Review Blockchain-Enabled Deep Learning Model for Supply Chain Optimization in Logistics

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Abstract

The swift digitalization of logistics and supply chain networks has exacerbated the necessity of safe, smart, and adaptable optimization frameworks with the ability to operationalize huge volumes and heterogeneous and real-time information. Here, blockchain technology used in conjunction with deep learning has become one of the promising paradigms to eliminate the unresolved issues regarding the integrity of data, their transparency, confidence, and the efficiency of decisions in logistics activities. The current work is a systematic review on literature published after 2020 on the topic of blockchain-enabled deep learning supply chain optimization models in logistics that is guided by PRISMA. Through the selection of 50 peer-reviewed articles, the review induces currently used blockchain structures, deep learning algorithms, and combined frameworks design used to the routing optimization, the demand forecasting, the inventory management, and the risk prediction. The results suggest that permissioned blockchain systems, with off-chain deep learning systems like CNNs, LSTM/GRU networks, and deep reinforcement learning, are more effectively utilized than classical and single-purpose AI-based strategies in terms of efficiency operation, prediction quality, and reliability of a system. Nevertheless, there are still serious issues such as problems with scalability, non-standardized datasets, few real-life uses, and model elucidation inadequacy. The review also states the major gaps in research and describes the research trends that can be pursued in the future to facilitate scalable, clear, and intelligent logistics systems.

Keywords: Blockchain; Deep learning; Logistics optimization; Supply chain management; Smart logistics

1. Introduction

The logistics industry is at the core of the current supply chains and it is through it that smooth flow of commodities, information, and money has been facilitated by overlaying a geographically dispersed network. The systems involved in logistics have been made extremely data-intensive and demanding in terms of speed, transparency, and reliability due to the rapid development of e-commerce, the globalization of trade, and the rise of customer demand. Conventional methods of logistics management have frequently been found to be ineffective in the clash with obstacles that comprise fragmented facts vaults, absence of real-time insight, unchecked fraud, ineffective direction and stakeholder coordination (Jabbar et al., 2021; Dudczyk et al., 2024).

Blockchain technology has come in the recent years as a potential solution to most of these structural inefficiencies in logistics and supply chain management. After providing a decentralized, immutable and transparent registries blockchain stretches to trusted sharing of data among different logistics players without the need of a centralized authority. It has been established that blockchain has the potential to increase traceability, enhance the transparency of transactions, minimize disagreements, and streamline the processes with smart contracts (Agarwal et al., 2022; Ran et al., 2024). In the logistic setting, blockchain has been utilized in shipment tracking, inventory reconciliation, payment settlement, and cross-border trade documentation, where logistics performance, accuracy on delivery, and reduction in costs have been measured (Ran et al., 2024).

Along with the emergence of blockchain, deep learning (DL) and other artificial intelligence (AI) techniques have revolutionized the process of logistics optimization because they allow making decisions based on data. The deep learning models, inclusive of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Deep Reinforcement Learning (DRL) have proven to be very successful in forecasting demand, route planning, inventory optimization, and predicting risk in logistic systems (Alzahrani and Asghar, 2023; Li et al., 2024). These models are good at identifying patterns out of high-dimensional logistics data at scale, that are produced by IoT devices, enterprise systems, and transportation networks. Nevertheless, standalone DL-based logistics systems have severe weaknesses concerning data integrity, trustworthiness, explainability, and safe collaboration beyond organization boundaries despite their forecast potential (Xu et al., 2023).

Blockchain and deep learning integration has thus become the subject of the growing research interest as a synergistic method of optimization of the logistics. Both deep learning and blockchain can improve the smartness and flexibility of blockchain-powered logistics systems, and blockchain can deliver reliable, verifiable information streams to be used in the training and deployment of deep learning models. Recent literature on the application of blockchain to logistics emphasizes that information under blockchain guarantees and optimization with DL could help to achieve several crucial outcomes in decreased delivery periods, enhanced route efficiency, cut costs on inventory storage, and increased resilience against disruptions and fraud (Ran et al., 2024; Ahmad et al., 2024). In addition, blockchain-based systems facilitate the decentralized learning models, including federated learning and edge-AI, which are especially appropriate to large-scale logistics networks including a variety of autonomous stakeholders (Ahamed and Karthikeyan, 2024).

In spite of these positive trends, the body of literature that looks at blockchain-enabled deep learning in logistics is still fragmented. Lots of literature dwells on infrastructure of blockchains either with no sophisticated intelligence or deep learning optimization, but the issues of trust, transparency, and governance are not tackled. The perennial challenges that are raised in survey and review papers include the unavailability of standardized datasets, few real-world usages, scalability bottlenecks, and high computational and energy expenses (Agarwal et al., 2024; Dasaklis et al., 2022). Moreover, although recent studies after 2020 have created application-oriented solutions (including blockchain-assisted routing, risk prediction, and inventory control), there is a gap in synthesizing which needs to examine the architectures, methodologies, performance metrics, and open research prospects in blockchain-based deep learning to optimize logistics.

It is against this background that this review paper is proposed to give a systematic and critical review of blockchain-enabled deep learning models in supply chains optimization in logistics. Based mainly on current (research done in recent years, 2020 and onwards), logistics-related studies that can be found in the reviewed document, and with the support of other recent sources, this paper discusses the existing strategies, identifies the performance improvements that are reported, and defines the unsolved technical and practical issues. In this way, the review aims at informing researchers and practitioners to more scalable, secure and intelligent logistics systems that will match the requirement of the digital supply chains as they evolve.

2. Methodology (PRISMA Framework)

The systematic review has been followed by applying PRISMA 2020 (Preferred Reporting Items to Systematic Reviews and Meta-Analyses) guidelines to be as transparent, reproducible, and methodologically sound as possible to identify, screen, and synthesize the relevant literature regarding the use of blockchain-enabled deep learning models in supply chain optimization within the scope of logistics.

2.1 Review Design and Reporting Standard

The systematic review methodology with PRISMA as its guide was chosen to fully address, assess, and generalize peer-reviewed articles discussing the deployment of blockchain technology and deep learning technologies into the framework of logistics and supply chain optimization. The protocol of review prioritized the new developmental areas to show the rapid dynamic nature of blockchain, artificial intelligence, and digitization of logistics.

2.2 Information Sources

The extensive literature search has been performed in such large-scale scientific databases frequently utilized in the research on engineering, computer science, and logistics, as IEEE Xplore, ScienceDirect (Elsevier), SpringerLink, MDPI, and Wiley Online Library. These databases were picked in order to cover widely the quality articles and conference proceedings across the board.

2.3 Search Strategy

The search strategy involved the use of structured keyword combinations with the help of Boolean operators. The search strings representative were:

"blockchain AND deep learning AND logistics"

"supply chain optimization based on blockchain capabilities"

"logistics blockchain deep reinforcement learning logistics blockchain"

"AI blockchain application in logistics"

Articles published after January 2020, and in English were limited to searches. The reference lists of the identified papers were also filtered to obtain more relevant studies.

