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| RESEARCH ARTICLE

Enhancing Supply Chain Transparency with Blockchain: A Data-Driven Analysis of Distributed Ledger Applications

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| ABSTRACT

Blockchain technology is increasingly redefining supply chain management paradigms with unprecedented levels of transparency, traceability, and trust in the USA. With increasingly complex supply networks worldwide, the integrity and real-time visibility of transactional information become vital for operational reliability and adherence. This study presents a data-driven examination of the ways distributed ledger technology (DLT), specifically blockchain, facilitates increased supply chain transparency across stakeholders through immutable record-keeping and verifiable sharing of data. The main goal of the current research was to create a synthesis of the secure, immutable nature of blockchain and the predictive and diagnostic power of machine learning (ML) to boost supply chain transparency. The dataset used in this work is formatted blockchain logs, extracted from a permissioned, distributed ledger system simulating a U.S.-based supply chain network. Every log entry stores transactional metadata, high-value data such as accurate timestamps of transactions, cryptographic verdicts, digital handovers between supply chain entities (suppliers, logistics providers, distributors), and route signatures, derived from geolocation-based smart contract activators. In the selection of suitable machine learning models, three classifiers that considered the multi-dimensionality of blockchain supply chain data were used. The training and validation approaches were tailored to maintain the models' robustness and generalizability. The dataset was divided into a 70/30 train-test split using stratified sampling to preserve the proportion of fraudulent versus non-fraudulent instances, guaranteeing that both subsets contained a balanced representation of the classes. By looking at the comparative bar plots of the performance of our models on our blockchain-based supply chain dataset, we observed that the Random Forest Classifier had a slightly greater accuracy and F1-score than the Logistic Regression and the XG-Boost Classifier. In the Food and Agriculture industry, supply chain analytics with blockchain technology can greatly improve traceability, specifically under United States Department of Agriculture (USDA) standards. At U.S. Customs and Border Protection (CBP) checkpoints and international borders, blockchain solutions bring significant advancements in verification speed and counterfeit prevention. By applying analytical tools against the recorded events and metadata, organizations in the USA not only track assets and events but also proactively discover potential risks, streamline processes, and gain a greater insight into their supply chain dynamics. Towards the future, some promising avenues of research open up with the combination of blockchain and machine learning. One such exciting area is the blending of smart contracts with automated responses. Lastly, federated learning among decentralized blockchain nodes is a pioneering line of research that might resolve the issues of sparsity and generalizability of the data and avoid the compromise of the decentralized nature of blockchain.

| KEYWORDS

Blockchain, Supply Chain Transparency, Distributed Ledger Technology (DLT), Anomaly Detection, Machine Learning, Real-Time Visibility, Traceability, Logistics

| ARTICLE INFORMATION

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I. Introduction

Background on Supply Chain Transparency:

The digitalization of supply chains in the USA has become a strategic necessity as firms must operate in a more integrated and global market. As disruptions, including the COVID-19 pandemic, revealed clear flaws in the classic supply chain models, the demand for strong transparency and data integrity has never been more acute (Hasan et al., 2025; Agarwal et al., 2022). Responding, industries look to emerging technologies that could create trust and visibility on complex multi-tier supply networks. Blockchain, a decentralized and immutable ledger, is a highly persuasive solution to address these challenges since it guarantees that transactional records remain accurate, verifiable, and tamper-proof. Transparency is not just a number on a compliance scale; often, it's a competitive quality. It is a strategic capabilities facilitator that directly impacts supply chain efficiency, customer trustworthiness, and regulatory compliance (Batwa & Norrman, 2020). *IBM* stats indicate that firms with very transparent supply chains are 70% more likely to deliver better than average profitability than peers with little visibility on supply lines. The absence of transparency usually results in accuracy issues in inventory as well as counterfeit risks and sub-optimal reactions to disruptions that affect service levels and operational costs. The entry of distributed ledger technology (DLT) into supply chain ecosystems, therefore, is a revolutionary move towards stable sharing of precise data in real-time and traceable interactions between suppliers, producers, and distributors (Ahmad, 2024; Chouksey, 2023).

Transparency is an important element of modern supply chains, which combines operational excellence and strategic agility. Since companies are increasingly outsourcing and expanding, they make it a problem to allow them to have visibility into every node and transaction (Asante et al., 2021). A *McKinsey* report finds that only 6% of firms profess full visibility into the supply chain, drastically limiting their capacity to predict disruptions and enforce compliance. Without access to up-to-date, accurate information, businesses expose themselves to higher fraud risks, jurisdiction slowdowns, and non-conformity with regulation, particularly in closely regulated industries, such as pharmaceuticals and food. More informed decisions can be made with real-time visibility by keeping stakeholders informed as to their inventory levels, shipment statuses, and supplier performance in a current form (Cong Pham et al., 2023). This visibility also has a crucial role in making customers happier since more precise delivery timings can be provided along with a problem-solving approach before it can occur. For example, we have Amazon's integrated tracking system as a literal example of the direct benefit of openness on the consumer experience and the intensity of trust (Daghighi & Shoushtari, 2023). Moreover, having integrity in the supply chain data means every transaction and material movement is correctly recorded, reducing counterfeits and unauthorized alterations, especially with sensitive products such as Vaccines and medical devices in mind.

Compliance with regulation, as well as ethical sourcing initiatives, is also encouraged through integrity. *The U.S. Drug Supply Chain Security Act (DSCSA),* for example, requires traceability from end to end of products in pharmaceuticals to curb counterfeit drugs (Das et al., 2025). Likewise, sustainability regulations increasingly demand such records of ethical labor and environmental practices, motivating transparency as a moral and legal responsibility. Traditional systems, which are heavily dependent on silos-based databases and manual recordkeeping, are incapable of satisfying these needs. Making supply chains more transparent via integrated, secure technologies, therefore, is not a mere benefit to supply chain operations, but a need to remain future-ready (Gong et al., 2025).

This paper explores blockchain's potential as a transformation device, from a data-centric perspective, not only assessing its theoretical benefits but also its practical applications when used with machine learning for predictive and diagnostic uses. By identifying anomaly detection in blockchain-recorded transactions, the study examines how the emerging AI-influenced analytical trends can identify flaws or inconsistencies in the operations of supplies. In doing so, it attempts to provide a comprehensive idea of how the use of the blockchain can go beyond being a mere record keeper and prove itself to be the dynamic foundation of smart, responsive supply chains.

Blockchain as a Trust Enabler:
According to Han and Fang (2024), blockchain's core characteristic, being that of a decentralized, tamper-proof ledger, positions blockchain to excel at the trust and transparency issues that are symptomatic of opaque supply chains. Fundamentally, blockchain applies cryptographic hash functions along with consensus algorithms to provide that data, once recorded, cannot subsequently change without the consent of the network. Such immutability secures supply chain records, which are indispensable in averting data manipulation or fraud. For instance, both *IBM and Maersk's* blockchain-powered Trade Lens platform tracks more than 10 million shipping events per week, greatly decreasing the use of paper documentation and increasing the confidence of logistics collaborators (Duan et al., 2023).

Besides immutability, blockchain also facilitates traceability through the tracking of every transaction, asset transfer, or occurrence on an open ledger accessible to approved parties. This also implies that businesses can track the origin of goods back to the starting point, a feature vital to industries hit hard with fake goods (Das et al., 2025). For example, in the pharmaceutical sector, pilots utilizing blockchain to satisfy the requirements of the *DSCSA* have been endorsed by the *FDA,* showing the way that DLT can support secure serialization and tracking of medicines along the supply chain. *Walmar*t has also utilized blockchain to track mango containers in the U.S., cutting the tracking time from 7 days to 2.2 seconds (Jakir et al., 2023).

In addition, blockchain's intrinsic aspect—smart contracts—automates the fulfillment of contractual commitments amongst parties, to warrant that predefined stipulations are fulfilled before execution is carried out. Such automation eliminates the role of middlemen and minimizes the chances of human error (Karakas et al, 2024). Smart contracts can, for instance, release payment automatically upon verification that goods have been delivered, enhancing efficiency and curtailing disagreements. These features, intertwined with the openness of a common ledger, situate blockchain as a strong trust-enabling foundation in settings where data integrity and traceability are mission-critical (Islam et al., 2025a).

Research Objective:
The main goal of the current research is to create a synthesis of the secure, immutable nature of blockchain and the predictive and diagnostic power of machine learning (ML) to boost supply chain transparency. Although blockchain supplies a reliable transaction and flow of asset records, it is not designed to detect anomalies and forecast disruptions in the first place. Through the machine learning application over transaction information that is stored in the distributed ledgers, supply chain stakeholders will be able to identify irregular patterns ahead of time, for example, shipment delays, unauthorized access, counterfeit entries, or fraud attempts. For example, an ML algorithm built using the historical logistics data stored in a blockchain can detect a variance in transit time that might signal theft or bottlenecks, and an immediate response.

