Revue Internationale des Sciences de Gestion
ISSN: 2665-7473
Volume 8 : Numéro 3

Framework for blockchain-based federated learning integration into Port Community System : A Literature Review

Cadre pour l'intégration de l'Apprentissage Fédéré basé sur la Blockchain dans les Systèmes de Communauté Portuaire: Une Revue de la Littérature

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Date submitted : 15/06/2025

Date of acceptance : 04/08/2025

To cite this article :

SERROUKH B. & al. (2025) « Framework for blockchain-based federated learning integration into Port Community System : A Literature Review», Revue Internationale des Sciences de Gestion « Volume 8 : Numéro 3 » pp : 1017 - 1045

Abstract

AI-based predictive analytics in the Port Community System (PCS) is critical for enhancing operational efficiency, resilience, and sustainability in the maritime supply chain. Recognizing this, the International Maritime Organization emphasizes integrating AI predictive analytics in the PCS as a value-added function. Synergy of blockchain and federated learning has emerged as a significant technology that can enhance predictive analytics by enabling secure, decentralized, and collaborative model training. However, there is currently no research integrating blockchain and FL within PCS.

A systematic literature review identified 45 articles published between 2016 and 2025. Content analysis examined existing literature on blockchain and FL applications in Ports and supply chains, assessing the potential relevance and feasibility within PCS.

The study finds that blockchain-FL applications in the supply chain remain in the exploratory stages, with no research currently investigating their Integration within PCS. This study makes a theoretical contribution by identifying the architectural requirements for implementing blockchain-FL in PSC. The proposed conceptual framework serves as a guide for further empirical research. It provides PCS stakeholders with insights into integrating ML functions into PCS, fostering a more intelligent, collaborative, and secure port ecosystem.

Keywords: Blockchain, Federated Learning, Supply Chain, Port, Port Community System

Résumé

L'analytique prédictive basée sur l'intelligence artificielle dans le Système Communautaire Portuaire (SCP) s'avère cruciale pour améliorer l'efficacité opérationnelle, la résilience et la durabilité de la chaîne d'approvisionnement maritime. L'Organisation Maritime Internationale souligne l'intégration de l'analytique prédictive par IA dans le SCP comme fonction à valeur ajoutée. La synergie entre la blockchain et l'apprentissage fédéré constitue une technologie significative capable d'améliorer l'analytique prédictive en permettant un entraînement de modèles sécurisé, décentralisé et collaboratif. Néanmoins, aucune recherche n'intègre actuellement ces technologies au sein du SCP.

Une revue systématique de la littérature a identifié 45 articles publiés entre 2016 et 2025. L'analyse de contenu a examiné la littérature existante sur les applications de la blockchain et de l'apprentissage fédéré dans les ports et chaînes d'approvisionnement, évaluant leur pertinence et faisabilité dans le SCP.

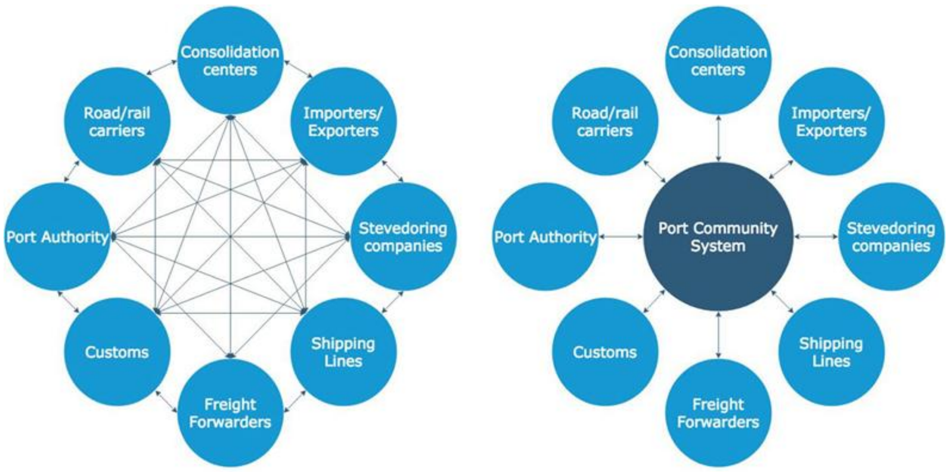
L'étude révèle que les applications blockchain-apprentissage fédéré demeurent à un stade exploratoire, sans recherche examinant leur intégration dans le SCP. Cette étude contribue théoriquement en identifiant les exigences architecturales pour l'implémentation blockchain-apprentissage fédéré dans le SCP. Le cadre conceptuel proposé guide les futures recherches empiriques et fournit aux parties prenantes des perspectives sur l'intégration des fonctions d'apprentissage automatique, favorisant un écosystème portuaire plus intelligent et sécurisé.

Mots-clés : Blockchain, Apprentissage Fédéré, Chaîne d'Approvisionnement, Port, Système Communautaire Portuaire

Introduction

Maritime ports are the backbone of the shipping trade, facilitating transportation and handling of cargo between the ocean and land. The effectiveness of port systems is fundamental to the efficiency of port operations across many ports worldwide. A Port Community System (PCS) is a centralized digital platform where port private and public stakeholders collaboratively exchange information to facilitate trade involving ports and terminal operators. Furthermore, it is an open system where actors, through accelerated digitalization, can remotely and in real-time access and process data to provide value-added services such as Artificial Intelligence (AI) predictive analytics of port activities, ensuring efficiency
and sustainability (IMO, 2024). As shown in Figure 1, PCS consists of port authorities, customs, freight forwarders, shipping lines, stevedoring companies, importers & exporters, consolidation centers, and road or rail carriers participating and exchanging trade information with one another (Carlan et al., 2016) ;(Tsiulinet al., 2020).

Figure 1: Actors and information exchange in the PCS



Source: Modified from van Baalenet al.(2008).Carlan et al. (2016). Rodrigue (2020)

The value of PCS in its potential for effective information exchange can reduce logistics costs significantly. For instance, the Port of Rotterdam realized €245 million in cost reductions from the PCS known as PORTBASE (World Bank, 2023).