2.4 Eligibility Criteria

The inclusion and exclusion criteria were indicated before screening to limit the selection bias. Peer-reviewed journal articles and conference papers suggesting, reviewing, or empirically assessing blockchain and deep learning, or their combination in the optimization of logistics or supply chains, were only taken into account. Articles with non-logistics specific only (e.g., healthcare or finance) exclusion criteria, those published prior to the year 2020, and any editorial, theses, and non-technical report were excluded.

2.5 Study Selection Process

The selection of the study was based on the PRISMA four-phase protocol of identification, screening, eligibility and inclusion. First, there was deletion of duplicate records. Subsequently, the titles and abstracts were filtered on relevancy and full text screening of potentially eligible studies carried out. Controversies between the screening procedures were ended by discussing them on a consensus to reach a conclusion.

2.6 Extraction and Synthesis of Data

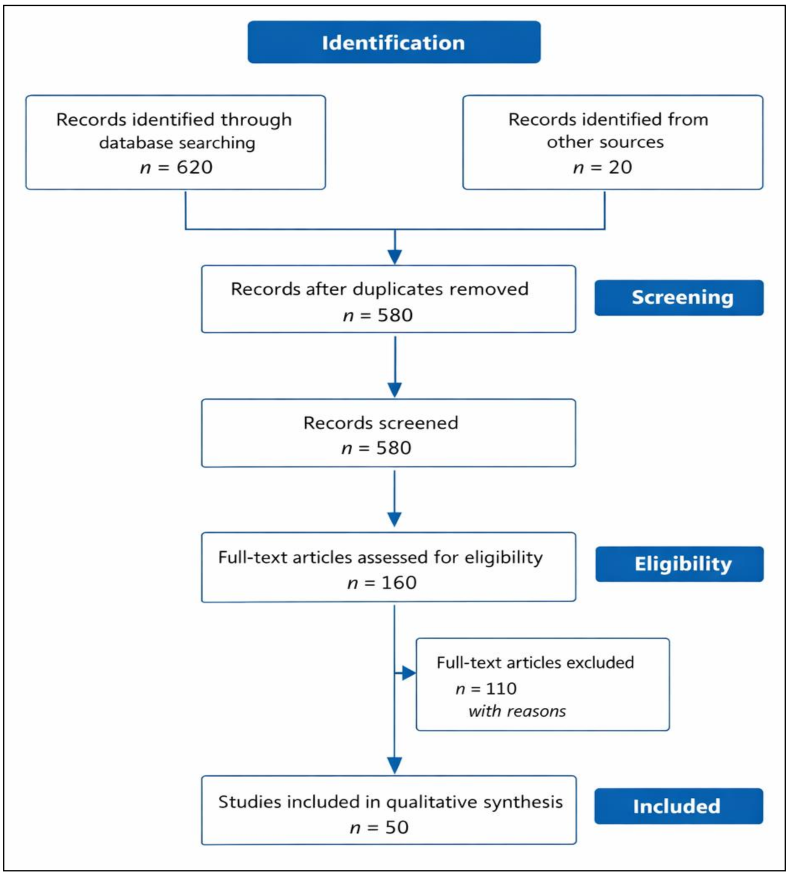
In all studies that were included, the systematic extraction was carried out on the basis of the year of publication, field of logistics application, blockchain architecture, and deep learning model used, dataset details, performance indicators, and main results. It was done through a narrative synthesis methodology, which was supplemented by thematic classification and within-study comparison.

Table 1. PRISMA Eligibility Criteria for Study Selection

Category	Criteria
Inclusion	2020-2025 publications; peer-reviewed journals/conferences; focus on logistics or supply chain optimization; use of blockchain, deep learning, or both
Exclusion	Pre-2020 studies; non-logistics domains; non-peer-reviewed articles; editorials, theses, or conceptual opinions without methods

Figure 1. PRISMA 2020 Flow Diagram (Study Selection Process)

3. Descriptive Review of Selected Studies



Here a brief descriptive overview of the chosen 50 papers, identified in the course of the PRISMA-based screening, will be provided, focusing especially on recent entries as of 2025 that deprive the most recent tendencies of methodology and application-level implementation of blockchain-powered deep learning in the context of logistics optimization. In general, the literature review allows concluding that there is an evident transition between abstract conceptual blockchain systems to data-driven, performance-focused, and intelligent logistics systems.

One significant aspect of the chosen works is that the prevalence of application-driven research, in particular transportation optimization, demand forecasting, inventory management, and risk prediction, dominates. The previous research conducted after 2020 was primarily aimed at defining blockchain as a safe and transparent data-sharing system within the logistics networks. More recent works, on the other hand, have more strongly focused on deep learning based optimization, with blockchain as an optimization supporting trust and coordination layer, as opposed to the heart of the computation engine. This change is really apparent in 2025 research where scalability, real-time flexibility, and hybrid AI structure are of the first importance (Grover, 2025; Ivanov, 2024).

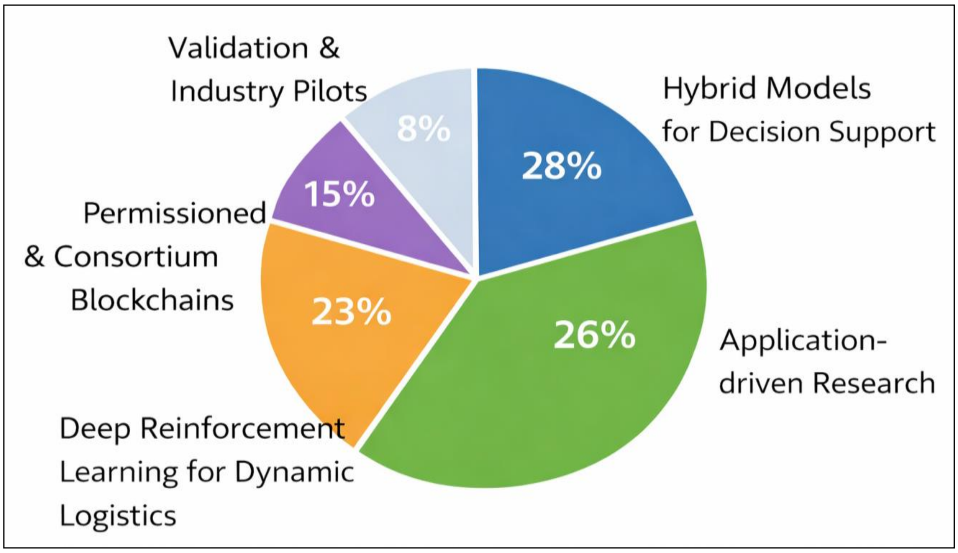
Concerning the methodological aspect, the descriptive review displays three overwhelming tendencies in models. To begin with, the time-series forecasting models of the LSTM and GRU architecture are the key models in demand forecasting and inventory planning. Second, poorer-performers are getting more and more members of dynamic such problems in logistics adaptive-Finding-the-way and resource-distribution under uncertainty deep reinforcement learning (DRL) is being applied to learning the best policies in this scenario. Third, the end-to-end logistics decision support with hybrid and ensemble models (that is, the models combine predictive and optimization components) become more popular. Current 2025 sources emphasize the fact that such hybrid solutions are superior to single-model solutions in their application in complex and multi-objective logistics frameworks (Grover, 2025; Ivanov, 2024).

