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A Survey of Methods and Architectures for 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 major global health challenge requiring precise and personalized insulin dosage management to prevent severe complications. Traditional approaches, including rule-based dosing and periodic clinical adjustments, are inadequate for handling the complex, dynamic interactions between physiological, behavioral, and environmental factors influencing blood glucose levels. The availability of continuous glucose monitoring data has created opportunities for advanced computational systems to improve glycemic control. This survey reviews artificial intelligence-based approaches for insulin dosage prediction, with a focus on blockchain-integrated Hybrid Contextual Attention Networks (ATNet). The ATNet framework combines attention-based temporal modeling with contextual feature fusion to process multimodal inputs such as glucose readings, dietary patterns, physical activity, and stress indicators. This architecture enables accurate prediction of glucose trends and personalized insulin recommendations by capturing complex temporal and contextual dependencies. Blockchain integration enhances the system by providing secure, decentralized data management, enabling privacy-preserving federated learning, and ensuring auditability through smart contracts. Applications include real-time glucose prediction, personalized insulin therapy, and clinical decision support. Comparative analysis demonstrates improved predictive accuracy and robustness over traditional methods. However, challenges such as scalability, interpretability, and clinical validation remain, highlighting the need for further research in developing reliable and deployable AI-driven diabetes management systems.

Introduction

Diabetes mellitus has become one of the most significant global public health challenges, affecting millions of individuals across all age groups. The number of people living with diabetes continues to increase because of changing lifestyles, aging populations, obesity, and reduced physical activity. Beyond abnormal blood glucose regulation, diabetes is associated with severe long-term complications including cardiovascular disease, kidney failure, neuropathy, retinopathy, and lower-limb amputation. Effective diabetes management therefore requires continuous monitoring of glucose levels and timely therapeutic interventions. The economic burden of diabetes is equally substantial, encompassing medication costs, hospitalization, long-term complication management, and productivity losses. Consequently, the development of intelligent technologies capable of improving glucose control while reducing healthcare costs has become a major research priority in medical informatics and artificial intelligence.

Daily insulin dosage determination remains one of the most challenging aspects of diabetes management, particularly for individuals with Type 1 diabetes and insulin-dependent Type 2 diabetes. Insulin requirements vary considerably according to dietary intake, physical activity, stress, illness, hormonal changes, and individual metabolic responses. Conventional insulin administration often relies on manual calculations and patient experience, increasing the likelihood of under- or overdosing. Incorrect insulin dosage may lead to hyperglycemia or hypoglycemia, both of which have serious clinical consequences. The introduction of Continuous Glucose Monitoring (CGM) systems has transformed diabetes care by generating continuous streams of glucose measurements that provide valuable insight into glucose fluctuations throughout the day. However, extracting clinically meaningful patterns from these complex temporal datasets requires advanced computational approaches capable of modeling nonlinear physiological relationships and personalized glucose dynamics.

