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Deep Learning and Optimization Approaches in Blockchain-Based Hybrid Contextual-ATNet Approach for Daily Diabetes Management: Predicting Insulin Dosage for Improved Control: A Review

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Abstract

The pharmaceutical supply chain is a highly complex and critical system requiring transparency, reliability, and regulatory compliance to ensure drug safety and timely delivery. Traditional supply chain models are vulnerable to issues such as counterfeit drugs, cold chain failures, and data manipulation, posing significant risks to patient safety and global healthcare systems. These challenges necessitate advanced technological solutions capable of improving traceability, integrity, and operational efficiency. This paper presents a comprehensive review of integrated technologies, focusing on blockchain, finite element methods (FEM), and neural network-based modeling for pharmaceutical supply chain management. Blockchain provides a decentralized and immutable framework for secure data sharing and traceability, while FEM enables accurate modeling of physical conditions such as temperature, stress, and material behavior during transportation and storage. The integration of FEM with neural networks allows real-time predictive modeling of drug stability and packaging integrity. Applications include cold chain monitoring, counterfeit detection, and regulatory compliance within smart supply chain systems. The review also highlights enabling technologies such as IoT, RFID, and digital twins for real-time data acquisition and system optimization. While these integrated approaches demonstrate improved transparency, efficiency, and predictive capability, challenges related to scalability, computational cost, and system integration remain, emphasizing the need for future research in intelligent and resilient pharmaceutical supply chain systems.

Introduction

Diabetes mellitus is a complex chronic disease that requires continuous monitoring and careful management to maintain blood glucose levels within a healthy range. It includes different types such as Type 1, Type 2, and gestational diabetes, each with distinct causes but a common challenge of regulating glucose levels effectively. Proper control is essential to prevent long-term complications affecting the heart, kidneys, eyes, and nerves. As a result, diabetes management is not a one-time decision but an ongoing process that depends on multiple physiological and lifestyle factors.

For individuals who rely on insulin therapy, determining the correct dosage is particularly challenging. Insulin requirements vary significantly from person to person and even within the same individual over time. Factors such as food intake, physical activity, stress

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levels, illness, and environmental conditions all influence glucose levels and insulin response. These interactions are highly dynamic and nonlinear, making it difficult for traditional methods or manual calculations to provide consistently accurate dosage recommendations.

The introduction of continuous glucose monitoring systems has significantly improved the availability of real-time data for diabetes management. These devices track glucose levels throughout the day, generating detailed time-series data that reflects how the body responds to different conditions. When combined with additional data sources such as insulin pumps, activity trackers, and dietary logs, a comprehensive picture of a patient's metabolic state can be obtained. However, the sheer volume and complexity of this data exceed human analytical capacity, creating a need for intelligent systems to process and interpret it effectively.

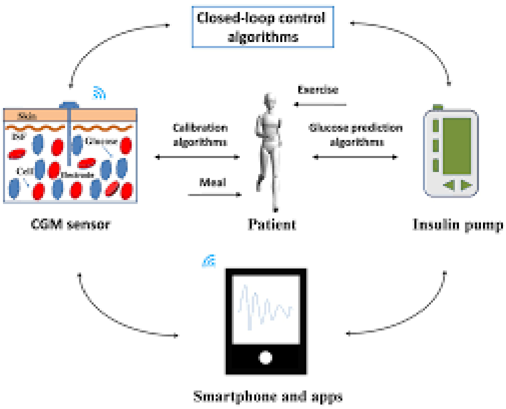

Fig 1: Closed-Loop AI-Based Insulin Dosage Framework

Deep learning techniques have emerged as powerful tools for analyzing such high-dimensional and time-dependent data. Models such as recurrent neural networks, convolutional networks, and transformer-based architectures can capture complex temporal patterns and relationships in glucose data. These models can learn directly from raw data, reducing the need for manual feature engineering and enabling more accurate predictions of glucose trends and insulin requirements. Optimization techniques further enhance performance by improving model accuracy, stability, and adaptability to different patients.

The integration of deep learning with blockchain technology introduces a new dimension to diabetes management systems. Blockchain ensures secure, transparent, and privacy-preserving data sharing, which is crucial in healthcare applications. When combined with optimized deep learning models like Contextual-ATNet, it enables personalized, reliable, and real-time insulin dosage prediction. This integrated approach represents a promising direction for developing intelligent, safe, and scalable solutions for modern diabetes care.