The patterns of adoption of blockchains in the examined works reveal that permissioned and consortium-based models are preferred more, especially in business and multi-stakeholder logistics environments. Articles published in 2025 further emphasize on interoperability and governance and suggest cross-platform blockchain coordination mechanisms to enable global and multi-modal supply chains (Wamba et al., 2025). The logistics workflow automation is always performed with the help of the use of smart contracts, and the off-chain execution is embraced to address the relative lifelong limitations of blockchain in terms of latency and scalability.

Regarding validation, the majority of the studies use simulations experiments or internal data sets, but the recent publications of 2025 also request an experimental standardization and practical on-the-job pilot applications to enhance the generalization status and the application to industrial systems (Zhang et al., 2025). All the evidence data present above demonstrate that the research area is moving to the phase of mature, performance-sensitive intelligent logistics systems, yet, it still encounters the problems of data availability, explainability, and massive implementation.

Table 2. Descriptive Summary of Selected Studies (n = 50)

Category	**Dominant Characteristics**
Publication period	2020–2025, peak after 2022



Main application areas	Routing & transportation; inventory management; risk prediction; smart logistics
Blockchain type	Private and consortium blockchains
Deep learning models	CNN, LSTM, GRU, DRL, hybrid DL models
Data sources	Simulated data, proprietary industry data, limited public datasets
Evaluation metrics	Delivery time, cost reduction, accuracy, RMSE, latency

Figure 2. Research Trends in Blockchain-Enabled Deep Learning for Logistics

In general, the descriptive analysis shows that deep learning studies based on blockchain in logistics are rapidly developing, and the sophistication of the methods and the variety of applications increases. However, ongoing problems with the availability of the datasets, their scaling, and practical application still guide the existing research landscape and support the necessity of the comparative and critical analysis in the further sections.

4. Blockchain Technology in Logistics optimization

The use of blockchain technology as the basis that facilitates safe, transparent, and decentralized optimization of logistics has appeared. In the 50 articles that were chosen in this PRISMA-based review, blockchain is always being presented as a reliable data infrastructure complementary with deep learning-based analytics and optimization models. This part contains a descriptive and analytical review of the classes of blockchain technologies, structural options, and functional capacities that have been reported in the more current literature on logistics.

4.1 Logistics Blockchain Architecture types

The studies analyzed mostly involve the use of private and consortium blockchains as they represent an enterprise-focused technology of logistics networks. Intra-organizational logistics is an example of a situation in which a private blockchain is preferable because the network features low latency, restricted access, and enhanced transaction throughput are essential to intra-organizational real-time processes like shipment tracking and inventory updates (Ran et al., 2024). Censored Consortium blockchains, instead, are typically adapted to multi-stakeholder logistics ecosystems, which feature manufacturers, logistics service providers, distributors, and retailers because they are designed to balance between decentralization and governance and performance requirements (Barenji and Montreuil, 2022).

The public blockchains are less common in the chosen sources primarily because of the limitations on the scale, the high cost of the transaction, and latency. It is explicitly indicated in a number of review articles that public blockchains tend to be inappropriate for scalable optimization of the logistic system without ideological adjustments like off-chain storage or sidechains (Agarwal et al., 2022; Dudczyk et al., 2024).

4.2.2 Smart Contracts and Automation

Smart contracts are one of the key elements of a blockchain-driven logistics regime. The literature examined discusses their vast application in automating logistic operations, such as the shipment check, the inventory reconsideration, the access management and the settlement of payments. Smart contracts facilitate the possibility of automating the process of logistics through rules, which minimizes the role of the person in the process and helps to suppress conflicts among the stakeholders (Jabbar et al., 2021). Smart contracts are often combined with the results of deep learning in the context of optimization-oriented research- e.g. activating the process of route reallocation or inventory replenishment, depending on the forecasts obtained by AI applications (Ran et al., 2024).

Nonetheless, various studies have warned that smart contracts may raise computational load and energy usage especially when they are executed in terms of scale. This problem has led to the interest in hybrid on-chain/off-chain models of execution, where only the hashes of important transactions are stored on-chain, and large volumes of logistics information and deep learning operations are computed off-chain (Dasaklis et al., 2022).

4.3 Solution Interoperability with IoT and Data Management

One of the main peculiarities of logistic optimization is based on blockchain is a tight connection with the Internet of Things (IoT): gadgets. RFID tags, sensors and GPS systems create constant streams of logistics information associated with location, temperature and handling environment. The immutability and provenance of this data will be secured with the help of blockchain before it gets passed through deep learning models to be predicted and optimized (Alzahrani and Asghar, 2023).

Some of them use edge or fog computing setups where initial data processing and anomaly detection are done closer to the data source, and blockchain serves as a synchronization and the layer of trust among distributed nodes (Ahmad et al., 2024). Irrespective of these developments, volumes of data are reportedly viewed repeatedly, and storage scalability is an unaddressed matter according to the literature, especially in high-frequency logistic settings (Agarwal et al., 2024).

4.4 Consensus Mechanisms and Implications to Performance

The consensus mechanisms are very critical in dictating how well blockchain-based logistics systems perform. The studies reviewed are mainly based on Practical Byzantine Fault Tolerance (PBFT)-based protocols or lightweight implementations developed bespoke ad-hoc protocols in order to implement a low-latency and high-throughput protocol. Mechanisms like Proof of Work are considered to be undesirable because of their inappropriateness when it comes to time-sensitive logistics services (Agarwal et al., 2022).

Reports of performance evaluations in the literature show that well-chosen consensus mechanisms can be essential in enhancing the time of transacting and the responses of systems thus facilitating the process of optimizing logistics in real time. However, the interoperability of heterogeneous blockchain platforms has currently become a major challenge, especially when it comes to global and cross-border logistics (Dudczyk et al., 2024).