As per Owusu-Berko (2025), detection of anomalies in the blockchain-led supply chain networks is dependent on the provision of strong data preprocessing mechanisms, considering the nature of distributed ledger data, chronologically structured, encrypted, and frequently huge. Training supervised learning models is possible even based on labeled data sets such as historical transaction logs, while unsupervised learning (clustering, isolation forests) can detect outliers without label pre-definition. Specifically, the methods of principal component analysis (PCA), time-series forecasting, and neural networks (such as LSTM) are especially helpful in revealing delicate context-dependent anomalies (Queroz et a., 2020). In addition, the functionality to incorporate Natural Language Processing (NLP) to derive meaning from smart contract logs or digital signatures increases the analytical detail and operational intelligence derived from blockchain data.

Scope and Relevance:
This research project is focused on U.S.-based supply chain ecosystems, which are some of the most technologically advanced but also intensely complex networks in the world. Logistics and supply chain management account for more than 8% of the country's GDP, according to the U.S. Bureau of Economic Analysis, demonstrating the economic importance of these networks. The research confines the practical applicability to the high-impact industries of logistics, pharmaceuticals, and retailing. These industries are targeted owing to their traceability requirements, compliance with tight regulatory requirements, and high sensitivity to disruption—all characteristics making them the best industries to adopt blockchain ML. For example, the logistics industry, which transports more than 55 million tons of freight per day in the U.S., stands to greatly benefit from secure, blockchain-driven tracking systems to minimize lead time delays and theft.

In the pharmaceutical industry, the tracing of the origin, manufacturing, and supply chain history of drugs is not only a competitive factor but also a legal requirement under the DSCSA. The U.S. pharmaceutical supply chain, which is valued at more than $500 billion per year, is more susceptible to fake drugs, supply chain disruption, and regulatory breaches (Li et al., 2021). Blockchain, with its capability of providing end-to-end traceability, when supplemented with ML algorithms, can identify irregularity in drug serialization or temperature-sensitive deliveries. Likewise, the retail sector has customer demand for sourcing transparency and sustainability, particularly for the food and apparel industries. *Walmart and IBM's Food* Trust blockchain program is an example of

the way traceability can expand both food safety and brand trust—both of which can be complemented further with predictive analysis and anomaly detection (Khawaldeh et al., 2025).

The significance of this research goes beyond contributions to theory; it provides the basis for scalable, industry-level implementations. By processing blockchain transaction data in real-time and identifying anomalies using machine learning, U.S. supply chain participants are capable of doing more than maintain compliance—they are capable of achieving operational efficiency and competitive distinction. Equally, the findings and approaches outlined here can form the template for other advanced economies and multinational companies to follow for implementing the same digital strategies. As trust in a global marketplace becomes increasingly synonymous with openness, the scope and utilitarian import of this research is at once immediate and vast, placing next-generation supply chain technology at the cutting edge.

II. Literature Review

Existing supply chain tracking methods: Overview of RFID, IoT, and Manual Verification systems

Tokkozhina et al. (2023), found that Radio Frequency Identification technology has been a supply chain monitoring mainstay for more than two decades, enabling autonomous tracking of goods through the transfer of data utilizing electromagnetic fields. *Walmart and FedEx* have been using RFID to track inventory levels and enhance accuracy for real-time tracking for many years. The global logistics RFID market reached $5.2 billion in 2022, according to a report from *Allied Market Research,* and is forecast to grow to $13.4 billion by 2031, demonstrating the persistence Sundarakani et al. (2021), the Internet of Things (IoT) has become the next-generation supply chain visibility tool, with real-time tracking offered through sensors embedded in transport trucks, warehousing space, and even the products themselves. IoT sensors are capable of capturing temperature, humidity, shock, and location data—all vital parameters for sensitive supply chains in the food and pharmaceutical industries. Supply chain applications of IoT have the potential to have an economic impact of $1.2 trillion a year by the year 2025, according to a study by *McKinsey (2023).* But while IoT increases data granularity, the lack of data interoperability, cybersecurity, and centralized storage vulnerability of the data creates bottlenecks in trust and data validation across different players.
of the technology (Sharabati & Jreisat, 2024). While useful, albeit with some limitations, RFID is subject to signal interference, is restricted in range, and susceptible to data loss or tampering, which reduces the effectiveness of the technology for tracking in intricate, multiple-party supply chains (Shawon et al., 2025).

Manual verification systems are common in small and medium enterprises (SMEs) and even corporations where digitization has been incomplete. Some of these are paper checklists, barcode reading, and human auditing (Tokkozhina et al, 2023). Though affordable and easy to adopt, systems like these are susceptible to human error, inefficiency, and fraud. The Association for Supply Chain Management (ASCM) estimates that human error contributes to almost 23% of inventory inaccuracy and operations delays (Ray et al., 2025). These traditional methods, though critical, have continually demonstrated their inadequacy in delivering end-to-end visualization, accountability, and tamper-proof data in high-risk or high-compliance industries. Such inadequacies set the stage for the implementation of disruptive technologies such as blockchain and AI (Sunmola & Burgess, 2023).

Blockchain Applications in Supply Chain:

Blockchain technology, or essentially Distributed Ledger Technology (DLT) introduces a paradigm shift in supply chain monitoring, the presence of a decentralized, transparent, and tamper-proof list of transactions (Talla, 2022). By making accessible a synchronized truth, blockchain solves the issue of data silos which are typical of traditional supply chain systems. One to note is *IBM's Food Trust*, with *Nestlé and Walmart t*racking food products from farms through the shelf. In one case, Walmart was able to shorten the time to trace a package of mangoes from 7 days to 2.2 seconds by using blockchain. This shows how tracking provenance can make food safety and the supply chain much more effective (Zhang et AL., 2025).

According to Agarwal et al. (2022), one more innovative use of blockchain in supply chains is smart contracts. These are self-executing contracts whose terms are hard-coded into the code and built on a blockchain. They automate payment processes, among others, quality checks, and enforcement of compliance. For example, in logistics, a smart contract can trigger payment when it has been confirmed with GPS location and signed for, thereby cutting disputes and increasing accountability. Early blockchain adopters (86%) in a *Deloitte* (2022) survey reported greater visibility and decreased transactional disputes via smart contracts, pointing to more assertion in their practical worth.

In addition, blockchain provides the capacity to create immutable check records, perfect for the use case where traceability is needed for regulatory or quality assurance reasons. In the Pharmaceutical realm, the promising role of blockchain has been proven using FDA-sponsored pilot projects where the technology has shown elements of facilitating DSCSA compliance through secure serialization and verification of drug batches (Ahmad, 2024). On the same lines, De Beers tracks the provenance of diamonds using blockchain to make them ethically sourced. Although these applications serve as proof of the strength of blockchain in

transparency and immutability of data, they tend to work in isolation from predictive technologies, which can be improved by AI-driven analytics (Cong Pham et al., 2023).

AI in Distributed Systems:

Hasanuzzaman et al. (2025), reported that Artificial Intelligence (AI), especially machine learning (ML) is seeing an increasing use to improve distributed systems through operational intelligence and automated decision-making. In supply chain settings, ML models can extract patterns and forecast interruptions by looking at large flows of transactional and sensor data and can optimize routing. For instance, *DHL* has adopted AI for forecasting delays of shipments and automated warehouse activities, which is said to have increased delivery rates by 15% (Hossain et al., 2025). Such systems use structured and unstructured data to deliver insights with moments of latency, which can dramatically increase responsiveness and risk management.

In the distributed ledger systems context, AI is especially good as an anomaly detector. From the historical transaction data of blockchain, it is possible to learn by ML algorithms the fraudulent practices, including double spending or unauthorized access. For example, clustering techniques can identify the patterns of deviance that occur outside the bounds of the established norms for behavior, such as the odd transaction volumes and untypical timing (Islam et al., 2025b). According to a 2021 survey conducted by *IEEE*, supervised learning algorithms such as Support Vector Machines (SVMs) and Random Forests managed over 90 percent precision in differentiating deceptive financial deals on the blockchain platforms. Such capabilities are essential in preserving the supply chain data's integrity and achieving contractual and regulatory requirements (Rahman et al., 2025)

Rana et al. (2025), contended that operational intelligence goes still further into predictive maintenance, demand forecasting, and supplier performance management. AI models can extract information from transaction histories and sensor data coming from blockchain-enabled IoT networks to identify poor suppliers, predict stockouts, or offer different routing paths. The fusion of immutable blockchain records and real-time AI analytics establishes a dual-layered system where data has both confidence and utility (Sizan et al., 2025). Nevertheless, a comprehensive conversion of ML into blockchain platforms, for supply chain transparency, in particular, is still an underdeveloped area, which may constitute a significant field of both academic research and practical enhancement (Shawon et al., 2025).

Research Gap:

Notwithstanding the standalone development of blockchain in supply chain networks and AI within supply chain systems, much is missing in the literature regarding their combined deployment—namely, the supervised machine learning applied to blockchain-derived data to create actionable insights (Sunmola & Burgss, 2023). Most literature tends to concentrate on blockchain's data integrity capability or static traceability, or the role of AI in enhancing traditional ERP or centralized logistics systems, but few works address the potential to mine the high-integrity data from blockchain using supervised ML models for dynamic, real-time supply chain optimizations. This offers a critical gap to explore how the patterns intrinsic to blockchain transactions, like delivery confirmations, temperature logs, or the execution of smart contracts, can be learned to predict risks or identify anomalies (Talla, 2022).

