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Blockchain-Enabled Real-Time Fleet Tracking

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Abstract: As the demand for Logistics, Transportation and Last-Mile Delivery Services continues to rapidly grow, there is an increasing requirement for secure, transparent and real-time Fleet Management Solutions. Current Fleet Management Systems are comprised of fragmented data, limited real-time visibility, security weaknesses and operational inefficiencies. Utilizing the advantages of Blockchain Technology may facilitate next-generation Fleet Tracking and Fleet Management Systems. This article provides insight into how Blockchain-Enabled Real-Time Fleet Tracking may enhance Operational Efficiency, Transparency and Stakeholder Trust. In addition, a comprehensive analysis of Fleet Management Architecture and recent advancements in Blockchain Technologies, the Internet of Things (IoT) and Artificial Intelligence (AI) will provide the data to support this research. The study examines how blockchain can be integrated into fleet management systems to improve data integrity, fraud prevention, real-time tracking, and regulatory compliance. Qualitative examination of fleet types (cars, bikes, and drones), quantitative performance evaluation using operational statistics, and case-based assessment of fuel efficiency and delivery performance supplemented by IoT-enabled tracking are used in a mixed-method research Results and discussion show that blockchain-based fleet tracking improves data immutability, real-time visibility, and smart contract automation. After exploring how blockchain integrates with both IoT and AI-powered analytical systems to enhance the efficiency of delivery, decrease fuel consumption, resolve conflict, and create a more secure environment for cyber-users, we determined that issues related to scalability, interoperability, regulatory/legislative frameworks, and initial implementation costs still impede widespread use. We believe that the ability to track fleets in real-time with an integrated blockchain system may help make fleet management "secure," "smart," and "transparent."

Overall, the study clearly demonstrates the value of utilizing blockchain technology to create cost-effective, sustainable, and future-ready fleet operations for the logistics sector (e.g., logistics providers) and legislators/technology developers.

Keywords: *Block Chain; Real - Time Fleet Tracking; Intelligent systems; Technology.*

INTRODUCTION

Modern supply chain operations require efficient fleet management due to the increasing growth of logistics, transportation, and on-demand delivery. Fleet management systems track vehicle location, fuel consumption, maintenance schedules, driver conduct, and delivery performance for cost-effective and timely operations. Conventional fleet management solutions are centralized and frequently have data fragmentation, lack of real-time transparency, cyberattack susceptibility, ineffective stakeholder coordination, and regulatory compliance issues [1, 2, 3]. With the complexity of different vehicles, third-party service providers, and global logistics networks, these constraints will only result in reduced efficiency and trust in the operations.

In recent years, new technologies such as blockchain, Internet of Things (IoT), and Artificial Intelligence (AI) have emerged as potential solutions to these issues. The ledger system of blockchain technology offers a decentralized, immutable, and transparent platform for sharing and managing fleet data between multiple parties without the requirement of third-party intermediaries, thus providing a secure method of managing and exchanging fleet data [2, 3, 4]. The IoT sensors and real-time fleet tracking devices can be used to authenticate vehicle location data, fuel transactions, maintenance data, and compliance data using blockchain technology [3, 4]. Smart contracts can also automate many operational functions, reducing the need for human intervention, minimizing disputes, and expediting payment and service level agreement processes, among other advantages [6, 7, 8]. While there is a great deal of promise regarding the use of blockchain technology for fleet management purposes, there remain a number of concerns regarding the scalability of blockchain technology, its ability to operate in conjunction with current infrastructure, its ability to comply with regulatory requirements, and its cost to implement [3, 5].

The goal of this study is to evaluate how the implementation of blockchain technology in real-time fleet tracking and management, coupled with the integration of a blockchain-based architecture in fleet management systems, can increase the level of transparency, security, efficiency, and the quality of decision making for these systems.

LITERATURE REVIEW

The combination of Artificial Intelligence and Blockchain technology in smart transportation systems increases security, trust, and automation of data in complex transportation scenarios, according to Bijalwan et al. [6]. They provide evidence of how Blockchain can enable the secure transmission of data from connected vehicles to infrastructure and help support AI-based traffic planning and vehicle coordination. Ultimately, their findings highlight that Blockchain can provide an effective means to enable secure and efficient transportation infrastructure.