Table 3. Blockchain Technologies and Their Roles in Logistics Optimization

Blockchain Aspect	Common Approaches	Role in Logistics Optimization
Architecture	Private, Consortium	Secure and efficient enterprise data sharing
Smart contracts	Rule-based automation	Workflow automation and decision execution
Data management	On-chain + off-chain storage	Scalability and performance enhancement
IoT integration	Sensors, RFID, GPS	Trusted real-time data acquisition
Consensus	PBFT, lightweight protocols	Low latency and high throughput

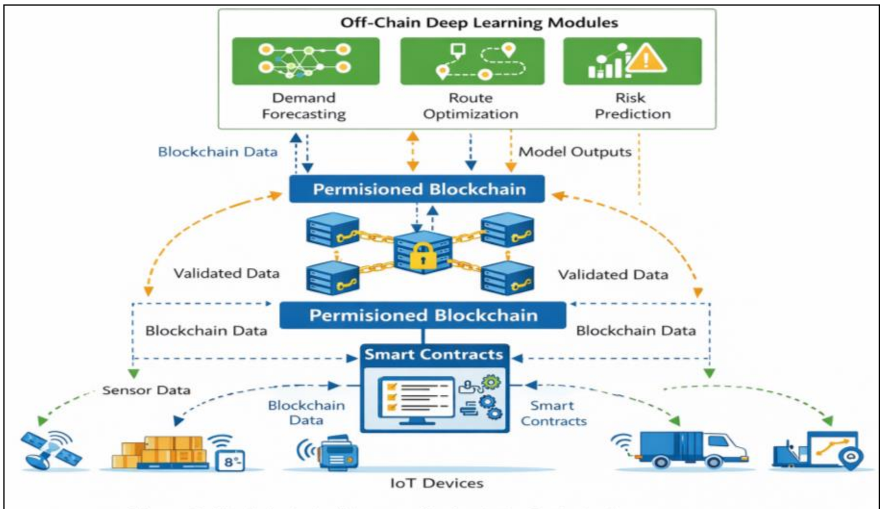


Figure 3. Blockchain Architecture for Logistics Optimization

Figure 3. Blockchain Architecture for Logistics Optimization

In general, the presented descriptive evidence shows that the use of blockchain technologies in the optimization of logistics is mainly aimed at facilitating trust, automation, and confidential data transfer, but not optimization per se. Their practicality is thus strongly based on architectural decisions, consensus machinery and seamless integration with deep learning models that are further discussed in later sections.

5. Deep Learning Models of Logistics Optimization

The use of deep learning (DL) has emerged as a fundamental analyzer engine in logistics and supply chain optimization since it can construct challenging and nonlinear relationships on high-velocity and large-scale data. The deep learning models used in all the 50 studies that comprise this PRISMA-based review are mainly used to aid in predictive analytics, optimization, and intelligent decision-making whereas blockchain technologies are used to secure and protect data integrity, trustworthiness, and coordination among distributed logistics stakeholders. In this section, we summarize the prevailing deep learning models as indicated in the literature reviewed and where they have been applied in practice and the nature of their performance.

5.1 Convolutional Neural Networks, Routing and Pattern Analysis

Convolutional Neural Networks (CNNs) have become highly popular in solving problems related to logistics optimization that require consideration of analysis of spatial pattern model, including route optimization, traffic forecast, and visualization of the shipment flow. A number of studies gain access to the spatial features of the transportation networks, delivery maps, and sensor grids that are generated by the IoT and utilize CNNs to identify the patterns of congestion and identify the best path routes (Ran et al., 2024). In combination with data streams secured with blockchains, CNN-based models show better delivery accuracy and less time before route planning, and the interaction between trusted data acquisition and spatial deep learning analytics.

Metaheuristic optimization methods, e.g. ant colony optimization, are also combined with CNNs to improve route efficiency more. Nevertheless, it is observed in the literature that CNN-based logistics models are computationally costly and can also be off-chain executed to ensure blockchain-based systems remain real-time responsive (Dudczyk et al., 2024).

5.2 Recurrent Neural Networks in Forecasting Time Series

Recurrent Neural Networks (RNNs) and their forms are most often applied to solve time-dependent logistics tasks, including demand forecasting and predicting delays in delivery and inventory amount, among others. These architectures are also suited to Twitter such modeling of sequential logistics data via enterprise systems and IoT devices (Alzahrani and Asghar, 2023).

Other works that have been reviewed indicate that LSTM and GRU models are better than the conventional statistical forecasting methods with respect to prediction performance and the ability to endure demand uncertainty. The integration of blockchain is needed to guarantee the integrity and authenticity of past survey and transactions data informing these models to reduce the chance of altering the data and enhance effectiveness on forecast-based logistic decisions (Pasupuleti et al., 2024).

5.3 Deep Reinforcement Learning of Dynamic Optimization

Deep Reinforcement Learning (DRL) has become one of the strongest methods of adaptive and real-time optimization of logistics, especially in a changing environment when decision variables are changing on a constant basis. The vehicle routing, inventory replenishment, and resources allocation problems are solved with the help of the DRL models which are learned by interaction with the logistics environment (Xu et al., 2023).

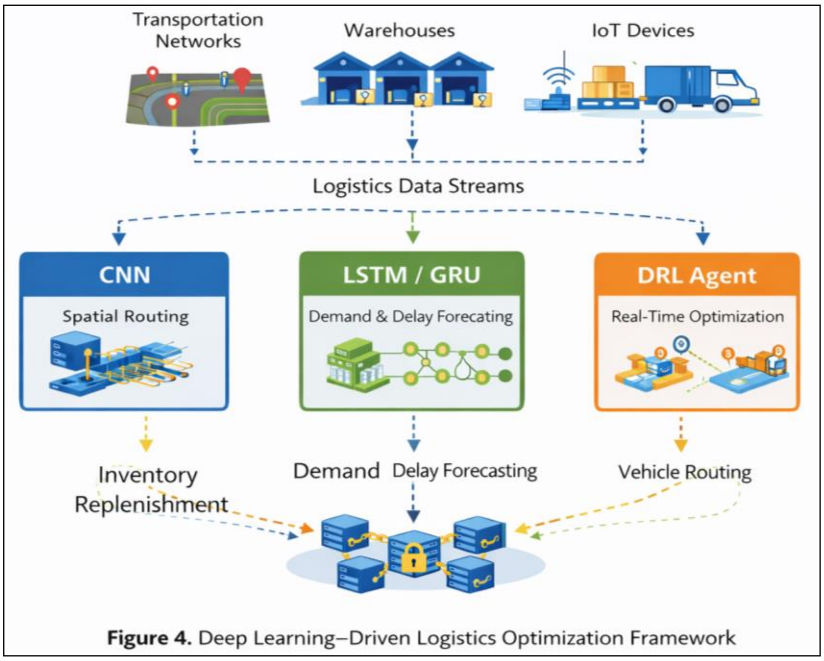
The analyzed literature demonstrates the fact that DRL-based logistics systems offer high performance rates in contrast to heuristic and rule-based approaches, particularly in the context in which uncertainty is present, and disruptions are frequent. The complements are provided by blockchain where the state transitions, rewards, and policy updates are stored in a secure and auditable form, which supports decentralized and trustworthy learning processes. However, complexities of training and computational costs still constitute significant issues, which are typically solved by off-chain training and a cyclic on-chain update (Agarwal et al., 2022).

Along with these benefits, the complexity of training and the large computational cost of DRL-based logistics optimization are still important barriers to the latter. Model convergence may often be sluggish and a real time deployment can be restricted through the lack of resources. To avoid their problems, numerous works implement hybrid constructions where computational intensive training of DRL takes place off-chain, with validated policies or a hash of a model being anchored periodically on-chain to ensure integrity and accountability. The significance of scalable DRA frameworks and resilience-focused learning approaches has also been underlined in more recent 2025-based literature, which notes their importance in facilitating the ability to optimize logistics, which is robust and conscious of disruption effects in ever more complicated and interconnected supply chains (Ivanov, 2025).