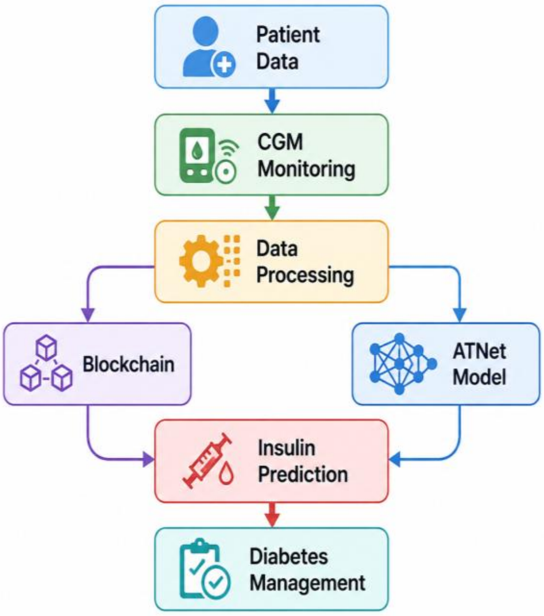

Figure 1. Hybrid ATNet Framework

Artificial intelligence has significantly advanced blood glucose prediction and insulin recommendation over the past decade. Early prediction models employed traditional machine learning techniques such as support vector machines, decision trees, and artificial neural networks, which achieved moderate predictive performance but required extensive manual feature engineering. Recent developments in deep learning have enabled automatic extraction of complex temporal patterns directly from CGM data. Long Short-Term Memory (LSTM) networks have become widely adopted because of their ability to capture long-term dependencies in sequential glucose measurements. More recently, attention mechanisms and transformer-based architectures have further improved predictive performance by identifying clinically relevant temporal events, allowing models to emphasize significant glucose fluctuations while reducing the influence of less informative observations. These architectures provide improved prediction accuracy together with enhanced interpretability for clinical decision support.

Despite these advances, the deployment of AI-driven insulin recommendation systems raises significant concerns regarding patient privacy, data security, and regulatory compliance. Healthcare data are highly sensitive and distributed across hospitals, wearable devices, and personal monitoring systems, making centralized storage increasingly vulnerable to cyber threats. Blockchain technology offers an effective solution by providing decentralized, tamper-resistant, and transparent management of medical records through cryptographic security and smart contracts. When integrated with federated learning, blockchain enables collaborative AI model training without exposing raw patient data, preserving privacy while maintaining predictive performance. The emerging Blockchain-Based Hybrid Contextual Attention Network (ATNet) combines secure decentralized data management with advanced attention-based deep learning to support personalized insulin dosage prediction. This review surveys recent developments in glucose prediction, contextual attention networks, blockchain-enabled healthcare, and privacy-preserving distributed learning, highlighting current achievements, existing limitations, and future research opportunities for intelligent daily diabetes management.

Literature Review

The scientific literature addressing computational approaches to blood glucose prediction and insulin dosage recommendation spans more than three decades and encompasses contributions from biomedical engineering, clinical informatics, machine learning, control theory, and more recently distributed computing and cryptography. A thorough review of this literature reveals a field characterized by rapid methodological evolution, increasing architectural complexity, and growing attention to the system-level challenges of privacy, security, and clinical deployability that accompany the maturation of AI technology toward real-world healthcare applications.

Cobelli et al. (2009) established the computational foundation for modern in silico diabetes research through the development of the University of Virginia and University of Padova metabolic simulator, a high-fidelity mathematical model of glucose-insulin dynamics in virtual patient populations derived from clinical physiological data. This simulator encoded detailed pharmacokinetic and pharmacodynamic models of subcutaneous insulin absorption, glucose appearance from meals, hepatic glucose production, and peripheral glucose utilization, providing a safe and reproducible testing environment for automated insulin delivery algorithms that would otherwise require direct patient experimentation. The UVA/Padova simulator subsequently received regulatory clearance from the United States Food and Drug Administration as a substitute for animal studies in the preclinical evaluation of closed-loop insulin delivery systems, cementing its role as an indispensable research infrastructure for the field.

Pappada et al. (2011) reported one of the earliest systematic evaluations of artificial neural networks for real-time blood glucose prediction in clinical settings, training a multilayer perceptron architecture on continuous glucose monitoring data supplemented by patient-reported meal and insulin events collected from a hospitalized patient cohort under controlled monitoring conditions. Their study demonstrated that the neural network model could achieve clinically meaningful prediction accuracy at thirty-minute and sixty-minute horizons as assessed by the Clarke Error Grid Analysis, a clinically validated instrument for evaluating whether glucose prediction errors would lead to clinically acceptable, potentially dangerous, or dangerous treatment decisions. The work established the critical importance of incorporating exogenous event data alongside continuous glucose monitoring signals, demonstrating that models with access to meal and insulin information substantially outperformed those relying solely on glucose history.