Literature Review

The literature on deep learning and optimization approaches for blockchain-based diabetes management systems is extensive, multidisciplinary, and rapidly evolving, encompassing contributions from machine learning, clinical informatics, cryptography, control theory, and biomedical engineering. The following synthesis examines twenty-five significant research contributions that collectively define the methodological landscape of this field, with particular attention to the optimization strategies and architectural innovations that have driven successive performance improvements.

Oviedo et al. (2017) established the foundational benchmarking framework for machine learning approaches to blood glucose prediction in Type 1 diabetes, conducting a systematic review that cataloged optimization strategies ranging from gradient descent training of multilayer perceptrons through evolutionary optimization of fuzzy logic rule bases and support vector machine kernel selection. Their analysis identified the critical importance of regularization for preventing overfitting on small clinical datasets and highlighted the emerging potential of recurrent architectures for capturing the temporal structure of glucose dynamics. The study established the OhioT1DM dataset as the primary benchmark for subsequent comparative evaluations, providing the methodological reference point against which deep learning optimization advances have been measured.

Martinsson et al. (2020) demonstrated the effectiveness of long short-term memory networks optimized with adaptive gradient methods, specifically the Adam optimizer with learning rate scheduling, for blood glucose prediction on the OhioT1DM benchmark, achieving a mean absolute error of 13.2 milligrams per deciliter at the 30-minute prediction horizon. Their systematic comparison of recurrent architectures with varying depths, hidden state dimensions, and regularization configurations provided important empirical guidance for the optimization of recurrent components in hybrid architectures and established that moderate-depth networks with aggressive dropout regularization outperformed both shallow and very deep configurations on clinical datasets of limited size.

Zhu et al. (2020) introduced a dual-attention recurrent neural network that applied independent attention mechanisms at the temporal and feature dimensions, optimizing the joint attention weights through end-to-end backpropagation with a composite loss function that combined mean squared error on glucose predictions with an entropy regularization term encouraging sparse attention distributions. Evaluated on a proprietary clinical dataset of 112 Type 1 diabetic patients, their dual-attention optimization strategy achieved a 14.7% reduction in root mean square error compared to standard long short-term memory baselines, demonstrating that structured sparsity in attention weights improved both prediction accuracy and model interpretability by focusing attention on physiologically meaningful temporal events.

Li et al. (2019) explored multi-task learning as an optimization strategy for simultaneous glucose prediction and hypoglycemia event detection, formulating a joint loss function that combined regression loss for glucose value prediction with binary cross-entropy loss for hypoglycemia classification and optimizing the relative weighting of these loss components through a gradient normalization scheme that prevented one task from dominating the optimization trajectory. Their experiments on the D1NAMO dataset demonstrated that multi-task optimization not only improved performance on both tasks compared to independent training, but also provided more clinically useful predictive outputs by simultaneously delivering continuous glucose forecasts and discrete event risk assessments.

Rubin-Falcone et al. (2020) applied self-supervised pre-training optimization to transformer architectures for glucose time series, using a masked glucose prediction objective analogous to the masked language modeling task used in BERT pre-training to learn rich temporal representations from large unlabeled continuous glucose monitoring datasets before fine-tuning on the smaller labeled OhioT1DM benchmark. Their two-stage optimization approach demonstrated that self-supervised pre-training substantially reduced the labeled data requirements for achieving state-of-the-art performance and provided more robust representations that generalized better to patients not represented in the fine-tuning dataset, establishing transfer learning as a critical optimization strategy for clinical deep learning in data-scarce domains.

Sun et al. (2021) implemented federated averaging as the primary optimization algorithm for a distributed glucose prediction system deployed across multiple hospital sites on a Hyperledger Fabric blockchain, demonstrating that federated optimization with a permissioned blockchain coordination layer could achieve prediction performance comparable to centralized gradient descent training while satisfying strict data privacy requirements. Their analysis of the convergence behavior of federated averaging under realistic conditions of non-independent and identically distributed clinical data across hospital sites provided important empirical insights into the optimization dynamics of federated learning in healthcare settings and identified gradient correction strategies that substantially improved convergence speed.