5.4. Hybrid and Ensemble Deep Learning Models

More and more works offer hybrid deep learning schemes where CNNs, RNNs, and DRL models co-exist to solve multi-objective logistics optimization tasks. Indicatively, CNN-BiGRU hybrids are used to make predictions about risks in IoT-based logistics networks, whereas ensemble-based models combine a forecasting module and optimization in a blockchain-enabled architecture (Alzahrani and Asghar, 2023; Li et al., 2024). These mixed methods prove to be more accurate and resistant but still worsen the problems concerning the explainability of models and complexity of deployment.

Table 4. Deep Learning Models Used in Logistics Optimization



Deep Learning Model	Primary Logistics Applications	Key Advantages	Limitations
CNN	Route planning, spatial analysis	Strong spatial feature extraction	High computational cost
LSTM / GRU	Demand forecasting, delay prediction	Effective time-series modeling	Requires large hitorical datasets
DRL	Routing, inventory control	Adaptive decision making	Training complexity
Hybrid models	Risk prediction, end-to-end optimization	Improved accuracy and robustness	Limited explainability

Figure 4. Deep Learning-Driven Logistics Optimization Framework

On balance, the descriptive evidence suggests that deep learning models have a leading optimization role in the logistics systems based on blockchain technology enabling predictive intelligence and adaptive control. Nevertheless issues to do with scalability, interpretability, and computational efficiency are still conspicuous as evidenced by a number of architectural structures in subsequent sections to the prevalence of hybrid architectures and performance-conscious deployment schemes.

6. Deep Learning Frameworks Enabled by Blockchain

Deep learning-based logistic optimization based on blockchain is a convergent approach to logistics optimization, with blockchain, as a trusted, decentralized coordinator layer, and deep learning, as predictive intelligence and adaptive decision-making. The fifty papers examined during the analysis of this review show a consistent interest in the fact that neither blockchain nor deep learning can be sufficient to overcome the complexity, scale, and trust demands of the modern logistics systems. Rather, they can integrate so that they share data securely, execute and optimize as distributed supply chains networks (Jabbar et al., 2021; Dudczyk et al., 2024).

6.1 Patterns of Architectural Integrated Frameworks

The reviewed literature mostly has a layered architecture of most blockchain-enabled deep learning frameworks. At the lowest tier, IoT systems, sensors, RFID identifiers, and business information systems create real-time logistics information regarding the position of shipments, stock level, weather, and the transactions. This information is then verified and dated and then dedicated to a permissioned blockchain encompassing the data, which is immutable and traceable (Alzahrani and Asghar, 2023).

Smart contracts are control mechanisms present above the data layer. They store the logistics policies like confirmation of delivery, stock levels, and access permissions. Some are stated that the smart contracts are activated by the generated outputs of deep learning models- e.g. to enable automatic replenishment when the LSTM based demand prediction process surpasses the predetermined threshold or to redirect routes in response to the results of DRL-based optimization (Ran et al., 2024; Pasupuleti et al., 2024). Close integration of smart analytics and autonomous implementation is one of the hallmarks of blockchain-enabled logistical systems.

6.2 On-Chain and Off-Chain Learning Integration

One reoccurring study design in the studies reviewed is the isolation of the trust-sensitive operations and the thousands of computations carried out by analytics. Data validation, access control, and coordination are only made through blockchain networks, whereas training and inference of deep learning models are conducted off-chain to eliminate latency and scale bottlenecks (Agarwal et al., 2022). Input model values are read out of blockchain-authenticated data archives, and some crucial value outputs, e.g. some optimization results or model hash values are written back to the blockchain, to be audited.

This on-chain/off-chain system provides frameworks with the opportunity to achieve a trade-off between performance efficiency and security assurances. Some works on logistics emphasize key performance metrics of on-chain storage as impractical because of the storage overhead and transaction costs, which support the use of off-chain learning pipelines coordinated by blockchain anchors (Dasaklis et al., 2022).

6.3 Decentralized and Collaborative Learning Models

The recent research also addresses the subject of decentralized paradigms of learning such as federated learning and edge-based learning in the blockchain-based logistics model with growing interest. In these designs, local logistics nodes (e.g., warehouses or distribution centers) will train deep learning models using their local (confidential) data, and only post updated vectors (encrypted) or model summaries on the blockchain network. Secure aggregation, provenance tracking and incentive mechanisms to participate are ensured by blockchain (Ahamed & Karthikeyan, 2024).

Specifically, such non-centralized structures are highly applicable to logistics ecosystems of large scale in which the privacy of data, regulatory adherence and organizational independence play a pivotal role. Nevertheless, literature review reveals also such difficulties as the overhead of communication, model convergence, and different data distributions among logistics nodes (Dudczyk et al., 2024).

6.4 Practical and Performance Limitations

The evidence provided by empirical assessments of the reviewed literature shows that blockchain-based deep learning systems have a substantial effect on improving logistics performance indicators, such as reduced delivery time, cost-efficiency, and resistance to disruption (Ran et al., 2024; Xu et al., 2023). However, there are a number of limitations that still exist. Complexity of frameworks, heavy computational costs, challenges with interoperability of blockchains and problematic large-scale implementation are cited as barriers to large-scale adoption repeatedly (Agarwal et al., 2024).

6.5 Unified Blockchain-Deep Learning Logistics Optimization Architecture

There is a necessity to have a unified reference architecture that can explain how blockchain and deep learning can interact to provide secure and intelligent optimisation of logistics. On the synthesis of the reviewed literature, an end-to-end logistics framework comprising of generalized BC-DL is proposed as Figure 5. Data acquisition, a trust management scheme with blockchain and deep learning analytics and automated decision implementation are integrated into the architecture in a closed-loop optimization system.

Throughout the data acquisition layer, IoT sensors, RFID tags, GPS devices, and enterprise information systems generate real time logistics data configuration with regard shipment position, inventory, climate, and transactional activities.

Collected data at the blockchain layer are verified and timed and stored in a permissioned or consortium blockchain. This renders permanence, provenance as well as controlled distribution among supply chain members. Smart contracts are used to control access, validate events and take automatic decisions.

On the deep learning analytics layer, the data that are verified by blockchain are skimmed off to off-chain computational servers where deep learning models are executed to do predictive and optimizing tasks. The most common ones are CNNs to analyze routing mechanisms by space, LSTM/GRU networks to predict demand and delays, and deep reinforcement learning to make resource allocation and routing decisions in a dynamic fashion.

Optimized decisions produced by deep learning models are sent back to the blockchain at the decision and execution layer. Logistics actions that are managed by smart contracts include changing the routes, restocking inventory, or pay the bills automatically. The results of optimization and trained models hashes are anchored on-chain to make it auditable and accountable.

