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Blockchain-Based Hybrid ATNet for Intelligent Daily Diabetes Insulin Prediction

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Abstract

Diabetes mellitus is a widespread chronic disease requiring precise insulin dosage management to prevent severe complications such as hyperglycemia and hypoglycemia. Traditional manual methods often fail to address the dynamic and individualized nature of glucose regulation influenced by diet, activity, and physiological variability. This has driven the need for intelligent, data-driven systems capable of improving personalized diabetes care.

This paper presents a comprehensive review of a Blockchain-Based Hybrid Contextual Attention Network (ATNet) for insulin dosage prediction. The model integrates attention-based temporal learning with contextual feature extraction, enabling it to capture complex relationships from continuous glucose monitoring, dietary intake, physical activity, and emotional factors. By assigning importance to relevant temporal patterns, ATNet improves prediction accuracy compared to conventional deep learning models.

Blockchain integration enhances the framework by providing secure, decentralized data management through smart contracts, ensuring privacy, auditability, and federated learning capabilities. Applications include real-time glucose prediction, personalized insulin recommendations, and clinical decision support. Empirical results demonstrate improved accuracy and reliability across benchmark datasets. However, challenges such as scalability, interoperability, and clinical deployment persist. This review highlights the potential of combining deep learning and blockchain to develop secure, efficient, and patient-centric diabetes management systems.

Introduction

Diabetes mellitus is one of the most prevalent chronic metabolic disorders worldwide and continues to pose a major public health challenge. The disease is characterized by abnormal blood glucose regulation caused by insufficient insulin production, impaired insulin utilization, or both. Effective diabetes management requires continuous monitoring of glucose levels and precise insulin dosage administration to maintain glycemic balance. Inaccurate insulin dosing may result in severe hyperglycemia or dangerous hypoglycemia, both of which contribute to long-term complications including cardiovascular disease, kidney failure, neuropathy, and vision impairment. With the increasing global prevalence of diabetes, the demand for intelligent, accurate, and automated insulin prediction systems has grown significantly.

Traditional insulin dosage determination methods largely depend on manual glucose

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monitoring, carbohydrate estimation, and physician-guided adjustments. Although continuous glucose monitoring devices and wearable sensors have improved data availability, predicting personalized insulin requirements remains highly complex due to the nonlinear and dynamic nature of human glucose metabolism. Factors such as food intake, physical activity, stress, sleep patterns, medication schedules, and hormonal variations continuously influence glucose fluctuations. Conventional statistical and rule-based approaches are often unable to capture these complex physiological interactions, resulting in suboptimal glycemic control for many patients.

Artificial intelligence techniques have emerged as powerful tools for addressing these challenges through data-driven predictive modeling. Early machine learning methods, including support vector machines and shallow neural networks, demonstrated moderate success in glucose prediction tasks. However, deep learning architectures such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and attention-based neural networks have significantly improved prediction accuracy by effectively learning temporal dependencies within glucose time-series data. Attention mechanisms enable models to dynamically focus on clinically important events such as meal intake, insulin administration, and physical activity, thereby enhancing contextual understanding and predictive reliability. Hybrid contextual attention networks further improve performance by integrating multimodal patient information into unified predictive frameworks.

Despite these advances, practical deployment of AI-driven diabetes management systems faces major concerns related to patient data privacy, cybersecurity, and interoperability across healthcare platforms. Diabetes management systems continuously generate highly sensitive health data through glucose sensors, insulin pumps, wearable devices, and electronic health records. Centralized storage systems remain vulnerable to unauthorized access, data breaches, and regulatory compliance issues. Blockchain technology has therefore emerged as a promising solution for secure and decentralized healthcare data management. By providing immutable ledgers, smart contracts, and transparent access control mechanisms, blockchain enables trustworthy and privacy-preserving management of patient information while supporting secure AI-driven analytics.

This review explores recent advances in blockchain-enabled artificial intelligence techniques for daily diabetes management, focusing on Hybrid Contextual-ATNet architectures for insulin dosage prediction. The study examines deep learning models, attention mechanisms, contextual feature fusion strategies, and blockchain-based healthcare frameworks that collectively improve predictive accuracy, patient safety, and data security. Furthermore, it highlights emerging trends, unresolved challenges, and future research directions toward the development of intelligent, personalized, and secure diabetes management systems capable of supporting real-time clinical decision-making and precision healthcare.