Peelam, Chamola, and Chaurasia proposed a blockchain-enabled intrusion detection system for real-time vehicle monitoring to address cybersecurity issues in connected and autonomous vehicles [7]. The research noted that blockchain's immutability and distributed architecture boost vehicle network intrusion detection and cyberattack resilience. Their findings demonstrate blockchain's usefulness in real-time fleet data security and operational reliability.

Syed et al. developed a blockchain-based architecture for car registration, ownership transfer, maintenance data, and operational history [8]. Immutable and transparent record-keeping was found to enhance the accountability, compliance, and trust of fleet stakeholders. Fleet management systems requiring accurate historical and real-time vehicle data will benefit from this initiative.

O'Brien et al. evaluated the blockchain-enabled road vehicle emissions monitoring and proposed a secure, scalable, and privacy-preserving regulatory compliance system [9]. Blockchain enabled data confidentiality and reliable emissions reporting for sustainability-driven fleet operations, the authors demonstrated. Ning et al. proposed a distributed crowdsensing framework for intelligent transportation systems, improving data reliability, scalability, and stakeholder confidence [10].

Khuwuthyakorn et al. introduced a blockchain-enabled self-autonomous intelligent transport system for edge cloud drone job workflows [11]. For Internet of Vehicles traffic rerouting and work offloading, Devarajan et al. used federated learning and blockchain to ensure secure collaboration without centralized data sharing [12]. TRACE, Rehman et al.'s blockchain-based system for real-time cargo tracking and business analytics, proved blockchain's feasibility in operational logistics [13].

Research Gap

Existing studies show blockchain's potential in transportation and vehicle applications, but they focus on security, pollution monitoring, drone coordination, and life cycle tracking. A thorough study of blockchain-enabled real-time fleet tracking as an integrated solution to improve operational efficiency, transparency, security, and decision-making across varied fleet types is lacking. This article evaluates blockchain's function in unifying tracking, data integrity, automation, and performance optimisation in modern fleet ecosystems to determine its potential uses in real-time fleet management.

METHODOLOGY

The methodology of this study can be explained using the following points:

Research Design

The effectiveness of a blockchain-enabled intelligent fleet management system in food technology is assessed in this mixed-method study. To measure operational efficiency, cost reduction, and security improvements from blockchain integration, the research design uses qualitative exploratory analysis and quantitative empirical analysis. The workflow in figure 1 unites research design, data collecting, blockchain processing, data analysis, and result interpretation.

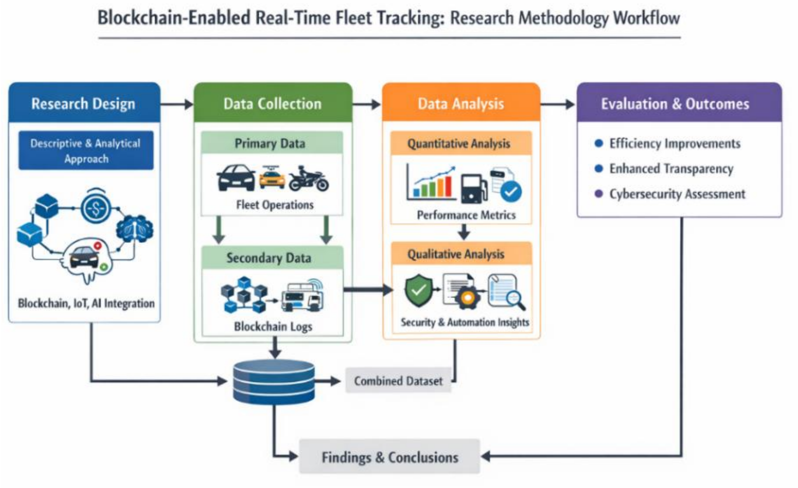

Figure 1. Proposed Research Methodology.

Sample and participants

Relevant fleet-based food delivery stakeholders are selected using purposive sampling. The study targets restaurants, drivers, logistics businesses, fleet managers, and blockchain–IoT professionals. The sample includes 3–4 fleet types for qualitative fleet-level analysis, 5–10 restaurants for operational case evaluation, 35–50 drivers for qualitative and quantitative assessment, and nearly 100,000 delivery orders for large-scale quantitative analysis for empirical validation. This sampling strategy covers fleet ecosystem operational, managerial, and technological aspects.