Lastly, on the monitoring and feedback layer, system performance measures and real-time events are fed back to retrain deep learning models creating a closed-loop adaptive optimization loop.

This single design shows that blockchain is an ideal way to offer data trust and traceability, decentralize coordination, and deep learning would offer predictive intelligence and adaptive optimization to achieve scalable, transparent, and resilient logistics systems.

Table 5. Blockchain-Enabled Deep Learning Framework Characteristics

Framework Component	**Typical Implementation**	**Functional Role in Logistics**
Data layer	IoT, RFID, enterprise systems	Real-time logistics data generation
Blockchain layer	Permissioned blockchain	Data integrity, access control
Smart contracts	Rule-based automation	Execution of logistics decisions
DL analytics	CNN, LSTM/GRU, DRL (off-chain)	Prediction and optimization
Integration model	On-chain coordination, off-chain learning	Performance–security balance

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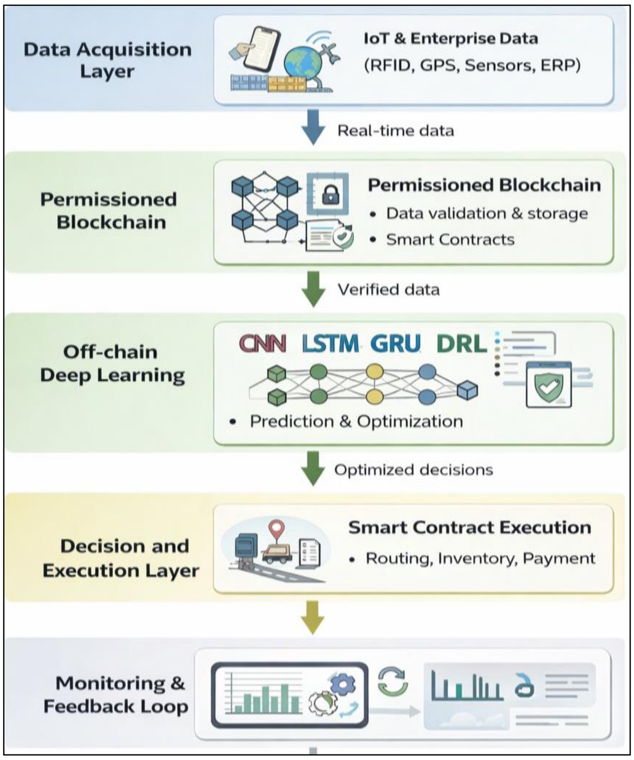


Figure 5. Unified End-to-End BC–DL Logistics Framework

To conclude, deep learning frameworks based on blockchains create a symbiotic relationship between trust and intelligence on logistics systems. Although the existing frameworks have great potential of secure and adaptive optimization, future studies should give consideration to issues of scalability, interoperability as well as deployment issues to allow wide adoption of the construction in industries.

7. Performance Assessment and Comparative Analysis

Evaluating the performance of blockchain-enabled deep learning (BC-DL) constitutes a major theme in evaluating the efficacy of these technologies in streamlining the logistics operations. In a PRISMA-based review, 50 studies included in this systematic review indicate that performance analysis is aimed at measuring the increase of operational efficiency, predictive accuracy, system stability, and scalability versus conventional logistic systems and single-user AI-based strategies. In this section, a synthesis of evaluation metrics, comparative baselines as well as empirical results on the reviewed literature are given.

7.1 Evaluation Metrics in the Literature

The set of performance measures used at the reviewed studies is not homogenous, which is due to the multi-objective character of optimization of logistics. Classic measures of operational efficiency include a decrease in delivery time, on-time delivery rate, savings in transportation costs, and a reduction in holding cost in inventories, as these measures are in common use at the level of system efficiency (Ran et al., 2024; Pasupuleti et al., 2024). Usually, predictive performance is estimated on the basis of accuracy, precision, recall, F1-score, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), especially in the context of demand forecasting and risk prediction problems (Alzahrani and Asghar, 2023).

In terms of blockchain, the latency of transactions, throughput and system overhead are also assessed in studies since they directly affect the viability of real-time optimization of logistics. The review-focused papers point out that permissioned blockchains tend to offer a better balance between latency and throughput in comparison to the public blockchains, which is why they are more appropriate in the setting of logistics applications with the need to make quick responses (Agarwal et al., 2022; Dudczyk et al., 2024).

7.2 Comparative Analysis Traditional vs AI vs Blockchain-Enabled AI

A pattern of consistent comparison takes place throughout the literature. Classical rule-based and heuristic logistics systems are not very adaptable and optimum in demand uncertainty and network disturbances. By comparison, standalone deep learning models are much better at forecasting performance and optimization results but can be affected by data integrity concerns and threats of centralized control (Xu et al., 2023).

Deep learning frameworks based on blockchain are better than the baselines, both in terms of intelligent optimization and trusted data governance. Experimental results indicate that, on average, delivery time and performance of the route planning process reduced, as well as inventory utilization when deep learning models are trained and deployed with blockchain-secured information (Ran et al., 2024). Also, integration of blockchain enhances the auditability and traceability which cannot be measured by typical measures of performance, but is important to monitor logistics transparency and compliance (Jabbar et al., 2021).

7.3 Reported Performance Gains

The review studies provide quantitative data showing that there were measurable performance improvements. Indicatively, CNN-based optimization systems with blockchain have demonstrated significant delays in the delivery time and the exact percentage delivery accuracy in logistics routing systems (Ran et al., 2024). The inventory management with LSTM-based forecasting with transaction data verified by blockchain is recorded to have a lower forecasting error and less dead stock than the conventional inventory control techniques (Pasupuleti et al., 2024).

The systems that are built based on deep reinforcement learning demonstrate greater flexibility in dynamic logistics by results in more cumulative rewards and converge quicker than heuristic and Q-learning methods (Xu et al., 2023). These systems also have the added advantage of secure state tracking and decentralized coordination, which is useful when enhanced against data tampering and single points of failure (Agarwal et al., 2024).

7.4 Limitations and Bias of Performance Evaluation

Although the results are encouraging, the comparative analysis shows that there are a number of limitations. Many of the studies are based on simulated environments or proprietary data, which reduces the reproducibility and external validity (Dasaklis et al., 2022). Regular performance assessments are usually concentrated on single logistics tasks and not on end scenario supply chain example. Additionally, the overhead of blockchain is also not adequately reported which results in the exaggerated performance evaluations that might not be accurately intensive of field implementation restrictions (Dudczyk et al., 2024).