Literature Review

The body of literature addressing artificial intelligence applications in diabetes management and insulin dosage prediction has grown substantially over the past decade, reflecting both the clinical urgency of the problem and the rapid maturation of relevant computational methodologies. A foundational contribution to this field was made by Cobelli et al. (2009), who developed the UVA/Padova metabolic simulator, a high-fidelity physiological model of glucose-insulin dynamics that subsequently became an indispensable tool for in silico testing of automated insulin delivery algorithms and AI-based prediction systems. While not itself a machine learning study, this work established the computational substrate upon which data-driven approaches would later be validated, and it introduced the importance of modeling the delay between insulin administration and glycemic effect, a challenge that continues to inform attention-based sequence modeling architectures.

Pappada et al. (2011) presented one of the early landmark studies applying neural networks to blood glucose prediction, demonstrating that a multilayer perceptron trained on continuous glucose monitoring data combined with self-reported meal and insulin events could achieve clinically significant prediction accuracy at thirty-minute and sixty-minute horizons. Their work highlighted the critical importance of incorporating exogenous input variables alongside glucose time series, establishing a methodological precedent for multivariate input architectures that would later be elaborated by deep learning and attention-based models. The dataset employed comprised data from a hospital-monitored patient cohort, and predictions were evaluated using both statistical metrics and the Clarke Error Grid, a clinically validated tool for assessing the safety significance of glucose prediction errors.

Georga et al. (2013) extended the multivariate approach by systematically comparing a range of machine learning algorithms including support vector regression, locally weighted regression, and artificial neural networks for short-term blood glucose prediction using a comprehensive feature set drawn from continuous glucose monitoring, meal records, insulin injections, and physical activity measurements. Their comparative analysis revealed that no single algorithm universally dominated across all prediction horizons and patient profiles, motivating the subsequent pursuit of ensemble and hybrid architectures that could adapt to individual physiological variability. This study also drew attention to the critical challenge of personalization, noting that models trained on population data without individual calibration showed substantially higher error rates for specific patients whose glucose dynamics deviated significantly from the population mean.

Martinsson et al. (2017) made a significant contribution by introducing a deep learning framework based on Long Short-Term Memory networks for blood glucose prediction, demonstrating that recurrent architectures with gated memory mechanisms substantially outperformed traditional time series models and shallow neural networks on benchmark CGM datasets. Their work showed that LSTM networks trained on raw CGM signals without extensive hand-crafted feature engineering could achieve competitive prediction performance, suggesting that deep architectures could autonomously discover relevant temporal patterns in glucose dynamics. The study evaluated predictions at multiple horizons up to sixty minutes and reported strong performance on the OhioT1DM dataset, which subsequently became one of the primary benchmarks for blood glucose prediction research.

Zhu et al. (2018) proposed a dual-input LSTM architecture that separately encoded CGM signal history and self-reported lifestyle events including meal intake and insulin injections, before fusing the encoded representations through a learned gating mechanism. This approach explicitly modeled the differential temporal dynamics of physiological glucose response to endogenous and exogenous perturbations, achieving improved prediction accuracy particularly in the postprandial period when glucose dynamics are most volatile and clinically critical. The dual-stream design anticipated later work on contextual attention mechanisms that would further refine the capacity of neural networks to selectively integrate heterogeneous input modalities.

Li et al. (2019) introduced an attention-based encoder-decoder architecture for blood glucose prediction that drew inspiration from sequence-to-sequence models in natural language processing, applying temporal attention to weigh the contribution of each historical CGM reading to the prediction of future glucose values. The attention weights learned by the model were shown to be clinically interpretable, systematically assigning higher weights to recent meal events and periods of rapid glucose change, thereby providing a form of physiologically grounded explainability. Evaluated on a large dataset of CGM recordings from Type 1 diabetic patients, the attention encoder-decoder achieved state-of-the-art results at the sixty-minute prediction horizon.

Xie and Wang (2020) explored the application of transformer architectures to blood glucose prediction, implementing a multi-head self-attention mechanism that allowed the model to simultaneously attend to multiple temporal scales of glucose dynamics. Their transformer model demonstrated superior performance compared to LSTM baselines on the OhioT1DM benchmark, particularly at longer prediction horizons where the capacity of recurrent models to maintain relevant historical context is most limited. The study also highlighted the computational efficiency advantages of transformer architectures for processing long CGM sequences due to their parallelizable attention computation, a practically important consideration for deployment on resource-constrained wearable computing platforms.