Operational Definitions of Variables: The study measures fleet efficiency, operational costs, security, and transparency using average delivery time, fuel consumption per trip, vehicle downtime, maintenance and administrative costs, fraudulent transactions, and data integrity breaches. Blockchain attributes (smart contracts, consensus mechanisms, transaction speed), fleet characteristics (fleet size, vehicle type, maintenance schedules), technology integration (IoT sensors, GPS accuracy, AI-based analytics), operational policies (route optimization, load allocation, driver shifts), and external factors are independent variables. To examine how blockchain-enabled features affect fleet performance, several variables are compared.

Data Collection and Analysis: Use system logs, IoT sensor outputs, blockchain transaction records, surveys, interviews, and case studies to collect data over a year. For qualitative performance analysis of fleet types (cars, motorcycles, and drones) and delivered orders, ANOVA is used. A targeted case study compares bike fleet fuel usage and efficiency in July (without IoV) with August (with Internet of Vehicles (IoV) and blockchain-based tracking). Statistical methods study quantitative data, while theme analysis analyses qualitative insights. The workflow diagram depicts this methodical technique.

Through informed permission, restricted access to sensitive data, and anonymization of participant information, the study process is ethical and confidential.

RESULTS AND DISCUSSIONS

This section displays and discusses the empirical findings from a one-year statistical analysis of fleet delivery data for automobiles, bikes, and drones. The analysis quantifies fleet behaviour in a blockchain-enabled intelligent fleet management system by comparing delivery performance, operational efficiency, and order distribution patterns across fleet categories.

Weekly Order Distribution Across Fleet Types

The number of weekly deliveries for car, bike, and drone fleets is presented in Table 1. On average, bike fleets have the highest number of orders to be delivered weekly, followed by auto fleets and drones. In Week 1, bike fleets delivered 273,000 orders, auto fleets 56,000, and drones 21,000, making a total of 350,000 orders. Bikes lead in Week 52 with 269,610 orders.

Tab 1. ANOVA Analysis on Fleet Type – A Sample Case Study.

Weeks	CAR	BIKE	DRONE	Total Orders
Week 1	56000	273000	21000	350000
Week 2	44000	214500	16500	275000
Week 3	87472	426426	32802	546700
Week 4	106542	519392	39953	665887
Week 5	102238	498410	38339	638987
Week 6	86828	423289	32561	542678
Week 7	90062	439054	33773	562890
Week 8	69708	339829	26141	435678
…	…	...	…	…
Week 52	55305	269610	20739	345654

In urban food delivery, bike fleets dominate due to their short-distance, high-frequency delivery capabilities. Demand fluctuates throughout weeks due to seasonality, consumer behaviour, and operational restrictions. Real-time, tamper-proof order data helps fleets track demand and performance.

Order Delivery Range and Data Segregation

The minimum and maximum ranges for the type of fleet are shown in Table 2. The range for car delivery is 44,000 to 158,912, bike delivery is 214,500 to 774,694, and drone delivery is 16,500 to 59,592. A total of 275,000 to 993,197 orders are.

Tab 2. Order delivered Ranges – MIN and MAX.

	CAR	BIKE	DRONE	Total Orders
MIN	44000	214500	16500	275000
MAX	158912	774694	59592	993197
Data Range	40K-160K	200K-800K	15K-60K	250K-1000K

Which can be segregated based on the data range mentioned in below tabular format:
According to the range classification table, these ranges are further divided into data intervals. Stratification allows fleet type comparison and statistical modelling. Bike fleets have a large delivery range, indicating scalability and versatility, but drones have legal, technological, and payload limits.

Descriptive Statistical Analysis of Fleet Performance

Each fleet type and total orders are described statistically in Table 3. Bikes (452,266) have the most deliveries, followed by vehicles (92,773) and drones (34,790). This confirms motorcycles' centrality in delivering. Bike fleets (117,695) have high standard deviation values, indicating variable demand and dynamic routing.

Tab 3. Fleet Delivery Type – Descriptive Statistical Analysis.