Before 2024, it was the discretion of a port to establish a PCS; however, as of January 2024, the IMO directive mandates the member states to comply with the compulsory establishment of a Maritime Single Window (MSW) to achieve a reliable and smooth exchange of trade information. (IMO, 2023). These developments follow the severe impact of the recent disruptive event. The COVID-19 pandemic and the ongoing geopolitical tensions in the Red Sea, Ukraine-Russia, and Israel-Palestine wars have exposed the vulnerabilities of the maritime industry and ports supply chain in particular (Notteboom et al., 2024). Hence, predictive analytics play a crucial role in improving scheduling in ports, logistics optimization, and traffic management, thereby reducing delays, optimizing resource allocations, enhancing decision making and reducing costs (El Idrissi & Haidine, 2023); (Oudani et al., 2023); (Rao et al., 2024). Previous studies showed that AI or Machine Learning (ML) techniques could provide economic and environmental benefits for the port supply chains through effective data-driven and accurate predictive analytics in real time (Farzadmehr et al., 2023, 2024); (Kuo et al., 2022); (Yassen et al., 2021); (Zhang et al., 2024). In contrast, the accuracy of AI-based predictions is highly dependent on big data, which remains a barrier. The digitalization of supply chains, particularly through technologies such as blockchain and IoT, has been identified as a response to transparency and resilience challenges (Mounaim & Boutakbout, 2020). Within the port context, the integration of blockchain-based federated learning could thus enhance data security while optimizing coordination among stakeholders.

Furthermore, while (Farzadmehr et al. 2023, 2024) encourage the collaborative application of AI leveraging combined data, data privacy concerns, a surge in cyber-attacks, and lack of trust cause hindrances (DNV Cyber, 2025); (Kuhn et al., 2021).

Some researchers address these challenges by integrating blockchain and ML distributed techniques to model global predictive models without sharing raw data. This approach improves trust and bridges the limitation gap of blockchain in a multi-party environment, such as the 51% attack risk (Xie & Li, 2024); (Zhu et al., 2023). This attack is a threat to a cryptocurrency blockchain by a group of miners who control over 50% of the network mining hash rate and have yet again confirmed that there is no 100% cybersecurity solution (Aponte-Novoa et al., 2021). Hence, robust cyber security remains a continuous challenge identified by various researchers (Breda et al., 2023); (Carlan et al., 2017); (Shanmugam et al., 2023).

There is a significant lack of studies focusing on blockchain and Federated Learning (FL) in the context of the port supply chain, particularly leveraging the latter of the PCS to collaboratively model global predictive models for port activities to improve efficiency and sustainability. The current study reviews the literature on FL and blockchain applications in port and supply chains and proposes a conceptual framework for integrating Blockchain and FL in the PCS. To achieve these objectives, the authors set four research questions.

1. What are the Blockchain-FL applications in the supply chain?

2. What are the challenges of implementing Blockchain-FL in the Supply chain?
3. What are the potential benefits of Blockchain-FL for PCS stakeholders?
4. How can Blockchain-FL be integrated into PCS?

The current study expands the work of (Xie & Li 2024), which focuses on blockchain multi-chain FL framework for enhancing the security and efficiency of Intelligent unmanned ports. The current study explores the synergy of these technologies from the perspective of PCS, an area also identified by (IMO 2024) as necessary for advancing the Integration of AI/ML-based innovative functions within the PCS. Addressing these questions will advance sustainable innovation in the maritime supply chain and guide other researchers and policymakers to further this research agenda while ensuring efficient and resilient port operations.

To address these research objectives, this study adopts a systematic literature review approach. A comprehensive search strategy was implemented across major academic databases to identify relevant publications on blockchain and federated learning applications in ports and supply chain management published between 2016 and 2025. The final corpus of 45 articles underwent rigorous content analysis to examine current implementations, identify gaps, and assess the potential relevance and feasibility of these technologies within Port Community Systems. This methodology ensures a thorough examination of the existing knowledge base while providing a solid foundation for evaluating the integration potential of blockchain and federated learning in maritime port environments.

The remainder of this paper is organized as follows: Section 1 outlines the research methodology employed in this study. Section 2 presents a systematic literature review of FL and blockchain in ports and supply chains. Section 3 presents Blockchain-FL integration challenges;4 presents a conceptual framework for Blockchain-FL in PCS. Section 5 discusses the results, challenges, and future research directions. Finally, the study concludes.

1.Methodology

This section outlines the research process followed to conduct a systematic literature review in a structured and reproducible way. The review combines the systematic literature review and meta-analysis involving planning and preparation consisting of (i) the design, development, inclusion, and exclusion criteria and literature research approach, (ii) conducting data screening, synthesis, and analysis, and (iii) reporting (Moher et al., 2015).

1.1.Planning and preparation

Planning involves identifying relevant literature to be reviewed and analyzed from reputable databases and journals. The current study collected literature from the Scopus database. While WoS is also a reputable database, studies show that Scopus covers more than 96% of WoS, leaving an insignificant difference for consideration (Mongeon & Paul-Hus, 2016); (Singh et al., 2021). Google Scholar is a secondary source that ensures the coverage of relevant literature. Material is identified by combining the keywords shown in Table 1 through Boolean operators "AND" and "OR." Since the current study focuses on federated learning and blockchain in the Port community system, the authors used the keywords blockchain, federated learning, port, and supply chain as the main words for the search.

"Federated learning" AND "Supply Chain"
"Blockchain" AND "Federated learning" AND ("Supply chain" OR "Port")
("Blockchain" OR "Federated learning") AND "Port Community System"
"Blockchain" AND "Port" OR "Port Community System"

To ensure the relevance of the literature, we considered articles based on the article title, abstract, and keywords. The types of studies include journal articles, conference papers, book chapters, and industry reports. The search was limited to research studies published in English between 2016 and 2025 on January 31. FL emerged in 2016, hence the search scope within the given time frame. We exported the articles to CSV and cleaned them to exclude duplicates, resulting in 545 articles for selection. Articles mentioning blockchain or FL and not in line with the objective of our study were excluded. Only articles studying blockchain and FL's implementation and/or impact are considered. The final total of 45 articles were selected for full review.

1.2.Execution

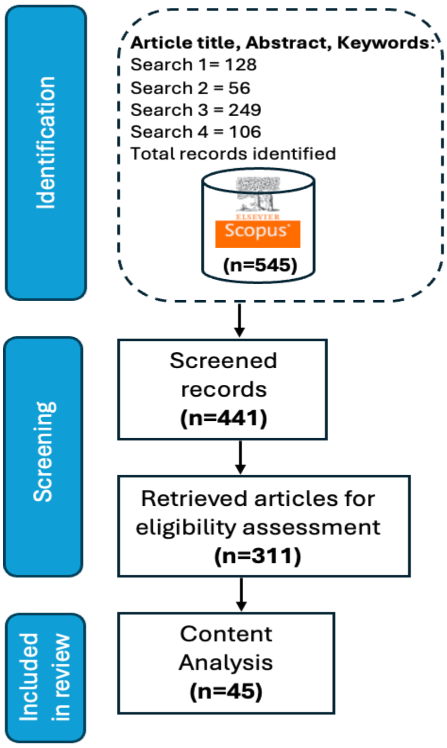
The identified articles were read in detail to synthesize their content. The data collection and synthesis of the literature is limited to port and supply chain. In the general process of this systematic review study, the overview, strategies, applications, tools, and future directions of federated learning-based blockchain were extensively investigated. The publications are evaluated by carefully reading the article title and abstract. Subsequently, the introduction and conclusion are ready to decide on the relevance of inclusion. Selected publications for inclusion are read in full and analyzed based on their content. The developed framework is validated through interviews with industry experts in port and technology domains.