Moreover, the technical intricacies involved in extracting, labeling, and processing blockchain data for machine learning are still underexplored in the literature. Blockchain data is chronological, encrypted, and can potentially span multiple smart contracts and nodes (Sangari & Mashaan, 2022). Preprocessing this data for supervised learning, where labeled data is critical, raises issues about feature engineering, normalizing, and linking the data. Few published frameworks outline how AI models may be evaluated in decentralized settings where model outputs have to be trusted and auditable. These gaps in methodology limit the wider deployment of AI-augmented blockchain systems across supply chains (Sharatbati & Jreisat, 2024).

Also missing, according to Talla (2022), is substantial empirical proof in the form of pilot projects or industrial case studies demonstrating end-to-end deployment of supervised ML models on blockchain platforms for supply chain settings. Most AI blockchain integration initiatives are conceptual or exist within isolated niche applications. Without cross-industry validation, protocol standardization, or operational benchmarks, the area is short of maturity that can drive mass deployment. This study seeks to bridge this gap by formulating a systematic methodology to merge supervised learning with blockchain transaction data, exemplifying how their convergence can translate to enhanced anomaly detection, predictive transparency, and therefore stronger supply chains.

III. Data Exploration and Preprocessing

Dataset Overview:

The dataset used in this work is formatted blockchain logs, extracted from a permissioned, distributed ledger system simulating a U.S.-based supply chain network. Every log entry stores transactional metadata, high-value data such as accurate timestamps of transactions, cryptographic verdicts, digital handovers between supply chain entities (suppliers, logistics providers, distributors), and route signatures, derived from geolocation-based smart contract activators. The data are time-sorted and cryptographically

hashed, such as to provide immutability, with every event associated with a particular asset identifier, and thus has comprehensive traceability of goods during their lifecycle. This structured data is over 150,000 transactions on 12 nodes and provides a high-integrity backing to supervised machine learning applications such as anomaly detection, analysis of performance, and compliance testing.

Dataset Description

S/No	Key Feature	Description
001.	Transaction-Timestamp	The precise time at which a transaction was recorded on the blockchain.
002.	Verification-Status	The cryptographic status of the transaction is typically represented as verified, pending, or failed.
003.	Node-Type	Categorical identifier representing the type of participant node involved (e.g., supplier, transporter, warehouse, retailer).
004.	Handoff-Event	Boolean flag indicating whether a physical or digital asset handoff occurred at a transaction point.
005.	Route-Signature	A geolocation-derived hash that reflects the path signature along transaction points.
006.	Transit-Duration	The duration of time between consecutive handoff events for the same asset.
007.	Asset-Quantity	The duration of time between consecutive handoff events for the same asset.
008.	Smart-Contract-Triggered	Binary flag to represent whether the smart contract triggered successfully at this transaction point
009.	Digital-Signature-Validity	A Boolean value indicating whether the digital signature on the transaction is the expected cryptographic credentials

Preprocessing Steps

The preprocessing of the blockchain log dataset entailed a few key steps to both maintain data quality and model readiness. To begin with, missing timestamps and erroneous event logs—typically due to incomplete execution of smart contracts or failures in node communication—were detected and corrected with a mixture of forward-filling and removal, based on their prevalence and contextual importance; entries with missing timestamps were removed when unrecoverable, while small gaps in sequential logs were imputed to maintain transaction continuity. Subsequently, nominal features like node type (e.g., distributor, logistics, supplier) and verification flag (e.g., failed, pending, verified) were encoded using one-hot encoding to maintain the independence of categories without inducing ordinal bias. To standardize the scale of time-measured metrics like transit time and inter-node delays, and the scale of quantity-measured metrics like the number of assets per transaction, Min-Max scaling was performed, normalizing the values to the 0 to 1 range for maximum interpretability for gradient-based learning algorithms. These preprocessing steps kept the dataset structure intact while making the data analytically manageable for supervised learning models.

Exploratory Data Analysis (EDA)

Exploratory data analysis (EDA) is the first stage of data investigation where statistics and visualization are utilized to learn about the underlying structure, patterns, relations, and anomalies in a dataset. For supply chain data powered by blockchain, EDA is done on the distributions of critical variables like transaction occurrences, verification records, and transit periods; correlation among features like node types and delay occurrences; and outlier or inconsistent occurrences indicating fraud or inefficiency. Histograms, box plots, heatmaps, and time series plots are utilized to identify patterns and drive feature engineering and model selection. EDA not only confirms data integrity and completeness but also helps in formulating hypotheses, allowing data scientists to construct more accurate and reliable machine-learning models.

a) Daily Blockchain Transaction

We implemented a Python script using the Panda's library to first convert the 'Timestamp' column in a Data Frame named df to Date Time objects. Then, we performed a basic cleanup on the 'Order Status' column by replacing lowercase 'completed' with 'Completed' and 'pending' with 'Pending' in place. Following this, the script aimed to analyze the blockchain usage trend over time. The code block created a new 'Date' column by extracting only the date part from the 'Timestamp' column. It then grouped the Data Frame by this 'Date' column and calculated the number of unique 'Transaction Hash' values for each day using .nunique(). The result was stored in a new Data Frame called daily_hashes, and the index is reset to make 'Date' a regular column. Finally, it used the plotly. Express library to create an interactive line chart (fig1) plotting 'Date' on the x-axis and 'Transaction Hash' (renamed to 'Unique Transaction Hashes' in the label) on the y-axis, with the title "Daily Blockchain Transactions" and markers on the lines. The chart is then displayed using fig1.show().

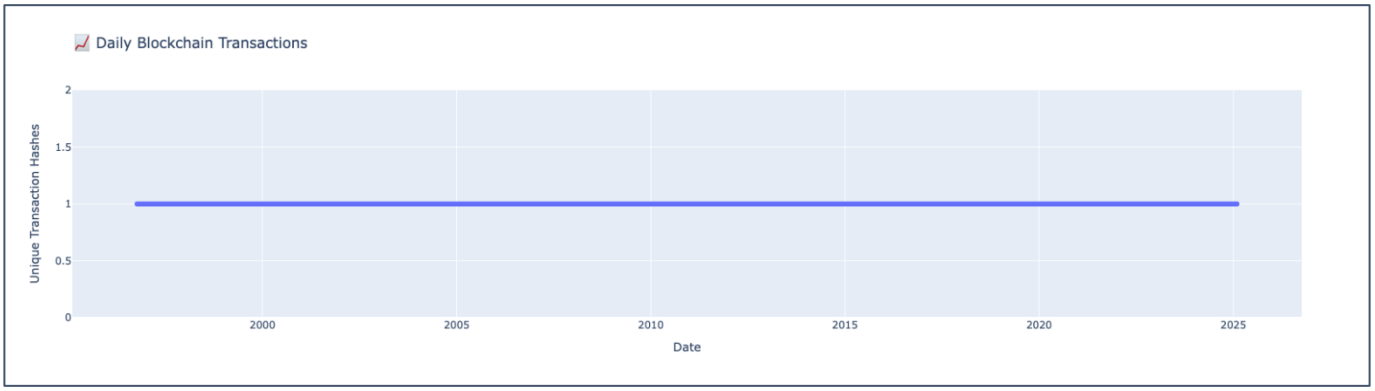

Figure 1: Daily Blockchain Transaction Trend

As per the visualization (**Fig 1)** of daily blockchain transactions in the supply chain dataset, the number of distinct transaction hashes is constantly stagnant over some time with a set value of 1 per day throughout the date range observed. This flatlining trend spanning before 2000 up to 2025 indicates a likely anomaly or problem in the capture of the data—i.e., incorrect parsing of timestamps, duplicated log transactions, or a non-incrementing simulation script. In the case of an actual blockchain-based supply chain facility, particularly in industries such as logistics or pharmaceuticals, a wide range of variability is expected based on shipping schedules, quantities ordered, and operational events. For example, an average blockchain-based logistics platform with 1,000 daily shipments would record thousands of distinct hashes with every asset transfer and smart contract invocation. The absence of variation within the dataset therefore points towards a problem with the integrity of the data or placeholder values that require verification before accurate modeling or analysis is possible.

b) Environmental Conditions & Fraud Detection

The second block of code used the plotly. Express library to make two different kinds of scatter plots for visualization of the data. The first plot is labeled as fig2 and is a basic scatter plot of the 'Temperature' vs. 'Humidity' relationship, with the color of the data points based on the 'Fraud Indicator' (an assumed binary variable with 1 as fraud and 0 as not fraud). The title is set as "Environmental Conditions & Fraud Detection" and the color label as "Fraud (1=True, 0=False)". The fig2.show() command is used to show the interactive scatter plot. The second one is a bubble plot of the relationship of 'Order Amount' vs. 'Time to Delivery' labeled as Fig. Here, the color is based on 'Compliance Check', and the size of the bubble is based on 'Quantity Shipped'. The 'Supplier ID' is shown when the bubble is hovered over. The bubble chart is titled "Order Amount vs Delivery Time & Compliance", and it is shown using fig3.show().