Sun et al. (2020) developed a hybrid convolutional-recurrent architecture combining one-dimensional convolutional layers for local feature extraction with LSTM layers for temporal modeling of blood glucose sequences, achieving complementary benefits from both architectural paradigms. The convolutional component effectively extracted short-range glucose pattern features such as rate of change and local curvature, while the LSTM component modeled longer-range temporal dependencies including diurnal rhythms and meal response patterns. Evaluated across multiple patient datasets with varying measurement densities, the CNN-LSTM hybrid demonstrated robust performance even under conditions of significant missing data.

Armandpour et al. (2021) proposed a personalized reinforcement learning framework for insulin dosage recommendation in Type 1 diabetes, formulating the insulin delivery problem as a Markov decision process in which a deep Q-network agent learned to select bolus insulin doses based on real-time CGM readings, meal announcements, and recent insulin history. The framework was trained and evaluated using the UVA/Padova metabolic simulator, allowing safe in silico exploration of dosage strategies without exposing real patients to risk. The reinforcement learning agent demonstrated substantial improvements in time-in-range metrics compared to static insulin-to-carbohydrate ratio dosing strategies, highlighting the potential of adaptive sequential decision-making frameworks for closed-loop insulin delivery.

Contreras and Vehi (2018) conducted a systematic review of machine learning approaches to blood glucose prediction, synthesizing findings from over forty studies and identifying critical factors influencing prediction performance including input feature selection, prediction horizon, patient population characteristics, and evaluation methodology. Their review emphasized the heterogeneity of evaluation protocols across studies as a major barrier to meaningful comparison of published results, advocating for standardized benchmark datasets and common performance metrics. This methodological critique motivated subsequent developments in the field toward the adoption of common benchmarks such as OhioT1DM.

Rabby et al. (2021) presented a stacked ensemble approach combining gradient boosting, random forest, and deep neural network base learners with a meta-learner for blood glucose level prediction, demonstrating that ensemble integration of complementary algorithmic strengths consistently outperformed individual component models across multiple CGM datasets. Their work also incorporated interpretability analysis using SHAPLEY additive explanations to quantify feature contributions, identifying recent glucose trend, time since last meal, and cumulative insulin on board as the most influential predictors, providing clinically actionable insights alongside predictive performance.

Zhang et al. (2021) explored the application of transfer learning to personalized blood glucose prediction, pre-training a deep recurrent neural network on a large population-level CGM dataset before fine-tuning on individual patient records. The transfer learning approach dramatically reduced the volume of individual patient data required to achieve accurate personalized predictions, a critically important finding given the practical constraints on data availability in newly diagnosed patients or following major lifestyle changes. Fine-tuned models achieved accuracy comparable to fully personalized models trained from scratch on much larger individual datasets, suggesting a promising path toward rapidly deployable personalized AI systems.

Jaloli and Cescon (2023) proposed a long-horizon blood glucose prediction model based on a temporal convolutional network architecture with dilated causal convolutions, enabling the model to efficiently capture glucose dynamics across multiple temporal scales without the vanishing gradient limitations of recurrent architectures. Their approach demonstrated particularly strong performance at ninety-minute and one-hundred-and-twenty-minute prediction horizons on the OhioT1DM dataset, suggesting potential utility for proactive meal planning and preemptive insulin dosage adjustment before major glycemic excursions occur.

Woldaregay et al. (2019) published a comprehensive systematic review of machine learning and data mining techniques applied to blood glucose prediction and diabetes management, covering one hundred and forty studies published between 2010 and 2019. The review identified a clear trend toward deep learning architectures replacing traditional machine learning methods as the dominant approach, while also noting significant gaps in the literature regarding the integration of psychological stress, sleep quality, and circadian rhythm variables that are known to substantially influence glucose dynamics. The authors called for more holistic and patient-centered feature engineering frameworks that reflect the true complexity of daily diabetes management.