Revue Internationale des Sciences de Gestion
ISSN: 2665-7473
Volume 8 : Numéro 3

1.3.Reporting

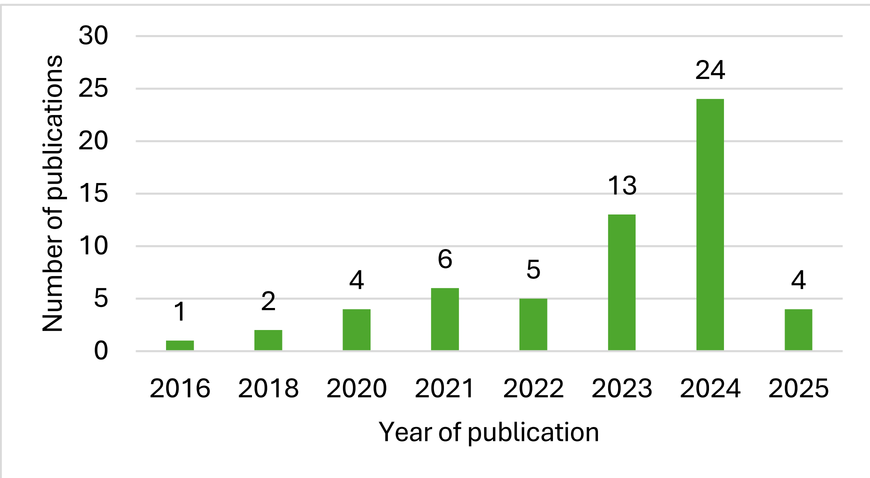
The reporting is done in line with the research questions.

Figure 2: Literature selection process



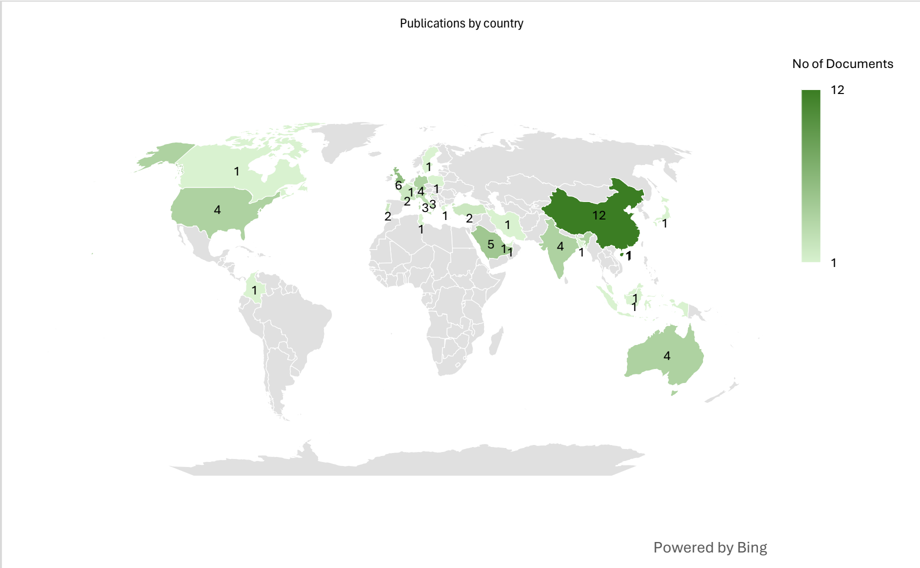
Source: own compilation

Figure 3: Publication distribution by year



Source: own compilation

Figure 4: Publications distribution by country



Source: own compilation

The Discussion section systematically addresses the study's research questions by integrating insights from the systematic literature review and the proposed conceptual framework. First, it examines the current applications of Blockchain-FL in supply chains, such as provenance tracking and food supply resilience, while highlighting the absence of research specific to PCS. Second, it identifies key challenges in Blockchain-FL implementation, categorizing them into technical, operational, and strategic dimensions, supported by existing literature on latency, cybersecurity risks, and interoperability concerns. Third, the potential benefits for PCS stakeholders are explored, emphasizing improvements in predictive accuracy through federated learning, enhanced data privacy, and increased trust via blockchain's transparency and tokenized incentives. Finally, the study proposes a five-layer architectural framework that aligns Blockchain-FL with PCS operational workflows, demonstrating how decentralized collaboration facilitates real-time decision-making and smart contract execution. The findings are contextualized within the International Maritime Organization's regulatory mandates, with a discussion on limitations, including the need for empirical validation, positioning the study within broader academic and practical frameworks.

2. Systematic literature review

2.1.PCS and predictive analytics

Research in PCS was studied extensively, focusing on its development, implementation, performance, governance, economic impact, and integration of advanced technologies. (Aydogdu & Aksoy 2015) developed a simulation model to quantify its effects on time and cost performance. Their study identified potential in both savings; however, its validation was based on a hypothetical case study. (Bisogno et al. 2015) proposed an architecture for a Smart Tunnel, analyzing the transitional inter-organizational routines to a proposed prototype. Their research is grounded in an evolutionary economic approach, highlighting the significant role of PCS in enhancing port competitiveness and efficiency by reducing costs and transit times. While both studies explore PCS from an economic perspective, neither provides a comprehensive framework for quantifying all relevant costs and benefits. (Carlan et al. 2016) addressed this research gap by developing a cost-benefit framework to assess PCS's contribution to port competitiveness, emphasizing the advantages of collaborative PCS for all stakeholders.

(Nota et al. 2018) proposed a three-level, top-down methodology for PCS as a complex service-oriented network, focusing on architectural design, service integration, and value co-creation. While their study underscores efficiency gains through improved inter-organizational interactions, optimized information flow, and service-oriented architecture, it also identifies challenges in managing big data due to governmental and technical barriers. Chandra & van (Hillegersberg 2018) examined the inter-organizational governance within PCS at the Port of Rotterdam through a lifecycle paradigm, analyzing collaboration mechanisms, roles, and models. However, their reliance on a single case limits the generalizability of their findings. Similarly, (Tijan et al. 2021) explored the role of port authorities in PCS implementation, suggesting that ports can enhance real-time information exchange among stakeholders but did not comprehensively address data privacy concerns in the proposed framework.