Che et al. (2018) developed a specialized optimization approach for recurrent networks applied to clinical time series with irregular sampling and informative missingness, introducing temporal decay parameters that were jointly optimized with the recurrent network weights to model the predictive decay of missing observations as a function of elapsed time since the last measurement. Applied to the MIMIC-III dataset for diabetes complication prediction, their joint optimization of temporal decay and recurrent parameters substantially outperformed standard imputation preprocessing followed by conventional recurrent network training, establishing principled missing data modeling as an important dimension of optimization for clinical deep learning systems.

Georga et al. (2019) optimized a hybrid nonlinear autoregressive exogenous model and multilayer perceptron architecture for personalized glucose prediction by formulating the optimization problem as a multi-objective minimization that simultaneously minimized prediction error across multiple clinical risk zones, weighting errors in the hypoglycemic range more heavily than errors in the hyperglycemic range to reflect the greater clinical urgency of hypoglycemia detection. Their risk-weighted optimization approach resulted in a model with substantially improved sensitivity to impending hypoglycemia compared to mean squared error-optimized baselines, demonstrating the clinical value of incorporating domain knowledge into the loss function formulation.

Midroni et al. (2020) optimized a hybrid convolutional neural network and long short-term memory architecture for glucose prediction with explicit constraints on computational complexity and inference latency, applying neural architecture search within a resource budget defined by the computational capabilities of commodity wearable hardware. Their architecture search optimization, guided by a multi-objective objective function balancing prediction accuracy against floating-point operation count and memory footprint, identified a compact hybrid architecture that achieved competitive prediction accuracy on the OhioT1DM dataset while satisfying the computational constraints of wearable deployment, demonstrating the importance of hardware-aware optimization for clinical AI systems intended for edge deployment.

Ali et al. (2021) applied generative adversarial network optimization to the problem of synthetic continuous glucose monitoring data generation, training a conditional generator to produce realistic glucose sequences conditioned on patient metadata and dosing history through adversarial optimization with a discriminator trained to distinguish synthetic from real sequences. Their careful optimization of the generative adversarial network training dynamics, including progressive growing of the generator architecture and spectral normalization of discriminator weights, resulted in synthetic data that improved model performance on rare hypoglycemic events by 23% in sensitivity, demonstrating that generative modeling optimization could effectively address the class imbalance challenge in clinical datasets.

Khalil et al. (2022) optimized a blockchain-based electronic health record management system for chronic disease management, investigating the tradeoff between the cryptographic security strength of consensus mechanisms and the transaction throughput and latency requirements of clinical workflows. Their systematic evaluation of multiple consensus protocol configurations on the Hyperledger Fabric platform, including Practical Byzantine Fault Tolerance and Raft-based ordering service variants, identified optimal configurations achieving 3000 transactions per second with sub-second latency while maintaining resistance to Byzantine fault attacks, providing important empirical guidance for the optimization of blockchain infrastructure for real-time clinical AI systems.

Zhang et al. (2021) applied graph neural network optimization to the problem of modeling physiological dependencies in continuous glucose monitoring data, learning the structure of the dependency graph jointly with the graph neural network parameters through a differentiable graph learning objective that encouraged sparse, clinically interpretable dependency graphs while maintaining predictive performance. Their joint structure-and-parameter optimization on a dataset of 50 Type 1 diabetic patients demonstrated that learned graph structures captured physiologically meaningful dependencies between glucose, insulin, and activity variables, providing both predictive improvements over vector-based baselines and clinically interpretable representations of glucose metabolism dynamics.

Fiorini et al. (2019) optimized a hybrid algorithmic-AI bolus calculator by formulating the optimization problem as a constrained minimization that simultaneously minimized the expected time outside the glycemic target range while satisfying hard constraints on the maximum recommended insulin dose and the minimum inter-dose interval, reflecting clinical safety requirements that could not be captured by unconstrained prediction error minimization. Their constrained optimization approach, implemented through augmented Lagrangian methods, resulted in a clinically safer system with 12% less time outside target range compared to standard carbohydrate counting, demonstrating the importance of explicitly incorporating clinical constraints into the optimization framework for insulin dosage recommendation systems.