Fleet Type: Car Delivery		**Fleet Type: Bike Delivery**		**Fleet Type: Drone Delivery**		**Total Delivery Orders Analysis**	
Mean	92773	Mean	452266	Mean	34790	Mean	579828
Standard Error	3348	Standard Error	16321	Standard Error	1255	Standard Error	20925
Median	89492	Median	436272	Median	33559	Median	559323
Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A
Standard Deviation	24143	Standard Deviation	117695	Standard Deviation	9053	Standard Deviation	150891
Sample Variance	582864770	Sample Variance	13852145556	Sample Variance	81965358	Sample Variance	22768155089
Kurtosis	0	Kurtosis	0	Kurtosis	0	Kurtosis	0
Skewness	0	Skewness	0	Skewness	0	Skewness	0
Range	114912	Range	560194	Range	43092	Range	718197
Minimum	44000	Minimum	214500	Minimum	16500	Minimum	275000
Maximum	158912	Maximum	774694	Maximum	59592	Maximum	993197
Sum	4824171	Sum	23517833	Sum	1809064	Sum	30151068
Count	52	Count	52	Count	52	Count	52
Largest(1)	158912	Largest(1)	774694	Largest(1)	59592	Largest(1)	993197
Smallest(1)	44000	Smallest(1)	214500	Smallest(1)	16500	Smallest(1)	275000
Confidence Level (95.0 %)	6721	Confidence Level (95.0 %)	32767	Confidence Level (95.0 %)	2521	Confidence Level (95.0 %)	42008

Medians and means match, demonstrating symmetrical fleet type distributions. The absence of mode values suggests continuous data without frequent repeat, typical of large-scale delivery operations. Zero skewness and kurtosis values support parametric statistical methods like ANOVA, implying approximately normal distributions. Bike fleets had the widest 95% confidence ranges, indicating increased operational uncertainty and demand unpredictability. Real-time data validation and transparent record-keeping are essential for accurate performance monitoring due to these statistical features.

Percentile-Based Performance Evaluation

Fleet type percentiles (P10–P99) are shown in Table 4. Bike fleets deliver 436,272 orders at the 50th percentile (median), far more than automobile and drone fleets. Bike fleets may scale to 706,257 orders at the 99th percentile. Drone fleets rise modestly, with 54,327 orders in the 99th percentile. Peak demand responses of several fleet types are seen in this percentile study. Intelligent fleet systems require threshold identification for dynamic fleet allocation and operational planning.

Tab 4. Calculation of Percentile Based on Different Fleet Type.

Percentiles Table		**CAR**	**BIKE**	**DRONE**	**Total Orders**
P10	10%	65565	319631	24587	**409784**
P25	25%	74825	364770	28059	**467654**
P50	50%	89492	436272	33559	**559323**
P75	75%	109490	533763	41059	**684312**
P90	90%	123736	603211	46401	**773347**
P99	99%	144873	706257	54327	**905458**

Frequency Distribution and Histogram Interpretation

Tables 5 and 6, together with Figure 2, provide fleet type and order frequency distributions and histograms. Car deliveries are typically 80K–120K, while bike deliveries are 400K–600K. Drone deliveries generally fall between 30K and 45K.

Tab 5. Calculation of Frequency on Different Fleet Types.

Frequency cy - CAR		**Frequency - BIKE**		**Frequency - DRONE**		**Frequency - ALL ORDERS**	
Upper Bin	Frequency cy	Upper Bin	Frequency cy	Upper Bin	Frequency cy	Upper Bin	Frequency cy
40000	0	200000	0	15000	0	250000	0
80000	17	400000	18	30000	17	500000	17
120000	26	600000	28	45000	26	750000	26
150000	8	700000	5	50000	8	900000	8
More	1	More	1	More	1	More	1

Tab 6. Lower and Upper Bin Frequency.

Orders Delivered - CAR	**Lower Bin**	**Upper Bin**	**Orders Delivered - BIKE**	**Lower Bin**	**Upper Bin**	**Orders Delivered - DRONE**	**Lower Bin**	**Upper Bin**	**Orders Delivered - ALL+**	**Lower Bin**	**Upper Bin**
									0 to 250K	**0**	**250000**
0 to 40K	0	40000	0 to 200K	0	200000	0 to 15K	0	15000	250K to 500K	250000	500000
40K to 80K	40000	80000	200K to 400K	200000	400000	15K to 30K	15000	30000	500K to 750K	500000	750000
80K to 120K	80000	120000	400K to 600K	400000	600000	30K to 45K	30000	45000	750K to 900K	750000	900000
120K to 150K	120000	150000	600K to 700K	600000	700000	45k to 50K	45000	50000	900K and more	900000	
150K and more	150000		700K and more	700000		50K and more	50000				