(Fedi et al. 2019) investigated the impact of Information technology on port logistics under regulatory and competitive pressure, using a multi-method approach to assess compliance with new regulations. Their findings suggest that enforcing Verified Gross Mass regulations, and the maritime supply chain reinforces the role of PCS in facilitating seamless regulatory compliance. (Torlak et al. 2020) developed a national PCS model for Croatian ports, analyzing the Port of Ploče and Rijeka to improve vessel arrival efficiency. Their study demonstrated that data integration and automation enhance efficiency and reduce labor costs.

(Moros-Daza et al. 2020) compiled a global PCS inventory and developed a taxonomy categorizing research into business, integration, and regulation. Their study highlighted gaps in PCS research innovation, particularly in integrating emerging technologies. (Irannezhad ,2020) explored the potential of blockchain integration in PCS, analyzing and assessing business value and blockchain platforms. However, their study lacks empirical validation and feasibility analysis. (Caldeirinha et al. 2020) examined the impact of PCS attributes on port performance through practical component analysis and structural equation modeling, showing that advanced services enable ports to evolve PCS by developing new features. Their findings emphasize the need for AI-driven innovation to support predictive functions in PCS, aligning with Moros-(Daza et al. 2020) and the recent PCS development guidelines (IMO, 2024).

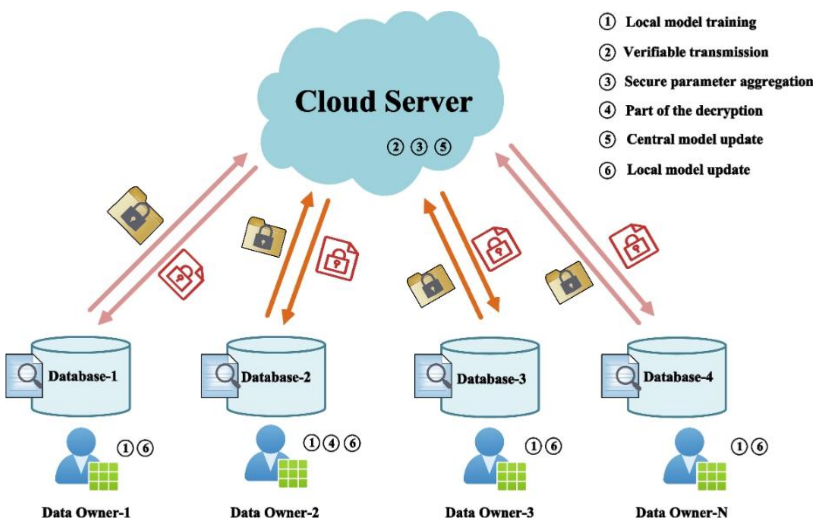
(Simoni et al. 2020) analyzed the distribution of benefits among PCS stakeholders, finding that innovative digital solutions improve service quality, efficiency, and data usability. (Caldeirinha et al. 2022) investigated PCS evolution amid rapid digitalization, identifying business factors that enhance supply chain performance and future digital innovations. While prior studies outline the evolution of PCS in four phases (Caldeirinha et al., 2022); (Tijan et al., 2021), (Caldeirinha et al. 2022) proposed a fifth phase toward a 'physical internet,' emphasizing AI and big data integration to enhance supply chain performance. (Iida & Watanabe 2023) identified key features for developing and operating PCS effectively, stressing the need to avoid functional duplication between nationwide and single port PCS.

Despite these advancements, there is a notable lack of research on secure and privacy-preserving mechanisms in PCS, particularly integrating ML distributed models and blockchain. Current studies explore the role of blockchain in PCS (Irannezhad, 2020) but fail to address its limitations, such as 51% attack and data privacy preservation concerns. As PCS evolves towards AI and big data-driven solutions, ensuring secure, decentralized, and privacy-preserving data-sharing mechanisms is crucial. Hence, the current study explores the integration of blockchain-based FL within PCS as an added AI-enabled function to enable collaborative model training while maintaining data confidentiality. Addressing these aspects is essential for the next phase of PCS evolution, ensuring robust, secure, and efficient digital transformation in port operations.

2.2.Federated Learning in Collaborative AI

FL is a decentralized machine-learning approach that allows multiple parties to train models collaboratively without sharing their data. The successful implementation can benefit participants by improving the trained model and achieving accurate prediction of events. The lack of data availability for entities, especially small-medium and new entrants, can leverage collective data within the ecosystem to advance digital innovation while improving collaboration. FL involves learning coordinators who are system owners, contributor clients, and user clients. Learning coordinators are the initial providers of the FL platform, contributor clients are data distributors and local model trainers, and user clients are new model users. They become contributor clients when they retrain the model, contributing to the aggregate global model. As shown in Figure 2, data owners 1,2,3 and N are the clients, also known as Nodes. Databases are the local servers where individual clients train models. The cloud server is a centralized environment where locally trained models are aggregated and sent back to the local servers for another round of training.

Figure 5: A typical prediction-based FL workflow



Source: (Hu et al., 2024)

A public key is created to encrypt the model during transmission to the global server, and a private key is designed for the aggregated model to be sent back to the local server. FL model is processed over five steps per round.

The initial model includes task scripts and training hyperparameters. The model training is performed locally across clients' devices regardless of systems heterogeneity. Each round of training takes one step of gradient descent on the latest model using each client's data. Gradient descent is uploaded to the central server, aggregated, and returned to the local servers. The new model version needs to be maintained. This cyclical process iterates until the global model converges. The converged model remains the latest model until the next update. Other researchers integrated blockchain technology with FL to enhance transparency, data security, and privacy preservation. While there are studies combining blockchain and FL, few focus on PCS. The anticipation of AI predictive analytics integrated into the PCS by the (IMO 2024) suggests the need to explore the feasibility of Blockchain-FL within PCS. Many studies implement blockchain in PCS; however, at the time of this research, there was only one research integrating blockchain and FL, but it was in the context of two competing unmanned ports (Xie & Li, 2024). Their study developed a blockchain multi-chain FL framework for two ports, exploring the security and efficiency of unmanned ports.