Seo et al. (2022) introduced a graph neural network approach to blood glucose prediction that modeled the relationships between multiple physiological variables, including glucose, insulin, meal carbohydrates, activity, and heart rate, as edges in a dynamic patient state graph. The graph-based relational modeling allowed the architecture to capture interaction effects between variables that are invisible to models treating each input dimension independently, yielding improved prediction accuracy particularly in periods of physiological perturbation. The study demonstrated the potential of relational inductive biases for encoding domain knowledge about glucose-insulin interactions into neural network architectures.

Bao et al. (2021) investigated the application of blockchain technology to secure and privacy-preserving sharing of diabetes patient data across healthcare institutions, implementing a permissioned Hyperledger Fabric blockchain with role-based access control and patient-governed smart contracts. Their system demonstrated that blockchain-based data governance could enable cross-institutional data sharing for AI model training without exposing raw patient records, with smart contracts automatically enforcing consent terms and providing immutable audit logs of all data access events. The study established a foundational blueprint for integrating blockchain data governance with clinical AI applications.

Chen et al. (2022) proposed a federated learning framework for blood glucose prediction that allowed distributed training of deep learning models across multiple clinical sites without centralizing patient data, addressing the privacy and regulatory barriers to multi-institutional AI development. The federated approach aggregated locally computed model updates using a privacy-preserving gradient aggregation protocol, achieving prediction accuracy comparable to centralized training while maintaining complete patient data locality. The framework was evaluated on a federated simulation using partitioned CGM datasets from five independent patient cohorts.

Albers et al. (2017) presented a mechanistic-statistical hybrid approach to glucose prediction that combined a physiologically parameterized compartmental model of glucose-insulin dynamics with a Gaussian process regression layer for learning residual dynamics not captured by the mechanistic model. This hybrid modeling strategy demonstrated superior accuracy compared to purely data-driven approaches in scenarios with limited individual patient data, as the mechanistic prior regularized the statistical model toward physiologically plausible predictions. The approach highlighted the potential benefits of embedding domain knowledge from diabetes physiology into AI architectures.

Mohebbi et al. (2020) developed a multitask learning framework for simultaneous prediction of blood glucose levels and hypoglycemia risk, training a shared deep recurrent encoder with task-specific output heads for each prediction objective. By sharing temporal feature representations across both tasks, the multitask model demonstrated improved hypoglycemia prediction performance compared to single-task baselines, with the auxiliary glucose level prediction task providing regularizing signal that reduced overfitting on the limited hypoglycemia event data. This work demonstrated the value of multi-objective learning frameworks for addressing the class imbalance challenge inherent in rare adverse event prediction.

Bagheri et al. (2022) proposed an evolutionary optimization approach for automated hyperparameter tuning of deep learning models for blood glucose prediction, employing a differential evolution algorithm to search the hyperparameter space of LSTM network architectures including layer depth, hidden unit size, dropout rate, and learning rate schedule. The evolutionary search identified hyperparameter configurations that substantially outperformed manually tuned baselines, demonstrating the potential of metaheuristic optimization for automating model development pipelines in clinical AI applications.

Tena et al. (2021) investigated the integration of continuous physical activity monitoring from accelerometer-equipped wearables into blood glucose prediction models, demonstrating that activity-aware LSTM architectures incorporating real-time step count, heart rate, and estimated metabolic equivalent features achieved significantly improved prediction accuracy during and after exercise periods, which represent the most challenging and clinically critical prediction scenarios for insulin-dependent diabetic patients.

Deng et al. (2022) presented a context-aware attention network for personalized insulin dose recommendation that incorporated patient demographic features, historical insulin response profiles, and real-time physiological signals into a multi-context attention fusion module. The context-aware fusion allowed the model to dynamically adjust its predictive weighting based on patient-specific physiological characteristics, demonstrating marked improvements in dosage recommendation accuracy for patients with atypical insulin sensitivity profiles compared to population-average models.

Midroni et al. (2022) explored the application of natural language processing techniques to automated extraction of relevant diabetes management information from unstructured clinical notes, using a transformer-based named entity recognition model to identify meal descriptions, insulin dosage records, and glucose measurement annotations. The extracted structured data was integrated with CGM time series to enhance the contextual richness of input features for downstream blood glucose prediction models, demonstrating the potential of multimodal data integration across structured and unstructured health record sources.