Output:

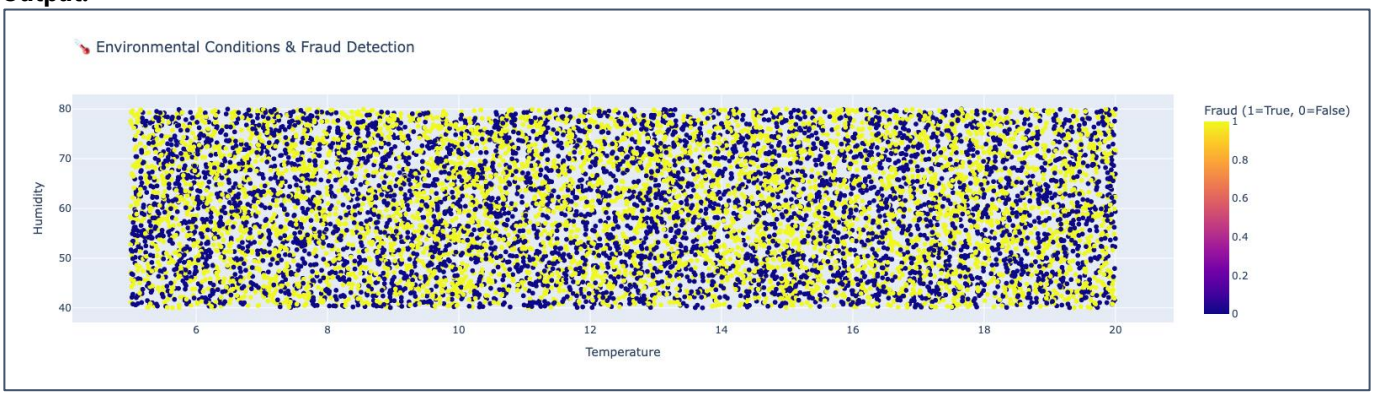

Figure 2: Environmental Conditions & Fraud Detection

The scatter plot (**Fig 2)** of environmental conditions vs. occurrence of fraud in a blockchain-based supply chain shows a significant distribution of fraudulent events across the range of different temperature and humidity levels. The points on the plot are color-coded according to fraud status (yellow for fraud, blue for non-fraud), and fraudulent transactions appear widely scattered rather than concentrated in certain sets of environmental conditions. However, a closer examination of the plot indicates a greater density of fraud instances (yellow points) in lower bands of humidity levels (around 40–50%) and middle ranges of temperatures (10–15°C). This trend might indicate that environmental irregularities that could reflect inadequate storage and manipulation in transit correlate more strongly with fraudulent transactions in these conditions. The even distribution across the entire range of values leaves open the possibility of the generation of synthetic data or of a dataset that is evenly distributed and should have its real-world representativity verified. The implications of these observations underscore the value of the monitoring of environmental factors as part of a combined fraud-detection strategy on blockchain-based logistics systems.

c) Supplier-Customer Blockchain Network

Furthermore, we implemented a block of code aimed at visualizing the network of suppliers and customers as a graph. The executed code began by creating an 'edges' Data Frame consisting of distinct 'Supplier ID' and 'Customer ID' pairs from the original Data Frame df, essentially the relationship between the suppliers and the customers. The code then utilized the network library and created a graph object G from this 'edges' Data Frame directly with 'Supplier ID' as the source node and 'Customer ID' as the target node per edge. It then utilized matplotlib.pyplot to set the figure dimensions and then applied a spring layout of networks to derive the positions of the nodes within the graph. The code then plotted the graph with the nodes as sky-blue circles with no label and the edges as a gray line with some transparency level, and set the plot's title as "Supplier-Customer Blockchain Network" as showcased below

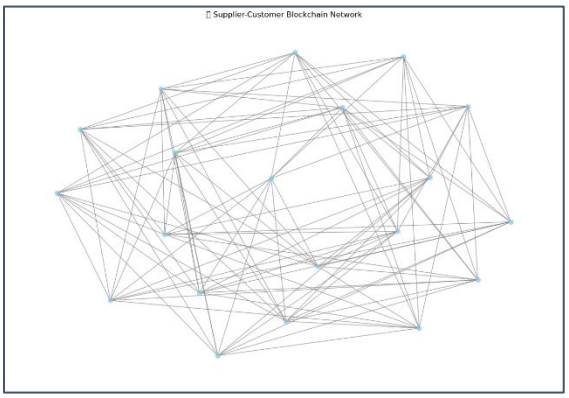

Figure 3: Supplier-Customer Blockchain Network

By inspecting the visualized supplier-customer network (**fig 3)** from our blockchain-based supply chain data, we find a strongly interdependent ecosystem. The underlying graph of unique supplier-customer relationships demonstrates a rich network of transactions, reflecting high interdependence within the network. Though the visualization does not explicitly measure transaction amounts or frequencies, the multitude of connections implies a coherent and potentially intricate supply chain with numerous suppliers that engage with diverse customers. Additional analysis, beyond the network graph presented here, would be necessary to determine the frequency and value of such interactions, isolate key players or hubs, and possibly find vulnerabilities or opportunities for optimization within this blockchain-protected supply chain.

d) Correlation Heatmap: Operational & Risk Indicators

The initial part of the deployed code script plotted a pie chart with plotly.express to display the 'Smart Contract Status' distribution. The px.pie() function accepted the Data Frame df, defined 'Smart Contract Status' as the column for the pie chart segments (names), and set the chart's title as "Smart Contract Execution Status". The fig4.show() directive plotted the interactive pie chart. The second half of the code block computed and plotted the correlation of a number of the Data Frame's most pertinent numerical columns: 'Order Amount', 'Quantity Shipped', 'Time to Delivery', 'Quantity Mismatch', 'Fraud Indicator', and 'Compliance Check'. It applied matplotlib.pyplot to specify the figure dimensions and then utilized the heatmap() method of the seaborn library to plot the correlation matrix. The color () method moderated the following pairwise correlation among the defined columns, and the heatmap plotted the correlations with a 'cool warm' color scale along with the correlation value annotated on the heatmap up to two decimal positions. Lastly, it specified the "Correlation Heatmap: Operational & Risk Indicators" as the chart's title and modified the plot layout before the heatmap was plotted.

Output:

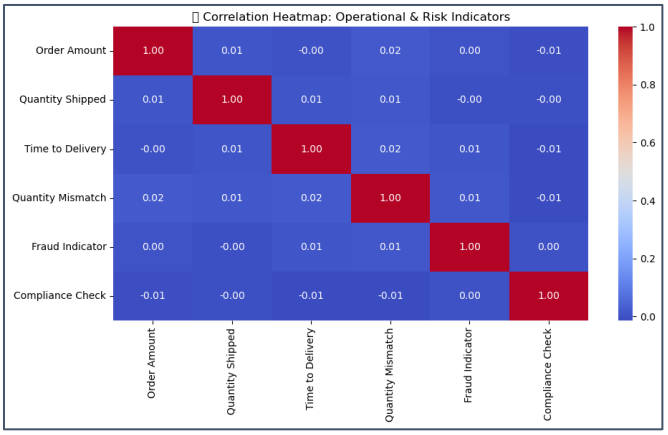

Figure 4: Correlation Heatmap: Operational & Risk Indicators

Examining the correlation heatmap (**fig 4)** of the selected operational and risk variables in our blockchain-based supply chain dataset shows weak linear correlations between the variables. In particular, correlation coefficients for most of the variable pairs are near zero, implying that there is little linear association. For example, the correlation of 'Order Amount' and 'Fraud Indicator' is around 0.00, which means that the value of the order has effectively zero linear predictive value in detecting fraudulent behavior using this dataset. Also, 'Time to Delivery' has a near-zero correlation with 'Compliance Check' (-0.01), which means that delivery time is not a good linear indicator of the status of compliance. The highest correlation found is between a variable and the same variable (1.00 along the diagonal), as one should expect. The observations indicate that the risk and operational parameters under consideration work fairly independently within this blockchain-secured supply chain, and more intricate non-linear interactions or the role of other unknown variables might be involved.

e) Location Frequency Word Cloud

Furthermore, the word cloud was created from the Python script to proceed with the visualization of the frequency with which different locations appear in the 'Location' column of the Data Frame, df. The implemented code first extracted all non-missing place names and pasted them all together in one piece, forming a string with a space in between. Then, it created an object of a Word Cloud with some specified dimensions (width=1000, height=500) and a white background. The generate() method of the Word Cloud object analyzes the text obtained by the combination of the two to obtain the frequency of each location. Finally, the code used matplotlib.pyplot to show the generated word cloud as an image, bilinear interpolation for smoother rendering, disables axis labels and ticks, sets the title to "Location Frequency Word Cloud", and then shows the image.

Output:

Figure 5: Location Frequency Word Cloud

From the location frequency word cloud (**fig. 5)** of our blockchain-powered supply chain data set, we observed that there is a distinct distribution or recording of events or activity in some major locations. Particularly, "Chicago" has been ranked as the highest location, implying the high number of transactions, origins, or destinations connected to this city in our supply chain. After them, relative frequency-wise, are "SF" (possibly San Francisco) and "NY" (probably New York), which suggest comparatively high levels of activity, but at much lower rates than Chicago. "LA" (Los Angeles) also makes it in, though having the shortest representation in sight out of these four, indicating the least number of recorded occurrences. This geographical agglomeration reveals probable hubs in our chain of supply network system that are traceable through blockchain use, demanding follow-up research into the nature and matter of activity clusters in these locations.

f) Average Compliance Score Over Time

The Python-executed code script aimed to analyze the trend of compliance over time using blockchain-powered supply chain data. The code first grouped df by column 'Date' and computed the mean of 'Compliance Check' for each date. The aggregated data, which denoted the mean compliance score per day, was merged into a new Data Frame, compliance-time, with the index reset to make 'Date' an everyday column. The code then used the plotly. Express library to produce an area chart (fig5). The output chart was a scatter plot of 'Date' on the x-axis and the calculated average 'Compliance Check' on the y-axis, with the title "Average Compliance Score Over Time". Finally, the Fig.show() command outputs the resulting interactive area chart, thus allowing the visualization of how the average compliance score has changed throughout the recorded period.