2.3.Blockchain

Blockchain is generally defined as a system that records a ledger of transactions or a history of changes to the system state (Carlan et al., 2020). Blockchain architecture is designed around key components, platforms, features, and validation mechanisms that ensure the system's security, scalability, and efficiency. Blockchain platforms can be categorized as public, such as Ethereum, or private, such as Hyper. Some blockchains adopt A permissioned model that restricts access to specific participants based on predefined rules. At the core of blockchain functionality is the distributed Ledger, composed of blocks that store transaction data and are maintained by client nodes. Cryptographic hashing algorithms ensure data integrity, which encrypts transaction data while making blockchain immutable. Blockchain uses digital signatures, timestamps, and chain identifiers to ensure secured transaction verification. There are various consensus mechanisms used in blockchain for decentralization, such as Proof of Work, Proof of Stake, Zero Knowledge Proof, Proof of Importance, etc.; however, they vary based on resource intensity (Irannezhad, 2020).

2.4.Blockchain-based FL in Supply Chain

Integrating blockchain and FL has emerged as a robust data privacy preservation, security, and efficiency approach across distinct fields, including IoT, supply chain, big data, and pharmaceutical. This section synthesizes the findings of studies focusing on the synergistic potential of blockchain and FL. The summary of the review's studies is shown in Table 2.

The quest for data privacy preservation, transparency, and data security drives the combination of blockchain and FL in the supply chain environment. In FL, multiple nodes or participants can train ML models collaboratively without sharing raw data, thereby preserving privacy. However, FL systems can be vulnerable to attacks without a robust security framework, such as local data tempering and unauthorized access. (Zhu et al., 2023). Blockchain provides a decentralized and tamperproof ledger that enhances the trustworthiness of the FL process by ensuring that only validated data contributes to model training (Gulati et al., 2023). For instance, (Agarwal et al. 2024) present a peer-to-peer FL approach, addressing blockchain protocols' energy consumption effects without continuously sharing raw data. Moreover, (Albany & El Khediri 2023) review literature emphasizing increasing integration of blockchain and FL for data security management. Their study indicates the significant improvement of data analytics platform security through blockchain and FL synergistic approach, thus raising user trust.

In the supply chain context, (Ahamed & Karthikeyan 2024) highlight how the food supply chain can optimize data exchanges among the chain participants through Blockchain-based FL, thereby establishing more resilience and sustainability against potential cyber threats. Similarly, (Kandil et al. 2024) explore horizontal FL to enhance visibility and secure data sharing within IoT-enabled supply chains, emphasizing the significance of blockchain integration underpinnings ineffective data sharing. While technology integration provides effective cyber systems among multiple parties in complex systems such as supply chains, governance and policy implications are also crucial. (Lee et al. 2023) propose a governance model for utilizing blockchain-based voting techniques, emphasizing their efficiency in enforcing policies within FL environments. This model enables accurate predictions and dynamic adjustment of strategies for stakeholders to respond to uncertain demand markets.

Furthermore, (Bandara et al. 2021) present the 'Let's Trace' platform, which combines blockchain and FL learning for cyber supply chain provenance. Its architecture affirms that this blockchain-FL fusion can enhance security and transparency across supply chain networks. Meanwhile, (Gulati et al. 2023) introduce an event-triggered asynchronous FL model, employing blockchain for fail-proof logging of events to bolster supply chain operations by synchronizing data without overwhelming the system with real-time demands. The synergy of advanced technologies continues to evolve with developments like those discussed by (Bandara et al. 2024). Their study highlights the potential of generative AI, blockchain, FL, Non-Fungible

Tokens, and Pipeline Bill of Materials in ensuring optimal performance on customer-grade hardware while enabling AI/ML model training in a secure and privacy-preserving manner. Lastly, (Zidi et al. 2024) address multi-objective optimization problems using the third-generation Non-dominated Sorting Genetic Algorithm (NSGA-III). This approach strengthens the defense mechanisms against attacks leveraging blockchain, which ensures veracity and optimum processing time and reduces the success rate of attack attempts.

Table 1: Blockchain-based FL in Supply Chain

Ref	Field	Objective	Framework	Architecture	B-FL Application
(Albany & El Khediri, 2023)	Big data analytics	Review the Integration of FL and blockchain for security.	N/A	N/A	A secure analytics framework leveraging data from multiple sources is needed.
(Bandara et al., 2021)	Cyber supply chain	Establish a provenance platform for cyber supply chain management.	N/A	TUF/In-To To compliant	Tracking data flows and establishing accountability in supply chains
(Bandara et al., 2024)	Metaverse 5G/6G	Create a data security architecture leveraging various technologies.	Blockchain + Generative-AI	PBOM Enabled Architecture	Multi-faceted data security architecture in emerging environments.
(Zidi et al., 2024)	FL optimization	Optimize multiple objectives of FL.	NSGA-III Algorithm	N/A	Enhancing output through optimization techniques in federated scenarios.
(Kandil et al., 2024)	Supply chain IoT	Enhance data sharing using horizontal FL.	Horizontal FL	IoT-enabled Architecture	Improving visibility in data management among partners
(Lee et al., 2023)	Governance or AI Policy	Establish decentralized governance using blockchain in FL.	Blockchain with Smart Contracts	Voting system for consensus	Enabling consensus in model updates through a voting mechanism.
(Zhu et al., 2023)	IoT Supply chain	Enhance data security and privacy in FL.	TEE + Blockchain	SGX-based TEE for	Improving the security of local

				security execution	data computations in IoT systems.
(Gulati et al., 2023)	Supply chain	Develop a blockchain-event trigged FL model.	Blockchain Event triggered FL	N/A	Asynchronous FL process in supply chain networks
(Ahamed & Karthikeyan, 2024)	Food supply chain	Develop a sustainable solution for food supply chains.	FL + Blockchain	N/A	Collaboration between supply chain participants while preserving data privacy.
(Agarwal et al., 2024)	General application	Propose a sustainable peer-to-peer FL model.	Peer-to-peer FL	N/A	Enabling collaboration without sharing raw data, reducing energy consumption

Source : Authors

3. AI-blockchain integration challenges

Integrating AI and blockchain into the port systems poses challenges that can be categorized into three dimensions: operational, technical, and strategic. In particular, combining blockchain and FL in port and supply chains presents several significant challenges that can be analyzed from the perspective of scalability, latency, security vulnerabilities, and sustainability.