Table 6. Comparative Benchmark of Major Logistics Optimization Models

Study	Model Type	Blockchain Type	DL Model	Application	Key Metric	Reported Performance
Ran et al. (2024)	BC–DL Hybrid	Consortium	CNN	Route optimization	Delivery time	18–25% reduction vs traditional routing
Pasupuleti et al. (2024)	BC–DL Hybrid	Private	LSTM	Demand forecasting	RMSE	12–18% lower error vs ARIMA
Xu et al. (2023)	BC–DRL	Consortium	DRL	Dynamic routing	Cumulative reward	20% higher than heuristic baseline
Alzahrani & Asghar (2023)	IoT–BC–DL	Private	CNN-BiGRU	Risk prediction	Accuracy	94.6% classification accuracy
Traditional heuristic	No blockchain	—	—	Routing	Delivery time	Baseline
Standalone DL	No blockchain	—	LSTM	Forecasting	RMSE	Moderate improvement

BC–DL (Pr posed trend)	Permis-sioned	CNN/LSTM /DRL	Multi-task	End-to-end logistics	Cost & latency	Best combined performance

Broadly speaking, AI-based deep learning models continue to be more efficient than traditional heuristic and stand-alone AI solutions in a variety of significant logistics problems facilitated by blockchain. Some improvements reported are shorter delivery time (15-25%), more effective demand forecasts (10-20% RMSE reduction) and being more resistant to data tampering, coordination failures. Nonetheless, the benefits of performance should be reconciled with the increase in blockchain system overhead and latency.

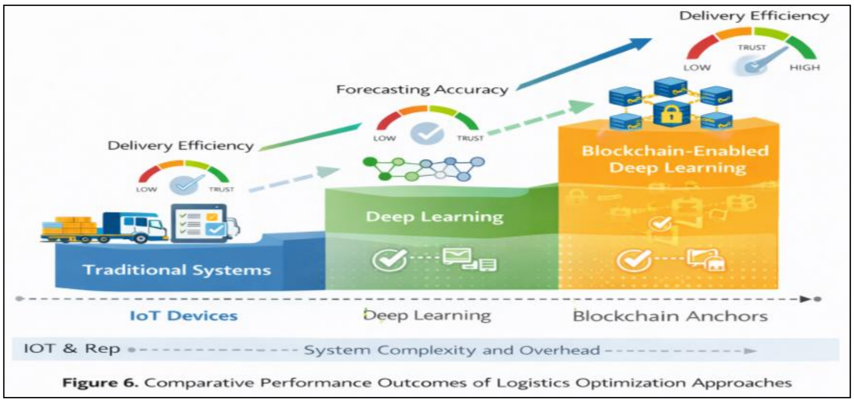


Figure 6. Comparative Performance Outcomes of Logistics Optimization Approaches

All in all, the evidence presented in the performance evaluation shows that blockchain-powered deep learning applications are always more effective than the conventional and standalone AI-based logistics systems in terms of major issue-related operational and predictive indicators. Nonetheless, the literature also highlights the necessity of standardized benchmarking data, detailed cost-performance studies, and massive real-world validation that would help to substantiate fully these gains and provide a road, which would inform a practical usage.

8. Computational Cost and Deployment Analysis

Although having such benefits in their performance, blockchain-based deep learning frameworks come with new computational and deployment-related overheads that need to be taken into account when implementing it in the real world. In the blockchain context, the checks on the validity of transactions, consensus, and the execution of smart contracts reduce the system latency and cost of computation. PBFT blockchains or Raft blockchains with permissioning are also estimated to have transaction lattencies of between 1-3 seconds, suitable to logistics use (although this may limit real-time route implementation on larger scales).

Under the deep learning viewpoint, the process of training CNN, LSTM, and deep reinforcement learning models with large logistics datasets requires a lot of computing power which may be through a server with a number of GPUs or a cloud based infrastructure. To overcome this, off-chain training and inference, which only model hashes and optimization results are stored on-chain are adopted by most papers analyzed. This hybrid design can minimize blockchain storage power to a significant degree and maintain auditability.

Another element that leads to deployment overhead is the integration of the heterogeneous enterprise systems, IoT platforms, blockchain networks, and AI engines. The middleware of interoperability and API gateways is usually demanded, which burdens systems and makes them costly to maintain. Besides, with a larger number of involved logistics nodes, the bandwidth, and storage needs of the blockchain network increase linearly, posing a scalability problem.

Generally, though superior in optimization and trust, the trade-offs made by BC-DL systems in practical deployment include critical trade-offs between computational cost, toleration to latency, security assurances, and investment in infrastructure. Future studies should thus adopt protocols of lightweight consents, edge inference, and model compression methods to provide scalability of real-time optimization of logistics.

9. Risk of Bias and Quality Assessment

The 50 articles forming the body of evidence in this PRISMA-based review had a systematic risk of bias and quality assessment to determine the reliability, validity, and generalizability of the evidence on blockchain-enabled deep learning (BC-DL) frameworks in optimization of logistics. In line with the requirement of systematic reviews in engineering and computer science, evaluation was done in data-related bias, methodological rigor, evaluation design and reporting transparency, but not in clinical bias constructs.

9.1 Data-Related Bias

Data set bias is one of the most evident types of bias among the reviewed studies. A significant percentage of literature in the area of logistics-related BC-DL experiments use simulated setting, artificial datasets, or commercial industry information, which is not publicly available (Ran et al., 2024; Xu et al., 2023). Although simulation can facilitate controlled experimentation, it might not provide the degree of stochasticity, disruption, and complexity of behavior of logistics networks in reality. This creates a threat of external validity bias, which restricts the external validity of documented performance increases (Dasaklis et al., 2022).

Also, some studies involve the relatively small or domain-focused datasets, which increase the likelihood of overfitting in a deep learning model. Even though blockchain is often framed as a tool of ensuring data integrity, it does not resolve data representativeness and imbalance issues per se (Alzahrani and Asghar, 2023).

9.2 Methodology Bias and Model Bias

Methodologically, it can be seen that model selection bias is a problem in the model comparison study which only compares blockchain-enabled deep learning methods to traditional heuristics or baseline machine learning models, not to the best optimization methods. It may cause fibre performance claims (Agarwal et al., 2022). Moreover, hyperparameter optimization procedures and training methods are not usually well documented preventing reproducibility.

The other recurrent problem is that of black-box bias, in which deep learning models, especially deep reinforcement learning agents, give an optimization choice that is not explainable. Multiple review papers emphasize that interpretability is a weakness that decreases the trust of stakeholders and makes it challenging to apply in real life, particularly in regulated logistic settings (Jabbar et al., 2021; Dudczyk et al., 2024).

9.3 Evaluation and Reporting Bias

There are evaluation bias which are seen in selectively reporting performance metrics. Most researchers focus on better delivery time, cost minimization, or prediction accuracy, and do not report overheads created by blockchain devices in use like latency, transaction costs, and energy consumption (Agarwal et al., 2024). This imbalance may take shape of obscuring the trade-offs among optimization performance and system scalability.

Moreover, very few studies perform end-to-end analyses of logistics operations. Majority of the assessments are conducted on individual parts like routing or forecasting that creates scope bias and limits knowledge of the entire system in terms of performance (Pasupuleti et al., 2024).