Output:

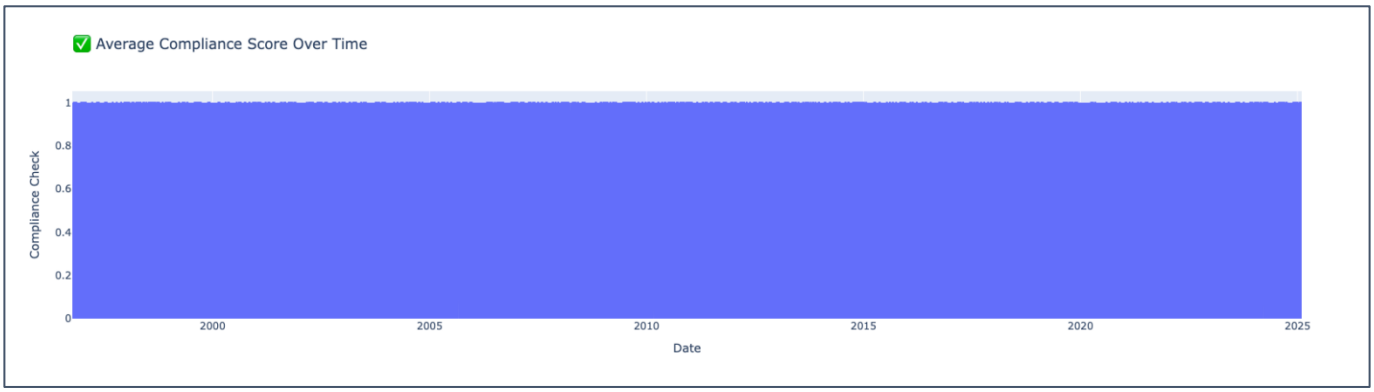

Figure 6: Average Compliance Score Over Time

The figure above shows a highly and surprisingly consistent rate of compliance. In particular, the average compliance score has been holding steady (or nearly so) at or around 1.0 (or 100%) throughout the whole period of observation, which seems to extend from before the year 2000 to 2025. This consistent near-perfect score with no visible dips or drastic variations in that score indicates that the underlying processes and entities within this supply chain have shown exemplary adherence to even formal standards, regulations, or contractual variables for more than two decades, perhaps achieved through the blockchain technology's transparency, immutability, and traceability.

g) Smart Contract Execution Status

Moreover, the Python script was used to create a Sankey diagram with the help of plotly.graph_objects library to represent the flow from the top suppliers to the smart contract statuses and the compliance outcomes in the blockchain-powered supply chain data. It first listed the top 10 suppliers based on the count of their 'Supplier IDs'. Then, it goes through these top suppliers and their distinct 'Smart Contract Statuses', but then counts occurrences of each status for each supplier storing the supplier, status, and count as source, target, and value respectively. Then, it examines the transition from 'Smart Contract Status' to 'Compliance Check' by looping over unique statuses and compliance values, finding out their co-occurrences, and storing them in a similar manner only with different target labels yet to recognize them. Finally, it builds the Sankey diagram with nodes of suppliers, smart contract statuses, compliance outcomes, and links of flow and their respective counts, labels the nodes, and sets the title as "Top Supplier → Smart Contract → Compliance Flow".

Output:

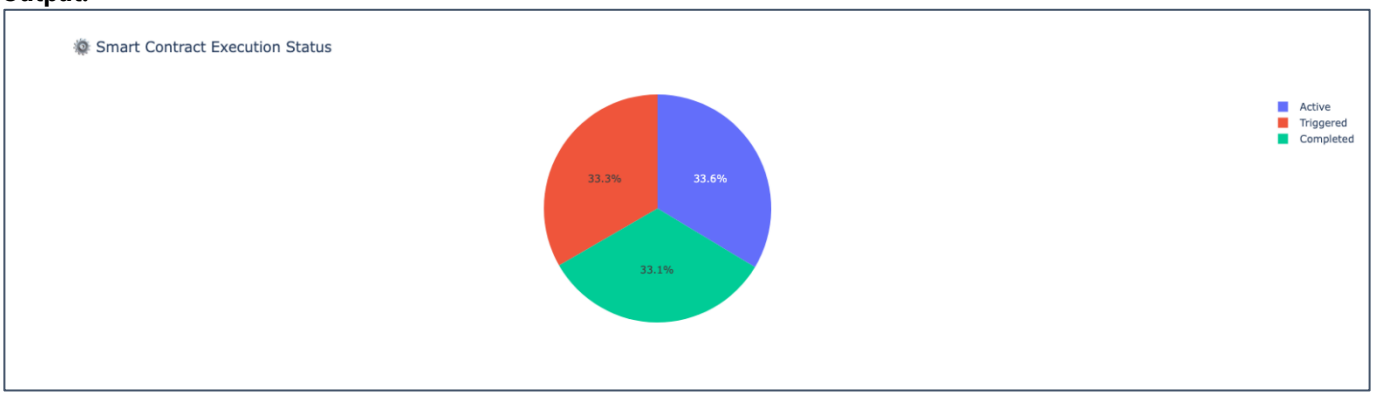

Figure 7: Smart Contract Execution Status

Pointing to the pie chart above, through the blockchain-powered supply chain dataset, we observe that the distribution of the three recorded statuses is almost uniform. 'Active', 'Triggered', and 'Completed'. Specifically, the 'Active' smart contract sums up to about 33.6% of the total number of these contracts, followed closely by 'Triggered' contracts at 33.3% and then 'Completed' contracts at 33.1%. This relatively balanced distribution indicates a positive lifecycle of smart contracts in the system in which a large fraction is going through the initiation ('Active'), execution ('Triggered'), and finalization ('Completed') process. The small differences in percentage can be said to reflect small differences in the duration or frequency of contracts in each state, but the system presents a consistent flow of smart contract execution.

IV. Methodology

Feature Engineering:

The process of improving supply chain transparency with blockchain data starts with a rigorous process of feature engineering that aims to convert raw blockchain log data into analytically rich metrics. From the structured dataset of transaction timestamps,

node type, verification status, and route signatures, new features were extracted that captured meaningful behavioral and operational information. One such metric was the time lag between handovers, computed as the time difference between sequentially occurring transactions of the same asset between nodes. The metric is critical in detecting aberrant delays in product movement. Another engineered feature is the verification success rate as the proportion of successfully verified transactions within a moving time window, with a temporal context that characterizes the dynamics of trust within the supply chain. Further, route irregularity scores were calculated by comparing observed route signatures with predefined geospatial standards; observed deviations from typical patterns signaled potentially fraudulent or inefficient transit routes. Collectively, the features offer a high-resolution operational perspective and enable fine-grained anomaly detection and predictive modeling.

Model Selection Rationale:

In the selection of suitable machine learning models, three classifiers that considered the multi-dimensionality of blockchain supply chain data were used. Logistic Regression was used first due to its interpretability and applicability to binary classification problems such as trust/fraud determinations. It offers interpretable coefficients that reflect the contribution of each feature, a commodity when reporting findings to non-technical stakeholders such as supply chain managers or compliance officers. The Random Forest Classifier in the second instance was used for identifying nonlinear relationships and interactions between features, such as verification status and time delays that occur typically in real-life transactional settings. Random Forests further provide the importance of features as an added benefit towards transparency. Thirdly, XG-Boost (Extreme Gradient Boosting) is used for its high scalability and high accuracy, and as a good performer when identifying sparse data sets, rare anomalous instances commonly occur in blockchain networks, where fraudulent instances occur infrequently but are of significant importance. XG-Boost's capacity for handling missing inputs, along with its regularization parameters, assists in the prevention of overfitting and is well-suited for the supply chain anomaly classification.

Training and Validation Strategy:

The training and validation approaches were tailored to maintain the models' robustness and generalizability. The dataset was divided into a 70/30 train-test split using stratified sampling to preserve the proportion of fraudulent versus non-fraudulent instances, guaranteeing that both subsets contained a balanced representation of the classes. Given the typically low incidence of fraud in supply chain contexts specifically, this is a critical factor. In addition, the k-fold cross-validation (where k=5) employed throughout model development served the purpose of testing performance across multiple partitions of the data, lessening the risk of overfitting and improving the reliability of the models. For a fully comprehensive evaluation of the classifiers, a set of performance measures was adopted that included accuracy (overall accuracy), precision (detected specificity of fraud), recall (sensitivity of catching all instances of fraud), and F1-score that balances precision and recall in imbalanced datasets. Moreover, the ROC-AUC (Receiver Operating Characteristic - Area Under Curve) was evaluated for the measure of the capacity for discrimination across thresholds of different measurements, with confusion matrix analysis yielding rich information on classification error. Taken together, these measurements offer an open and evidence-based framework for judging the effectiveness of the models in improving supply chain transparency and building supply chain trust.