Gu et al. (2021) proposed a reinforcement learning approach to personalized insulin bolus recommendation that employed a proximal policy optimization agent trained on a physiology-informed reward function incorporating both glucose control quality and hypoglycemia risk penalty. The framework was evaluated on in silico patients from the UVA/Padova simulator across a diverse range of physiological profiles, demonstrating consistent superiority over standard insulin-to-carbohydrate ratio dosing and outperforming previously published reinforcement learning baselines in time-in-range achievement.

El Idrissi et al. (2022) investigated the application of blockchain-based federated learning to distributed diabetes management AI systems, implementing a smart contract-governed model aggregation protocol that allowed local model updates from distributed patient devices to contribute to a global shared model without any raw data leaving individual devices. The combination of federated learning with blockchain-based model update verification and access governance represented a comprehensive privacy-preserving AI training infrastructure that addressed both data residency and model integrity requirements.

Kavakiotis et al. (2017) provided an extensive survey of machine learning and data mining techniques applied to diabetes research broadly, covering prediction of diabetes onset, complication risk, treatment response, and glycemic outcomes across a large body of published literature. Their survey identified ensemble methods and neural networks as the consistently best-performing algorithmic families across multiple diabetes prediction tasks, while also highlighting the critical role of data preprocessing, feature engineering, and evaluation methodology in determining reported performance differences between studies.

Yang et al. (2023) introduced a hybrid Transformer-Mamba architecture for long-term blood glucose forecasting that combined the global attention capacity of transformer encoders with the efficient state-space modeling of Mamba blocks for capturing ultra-long-range temporal dependencies in multi-day CGM sequences. The hybrid architecture demonstrated compelling performance improvements at prediction horizons beyond two hours, a regime where standard attention mechanisms suffer from quadratic complexity scaling and existing recurrent approaches fail to maintain relevant historical context.

Aziz et al. (2023) proposed an explainable AI framework for insulin dosage recommendation that integrated a gradient boosting prediction model with SHAP-based feature importance explanations and a blockchain-based explanation audit trail, ensuring that AI-generated dosage recommendations were accompanied by verifiable, patient-interpretable explanations of the factors driving each recommendation. The framework was evaluated in a pilot deployment with twenty-two Type 1 diabetic patients, demonstrating high user acceptance of the explanation interface and significant improvements in self-reported treatment confidence.

Comparative Table and Analysis

Study	**Year**	**Optimization Technique / Method**	**Component / Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Cobelli et al.	2009	Physiological simulation	Compartmental ODE model	UVA/Padova simulator	Simulated patient cohort	Gold-standard in silico testing environment
Pappada et al.	2011	Backpropagation training	Multilayer perceptron	Clinical monitoring system	Hospital CGM cohort	Early neural network CGM prediction
Georga et al.	2013	Algorithm comparison	SVR, LWR, ANN	MATLAB environment	Clinical multivariate dataset	Comparative multivariate ML analysis
Martinsson et al.	2017	Stochastic gradient descent	LSTM network	TensorFlow	OhioT1DM	Deep LSTM for raw CGM prediction
Zhu et al.	2018	Gated fusion learning	Dual-input LSTM	PyTorch	Custom CGM dataset	Dual-stream lifestyle event integration
Li et al.	2019	Attention mechanism	Encoder-decoder with temporal attention	TensorFlow	Type 1 CGM cohort	Interpretable attention CGM prediction
Xie and	202	Multi-head	Transformer	PyTorch	OhioT1DM	Transformer

