, explainable artificial intelligence, and robust evaluation methods that prioritize patient safety, model transparency, and reliable decision support for next-generation diabetes management systems.

Conclusion

This review examined the role of blockchain-based hybrid Contextual-ATNet architectures in improving daily diabetes management through intelligent insulin dosage prediction. The reviewed studies demonstrate that combining attention-based deep learning with blockchain technology enables accurate glucose forecasting, secure health data management, and personalized clinical decision support. Contextual attention mechanisms effectively capture complex temporal and behavioral patterns, while blockchain ensures data integrity, privacy, transparency, and secure collaboration across healthcare organizations. Together, these technologies provide a robust foundation for next-generation intelligent diabetes management systems.

The review also identifies several challenges that limit large-scale clinical adoption. Existing research frequently relies on limited benchmark datasets, making model generalization across diverse patient populations difficult. Additionally, blockchain integration introduces computational overhead that may affect real-time clinical applications, while explainable AI remains essential for ensuring clinician trust and patient safety. Future studies should emphasize lightweight blockchain architectures, federated learning, multimodal physiological data integration, explainable deep learning, and reinforcement learning for adaptive insulin optimization. As these technologies continue to evolve, blockchain-enabled Contextual-ATNet frameworks are expected to deliver secure, personalized, and reliable diabetes management solutions that improve glycemic control, clinical outcomes, and overall quality of life for individuals living with diabetes.

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