3.1 Operational challenges

Operational challenges span from the complexity of the port supply chain network to multiple parties with distinct processes, systems, and varied data and protocols. Furthermore, the unpredictability of weather and economic uncertainties are among the factors exacerbating these challenges. The traditional predictive analytical methods are static and struggle to cope with the ever-changing and dynamic environment, thus unable to provide accurate insights in uncertain times. According to (El Idrissi & Haidine 2023), port terminals can leverage deep learning and data analytics to estimate ship turnaround time accurately; however, the precision of these methods relies on large-scale data integration and real-time responsiveness. Data fragmentation, lack of standardization, data sharing deficiencies, and low trust can be cumbersome to full automation and data analytics of port terminals. Furthermore, (Farzadmehr et al. 2024) highlight the high cost of AI applications, emphasizing the need for a cost-benefit framework when integrating AI in ship arrival processes. Their study stresses that the intricacies of port operations can complicate quantifying the need for a Cost-Benefit framework and the quantification of return on investment.

3.2 Technical challenges

AI algorithms, in particular, require substantial computational resources, including skills and validation datasets. (Oudani et al. 2023) highlight the necessity of prescriptive analytics that rely on robust ML approaches for port logistics planning. Data quality and management of AI integration into existing systems create interoperability challenges (Kuo et al. 2022) due to the heterogeneity of data standardization and systems variabilities.

3.3 Strategic challenges

Incorporating AI tools can disrupt the normal process flow due to the interdependence of port activities. Furthermore, resistance to embrace new technology among stakeholders is another challenge underpinning the Integration of AI in ports. Hence, (Yassen et al. 2021) emphasize the significance of adaptive algorithms in quay crane scheduling. Nevertheless, the readiness assessment to embrace change among personnel involved in port operations is crucial to successful technology adoption. Moreover, the potential for AI to contribute to sustainable operational models underlines the need for ports to align their strategic objectives with technological advancements, as inadequate alignment may lead to suboptimal implementation of AI initiatives (Kuo et al., 2022). Integrating blockchain and FL in port and supply chains presents several significant challenges that can be analyzed from the perspective of scalability, latency, security vulnerabilities, and sustainability.

3.4 Blockchain-federated learning: scalability, latency, security vulnerability & sustainability

The existing Blockchain-FL frameworks often encounter high latencies and processing inefficiencies, especially when dealing with distributed and sparse data scenarios. Additionally, the intensive energy requirements for blockchain computation raise sustainability concerns, thus increasing scalability challenges in supply chain operations (Agarwal et al., 2024); (Gulati et al., 2023); (Xie & Li, 2024). These implications can create a seamless Integration of Blockchain-FL. Another critical challenge includes security and privacy concerns inherent in FL systems that operate within blockchain networks. While FL allows collaborative learning, it remains susceptible to potential security breaches, including local data tampering and attacks during the upload process (Hu et al., 2024); (Zhu et al., 2023). Furthermore, (Tsiulin, et al.2020) highlight the need for comprehensive frameworks in maritime documentation handling, suggesting the lack of mechanisms to ensure security and efficiency in port operations when adopting blockchain technologies. Integration of FL needs to incorporate robust security protocols to address any vulnerabilities while navigating the dynamics of supply chain management (Ahamed & Karthikeyan, 2024).

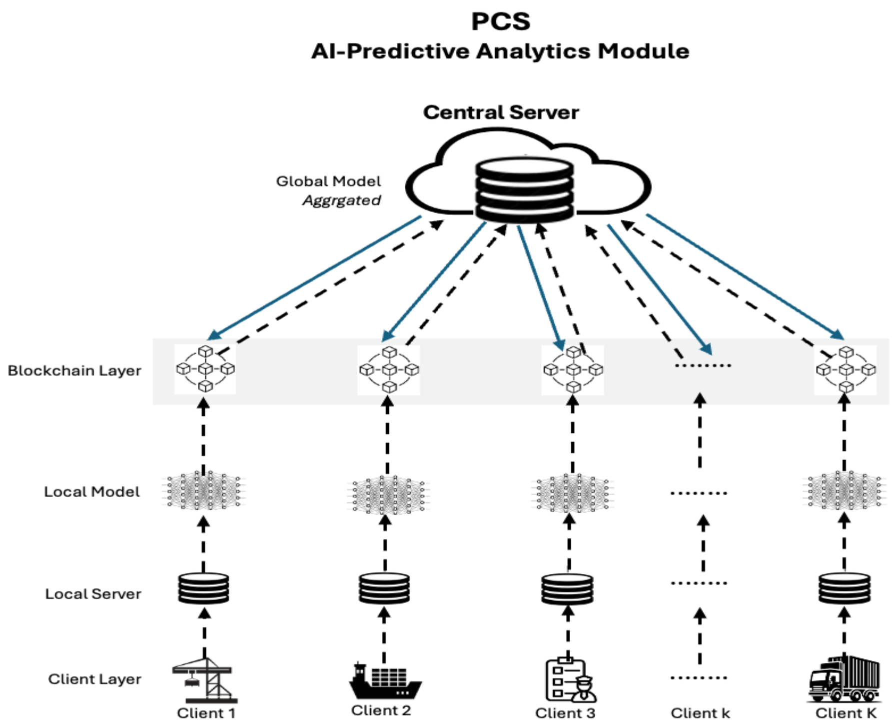
Integrating blockchain and federated learning (FL) into port systems and supply chains introduces multi-faceted challenges spanning operational, technical, strategic, and blockchain-FL-specific dimensions. Operationally, the inherent complexity of multi-stakeholder ecosystems marked by fragmented processes, divergent data protocols, and unpredictable external factors, weather, and economic volatility limits the efficacy of traditional predictive models and complicates real-time decision-making (El Idrissi & Haidine, 2023); (Farzadmehr et al., 2024). Technically, interoperability barriers arising from heterogeneous data formats, legacy systems, and the computational demands of AI algorithms hinder seamless integration, necessitating advanced prescriptive analytics and resource-intensive validation (Kuo et al., 2022); (Oudani et al., 2023). Strategically, resistance to technological adoption, misalignment with sustainability goals, and workflow disruptions underscore the need for stakeholder readiness assessments and governance frameworks (Yassen et al., 2021); (Kuo et al., 2022). Blockchain-FL-specific challenges further compound these issues: scalability bottlenecks and latency in distributed environments, energy-intensive consensus mechanisms Proof of Work, and vulnerabilities to data tampering or cyberattacks threaten both efficiency and security (Agarwal et al., 2024); (Zhu et al., 2023). Additionally, the absence of standardized regulatory frameworks for maritime documentation exacerbates risks (Tsiulin et al., 2020). Addressing these challenges requires hybrid solutions such as energy-efficient consensus protocols, Proof of Stake, robust encryption, and pilot deployments to harmonize technological innovation with operational realities, ensuring ports evolve into resilient, sustainable hubs aligned with global mandates like the IMO's Maritime Single Window.