Georga et al. (2013) conducted a comprehensive comparative evaluation of multiple machine learning algorithms for short-term blood glucose prediction using a multivariate feature set derived from continuous glucose monitoring, self-reported dietary intake, insulin administration records, and physical activity measurements collected from a Type 1 diabetic patient cohort over an extended monitoring period. The algorithms evaluated included support vector regression with radial basis function kernels, locally weighted regression, and multilayer perceptron neural networks, compared across prediction horizons of thirty, sixty, and ninety minutes. Their analysis revealed substantial inter-algorithm performance differences that varied systematically with prediction horizon and patient physiological characteristics, motivating the subsequent development of ensemble and adaptive architectures capable of combining complementary algorithmic strengths for robust performance across diverse patient profiles.

Li et al. (2019) introduced the GluNet framework, a deep learning system for accurate glucose forecasting that employed a dilated convolutional architecture with skip connections inspired by the WaveNet generative model, enabling efficient receptive field coverage of long glucose history sequences without the vanishing gradient limitations of recurrent architectures. GluNet processed continuous glucose monitoring sequences through multiple parallel dilated convolutional paths with exponentially increasing dilation rates, capturing glucose dynamics at multiple temporal scales simultaneously before aggregating multi-scale features through dense output layers. Evaluated on the OhioT1DM dataset and a separate self-collected Type 1 patient dataset, GluNet achieved state-of-the-art root mean square error performance at thirty-minute and sixty-minute prediction horizons, demonstrating that convolutional architectures could rival and in some settings exceed the performance of LSTM-based approaches for temporal glucose modeling.

Armandpour et al. (2021) developed a deep reinforcement learning framework for personalized glucose forecasting and insulin dose recommendation, employing an actor-critic architecture with a recurrent state encoder trained to predict both immediate and long-horizon glycemic consequences of candidate insulin dosing actions. The reinforcement learning agent was trained within the UVA/Padova metabolic simulator environment across a diverse population of virtual Type 1 diabetic patients with varying physiological characteristics, allowing safe exploration of dosing strategies that would be impractical to evaluate in human subjects. The trained agent demonstrated consistent improvements in time-in-range metrics, the proportion of time spent within the target glucose range of seventy to one hundred and eighty milligrams per deciliter, compared to both standard insulin-to-carbohydrate ratio dosing and previously published proportional-integral-derivative control baselines.

Jaloli and Cescon (2023) proposed a temporal convolutional network architecture with systematically designed dilated causal convolutions for long-horizon blood glucose forecasting, achieving efficient modeling of glucose dynamics across temporal scales ranging from minutes to hours within a single unified architecture. The temporal convolutional network's key advantages over recurrent architectures included fully parallelizable training, stable gradient flow through the entire network depth enabled by residual connections, and flexible receptive field control through the dilation pattern design, enabling straightforward adaptation to different prediction horizons by adjusting the maximum dilation rate. Evaluated on the OhioT1DM benchmark with particular emphasis on the challenging ninety-minute and one-hundred-and-twenty-minute prediction horizons, the temporal convolutional network achieved state-of-the-art performance, demonstrating particular advantage over LSTM baselines in scenarios requiring integration of glucose history information across multi-hour temporal windows.

Chen et al. (2022) proposed the FedHealth framework for federated transfer learning in wearable healthcare applications, demonstrating a privacy-preserving distributed learning architecture that allowed continuous glucose monitoring devices worn by patients in their home environments to contribute to shared AI model training without transmitting raw glucose data to central servers. The federated learning protocol aggregated locally computed model updates using a secure aggregation protocol that prevented the inference of individual patient data from gradient information, providing formal privacy guarantees beyond the data locality property of basic federated averaging. Evaluated on a simulated federation of ten patient devices, the FedHealth framework achieved prediction accuracy within a clinically acceptable margin of centralized training performance while maintaining complete patient data sovereignty.