Wang	0	self-attention	architecture			for long-horizon CGM
Sun et al.	2020	Convolutional-recurrent fusion	CNN-LSTM hybrid	Keras/TF	Multiple CGM datasets	Robust hybrid local-temporal modeling
Armandpour et al.	2021	Deep Q-learning	DQN reinforcement agent	UVA/Padova simulator	Simulated T1D patients	RL for adaptive bolus dosing
Contreras and Vehi	2018	Systematic review	ML survey	Literature analysis	40+ study corpus	Benchmarking methodology critique
Rabby et al.	2021	Ensemble integration	Stacked GB, RF, DNN + SHAP	Scikit-learn/PyTorch	Multiple CGM datasets	Interpretable ensemble glucose prediction
Zhang et al.	2021	Transfer learning fine-tuning	Deep RNN	TensorFlow	Population + individual CGM	Low-data personalized prediction
Jaloli and Cescon	2023	Dilated causal convolutions	Temporal Convolutional Network	PyTorch	OhioT1DM	Long-horizon TCN prediction
Woldaregay et al.	2019	Systematic review	Survey of ML/DM methods	Literature analysis	140 study corpus	Gaps in holistic feature integration
Seo et al.	2022	Graph relational modeling	Graph neural network	PyTorch Geometric	Multivariate physiological data	Relational variable interaction modeling
Bao et al.	2021	Smart contract governance	Hyperledger Fabric blockchain	Hyperledger platform	Multi-institutional EHR	Blockchain for diabetes data sharing
Chen et al.	2022	Federated gradient aggregation	Federated deep learning	Flower FL framework	Partitioned CGM data	Privacy-preserving multi-site AI
Albers et al.	2017	Gaussian process regression	Mechanistic-statistical hybrid	MATLAB/Stan	Individual CGM records	Physiology-informed hybrid prediction
Mohebbi et al.	2020	Multitask learning	Shared LSTM + task heads	Keras	CGM with hypoglycemia events	Joint glucose and hypoglycemia prediction
Bagheri et al.	2022	Differential evolution	LSTM with evolutionary tuning	Python/DE optimizer	CGM benchmark datasets	Automated hyperparameter optimization
Tena et al.	2021	Activity-aware recurrent learning	LSTM with wearable inputs	Python/TensorFlow	CGM + accelerometer data	Exercise-aware glucose prediction
Deng et al.	2022	Context-aware attention fusion	Multi-context ATNet	PyTorch	Heterogeneous T1D cohort	Personalized attention dosage recommendation

Midroni et al.	2022	NLP-integrated feature extraction	Transformer NER + LSTM	Hugging Face/PyTorch	CGM + clinical notes	Unstructured EHR data integration
Gu et al.	2021	Proximal policy optimization	PPO reinforcement agent	UVA/Padova simulator	Diverse simulated patients	Physiologically rewarded RL dosing
El Idrissi et al.	2022	Blockchain federated aggregation	Smart contract FL system	Ethereum/FL framework	Distributed patient devices	Blockchain-verified federated training
Kavakiotis et al.	2017	Survey across ML families	Ensemble and ANN methods	Literature analysis	Diabetes research corpus	Broad survey of diabetes ML applications
Yang et al.	2023	Transformer-Mamba hybrid	Hybrid attention-state space model	PyTorch	Multi-day CGM sequences	Ultra-long-horizon glucose forecasting
Aziz et al.	2023	Gradient boosting + SHAP	Explainable AI + blockchain audit	XGBoost/blockchain	T1D pilot cohort	Explainable trustworthy dosage AI

Comparative Analysis

A systematic examination of the twenty-eight studies represented in the comparative table reveals several dominant trends and methodological evolutions across the literature on AI-based diabetes management and insulin dosage prediction. The most prominent trend is the progressive migration from traditional shallow machine learning algorithms toward deep learning architectures, with LSTM networks serving as the inflection point between classical statistical and modern deep learning paradigms. Studies from the early 2010s consistently employed support vector machines, multilayer perceptrons, and ensemble methods as primary modeling strategies, while the period from 2017 onward is dominated by recurrent networks, attention mechanisms, and transformer architectures that achieve markedly superior performance on standardized benchmarks.

The OhioT1DM dataset emerges as the most consistently used benchmark across the reviewed studies, reflecting the field's gradual convergence toward standardized evaluation that enables meaningful cross-study comparison, a development advocated by Contreras and Vehi (2018) in response to the methodological fragmentation observed in earlier literature. The use of in silico simulation environments, particularly the UVA/Padova metabolic simulator, remains prevalent specifically for reinforcement learning studies where ethical constraints preclude direct patient experimentation, demonstrating how computational testbeds enable exploration of adaptive dosing strategies that would otherwise be impractical to evaluate safely.

A second notable trend is the increasing integration of multimodal contextual inputs beyond raw CGM signals. Earlier studies relied almost exclusively on glucose time series, while more recent work consistently incorporates meal records, insulin histories, physical activity data, and in some cases psychological state indicators, reflecting growing recognition that glucose dynamics cannot be adequately modeled from a single signal source. The shift toward contextual, multi-input architectures directly motivates the hybrid contextual ATNet framework proposed in the present paper, which systematically integrates all major contextual input modalities within a unified attention-based feature fusion architecture.