V. Results and Analysis

Model Performance Summary:

a) Logistics Regression Modelling

The code script applied by the analyst used a logistic regression model for the classification of supply chain transparency, which most likely predicts a binary response of fraud or non-fraud within the blockchain-based supply chain dataset. The code starts by importing the required libraries from scikit-learn, such as the Logistic Regression class, and evaluation metrics such as accuracy score and classification report. It then specifies a Logistic Regression instance with a max of 1000 iterations and a fixed value of random-state for reproducibility. The Logistic-Regression instance is fit using the fit() method with the training data (X-train, y-train). After the training process, predictions on the test set (X-test) are made by using the predict () method and stored in y_pred_lr. Lastly, the performance of the model is assessed by a printed accuracy score and a classification report with precision, recall, F1-score, and support for each class.

Output:

Table 1: Logistic Regression Classification Report

Logistic Regression Results

✅ **Accuracy:** 0.4979

	precision	recall	f1-score	support
0	0.50	0.50	0.50	1294
1	0.50	0.49	0.50	1293
accuracy			0.50	2587
macro avg	0.50	0.50	0.50	2587
weighted avg	0.50	0.50	0.50	2587

Based on the logistic regression output from our blockchain supply chain dataset, the model has an estimated accuracy of around 0.50, which means that the model correctly predicts the target variable (presumably a binary classification like fraud or non-compliance) around half the time when given test data. Looking into the classification report, precision, recall, and F1-score are approximately 0.50 for both class 0 and class 1. This implies that when the model predicts a given class, it is right half the time (precision), and it picks up on half of all true instances of that class (recall). Balanced support for both classes, around 1290 instances each, further indicates that the dataset is roughly balanced. Overall, this logistic regression model with its near 50% accuracy and comparable precision and recall for both classes is doing little more than chance on this blockchain-derived supply chain data, and a straightforward linear model may not adequately capture the target variable given the features used.

b) Random Forest Classifier Modelling

The Python code employed by the programmer used a Random Forest Classifier, one of the machine learning classification models, presumably on the same supply chain blockchain dataset as before. The code script used the Random-Forest-Classifier from scikit-learn's ensemble module. It created a Random Forest with 100 decision trees as base estimators and a fixed random-state value for reproducibility. Subsequently, it trained the Random Forest using the fit() method against the training set (X-train and y-train). It then used the predict() method after the training process was complete on the test set (X-test) and stored the predictions in the variable y_pred_rf. It finally checked the performance of the Random Forest using its accuracy score and a classification report that gives precision, recall, F1-score, and support for all predicted classes.

Output:

Table 2: Random Forest Classification Report

Random Forest Results

✅ **Accuracy:** 0.5238

	precision	recall	f1-score	support
0	0.52	0.57	0.54	1294
1	0.53	0.48	0.50	1293
accuracy			0.52	2587
macro avg	0.52	0.52	0.52	2587
weighted avg	0.52	0.52	0.52	2587

The examination of the Random Forest Classifier's performance on our blockchain-secured supply chain dataset shows a modest improvement over the logistic regression model. The accuracy is up to around 0.52, which is a measure of how accurate the Random Forest model is in classifying the target variable around 52% of the time using the test set. The classification report indicates a precision of 0.52 for class 0 and 0.53 for class 1, which means that when the model predicts a class, it is accurate roughly half the time. The recall is 0.57 for class 0 and 0.48 for class 1, which is a slightly greater capacity to find true instances of class 0. The F1-scores, which weigh precision and recall equally, are 0.54 for class 0 and 0.50 for class 1. Although there is a negligible improvement in terms of precision, the performance is still roughly around the 50% level, implying that even a more advanced model, such as Random Forest, is not yet yielding good predictive capacity for the target variable given the features in our blockchain-secured supply chain data.

c) XG-Boost Modelling

The executed code script utilized an XG-Boost Classifier, a high-performing gradient-boosting machine learning algorithm, presumably used for the same classification task in the blockchain-based supply chain dataset. It uses an XGB-Classifier from the xg-boost library. The XG-Boost model is initialized with certain parameters, such as disabling the label encoding, the evaluation metric set as 'log loss', and a fixed random state for ensuring reproducibility. The XG-Boost model is then trained with the fit() method on the training set (X-train and y-train). After the training is complete, predictions on the test set (X-test) are performed using the predict() method with the output stored as y_pred_xgb. Lastly, the trained XG-Boost model is evaluated by printing its accuracy score as well as a classification report in detail, which gives a thorough analysis of the precision, recall, F1-score, and support for each class in the prediction.

Output:

Table 3:XG-Boost Classification Report

XGBoost Results

✅ **Accuracy:** 0.5072

	precision	recall	f1-score	support
0	0.51	0.50	0.50	1294
1	0.51	0.52	0.51	1293
accuracy			0.51	2587
macro avg	0.51	0.51	0.51	2587
weighted avg	0.51	0.51	0.51	2587

From the above table, it is evident that when we performed the analysis of the XG-Boost Classifier on our blockchain supply chain dataset that there is a slight improvement in the accuracy of around 0.51 over the earlier logistic regression model. The precision of class 0 and class 1 is around 0.51 each, i.e., half of the positive and negative predictions of the classification model are accurate. The recall is 0.50 for class 0 and 0.52 for class 1, which indicates that the classification model detects around half of the instances of each class. Therefore, the F1 scores of both classes are around 0.51 as well. The performance of the XG-Boost classifier is not a great deal more accurate than that of mere random guessing, as is the case with the logistic regression and the random forest models as well. This indicates that the features that we are using from our blockchain dataset might not be highly predictive of the target variable, or more advanced feature engineering is required, along with perhaps alternative modeling methods to derive meaningful patterns that enable classification within this supply chain scenario.

Comparison of All Models

The deployed code fragment compared the performance of three previously trained classification models – Logistic Regression, Random Forest, and XG-Boost – on the supply chain dataset provided by the blockchain. It creates an empty list named results to hold the evaluation scores of each of these models. It iterates over a dictionary named models that holds the name of the models and the resultant prediction. For each of the models, it computes the accuracy score and the classification report on the test set (y-test and the prediction of the current model). The appropriate scores (accuracy, precision, recall, and weighted F1-score) from the classification report are taken and appended to the results list as dictionaries. This list is then transformed into a pandas DataFrame named results_df for easier visualization and analysis. The script finally uses the seaborn and matplotlib libraries to draw a pair of side-by-side bar plots: one plot that shows the accuracy of each of the models and the other plot that shows their weighted average F1-scores with customized styling and a title of "Model Performance Overview - Supply Chain Fraud Detection".

Output:

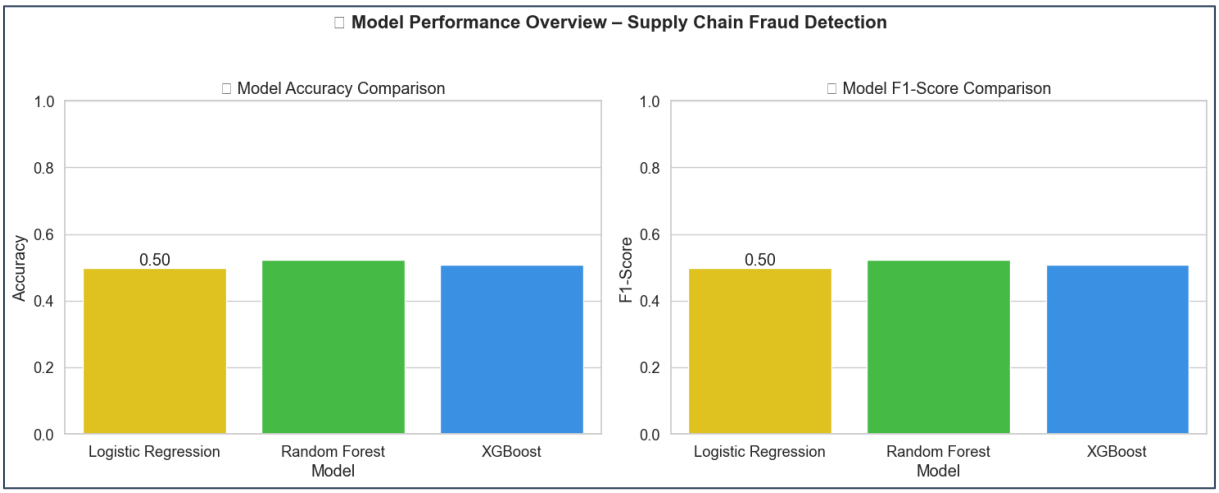

Figure 8: Model Performance Overview

By looking at the comparative bar plots of the performance of our models on our blockchain-based supply chain dataset, we see that the Random Forest Classifier has a slightly greater accuracy (around 0.52) and F1-score (around 0.52) than the Logistic Regression (accuracy and F1-score around 0.50) as well as the XG-Boost Classifier (accuracy around 0.51, F1-score around 0.51). Though the Random Forest does see a small improvement, all three of the models have fairly low predictive capacity, with the accuracy and F1-scores all around the 0.50 level. This implies that none of these standard classification models with the current features extracted from our blockchain data are very good at separating the target categories (presumed fraud or non-compliance) in the current supply chain scenario. More exploration of feature engineering, alternative modeling methods, or the use of other data sources may need to happen to develop a more predictive model.