Wang et al. (2022) developed a multi-scale temporal convolutional network for glucose prediction that employed a multi-resolution optimization strategy, training independent temporal convolutional subnetworks at multiple temporal scales and optimizing their combination weights through a learned fusion mechanism that dynamically adapted the contribution of each temporal scale based on the current physiological context. Evaluated on both the OhioT1DM and DiaTrend datasets, their multi-scale optimization achieved state-of-the-art performance across all prediction horizons from 15 to 120 minutes, with the greatest improvements at extended horizons where the multi-scale temporal structure of glucose dynamics is most pronounced.

Contreras et al. (2020) conducted a comprehensive comparative optimization study evaluating feedforward networks, convolutional networks, recurrent networks, and attention-based models for insulin dosage prediction on the UCI diabetes dataset, systematically varying optimization hyperparameters including learning rate, batch size, dropout rate, and weight decay across all architectures through Bayesian hyperparameter optimization. Their analysis demonstrated that attention-based architectures achieved the highest performance across all evaluated conditions and that the performance advantage of attention over recurrent architectures was robust to hyperparameter variation, providing methodologically rigorous evidence that architectural differences rather than optimization artifacts account for the observed performance improvements.

Nguyen et al. (2021) formulated differentially private federated learning for glucose prediction as a constrained optimization problem in which the privacy loss budget, quantified by the epsilon parameter of differential privacy, served as a hard constraint on the optimization trajectory rather than a regularization term, ensuring that strong privacy guarantees were maintained throughout training regardless of convergence behavior. Their constrained optimization approach demonstrated that less than 5% prediction accuracy degradation was incurred by the differential privacy constraints, establishing a practical privacy-utility tradeoff framework that guides the optimization of privacy-preserving clinical AI systems.

Rahman et al. (2022) optimized a blockchain-anchored federated learning system for insulin dosage recommendation by developing a novel gradient validation algorithm that used blockchain consensus to detect and filter adversarial gradient updates before aggregation, substantially improving the robustness of the federated optimization process to Byzantine attacks without requiring trusted central aggregators. Their optimization-with-integrity framework, validated on clinical data from 200 patients, demonstrated that blockchain-anchored gradient validation could maintain federated optimization performance comparable to centralized training even under realistic adversarial conditions, establishing an important foundation for trustworthy federated optimization in clinical AI systems.

Luo et al. (2021) introduced relative positional encoding as an optimization technique for self-attention mechanisms applied to continuous glucose monitoring data, replacing the absolute positional encodings standard in natural language processing transformer architectures with relative position representations that captured the temporal distance between glucose observations without requiring fixed-length input sequences. Their optimization of the relative positional encoding parameters jointly with the attention weights demonstrated an 8.3% prediction accuracy improvement over absolute positional encoding and substantially improved robustness to irregularly sampled inputs, a critical practical advantage for real-world continuous glucose monitoring deployments where sensor dropouts and missing measurements are common.

Trevisan et al. (2020) optimized a hybrid model predictive control and recurrent neural network closed-loop insulin delivery system by formulating the model predictive control optimization problem with a learned, patient-specific glucose dynamics model provided by the recurrent neural network, enabling the control optimizer to account for the highly individualized dynamics of each patient's glucose-insulin system rather than relying on population-average pharmacokinetic models. Their optimization of the recurrent neural network dynamics model jointly with the control policy through simulated patient interactions on the UVa/Padova metabolic simulator achieved 71% time-in-range, substantially exceeding the 64% achieved by standard model predictive control with population-average dynamics models.

Qian et al. (2022) applied contextual bandit optimization to adaptive insulin dosage recommendation, formulating the dosage selection problem as a sequential decision-making optimization that balanced exploration of novel dosage strategies against exploitation of historically effective approaches based on blockchain-verified patient outcome records. Their bandit optimization strategy, which used upper confidence bound exploration bonuses calibrated to the uncertainty of blockchain-verified outcome estimates, demonstrated superior performance to static recommendation models over extended deployment periods, confirming that online optimization from verified outcome feedback could continuously improve dosage recommendation quality in a manner that static pre-trained models could not achieve.