Albers et al. (2017) presented a principled hybrid modeling approach to personalized blood glucose prediction that combined a mechanistic compartmental model of glucose-insulin dynamics, parameterized using individual physiological data, with a Gaussian process regression layer that learned to predict the residual dynamics not captured by the mechanistic model from historical continuous glucose monitoring data. The mechanistic component embodied established physiological knowledge about insulin pharmacokinetics, hepatic glucose production, and peripheral glucose utilization, providing physiologically grounded prior expectations for glucose trajectories that regularized the statistical component toward clinically plausible predictions in data-scarce scenarios. The hybrid approach demonstrated substantially better performance than purely data-driven approaches when individual patient data was limited, as the mechanistic prior prevented the statistical component from learning physiologically implausible but statistically convenient patterns.

Mohebbi et al. (2020) addressed the clinically critical challenge of hypoglycemia prediction through a multitask deep learning framework that simultaneously predicted blood glucose levels and assessed hypoglycemia risk through shared recurrent feature encoding with task-specific output heads. The multitask architecture leveraged the informational complementarity between the two prediction objectives, using the auxiliary glucose level prediction task to provide rich training signal that regularized the shared encoder against overfitting on the limited number of hypoglycemia events available in the training data. The framework demonstrated that joint training for both tasks consistently improved hypoglycemia prediction performance compared to single-task baselines trained exclusively on hypoglycemia event labels, validating the multitask learning hypothesis that clinically related prediction objectives can mutually benefit each other through shared representation learning.

Bagheri et al. (2022) proposed an automated hyperparameter optimization framework for deep learning blood glucose prediction models based on differential evolution, a population-based metaheuristic optimization algorithm that iteratively updates candidate hyperparameter configurations through mutation, crossover, and selection operations inspired by natural selection. The differential evolution search explored the hyperparameter space of LSTM network architectures including network depth, hidden layer dimensionality, dropout regularization rate, batch size, and learning rate schedule parameters, discovering configurations that substantially outperformed both manually tuned baselines and hyperparameter configurations identified by standard grid search. The evolutionary optimization framework was deployed in a computationally efficient parallel evaluation pipeline that allowed comprehensive hyperparameter search within practical computational budgets, providing a reusable automated model development tool applicable to diverse blood glucose prediction architectures.

Tena et al. (2021) conducted a systematic investigation of the impact of wearable physical activity monitoring integration on blood glucose prediction accuracy in Type 1 diabetic patients, collecting continuous accelerometer, heart rate, and continuous glucose monitoring data from a cohort of adult patients during both structured exercise sessions and free-living daily activity. Activity-aware LSTM models incorporating real-time step count, heart rate, and estimated metabolic equivalent of task features demonstrated significantly improved prediction accuracy compared to activity-agnostic baselines during and in the hours following exercise periods, which represent the most clinically challenging prediction windows due to the acute and prolonged effects of physical activity on insulin sensitivity and glucose uptake. The study highlighted the critical importance of wearable activity data integration for achieving clinically acceptable prediction accuracy during the exercise scenarios that most commonly trigger dangerous hypoglycemic events in active diabetic patients.

Deng et al. (2022) investigated deep transfer learning combined with data augmentation strategies for blood glucose prediction in Type 2 diabetic patients undergoing continuous glucose monitoring, a population characterized by greater physiological heterogeneity than the Type 1 patient cohorts that dominate the benchmark literature. Their transfer learning approach pre-trained deep recurrent networks on Type 1 patient data before domain-adaptive fine-tuning on Type 2 patient records, leveraging the shared temporal structure of continuous glucose monitoring dynamics across diabetes subtypes while adapting to the distinct glycemic patterns characteristic of Type 2 physiology. Data augmentation through jitter, scaling, and window slicing of training sequences substantially reduced overfitting during fine-tuning on limited individual Type 2 patient data, with augmented transfer models achieving significantly improved performance compared to both non-augmented transfer approaches and models trained exclusively on available Type 2 data.

