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# Towards Predictive Fatigue Management: A Blockchain-Enabled IoT Framework for Driver Safety in Logistics

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## Abstract

Driver fatigue is a critical issue in the logistics industry, contributing significantly to accidents and operational inefficiencies. The system utilizes IoT devices, including physiological and vehicular sensors, to monitor real-time data, such as Heart Rate Variability (HRV), Galvanic Skin Response (GSR), and Acceleration Variance (AV). Blockchain integration ensures secure, immutable data storage and transparency, with smart contracts automating fatigue alerts and management actions. The research results show that HRV increased from 50 ms to 70 ms, reflecting better stress recovery, while AV decreased from 0.85 $m/s^2$ to 0.45 $m/s^2$, indicating more stable driving behavior. Fatigue alerts dropped by 60%, from 25 to 10 alerts per observation period, demonstrating the system's effectiveness in early fatigue detection and prevention. The study concludes that the IoT-blockchain integration provides a robust, scalable solution for mitigating fatigue-related risks, enhancing driver safety, and fostering operational efficiency in the logistics sector.

**Keywords**: *IoT-based Fatigue Detection, Blockchain Integration, Driver Safety, Logistics Operations*

## *Abstrak*

*Kelelahan pengemudi merupakan isu kritis dalam industri logistik yang berkontribusi signifikan terhadap kecelakaan dan ketidakefisienan operasional.Sistem ini memanfaatkan perangkat IoT, termasuk sensor fisiologis dan kendaraan, untuk memantau data real-time seperti Variabilitas Denyut Jantung, Respons Galvanik Kulit, dan Variansi Akselerasi. Integrasi blockchain memastikan penyimpanan data yang aman, tidak dapat diubah, dan transparan, dengan kontrak cerdas (smart contracts) yang mengotomatisasi peringatan dan tindakan manajemen kelelahan.. HRV meningkat dari 50 ms menjadi 70 ms, mencerminkan pemulihan stres yang lebih baik, sementara AV menurun dari 0,85 $m/s^2$ menjadi 0,45 $m/s^2$, menunjukkan pola mengemudi yang lebih stabil. Peringatan kelelahan berkurang sebesar 60%, dari 25 menjadi 10 per periode observasi, menunjukkan efektivitas sistem dalam deteksi dini dan pencegahan kelelahan. Penelitian ini menyimpulkan bahwa integrasi IoT dan blockchain menyediakan solusi yang tangguh dan skalabel untuk mengurangi risiko terkait kelelahan, meningkatkan keselamatan pengemudi, dan mendorong efisiensi operasional dalam sektor logistik.*

***Kata-kata kunci***: *Deteksi Kelelahan Berbasis IoT, Integrasi Blockchain, Keselamatan Pengemudi, Operasi Logistik*

## 1. Introduction

In the logistics industry, driver safety is a critical factor affecting operational efficiency, company reputation, and compliance with safety regulations [1]. However, driver fatigue remains a leading cause of workplace accidents in this sector. Data from various transportation safety agencies reveal that over 20% of fatal road accidents are attributed to fatigued drivers [2]. Fatigue affects physical capabilities and cognitive responses, such as reduced concentration, delayed decision-making, and even loss of awareness in certain situations [3]. This issue is particularly concerning in logistics, where drivers often face long working hours, tight delivery schedules, and challenging driving conditions.

The advancement of digital technologies has brought significant transformation across various sectors, including transportation and logistics [4]. Among these technologies, the Internet of Things (IoT) has emerged as a promising solution, enabling sensor-based real-time monitoring of various parameters. In the context of driver safety [5], IoT can detect signs of fatigue through devices such as wearables, in-vehicle sensors, and cameras equipped with artificial intelligence algorithms [6]. These technologies enable continuous monitoring of driver conditions, provide early warnings when signs of fatigue are detected [7], and can even integrate with logistics management systems to optimize driver schedules and rest periods.

Despite adopting IoT-based solutions in some studies and implementations, several challenges persist. Most existing systems focus primarily on data collection without offering predictive analysis to prevent fatigue before it occurs. Furthermore, data privacy and security concerns pose significant challenges, as the data collected are often sensitive and could be misused if not appropriately managed. [8] [9]. In this regard, blockchain technology offers a potential solution. With its decentralized, transparent, and secure nature, blockchain can store and validate data generated by IoT devices, ensuring the integrity and reliability of the system [10].