4.Blockchain-FL Framework for AI-Predictive Analytics in PCS

This section presents the conceptual framework of the blockchain-FL framework. The proposed framework Integrates AI predictive analytics through FL and blockchain. To enable collaborative yet privacy-preserving intelligence sharing among horizontal actors in PCS, such as shipping lines, terminal operators, trucking companies, customs, and logistics providers. The functional objective of this module is to enable AI-powered predictive analytics in PCS for vessel delay predictions, birth allocations, and cargo floor optimizations. Furthermore, it ensures privacy-preserving artificial intelligence training using FL, where stakeholders can train models locally without sharing. Raw data. Through transparent and secure means via blockchain to ensure verifiability and contributions and tamper proof model validations.

Additionally, the module in scientific advice data collaboration using smart contracts and tokenized rewards encourages active participation in AI training. Figure 3 depicts. The architectural framework and components that are integrated into the modeling of the AI-Predictive analytics framework.

Figure 6: Blockchain-FL Architectural Framework



Source: Own compilation

The proposed architectural structure of AI Predictive. The module for the PCS consists of six layers. That is the client layer, local server, and local model Blockchain layer. Global model and integration layer. The learning coordinator, in this instance, is the port through PCS. The FL function is an integrated functionality within the PCS that is a value-added service for clients.

Layer 1: Clients (Edge Nodes)

Multiple port stakeholders (clients) participate in the FL process at the network's edge. These include shipping companies, customs agencies, terminal operators, and trucking companies. Individual cloud node (client K) represents a scalable number of actors that can be added as the system expands. Each client node collects real-time and historical data from multiple sources such as the Automatic Identification System, IoT sensors, weather forecasts, truck movement logs, and customs clearance times. The key role of these clients is to observe operational patterns. Related to vessel arrivals, birth congestion, cargo processing, and inland transport movement. Instead of transmitting raw data, these clients process their data locally to maintain privacy and data sovereignty.

Layer 2: Local servers of each client

Each client node operates a dedicated local server where data is stored, pre-processed, and prepared for local AI model training. These local servers are private computing environments that host the FL and client infrastructure, ensuring that raw data never leaves. The organization's internal system. Data pre-processing techniques are applied at this stage to clean, normalize, and standardize the collected information. Differential privacy techniques and homomorphic encryption are implemented to obfuscate sensitive business insights while still allowing. The AI model to learn valuable patterns. These local servers are the gateway between the client nodes and the FL framework, transmitting only encrypted model parameters rather than the underlying raw data.

Layer 3: Local Model training on client servers.

Each cloud trains a local AI model using its operational data without exposing sensitive details. This step leverages deep learning techniques such as long short-term memory LSTM networks for time series forecasting, XG Boost for predictive analytics, and reinforcement learning for adaptive decision-making. Since every board stakeholder operates under different conditions, the primary objective is to develop highly accurate vessel eater predictions, congestion forecasts, and resource allocation recommendations. The local AI model is fine-tuned to reflect their specific use case. The trained local models are then prepared for aggregation, ensuring only model weight update gradients are sent to the central FL aggregator.

Layer 4: blockchain integration for security and transparency.

Before the local AI models are sent to the global FL aggregator, a blockchain-based validation layer ensures data integrity, traceability, and trust between participating clients. Each model update is recorded on a permission block. The same Ledger allows independent verification without revealing raw data. A proof of accuracy per consensus mechanism ensures that only highly accurate model contributions are accepted. If a model is deemed unreliable, it is excluded from the aggregation process. This layer also automates contract execution and issues incentive tokens to clients who contribute high-quality AI models. Additionally, blockchain secures data exchange agreements, participant authentication, and compliance tracking, making the FL process fully auditable.

Layer 5: Central FL Server for Global Model Aggregation

The Central FL server aggregates the encrypted model updates from all participating client nodes. This server applies Federated averaging fed AVG techniques to combine local model contributions into a more robust global AI model. The international model is continuously refined, improving accuracy for predicting vessel delays, birth availability, customs, processing times, and trucking schedules. The updated global model is then redistributed. The old client nodes allow each participant to benefit from collaborative AI insights while maintaining privacy.

Dynamic Birth allocation and AI-Based Decision making

Once the global AI model has been refined, it will be integrated into the PCS for real-time birth scheduling and vessel delay management. Terminal operators receive dynamically driven recommendations. With reallocation, crane scheduling, and cargo yard optimization, the AI system automatically reschedules birthing slots if a vessel is predicted to be delayed. It notifies logistics partners of revised arrival times. This minimizes idle birth time and prevents supply chain bottlenecks. Further, all inland transport schedules, trucks, rail, and multimodal logistics are adjusted to match the optimized birthing timeline.

Blockchain smart contracts for automated notifications and incentives

to facilitate seamless coordination, smart contracts on blockchain automatically trigger notifications and issue incentive rewards when the AI model detects a vessel delay and reassigns a birth Smart contract. Notify all relevant stakeholders, including trucking companies, freight forwarders, and customs officials. This ensures all court actors are aligned in real-time, reducing inefficiencies. Additionally, blockchain-based tokenized rewards encourage stakeholders to contribute actively. Accurate data and adjust schedules in response to a high prediction. These tokens can be redeemed for priority birth access, reduced demurrage fees, or operational discounts.

Continuous learning and real-time AI model improvements

Finally, the Federated learning model continuously evolves as new operational data flows into the system. IoT sensors at births, key cranes, container yards, and trucking checkpoints provide real-time validation of AI-generated. Predictions If a vessel's arrival time differs from the predicted eater, the system fine-tunes the AI model for future iterations. Additionally, blockchain maintains a secure audit trail of past predictions, birth assignments, and incentive distributions, making the entire AI. PCS is fully traceable and transparent. Overall, this continuous learning process enhances predictive accuracy, optimizes port efficiency, and reduces congestion

5.Discussion

Based on a systematic review of 45 articles (2016–2025), this study reveals that the combined applications of blockchain and FL in PCS remain non-existent despite their potential to address confidentiality, security, and multi-stakeholder collaboration challenges. Existing research on blockchain-FL primarily focuses on generic supply chains, such as provenance tracking (Bandara et al., 2021), food supply chain resilience (Ahamed & Karthikeyan, 2024), and decentralized governance (Lee et al., 2023). While these applications demonstrate improvements in transparency and responsiveness, they fail to address the unique complexities of port ecosystems, characterized by heterogeneous stakeholders' port authorities, customs, shipping companies' mission-critical operational data vessel delays, and berth allocation.