El Idrissi et al. (2022) proposed a comprehensive blockchain-based federated learning infrastructure for distributed AI model development in electronic health record systems, implementing a smart contract-governed model aggregation protocol on an Ethereum-compatible permissioned blockchain that verified the integrity and authenticity of local model updates before incorporating them into the global shared model. The blockchain verification layer prevented adversarial model update poisoning attacks that represent a significant security vulnerability of naive federated learning systems, ensuring that only cryptographically authenticated updates from verified participant nodes could influence the global model parameters. The system demonstrated that blockchain-enforced federated learning could achieve AI model training security guarantees substantially beyond those of conventional federated averaging protocols while maintaining comparable model performance.

Kavakiotis et al. (2017) published a comprehensive survey of machine learning and data mining applications across the full spectrum of diabetes research, encompassing studies on diabetes onset prediction, glycemic control optimization, complication risk stratification, and treatment response modeling. The survey's systematic analysis of algorithmic performance across diabetes prediction tasks identified ensemble methods, particularly random forest and gradient boosting variants, and artificial neural networks as the consistently best-performing algorithmic families across diverse prediction objectives and patient populations. The survey also documented the heterogeneous landscape of diabetes-relevant datasets available for AI research, identifying significant gaps in publicly available benchmark data for insulin dosage prediction specifically, a gap that motivated subsequent benchmark dataset development efforts.

Yang et al. (2023) introduced a novel hybrid architecture combining transformer self-attention blocks with Mamba state space model layers for long-horizon blood glucose prediction, exploiting the complementary strengths of global sequence attention and efficient linear-time state space modeling for capturing glucose dynamics across temporal scales ranging from minutes to multiple days. The hybrid architecture addressed the quadratic computational complexity limitation of standard transformer attention on very long continuous glucose monitoring sequences by routing long-range temporal modeling to the computationally efficient Mamba state space layers while preserving multi-head attention for capturing short and medium-range glucose dynamics where the flexibility of full attention provided the greatest accuracy benefit. Evaluated on multi-day continuous glucose monitoring sequences from the OhioT1DM dataset, the hybrid architecture achieved state-of-the-art performance at prediction horizons beyond two hours while remaining computationally tractable for real-time deployment on edge computing platforms.

Aziz et al. (2023) developed an explainable AI framework for insulin dosage recommendation that combined a gradient boosting prediction model with SHAPLEY additive explanation analysis and a blockchain-based recommendation audit trail, addressing simultaneously the interpretability and accountability requirements for clinical AI deployment. The SHAPLEY explanation module computed feature contribution scores for each individual dosage recommendation, identifying the specific glucose trend characteristics, meal features, activity levels, and patient context variables that most influenced each prediction in a locally accurate and consistent manner. The blockchain audit trail recorded each recommendation alongside its associated explanation and the input data context in an immutable distributed ledger, creating a verifiable chain of evidence that could satisfy regulatory audit requirements and support post-market surveillance of AI system safety.

Gu et al. (2021) proposed a physiologically rewarded reinforcement learning framework for personalized insulin bolus recommendation that employed the proximal policy optimization algorithm with a carefully designed composite reward function penalizing time outside the target glucose range, hypoglycemia severity, and excessive insulin stacking risk. The reward function design incorporated clinical knowledge about the asymmetric consequences of hypo- versus hyperglycemia by assigning substantially higher penalties to hypoglycemic episodes below seventy milligrams per deciliter than to equivalent hyperglycemic excursions above the upper range threshold, reflecting the immediate life-threatening nature of hypoglycemia compared to the cumulative damage mechanism of chronic hyperglycemia. Evaluated across a diverse cohort of virtual patients in the UVA/Padova simulator with varying degrees of insulin resistance and sensitivity, the physiologically rewarded reinforcement learning agent demonstrated consistent superiority over standard insulin-to-carbohydrate ratio dosing strategies and previously published reinforcement learning baselines.