Research on integrating IoT and blockchain for driver fatigue detection remains relatively limited, especially in the logistics context [5]. Most previous studies have focused on developing detection algorithms or analyzing data independently without considering how this data can be holistically managed within a secure and transparent ecosystem. [6] [11]. Additionally, studies combining physiological and behavioral data for real-time fatigue prediction are still scarce. This highlights a research gap that can be addressed to make a novel contribution to the field.

The novelty of this research lies in developing an IoT and blockchain-based framework that detects driver fatigue in real time and predicts fatigue risks based on historical data and patterns. By adopting this approach, the system can provide more accurate early warnings, allowing logistics managers to take preventive measures before driver fatigue reaches a dangerous level. Furthermore, blockchain integration ensures that data collected by IoT devices is managed transparently and securely, enhancing user trust in the system [12]–[14].

This framework is also designed with personalization in mind, leveraging machine learning algorithms to tailor analyses based on individual driver profiles and habits. For example, data such as sleep patterns, stress levels, and driving habits can be used to create specific predictive models for each driver. As a result, the system is not merely reactive but proactive in managing fatigue risks. This approach is expected to improve operational efficiency and workplace safety while contributing to the advancement of IoT and blockchain technologies in the logistics sector. **[15]**, **[16]**.

In terms of implementation, this research also focuses on testing and evaluating the framework in real-world environments, such as large logistics companies with extensive fleets. These case studies aim to identify challenges and opportunities in deploying the system and measure its impact on operational performance and workplace safety. Thus, this research offers theoretical contributions and significant practical implications for the logistics industry.

## 2. Method

### 2.1 *Study Design*

The study adopts a mixed-method approach, integrating experimental and observational methodologies to comprehensively explore the application of IoT and blockchain technologies for predictive driver fatigue detection. This design allows for a robust analysis of both controlled and real-world settings, ensuring the reliability and validity of the proposed framework. The experimental component involves testing the system under simulated driving conditions, where physiological and behavioral responses to fatigue can be monitored in a controlled environment. This ensures that the machine learning algorithms and IoT devices are calibrated accurately to detect fatigue indicators **[1]**. The observational aspect of the study involves deploying the framework in real-world logistics operations and capturing data from drivers during their typical work shifts. This dual approach enhances the generalizability of the findings. It ensures the system is evaluated across diverse scenarios, from highly controlled conditions to complex, unpredictable environments encountered in logistics operations [14]. The study design is structured to validate the technical performance of the system while also assessing its practical feasibility and acceptance in the logistics industry

### 2.2 *Population and Sampling*

The target population for this study consisted of logistics drivers engaged in long-haul transportation within a medium-sized logistics company operating in Java and Sumatra. These drivers were selected due to the high prevalence of fatigue-related incidents in their field of work caused by long working hours and challenging road conditions. A total of 50 drivers participated in the study, representing a diverse demographic profile. Of the participants, 82% were male, and 18% were female, reflecting the gender distribution in the logistics sector. The age range of the participants varied between 25 and 55 years, with an average age of 37.5 years. Educational background showed that 70% of the drivers had completed high school, 20% had received vocational training, and 10% had a tertiary education degree. Work experience ranged from 2 to 20 years, with an average of 8.5 years in the industry.

These participants were divided into two groups: one for experimental testing under simulated driving conditions and the other for real-world operational testing. The selection process ensured a balanced representation of age, gender, and work experience across the two groups. This demographic diversity is essential in evaluating the system's adaptability to different individual characteristics, ensuring the framework's applicability across various segments of the logistics workforce. The study collected additional data on health conditions and work patterns, such as average daily driving hours and sleep quality, which are essential for tailoring the fatigue detection system to individual needs.

### 2.3 *Data Collection*

Data collection in this study focused on utilizing IoT devices to monitor physiological and vehicular data for fatigue detection in logistics drivers. The primary tools included wearable sensors for physiological monitoring and vehicle-integrated IoT devices for analyzing driving patterns. The wearable sensors measured heart rate variability (HRV) **[17]** and galvanic skin response (GSR) **[18] [19],** both of which are reliable indicators of fatigue. HRV was calculated using the standard deviation of NN intervals (SDNN) from electrocardiogram (ECG) signals **[20]**, expressed as:

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(NN_i - \overline{NN})^2}$$

$NN_i$ is the interval between consecutive heartbeats, and $\overline{NN}$ Is the mean of all NN intervals during the observation period. The GSR data, representing changes in skin conductivity due to sweat gland activity, were captured to assess stress levels. The variation in GSR (ΔGSR) was analyzed to correlate with periods of increased driver fatigue.