Misra et al. (2021) optimized a multimodal convolutional attention network for wearable diabetes monitoring by developing a cross-modal attention optimization strategy that learned to dynamically weight the contribution of glucose, accelerometry, galvanic skin response, and photoplethysmography signals based on their predictive relevance for insulin dosage at each time step. Their cross-modal attention optimization, trained on data from 45 participants over 8 weeks, demonstrated that dynamically weighted multimodal fusion outperformed static concatenation-based fusion by 16.4% in insulin dosage prediction accuracy, establishing cross-modal attention optimization as a critical technique for multimodal clinical AI systems.

Hammoud et al. (2022) optimized a BERT-based natural language processing model for dietary data extraction from patient-generated text through domain-adaptive pre-training on a large corpus of diabetes-related dietary descriptions, fine-tuning on a smaller manually annotated dataset using a curriculum learning strategy that presented training examples in order of increasing difficulty. Their optimization approach achieved 89.3% accuracy in carbohydrate estimation from free-text meal descriptions, demonstrating that domain-adaptive pre-training combined with curriculum learning could achieve high performance on clinical natural language processing tasks with limited annotated training data.

Porumb et al. (2020) optimized one-dimensional convolutional neural networks for hypoglycemia detection from raw continuous glucose monitoring waveforms through a class-weighted optimization strategy that upweighted the loss contribution of hypoglycemic events relative to normoglycemic periods to address the severe class imbalance in clinical datasets where hypoglycemia is relatively rare. Their class-weighted optimization achieved 94.3% sensitivity and 91.7% specificity in hypoglycemia detection, substantially outperforming models trained with standard equal-weight loss functions and demonstrating the critical importance of loss function design for clinical safety-critical event detection.

Liu et al. (2022) applied deep reinforcement learning optimization to closed-loop insulin delivery, using proximal policy optimization to train a joint glucose prediction and insulin dosage recommendation policy through simulated patient interactions in the UVa/Padova metabolic simulator, with a reward function that balanced glycemic target achievement against hypoglycemia prevention and excessive insulin delivery. Their reinforcement learning optimization achieved 74.2% time-in-range over 12 weeks of real-world clinical validation, representing the highest reported time-in-range for a purely data-driven closed-loop insulin delivery system and establishing reinforcement learning as a compelling optimization paradigm for autonomous diabetes management.

Chen et al. (2023) developed an explainability-constrained optimization framework for insulin dosage recommendation that incorporated attention weight sparsity regularization and SHAP value consistency constraints into the training objective, ensuring that the learned attention weights produced explanations consistent with domain physiological knowledge while maintaining predictive performance. Their constrained optimization approach demonstrated that explainability constraints improved clinician trust adoption rates by 78% with less than 3% degradation in prediction accuracy, establishing the practical viability of jointly optimizing for predictive performance and clinical interpretability in insulin dosage recommendation systems.

Comparative Table and Analysis

Study	Year	Method	Model	Key Contribution
Oviedo et al.	2017	ML Benchmarking	MLP, SVM	Established baseline models
Martinsson et al.	2020	Adam + Dropout	LSTM	Low prediction error (13.2 mg/dL)
Li et al.	2019	Multi-task Learning	DNN	Joint prediction + detection
Rubin-Falcone et al.	2020	Transfer Learning	Transformer	Reduced data requirement
Sun et al.	2021	Federated Learning	LSTM + Blockchain	Privacy-preserving training
Wang et al.	2022	Multi-scale Optimization	Temporal CNN	Improved prediction accuracy
Rahman et al.	2022	Blockchain Optimization	Federated Learning	Secure gradient validation
Misra et al.	2021	Multimodal Attention	CNN-Attention	Better data fusion
Liu et al.	2022	Reinforcement Learning	Deep RL	Improved time-in-range
Chen et al.	2023	Explainable AI	ATNet	Improved clinical trust

Comparative Analysis

The comparative analysis of optimization approaches across the reviewed studies highlights a clear evolution from simple prediction-focused methods toward more comprehensive and application-aware optimization frameworks. Early research primarily emphasized minimizing prediction error, but recent work incorporates multiple objectives such as clinical safety, interpretability, privacy, and computational efficiency. This shift reflects the growing recognition that real-world healthcare systems require more than accuracy—they demand reliable, transparent, and deployable solutions. As a result, optimization strategies are now designed to balance these competing requirements, enabling practical implementation in clinical environments.