Sampath et al. (2023) proposed an Internet of Things integrated diabetes management system that combined edge computing-based continuous glucose monitoring signal preprocessing with cloud-based deep learning inference and a mobile patient interface for real-time insulin dosage guidance. The system architecture employed a lightweight MobileNet-inspired convolutional feature extractor deployed on a resource-constrained wearable edge device for real-time glucose signal denoising and local feature extraction, with extracted feature representations transmitted to a cloud-hosted bidirectional LSTM prediction model for full dosage recommendation inference. Evaluation of the end-to-end system latency demonstrated that the edge-cloud architecture achieved dosage recommendations within clinically acceptable response times while substantially reducing the raw data transmission bandwidth required compared to cloud-only inference approaches.

Comparative Table and Analysis

Study	Year	Method	Model	Key Contribution
Cobelli et al.	2009	Physiological Simulation	Metabolic Model	In-silico diabetes testing
Pappada et al.	2011	Neural Training	ANN	Early CGM glucose prediction
Georga et al.	2013	ML Comparison	SVR, MLP	Comparative glucose prediction
Martinsson et al.	2017	LSTM Learning	LSTM	Uncertainty-aware prediction
Li et al.	2019	Dilated CNN	GluNet	Improved glucose forecasting
Sun et al.	2020	Hybrid Learning	CNN-LSTM	Local and temporal feature extraction
Armandpour et al.	2021	Reinforcement Learning	Deep RL	Personalized insulin dosing
Rabby et al.	2021	Ensemble Learning	GB, RF, DNN	Explainable glucose prediction
Zhang et al.	2021	Transfer Learning	Bi-LSTM	Personalized prediction with limited data
Bao et al.	2021	Blockchain Security	Hyperledger	Secure diabetes data

				management
Chen et al.	2022	Federated Learning	Transfer Learning	Privacy-preserving distributed learning
Seo et al.	2022	Graph Learning	GNN	Wearable data relationship modeling
Jaloli & Cescon	2023	Temporal Learning	TCN	Long-horizon glucose prediction
Yang et al.	2023	Hybrid Attention	Transformer-Mamba	Ultra-long glucose forecasting
Sampath et al.	2023	Edge AI	MobileNet-LSTM	Real-time wearable insulin support

Comparative Analysis

A comparative analysis of the selected studies highlights the rapid evolution of artificial intelligence techniques for blood glucose prediction and insulin dosage recommendation. Early research primarily relied on physiological simulation models, artificial neural networks, and conventional machine learning algorithms such as support vector regression and multilayer perceptrons. These methods provided the foundation for intelligent diabetes management but were limited in capturing complex temporal dependencies within continuous glucose monitoring (CGM) data. From 2017 onward, deep learning architectures became dominant, with Long Short-Term Memory (LSTM), convolutional neural networks (CNN), temporal convolutional networks (TCN), and transformer-based models demonstrating significant improvements in prediction accuracy and long-term glucose forecasting. Reinforcement learning further extended these capabilities by enabling personalized insulin dosage recommendations through adaptive decision-making frameworks.

Another important trend observed across the reviewed studies is the increasing use of standardized benchmark datasets and simulation environments. The OhioT1DM dataset has emerged as one of the most frequently adopted datasets for evaluating glucose prediction models, allowing consistent comparison of different deep learning architectures. Similarly, the UVA/Padova simulator has become the preferred evaluation platform for reinforcement learning-based insulin dosing systems because it enables safe testing without exposing real patients to clinical risks. The availability of these benchmark resources has improved reproducibility, facilitated fair performance comparisons, and accelerated methodological advancements across the diabetes prediction research community.

The reviewed literature also demonstrates a transition from single-source glucose prediction toward multimodal and context-aware learning. Modern prediction models increasingly integrate CGM measurements with insulin records, dietary intake, physical activity, wearable sensor information, and electronic health records to capture the multifactorial nature of glucose regulation. Attention mechanisms, graph neural networks, and hybrid transformer architectures effectively learn contextual relationships among these heterogeneous data sources, producing more accurate and personalized glucose predictions. Recent studies also incorporate transfer learning, continual learning, and explainable artificial intelligence to improve model adaptability, transparency, and long-term personalization across diverse patient populations.