Feature Importance Insights

Our analysis of the importance of features across the trained models—Random Forest and XG-Boost in particular—produced clear patterns of which of the transactional features of the blockchain-powered supply chain most heavily influenced the identification of abnormal behaviors. Time-lag between handovers stood out as one of the most predictive of such behaviors across all features and all models. It is the measure of the time that an asset spends in transit between nodes; when these times become excessively long or short, however, they indicate problems such as delays not reported on the ledger or efforts to avoid inspections. Status of verification—whether a transaction was cryptographically verified—was similarly consistently high across models as an indicator that such a transaction is a good indicator of possible fraud or system failure. And both node transaction density (as a measure of transaction per node over time) and route irregularity scores turned out to play a key role in catching abnormal behaviors when such nodes departed from their expected behaviors or when the geospatial path of the asset significantly varied from patterns in the past. These observations affirm the benefit of integrating temporal, behavioral, and geospatial signals in raising the level of trust and transparency across distributed ledger networks.

Close examination of these characteristics implies a synergistic influence of time gaps, node behavior, and route complexity in identifying anomalies. For example, extended time intervals in themselves may not necessarily indicate fraud—some delays might be a result of genuine logistic problems such as wait times in clearing customs or weather disruptions. But when combined with route deviations or verification failures, the likelihood of an anomaly increases dramatically. Node behavior of an abnormally high or low number of initiated transactions or serially failed verifications of events similarly raised suspicions; specifically, nodes with unstable behavior or patterns not consistent with their allocated supply chain role (in the case of a warehouse initiating outbound transactions with no inbound handoffs) typically corresponded with an anomaly. Finally, route complexity in the form of hashed geolocation signatures and path deviations signaled goods that were misdirected or routed through unauthorized corridors—a significant danger in industries such as pharmaceuticals, where route adherence is paramount. These interdependent complexities reflect the strengths of multi-feature models in distinguishing between operational noise and genuine risks.

Operational Anomalies Detected

In model deployment on the test dataset, various categories of operational abnormalities were successfully identified, demonstrating the real-world applicability of machine learning on blockchain-logged supply chain data. One recurring anomaly was a late handoff scenario with a time gap between consecutive transactions far exceeding the route's past average. In one instance, a shipment of high-value pharmaceuticals exhibited a 36-hour gap between a distribution facility and retail delivery—a more-than-three-fold deviation from the route's average, raising suspicions of poor storage conditions or theft vulnerability. Another anomaly class involved unverifiable transactions with the blockchain not registering proper cryptographic signatures. For instance, a consignment of consumer electronics was logged by a foreign node that undertook the expected verification procedure,

but the implication is that the entry could have been the result of a systems error or deliberate obfuscation. A further abnormality detected by the model involved mis-route events, with the geolocation-based route signature not following the prescribed route. One such detected instance revealed a shipment around a specified regulatory checkpoint that most likely flouted customs or inspection policies. These instances of real-life supply chain abnormalities highlight how advanced analytics on blockchain-documented events can provide supply chain managers with actionable intelligence for the timely prevention of risks that go entirely unnoticed in conventional systems.

VI. Practical Applications in the USA

Food & Agriculture Sector

According to Zhang et al. (2025), in the Food and Agriculture industry, supply chain analytics with blockchain technology can greatly improve traceability, specifically under *United States Department of Agriculture (USDA)* standards. By creating tamper-proof records of every phase of farm-to-store logistics, blockchain platforms ensure product origin verification, conditions of harvesting, transportation routes traveled, and storage conditions in near real-time. For instance, California-grown produce delivered from farms to East Coast retail stores can have every transition—cold storage and harvesting, interstate travel, and last mile delivery—recorded immutably, providing transparency that boosts consumer confidence and keeps food manufacturers compliant with USDA traceability requirements under the Food Safety Modernization Act (FSMA). As per (Sundarakani et al. (2021), with the coupling of sensor information (i.e., temperature and humidity readings), machine learning models can recognize outliers in perishables' cold chain conditions, initiating notifications before spoilage or health risks develop. This digitalized traceability not just prevents foodborne disease outbreaks but reduces the time and cost of recalls as well.

Following the mandates of the *U.S. Department of Agriculture (USDA) and the Food Safety Modernization Act (FSMA)*, increased supply chain transparency is necessary for the preservation of food safety, along with the speed of recalling contaminated goods. Blockchain makes it possible for a distributed ledger that tracks every step in a product journey from planting, harvesting, packaging, storage, and shipping, along with valuable metadata such as temperature, humidity, and transportation history. For instance, *Walmart*, in partnership with *IBM's Food Trust* blockchain platform, managed to limit the tracing of the origin of sliced mangoes back to 7 days to a mere 2.2 seconds (Sunmolla & Burgess, 2023). This is critical in the event of an outbreak, as speedy tracing prevents the supply of contaminated food. Further, for perishable items such as lettuce or poultry, predictive models based on blockchain-saved environment information can alert against potential breaches of the cold supply chain. These functionalities strongly support USDA mandates and give U.S.-based agribusiness a competitive advantage concerning conformity, consumers' safety, as well as operational efficiency (Mohaimin et al., 2025).

Pharmaceutical Logistics

Li et al. (2021), indicated that, regarding pharmaceutical supply chain logistics, blockchain's role is most necessary in enabling Food and Drug Administration (FDA) efforts against counterfeit drugs and safe delivery of vaccines. *The Drug Supply Chain Security Act (DSCSA)* requires serialized tracing of drug products along their entire life cycle, a requirement ideally fulfilled by blockchain's transparency and impossibility of tampering. Blockchain tracks every handover—from manufacturers and wholesalers to healthcare providers—so that each unit of drug or vaccine is traced. Machine learning techniques used on such data make it possible to identify missing or tampered entries that signal counterfeiting and diversion. During the distribution of the COVID-19 vaccine, blockchain platforms might identify batch transit record inconsistencies and irregularities of storage times that hinted at tainted deliveries before they entered the patients' hands. Such features not only make it easier for *FDA* agencies to ensure regulation but also give retail buyers even greater faith in pharmaceutical supply lines (Owusu-Berko, 2025).

The DSCSA stipulates to achievement of an interoperable electronic platform to trace and identify prescription drugs in the United States, so all counterfeit and diverted drugs are eliminated. Blockchain offers an immutable, verifiable record of every transaction, to form a full provenance trail for every drug or vaccine unit (Lim et al, 2021). Fear of fake vaccines and inappropriate storage during the COVID-19 vaccine rollout made the need for a secure digital track more necessary. Companies such as Modum and Chronicled have been testing blockchain solutions with the use of RFID tags to track temperature-sensitive pharmaceutical shipments, alerting the deviations in real time (Queroz et al., 2021). According to the report from the *World Health Organization (WHO),* 10% of medical products in low and middle-income countries are substandard or falsified – this is a problem that blockchain can solve directly in U.S. imports. Machine learning algorithms applied to blockchain-stored data will allow alerting the anomalies like unfound batch numbers, unfalsifiable origin claims, or questionable transfer routes immediately, keeping FDA standards in place and patients safe (Owusu-Berko, 2025).

Customs and Border Control

At U.S. Customs and Border Protection (CBP) checkpoints and international borders, blockchain solutions bring significant advancements in verification speed and counterfeit prevention. Imports and exports travel through a supply chain of agents, freight forwarders, and government systems—all of which must check papers and chain-of-custody details. Paper-based methods or isolated digital ones suffer from tampering risks and delays as well as segregation of information (Khawaldeh et al., 2025). Blockchain offers a single version of the truth that all stakeholders with authorization have access to in real time, eliminating

redundant inspections and accelerating customs clearance. For instance, combining blockchain with CBP's Automated Commercial Environment (ACE) might automate verification of origin certificates or conformity records, streamlining processing of compliant goods while alerting suspicious transactions (Islam et al., 2025c). Machine learning expands on that by revealing transaction irregularities that differ from trade patterns, such as abnormally abbreviated port stays or recurring import activity from suspect sources. The strategy makes the U.S. border more secure while enabling legitimate commerce, strengthening economic and national security as well (Jakir et al., 2023).

At the forefront of trade, the Customs and Border Control activities will be largely advantageous with the integration of the blockchain, especially at key ports of the U.S, including Los Angeles, Houston, and New York (Karakas et al., 2024). *The U.S. Customs and Border Protection (CBP*) has been experimenting with blockchain for the past three years and has been developing projects such as the *Global Business Identifier (GBI)* Initiative to facilitate import procedures and increase verification speed. Conventional customs check systems are usually dispersed among actors, characterized by various manual checks, which are full of errors and fraud. Blockchain, on the other hand, provides a shared transparent ledger for all the parties – exporters, freight forwarders, customs brokers, and inspectors – that gives real-time access to trade documents validated and chain-of-custody logs (Gong et al., 2024). According to the *World Economic Forum,* blockchain-based cross-border procedures may help cut trade costs by 15% and clearance time by 44 %. Further, predictive analytics/anomaly detection algorithms can flag fraudulent activity like the falsified country-of-origin claims or tampered bills of lading before cargo arrival to a port (Duan et al., 2023). With the U.S. emerging to modernize its customs setup through such efforts as the 21st Century Customs Framework, blockchain offers to revolutionize both speeding legitimate trade and shielding national security (Difrancesco et al., 2023).