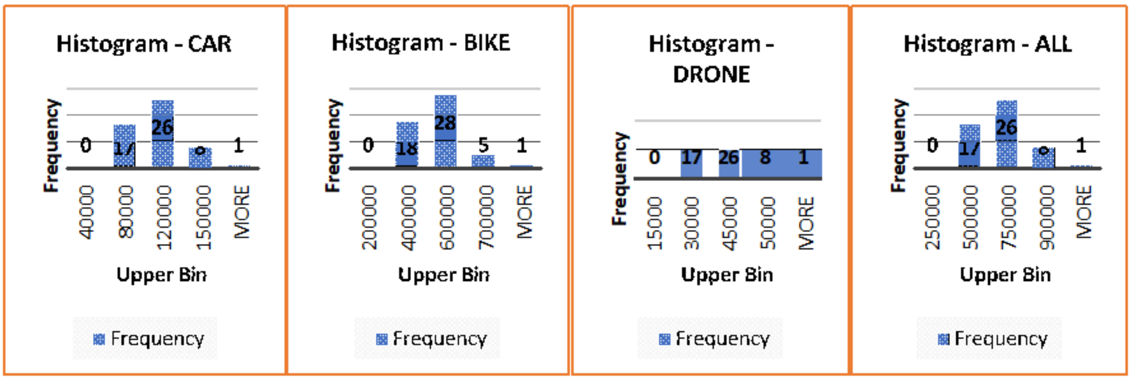

Figure 2. Histogram Chart – CAR, BIKE, DRONE and Overall.

Histograms show distribution patterns and support statistical conclusions. Similar frequency patterns across fleet types reflect continuous operational cycles, whereas motorcycles' higher-frequency bins show their dominance. These visuals help identify fleet delivery load concentration and operational stress locations.

ANOVA Results and Statistical Significance

The result of the single-factor ANOVA test to see if there is a statistically significant difference in the mean order delivery times among car, bike, and drone fleets is shown in Table 7. The F-value of the ANOVA summary is 549.63, which is much larger than the critical F-value of 3.055. Moreover, the p-value (1.43×10^{-70}) is also well below the 0.05 significance level. This indicates that there are statistically significant differences in the delivery performance among the three fleets. The high between-group sum of squares suggests fleet type strongly affects delivery volume. This supports varied fleet tactics over standard operating policies.

Tab 7. Anova: Single Factor Analysis for Fleet Types.

SUMMARY						
Groups	Count	Sum	Average	Variance		
Car	52	4824170.88	92772.51692	582864770.3		
Bike	52	23517833.04	452266.02	13852145556		
Drone	52	1809064.08	34789.69385	81965358.32		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	5.31932E+12	2	2.65966E+12	549.6314094	1.42952E-70	3.055161773
Within Groups	7.40366E+11	153	4838991895			
Total	6.05969E+12	155				

DISCUSSION

For IoT-driven transportation systems, Waseem et al. stressed secure identity management in real-time mobility scenarios and privacy-preserving and quantum-enhanced security [14]. GPS-enabled gasoline sensor–based IoT tracking improved fleet visibility and fuel efficiency for Nagesh et al., but they used centralized data management [15]. Bhutta and Ahmad validated real-time tracking in supply chain transparency without decentralized trust mechanisms in food transportation using secure IoT-based traceability [16]. da Costa et al.'s systematic study of real-time monitoring systems for food loss reduction shows IoT's potential across food supply chains [17]. However, this study integrates blockchain with IoT-enabled fleet tracking to offer decentralized data integrity, transparent analytics, and statistically validated performance assessment across heterogeneous delivery fleets.

CONCLUSION

The current research was focused on exploring various applications for real time fleet tracking technology through the use of blockchain in intelligent fleet management. The brain's ability to reformulate itself is referred to as neuroplasticity; this reformulation occurs through the formation of new neural pathways (connections) between neurons throughout life.

Neuroplasticity is extremely important in children, as their brains are going through both synaptic pruning and myelination. Research conducted on the effects of learning on the thickening of the cortex and on the dendritic branching of the neurons has demonstrated that both environmental stimulation as well as learning impact these changes. Furthermore, adults demonstrate a statistically significant degree of neuroplasticity and have shown that they can recover from brain injuries and acquire new motor skills through neuroplasticity. The implications of neuroplasticity are very important for educational psychology and rehabilitation medicine, as it suggests that interventions can improve cognitive outcomes.

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