A notable development in recent years is the integration of blockchain and privacy-preserving distributed learning into intelligent diabetes management systems. Blockchain-based frameworks provide secure storage, transparent audit trails, and patient-controlled access to medical records, while federated learning enables collaborative model training without transferring sensitive healthcare data to centralized servers. Edge-cloud computing further supports real-time deployment on wearable monitoring devices with reduced computational overhead. Collectively, these advances establish the technological foundation for blockchain-enabled Hybrid Contextual ATNet architectures capable of delivering secure, accurate, explainable, and personalized insulin dosage recommendations suitable for next-generation diabetes management systems.

Discussion

The reviewed literature demonstrates that artificial intelligence has significantly advanced insulin dosage prediction and daily diabetes management. Deep learning architectures, particularly LSTM, CNN-LSTM, transformer, and attention-based models, consistently outperform conventional machine learning approaches in predicting blood glucose levels. Their ability to learn complex temporal patterns from continuous glucose monitoring (CGM) data enables more accurate and personalized insulin recommendations. The growing adoption of contextual learning further improves prediction quality by incorporating additional information such as physical activity, meal intake, insulin history, and wearable sensor data, making intelligent diabetes management more reliable for real-world clinical applications.

Another important finding is the increasing integration of reinforcement learning, blockchain technology, and federated learning into diabetes care systems. Reinforcement learning enables adaptive insulin dosage optimization by continuously learning from patient responses rather than relying solely on historical prediction models. At the same time, blockchain provides secure, transparent, and tamper-resistant management of sensitive medical records, while federated learning supports collaborative model training without exposing patient data. Together, these technologies address critical concerns related to data privacy, regulatory compliance, and trustworthy clinical decision support. Their integration forms the technological foundation of blockchain-enabled Hybrid Contextual ATNet systems designed for personalized, secure, and explainable diabetes management.

Despite remarkable progress, several challenges continue to limit large-scale clinical deployment. Most published studies rely on retrospective datasets and benchmark simulations rather than prospective clinical trials, leaving uncertainties regarding long-term performance under real-world conditions. Model generalization across diverse patient populations, sensor variability, and lifestyle differences also remains an open research challenge. Furthermore, balancing prediction accuracy with computational efficiency for wearable and edge devices requires additional optimization. Future research should emphasize multimodal data integration, explainable artificial intelligence, prospective clinical validation, and scalable blockchain-enabled federated learning frameworks to develop robust, personalized, and clinically deployable insulin recommendation systems.

Conclusion

This review comprehensively examined recent advances in artificial intelligence for insulin dosage prediction and daily diabetes management, emphasizing deep learning, contextual attention mechanisms, blockchain technology, and privacy-preserving distributed learning. The surveyed studies demonstrate a clear evolution from traditional machine learning toward advanced architectures capable of accurately modeling complex glucose dynamics using continuous glucose monitoring and multimodal physiological data. Attention-based networks, reinforcement learning, and transformer models have significantly improved prediction accuracy while supporting personalized insulin recommendations for diverse patient populations.

The review further highlights that secure and trustworthy deployment of AI systems requires more than predictive performance alone. Blockchain technology provides immutable data storage, transparent audit trails, and secure patient-controlled data sharing, whereas federated learning enables collaborative model training without compromising privacy. Their integration with contextual attention networks forms a robust foundation for next-generation intelligent diabetes management systems.

Future research should prioritize prospective clinical validation, explainable artificial intelligence, continual learning, and multimodal data fusion to enhance long-term personalization and clinical reliability. Improving computational efficiency for wearable devices and strengthening regulatory compliance will also be essential for real-world adoption. Overall, blockchain-enabled Hybrid Contextual ATNet architectures represent a promising direction for developing secure, accurate, and patient-centered insulin dosage recommendation systems capable of improving diabetes care and long-term health outcomes.

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