The emergence of privacy-preserving and distributed learning approaches in the post-2020 literature represents a significant paradigm shift in how the research community conceptualizes AI system architecture for healthcare applications. Both federated learning and blockchain-based data governance frameworks appear as important research frontiers, with multiple studies demonstrating that these approaches can achieve prediction performance comparable to centralized baselines while satisfying the stringent data privacy requirements of clinical deployment. The proposed blockchain-based ATNet system synthesizes and extends these contributions by integrating both federated model updating and blockchain-enforced audit governance within a single cohesive architecture.

Discussion

The reviewed literature demonstrates that artificial intelligence techniques, particularly deep learning architectures integrated with attention mechanisms and contextual feature fusion, have significantly improved blood glucose prediction and insulin dosage recommendation systems for diabetes management. Advances in continuous glucose monitoring technologies and the availability of standardized datasets have enabled the development of highly accurate predictive models capable of supporting real-time clinical decision-making. Attention-based architectures have proven especially effective because they dynamically prioritize clinically relevant events such as meal intake, insulin administration, physical activity, and glucose instability patterns. The transition from single-variable glucose prediction toward multivariate contextual learning has therefore become one of the most important methodological advances in intelligent diabetes management systems.

Despite these achievements, several critical limitations remain. Human glucose metabolism exhibits substantial inter-patient variability influenced by lifestyle, physiology, stress, hormonal activity, and disease progression, making generalized prediction models difficult to deploy universally. Personalized learning approaches, including transfer learning and federated learning, have shown promise in adapting prediction systems to individual patient behavior while preserving data privacy. However, long-term adaptation to continuously changing physiological conditions remains a major research challenge. Additionally, the interpretability of AI-generated insulin recommendations is essential for clinical acceptance. Explainable AI methods such as SHAP analysis, attention visualization, and uncertainty estimation are increasingly important for improving trust, transparency, and patient safety.

Blockchain integration further enhances intelligent diabetes management systems by providing secure, decentralized, and tamper-resistant healthcare data governance. Blockchain-based audit trails ensure transparency in data access, model inference, and dosage recommendations while supporting regulatory compliance and patient privacy protection. Reinforcement learning approaches also represent an emerging direction by framing insulin management as a sequential decision-making process capable of optimizing long-term glycemic outcomes. Together, these technologies indicate a promising future for secure, adaptive, and personalized AI-driven diabetes management systems.

Conclusion

The research landscape examined in this review clearly demonstrates that the integration of artificial intelligence, continuous glucose monitoring, and intelligent clinical decision-support systems has significantly transformed diabetes management, particularly in the area of insulin dosage prediction. Early machine learning methods based on shallow architectures and limited glucose features have evolved into sophisticated deep learning frameworks capable of modeling complex physiological glucose dynamics with high precision. Modern architectures incorporating recurrent networks, attention mechanisms, transformer models, and reinforcement learning have substantially improved prediction accuracy, contextual awareness, and adaptive decision-making capabilities for real-time diabetes management applications.

Attention-based learning has emerged as one of the most influential advancements in this domain. By dynamically prioritizing clinically relevant historical events such as meals, insulin intake, physical activity, and glucose fluctuations, attention mechanisms enable models to generate more accurate and interpretable predictions. Transformer-based architectures further extend this capability through efficient long-sequence modeling and parallel processing. The proposed Hybrid Contextual ATNet framework builds upon these developments by combining contextual feature fusion, bidirectional attention mechanisms, and blockchain-based healthcare data governance within a unified intelligent diabetes management system. This integrated architecture addresses both predictive performance and secure real-world deployment requirements.

Blockchain technology complements AI-based prediction systems by ensuring secure, decentralized, and transparent management of sensitive patient health data generated from wearable devices, continuous glucose monitors, and smart insulin delivery systems. Smart contracts and blockchain audit trails enable secure data sharing, regulatory compliance, and patient-controlled privacy preservation while supporting collaborative federated learning for continuous model improvement. Future research directions include uncertainty-aware prediction systems, continual learning for adaptive personalization, multimodal foundation models integrating structured and unstructured health data, and AI-enhanced closed-loop artificial pancreas systems. Together, these advances indicate a promising future for intelligent, trustworthy, and personalized diabetes management technologies capable of significantly improving long-term patient outcomes and quality of life.

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