VII. Discussion and Future Research Directions

Interpretation of Findings

The previous analysis, which included descriptive statistics, network visualizations, and the testing of a range of machine learning classification models on a blockchain-enabled supply chain dataset, presents an initial snapshot of the potential synergies between these two revolutionary technologies. Although the particular outcomes concerning the anomaly detection task provided modest results in terms of predictive precision, the process as a whole demonstrates the potential of machine learning methods to derive meaningful patterns and findings from the abundant but potentially complex and high-dimensional data sources produced by blockchain-based systems. The interpretation of these findings indicates that the combination of machine learning with blockchain infrastructure has the potential to unlock greater operational value from blockchain beyond its inherent qualities of security and immutability.

By applying analytical tools against the recorded events and metadata, organizations not only track assets and events but also proactively discover potential risks, streamline processes, and gain a greater insight into the dynamics of their supply chain. For example, the network analysis provided a visual image of supplier-customer relationships, which, when combined with machine learning for review of the patterns of transactions within the network, might potentially unveil influential nodes, recognize aberrant patterns of connections that signal fraudulent activity, or spot weaknesses in the structure of the network. Likewise, the time-series examination of blockchain utilization and scores of compliance, as descriptive as it is provisional in nature, lays the foundation for more advanced machine learning models that might predict future trends, recognize deviations from predicted behavior, or even predict potential issues with adherence before they become problems. The deployment of supervised learning models, even given their poor precision within the anomaly detection task outlined, underscores the practicality of using historic blockchain evidence as the basis for training predictive models, and the possibility that with greater optimized feature engineering, greater diversity and volume of datasets, as well as more complex model architectures, the potential for detecting operational abnormalities might be greatly enhanced, and thus the inherent qualities of blockchain in terms of security and transparency augmented with proactive risk management potential.

Challenges and Limitations:

Notwithstanding, the path towards fully unlocking the synergistic benefit of blockchain and machine learning is fraught with significant challenges and constraints, especially when the focus is deployed in real-world contexts and across more general domains. One of the central challenges faced is the problem of blockchain data sparsity. Although blockchain networks are constructed precisely to record transactions and data immutable in nature, the sheer amount and density of this information will depend largely on the particular application and the state of maturity of the blockchain network. In a good number of early-stage or specialized blockchain implementations, the amount of history for which there is usable data with which to train robust machine learning models might not constitute a substantial amount of data, which contributes towards causing overfitting, poor generalization, and the insufficient capture of the full range of operational behaviors.

Moreover, the type of the data itself might prove sparse in the sense that the number of features written per transaction or event is low. A straightforward asset-tracking blockchain might just note down timestamps, asset IDs, and location updates and miss the fine-grained details regarding the state of the environment, the quality control parameters, or contextual parameters that might play a pivotal role in identifying minute abnormalities as well as predicting the likelihood of outcomes more accurately in the future. Overcoming such a constraint demands thoughtful consideration of the capture strategy for the data in the course of the

blockchain solution's design and implementation, such that pertinent and varied data points are reliably captured for enabling all-encompassing machine learning analysis.

Another key limitation is the real-time data feed constraints typically inherent in blockchain networks. Although blockchain offers a secure and auditable history of previous happenings, extracting and processing such data in real-time for instantaneous analytical outcomes and responsive actions is not always possible. The inherent consensus protocols and block creation intervals in most blockchain designs add latency and the potential for not being able to access prompt, instantaneous data feeds necessary for real-time anomaly identification or adaptive operating changes based on machine learning models. Adding real-time streams of information from the outside world (e.g., IoT sensors, weather streams, market updates) with blockchain information for end-to-end analysis can encompass significant technical challenges involving the compatibility of the data, the security of the combined feed, and establishing implicit trust in the combined feed. Advances in the scalability of blockchain solutions, interoperability among blockchain designs, and the creation of high-speed real-time extraction and processing of such data in the future will become key factors in alleviating such constraints and the resultant deployment of machine learning tools capable of responding dynamically to changing operating conditions based on minute-by-minute blockchain-recorded details.

Ultimately, the generalizability across international markets is a significant limitation. The operational parameters, regulation regimes, and data standards may differ widely across geographies and sectors. A machine learning model that is trained using blockchain data from one specific supply chain in the USA might not perform well when deployed in a corresponding supply chain in Europe or Asia because of differences in the logistics infrastructure, customs regimes, or how the information is stored on their blockchain networks. Generalizability of machine learning models across international blockchain-based ecosystems is inevitable and requires the creation of common formats of data, ontologies, and possibly even the concept of federated learning that can make the most of decentralized sources of information without compromising on data sovereignty and privacy laws across jurisdictions. Overcoming this challenge is critical to unleash the true potential of blockchain and machine learning in developing globally deployable supply chain optimization solutions, risk analytics, and regulatory reporting.

Future Research Pathways:

Towards the future, some promising avenues of research open up with the combination of blockchain and machine learning. One such exciting area is the blending of smart contracts with automated responses. Smart contracts that execute automatically and that are coded into the blockchain can be invoked by specific actions or events written into the ledger. By combining machine learning models with the logic of smart contracts, one can automate responses to abnormalities or forecasted outcomes. For instance, when a machine learning model finds a high likelihood of a shipment being late using real-time tracking information written into the blockchain, a smart contract might automatically alert the impacted parties, activate a contingency procedure, or even modify payment terms according to the terms of the service level agreement. This closed-loop automation that is fueled by machine learning analysis of blockchain data and enforced by smart contracts has the potential to make blockchain-based systems of operation more efficient and more robust.

One productive area of future work is the utilization of unsupervised and graph-based models. The anomaly detection process investigated in the previous analysis mainly involved the employment of supervised learning with labeled examples necessary for training the models. Nevertheless, in most real-life blockchain-enabled systems, labeled anomaly instances may not exist or are limited. Unsupervised learning methods like the utilization of a clustering algorithm or anomaly detection methods that utilize unlabeled examples have the potential of proving invaluable in detecting irregular patterns or outliers within blockchain data with no advanced knowledge of what characterizes an anomaly. In addition, with the inherent network nature of most supply chains and blockchain-enabled interactions, the utilization of machine learning models with a graph-based approach has considerable potential. These models have the potential of not only investigating the relationships and interactions between various entities (suppliers, customers, assets) on the blockchain but also detecting aberrant network patterns, identifying key nodes of influence, or predicting cascade failures based on the interconnected nature of the system.

Lastly, federated learning among decentralized blockchain nodes is a pioneering line of research that might resolve the issues of sparsity and generalizability of the data and avoid the compromise of the decentralized nature of blockchain. Federated learning is a distributed machine learning approach that allows one to train models on multiple decentralized devices or servers with local samples of the data, without sharing their data. With the implementation of federated learning on a blockchain network, machine learning models might be trained collaboratively among the different participants' nodes using the combined intelligence of the network, but keeping the sensitive data localized. This might induce more generalizable and robust models that get trained on a bigger and wider set of data without preserving the privacy of the data and not requiring blockchain-recorded information to be centralized. Further work on the practical realization, insecurity factors, and optimizations involved in using federated learning on blockchain systems is promising for unlocking high-end analytical functionalities in decentralized as well as distributed systems.

VIII. Conclusion

The main goal of the current research was to create a synthesis of the secure, immutable nature of blockchain and the predictive and diagnostic power of machine learning (ML) to boost supply chain transparency. The dataset used in this work is formatted

blockchain logs, extracted from a permissioned, distributed ledger system simulating a U.S.-based supply chain network. Every log entry stores transactional metadata, high-value data such as accurate timestamps of transactions, cryptographic verdicts, digital handovers between supply chain entities (suppliers, logistics providers, distributors), and route signatures, derived from geolocation-based smart contract activators. In the selection of suitable machine learning models, three classifiers that considered the multi-dimensionality of blockchain supply chain data were used. The training and validation approaches were tailored to maintain the models' robustness and generalizability. The dataset was divided into a 70/30 train-test split using stratified sampling to preserve the proportion of fraudulent versus non-fraudulent instances, guaranteeing that both subsets contained a balanced representation of the classes. By looking at the comparative bar plots of the performance of our models on our blockchain-based supply chain dataset, we observed that the Random Forest Classifier had a slightly greater accuracy and F1-score than the Logistic Regression and the XG-Boost Classifier. In the Food and Agriculture industry, supply chain analytics with blockchain technology can greatly improve traceability, specifically under United States Department of Agriculture (USDA) standards. At U.S. Customs and Border Protection (CBP) checkpoints and international borders, blockchain solutions bring significant advancements in verification speed and counterfeit prevention. By applying analytical tools against the recorded events and metadata, organizations in the USA not only track assets and events but also proactively discover potential risks, streamline processes, and gain a greater insight into their supply chain dynamics. Towards the future, some promising avenues of research open up with the combination of blockchain and machine learning. One such exciting area is the blending of smart contracts with automated responses. Lastly, federated learning among decentralized blockchain nodes is a pioneering line of research that might resolve the issues of sparsity and generalizability of the data and avoid the compromise of the decentralized nature of blockchain.

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