However, this integration faces multidimensional challenges. On a technical level, the scalability and latency of blockchain-FL architectures hinder their adoption in distributed environments like PCS, where data is often fragmented and high-throughput (Gulati et al., 2023). The energy consumption of consensus mechanisms Proof of Work also raises sustainability concerns, conflicting with port environmental objectives (Agarwal et al., 2024). Furthermore, while blockchain enhances transaction security, FL systems remain vulnerable to local model tampering or collusion risks (Zhu et al., 2023), exacerbated in multi-stakeholder contexts like PCS. Operationally, data format heterogeneity and stakeholders' reluctance to share sensitive information impede interoperability, while traditional predictive models struggle to adapt to the dynamic nature of port operations (El Idrissi & Haidine, 2023). Strategically, the absence of clear cost-benefit frameworks and the complexity of aligning technological goals with operational priorities complicate large-scale adoption (Farzadmehr et al., 2024).

The proposed conceptual framework (Figure 6) offers transformative advantages for PCS. Enabling collaborative AI model training without raw data sharing preserves the confidentiality of sensitive commercial information, customs logs, and weather forecasts while enhancing prediction accuracy, vessel delays, and congestion. Through a permissioned ledger and smart contracts, blockchain ensures the traceability of contributions model gradients and automates incentive tokens for priority berth access, fostering trust among competing stakeholders. For example, a terminal operator could dynamically adjust crane allocation using a globally refined model updated in real-time via IoT sensors, reducing vessel idle time. The resulting operational savings reduced demurrage fees justify initial investments, while immutable decision audits facilitate regulatory compliance IMO 2024 directives.

The successful integration of blockchain and FL within PCS hinges on a six-layer architectural framework designed to harmonize decentralized collaboration, privacy preservation, and operational efficiency. First, the Decentralized Collection (Client Layer) enables edge nodes such as customs agencies and shipping companies to aggregate heterogeneous data streams, AIS signals, IoT sensor outputs while preserving data sovereignty. Second, the Secure Pre-processing (Local Server Layer) employs homomorphic encryption and differential privacy techniques to sanitize raw data, mitigating leakage risks during transmission. Third, the *Contextual Training (Local Model Layer)* leverages machine learning algorithms like Long Short-Term Memory (LSTM) networks and XGBoost to generate localized predictive models tailored to site-specific conditions and weather patterns in Arctic ports. Fourth, the Blockchain Validation (Blockchain Layer) introduces a novel "proof-of-accuracy" consensus mechanism to audit model contributions, discarding unreliable updates and incentivizing participation through smart contract-driven token rewards. Fifth, the Global Aggregation (FL Server Layer) synthesizes validated model updates into a robust global AI framework, enabling continuous federated learning across stakeholders. Finally, the Dynamic Decision-Making (Integration Layer) translates predictive insights into real-time operational adjustments, such as AI-driven berth reallocation, with automated notifications to impacted stakeholders revised vessel schedules. This layered architecture addresses the technical and operational complexities of PCS. It aligns with the International Maritime Organization's (IMO) mandate for secure, interoperable digital ecosystems, setting a benchmark for AI adoption in global maritime logistics.

This approach addresses an academic gap by proposing a theoretical model tailored to PCS while aligning with the IMO's mandate for unified maritime windows. However, limitations persist, including the need for empirical validation of energy performance and harmonization of cross-border regulations. Future research should explore alternative consensus mechanisms, Proof of Stake, and pilot deployments in complex port ecosystems in Rotterdam, Singapore. In conclusion, this framework paves the way for smarter, more resilient ports, where secure collaboration and operational sustainability become tangible realities.

While this study advances a conceptual framework for integrating blockchain and FL into PCS, several limitations warrant acknowledgment. First, the proposed architecture requires empirical validation to assess its scalability and energy efficiency in real-world port environments, particularly in large-scale hubs with heterogeneous data flows. Second, the reliance on blockchain introduces sustainability concerns due to energy-intensive consensus mechanisms. Proof-of-Work necessitates future exploration of hybrid or alternative protocols. Proof-of-Stake and Byzantine Fault Tolerance should align with decarbonization goals. Third, the framework assumes a baseline level of stakeholder collaboration and technological readiness, which may not hold in fragmented or regulatory-diverse maritime ecosystems. Future research should prioritize pilot deployments in major ports to evaluate interoperability, latency, and cost-benefit ratios under operational stressors, peak cargo volumes, and cyberattacks. Additionally, interdisciplinary collaborations are needed to address cross-jurisdictional governance challenges, such as harmonizing data privacy laws, GDPR, and CCPA with blockchain's decentralized ethos.

This study pioneers a blockchain-FL framework tailored to the unique demands of Port Community Systems, addressing critical gaps in maritime AI research. By synthesizing decentralized learning with tamperproof data governance, the framework enables privacy-preserving predictive analytics for vessel scheduling, berth allocation, and congestion mitigation, the key to achieving the International Maritime Organization's vision of AI-driven smart ports. The proposed architecture mitigates risks of data fragmentation and cyber threats and fosters stakeholder trust through transparent, incentive-aligned collaboration. As global trade pivots toward digital resilience, this work provides a foundational blueprint for integrating emerging technologies into complex, multi-actor ecosystems. Future efforts must focus on empirical validation, energy-efficient consensus models, and regulatory innovation to unlock the full potential of blockchain-FL synergy, ensuring ports evolve as sustainable, secure, and intelligent hubs in the maritime supply.

Conclusion

This study proposes an innovative framework for the synergistic integration of blockchain and FL within PCS to enhance AI-driven predictive capabilities while preserving data confidentiality and securing transactional exchanges. A systematic review of 45 articles (2016–2025) identifies a critical gap in research on the combined application of these technologies in PCS, despite their potential to address challenges such as data fragmentation, cyber threats, and mistrust among heterogeneous stakeholders and port authorities, customs, and logistics providers. The analysis reveals that blockchain-FL applications in supply chains remain exploratory, facing technical barriers to interoperability, latency, energy consumption, operational hurdles, process complexity, resistance to change, and strategic misalignments in sustainability objectives. To address these, the study introduces a six-layer conceptual framework that integrates federated learning local model training without raw data sharing, blockchain transparent validation via permissioned ledgers and smart contracts, and IoT real-time data streams. This system enables collaborative predictive analytics for optimizing vessel berthing, dynamic quay allocation, and traffic management while automating incentives through exchangeable tokens. The theoretical implications emphasize the significance of decentralized architectures for port ecosystems, while practical applications align PCS with the International Maritime Organization's (IMO) 2024 directives on Maritime Single Windows. This research provides a roadmap for developing more resilient, intelligent, and sustainable ports by bridging an academic void. However, empirical validation of scalability and energy efficiency challenges remains a critical next step.

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