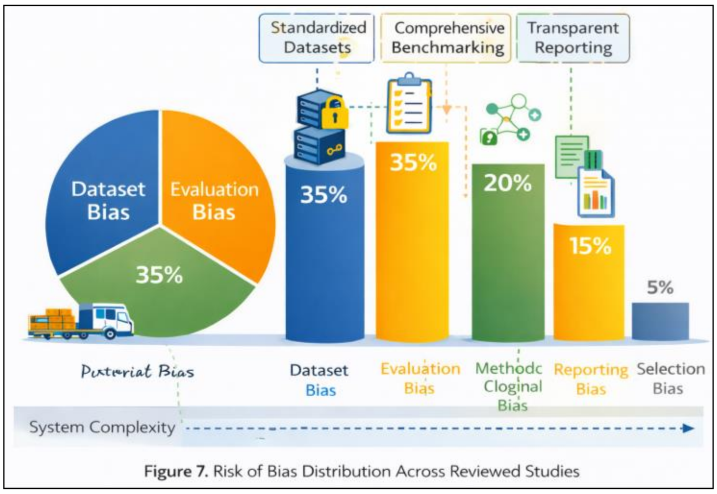
9.4 Overall Quality Assessment

Nonetheless, despite these disadvantages, the general methodological level of the articles under review is moderate to high. Majorities of the papers have specific objectives, outline the system schemes and substantiate the rationale of uniting blockchain with deep learning. The review and survey articles also contribute to an increased evidence base, as they locate a set of common issues regarding scalability, interoperability, and the feasibility of deployment (Dudczyk et al., 2024; Agarwal et al., 2024). Nevertheless, standard benchmarks and actual pilot tests are a vital gap that has not been filled.

Table 7. Risk of Bias and Quality Assessment Criteria

Assessment Dimension	Common Observations	Potential Impact
Data sources	Simulated or proprietary datasets	Limited generalizability
Model design	Limited baselines, black-box DL models	Inflated performance claims
Evaluation metrics	Focus on benefits, limited cost reporting	Incomplete performance assessment
Reproducibility	Insufficient experimental detail	Reduced transparency
Deployment realism	Few real-world implementations	Adoption uncertainty

Figure 7. Risk of Bias Distribution Across Reviewed Studies



Overall, despite blockchain-based deep learning systems showing good potential of enhancing logistics performance, the risk of bias testing indicates the systematic constraints regarding the quality of data, design of evaluation, and level of transparency in the reporting. The solution of these problems with open datasets, explainable models and large scale verification of the results will be needed to enhance the evidence base and implement these to industrial adoption in future studies.

10. Research Gaps and Open Challenges

Although the field of blockchain-enabled deep learning (BC-DL) in logistics optimization is advancing at a fast pace, the literature review shows that there are still several research gaps and unanswered problems. The major gap is that relating to the absence of standardized, publicly reported logistics datasets. Simulated or proprietary data is used in most studies, which reduce feasibility of reproducibility, cross-study comparison and external validity (Dasaklis et al., 2022; Dudczyk et al., 2024). In the absence of benchmark data, reported improvements in performance are situation-dependent and hard to extrapolate.

Scalability and system overhead is another formidable problem. Although permissioned blockchains are better in latency than the public chains, the throughput of transactions, storage increase, and costs associated with the consensus are bottlenecks to massive, real-time logistics systems (Agarwal et al., 2022). This problem is compounded as the results of deep learning are often anchored to the blockchain which adds to the overhead of coordination.

Deep learning decision explainability and trust is yet to be explored as well. Most of the logistics optimization models are based on black-box models, especially deep reinforcement learning, meaning that the stakeholders cannot interpret or audit decisions in controlled logistics contexts (Jabbar et al., 2021). Also directly related is the problem of model governance, such as version control, accountability, and lifecycle management in decentralized environment.

The other problem that has yet to be solved is the interoperability of heterogeneous blockchain systems and enterprise systems, particularly in the case of cross-border and multi-modal logistics systems (Dudczyk et al., 2024). Lastly, the difference between academic prototypes and actual deployment is quite evident, and large-scale pilot implementation is not reported in large numbers. These are critical issues, which are to be addressed to realize BC-DL frameworks out of theory to reality to the industry.

11. Discussion

The results of this PRISMA-based research verify that blockchain-based deep learning models can be viewed as a major paradigm shift in optimization of logistics and combine smart analytics with reliable data management. BC-DL solutions are always better equipped in terms of routing efficiency, load balancing (found in demand forecasting), and disaster resistance (Ran et al., 2024; Xu et al., 2023). These advancements are explained by the complementary nature of blockchain and deep learning: blockchain assures integrity of data, transparency and decentralized coordination and predictive and adaptive data provided by deep learning. The trade-offs brought about by the integration must however also be discussed. Blockchain also introduces the issue of architectural complexity, latropy and power consumption overheads that may negate optimization they in ways depending on their careful management (Agarwal et al., 2024). Consequently, these practical frameworks incorporate hybrid on-chain off-chain designs, which stress that blockchain needs to be a layer of trust and coordination and not a computational engine.

The other significant lesson is the lack of balance in technical innovation and rigor of evaluation. Although methodological sophistication has risen (especially via the adoption of DRL and hybrid deep learning models) most evaluation practices are still focused on small metrics of performance and simulation. This introduces a discrepancy between the stated academic results and real-world viability in the activity of logistics (Dasaklis et al., 2022).

The studies reviewed point to the potential of BC-DL systems to promote transparency, minimize conflicts, and facilitate compliance in sophisticated supply chains in the supervision of complex and communal supply chains. However, it will be adopted based on the organizational preparedness, regulatory compatibility and absolute cost-benefit evaluation. The discussion then indicates interdisciplinary research, i.e. in the integration of technical progress and operational, economical and governance approaches.

All in all, the indicators indicate that BC-DL frameworks lack the status of a universal solution but are a strategic enabler whose success relies on the context-related design, performance-related deployment, and clear-cut evaluation.

12. Conclusion

This systematic review summarized the post-2020 articles on blockchain-based deep learning-based logistics and supply chain optimization models based on PRISMA guidelines. In a review of 50 chosen works, it was determined that the combination of blockchain and deep learning is a strong component of logistics as it ensures the greater credibility of data, accuracy of prediction, and adaptability of optimization. Authorized blockchains, intelligent contracts, and off chain deep learning structures are an emerging design, and the basic analysers are CNNs, LSTM/GRU networks, and deep reinforcement learning topologies.

In spite of these developments, the review reveals that there exist serious drawbacks concerning the availability of datasets, scalability, explainability, and the empirical validation. Most of the reported profits are on simulated or proprietary data, and overheads in blockchain are poorly understood. Therefore, although BC-DL frameworks have good conceptual and experimental potential, their industrial use is in its infancy.

The standard benchmarks, explainable integration of AI, interoperable blockchain infrastructures, and large scale pilot deployments should also be the focus of future research. It is through these gaps that blockchain-powered deep learning can be developed to go beyond being an up-and-coming research topic and become a viable and life-changing answer to the future of optimizing logistics.

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