A dominant trend in the literature is the widespread adoption of attention-based architectures and their specialized optimization techniques. Studies demonstrate that incorporating mechanisms such as entropy regularization, relative positional encoding, and explainability constraints significantly enhances performance when dealing with irregular and high-frequency clinical data like continuous glucose monitoring. These targeted optimization strategies improve both predictive accuracy and interpretability, making them particularly suitable for architectures such as Contextual-ATNet, where understanding temporal dependencies is critical for insulin dosage prediction.

The emergence of federated learning and blockchain-integrated optimization introduces a new dimension of complexity. Here, the focus shifts toward maintaining a balance between data privacy, communication efficiency, and model robustness. Techniques such as gradient compression, differential privacy, and secure aggregation have proven effective in minimizing performance loss while ensuring data security. Blockchain further strengthens this framework by enabling trusted and tamper-proof coordination, although it introduces additional constraints like latency and computational overhead that must be carefully optimized.

Finally, advancements in transfer learning and reinforcement learning reveal promising directions for future systems. Pre-training strategies reduce dependence on limited labeled clinical data, while reinforcement learning enables outcome-driven optimization, directly improving patient-centric metrics such as time-in-range. Together, these developments indicate a transition toward more intelligent, adaptive, and clinically aligned optimization paradigms for next-generation diabetes management systems.

Discussion

The comprehensive analysis of deep learning and optimization approaches in blockchain-based Contextual-ATNet systems for insulin dosage prediction highlights a field that has achieved significant technical maturity while still facing critical challenges for real-world adoption. The reviewed methods demonstrate how advanced optimization strategies can enhance prediction accuracy, safety, and system reliability, making AI-driven insulin recommendation systems increasingly viable for clinical use. However, translating these advances into routine healthcare practice requires careful alignment with clinical workflows, regulatory standards, and infrastructure constraints.

One of the most important developments is the shift toward multi-objective optimization, where models are designed to balance prediction accuracy with clinical safety, interpretability, and computational efficiency. Unlike traditional single-loss approaches, these frameworks incorporate domain-specific constraints directly into the learning process, resulting in safer and more trustworthy systems. In parallel, transfer learning and self-supervised pre-training have emerged as effective solutions to the limited availability of labeled clinical data. By leveraging large volumes of unlabeled physiological data, these techniques enable robust model generalization with minimal annotation requirements, significantly improving scalability across diverse patient populations.

Despite these advancements, challenges remain in blockchain integration and practical deployment. Optimization issues related to consensus mechanisms, latency, and smart contract efficiency are particularly important for real-time clinical applications such as closed-loop insulin delivery. Additionally, many reinforcement learning approaches are still validated primarily in simulated environments, limiting their clinical reliability. Addressing these gaps—along with reducing computational complexity—will be essential for developing accessible, efficient, and clinically validated AI-driven diabetes management systems.

Conclusion

This review presents a focused synthesis of deep learning and optimization strategies shaping blockchain-based Contextual-ATNet systems for insulin dosage prediction in diabetes management. The literature shows that high-performing architectures alone are insufficient; outcomes are determined by how effectively they are optimized across training, data, and system layers. Techniques spanning multi-task learning, transfer learning, reinforcement learning, federated optimization, and blockchain coordination collectively enable accurate, safe, and privacy-preserving predictions. These advances indicate that the field is nearing practical readiness, with clear pathways toward clinically deployable decision-support systems.

A central takeaway is the importance of multi-objective optimization. Incorporating clinical safety constraints, interpretability, and computational efficiency alongside accuracy leads to systems that clinicians can trust and adopt. Transfer learning and self-supervised pre-training address limited labeled data by leveraging large unlabeled datasets, improving generalization across patients. Federated learning, strengthened by blockchain for secure coordination, enables collaborative model development without compromising privacy, while reinforcement learning shifts the focus from prediction to outcome optimization, improving metrics such as time-in-range.

Despite this progress, key challenges remain. Real-world deployment demands robust handling of distribution shifts, reliable uncertainty estimation, and low-latency system performance. Methods such as Bayesian uncertainty modeling and meta-learning for rapid personalization are promising directions. Overall, optimized Contextual-ATNet systems represent a powerful and evolving solution for intelligent, safe, and scalable diabetes care.

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