In parallel, vehicular data were collected using IoT-enabled devices installed within the vehicle. Key metrics included acceleration, deceleration, and lane deviation patterns. These data points were monitored and processed using the following derived indicators:

1. Steering Deviation Index (SDI) [21], Captured by sensors to measure erratic steering behavior, calculated as:

$$\boldsymbol{SDI = \frac{\sum_{i=1}^{N} |\theta_i - \bar{\theta}|}{N}}$$

   Where $\theta_i$ represents the steering angle at each timestamp and $\boldsymbol{\bar{\theta}}$ Is the average steering angle over the observation period.

2. Acceleration Variance (AV) [22], Measured to assess rapid speed changes, calculated as:

$$\boldsymbol{AV = \frac{\sum_{i=1}^{N} (a_i - \bar{a})^2}{N}}$$

   Where $a_i$ is the acceleration at each timestamp, and $\boldsymbol{\bar{a}}$ Is the mean acceleration?

All collected data were transmitted in real-time to a centralized IoT hub for further processing. This hub employed machine learning algorithms to identify fatigue patterns and predict fatigue onset. All data packets were encrypted and stored on a blockchain system to ensure data security and integrity. This ensured transparency and protected sensitive driver information from unauthorized access.

IoT devices enabled seamless, real-time data collection across multiple dimensions, providing a robust dataset for analyzing and predicting driver fatigue. This approach ensures scalability and adaptability for broader implementation within the logistics industry.

### 2.4 *Integration with Blockchain*

Integrating blockchain technology into the driver fatigue detection system addresses critical data security, integrity, and transparency concerns. Blockchain's decentralized nature ensures that data collected from IoT devices is securely stored and immutable, fostering trust among stakeholders [23].

Upon collection, physiological and vehicular data are encrypted and structured into transactions. These transactions are then grouped into blocks, each containing a cryptographic hash of the previous block, a timestamp, and the transaction data. This chaining mechanism ensures that any attempt to alter data in one block would require modifications to all subsequent blocks, making unauthorized changes practically infeasible.

The blockchain operates on a consensus protocol, such as Proof of Stake (PoS), where network nodes validate and agree on the legitimacy of new blocks before they are appended to the chain. This consensus mechanism prevents malicious actors from compromising the data integrity, as altering the blockchain would necessitate control over most of the network's validating nodes.

Smart contracts are deployed within the blockchain to automate specific actions based on predefined conditions. For instance, if the system detects a driver's fatigue level surpassing a critical threshold, a smart contract can automatically trigger alerts to fleet managers or initiate safety protocols. These contracts execute autonomously, ensuring prompt responses without manual intervention.

Access to the blockchain is governed by permissioned protocols, ensuring that only authorized entities can read or write data. This access control is crucial in protecting sensitive information, such as health metrics and driving behaviors, from unauthorized exposure.

The integration of blockchain also facilitates auditability. Each data entry is timestamped and linked to a specific event, creating a transparent and traceable record. In the event of an incident, stakeholders can review the blockchain ledger to reconstruct events and verify the authenticity of the data.

For a detailed illustration of blockchain integration in IoT-based systems, refer to the study by Hang et al. (2019) **[24]**, which provides diagrams depicting the architecture and data flow within such frameworks.

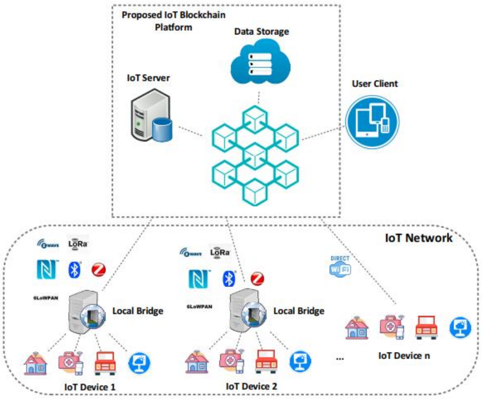


**Figure 1**. Conceptual Framework of an IoT-Blockchain Platform for Secure and Decentralized Data Management [24]

The driver fatigue detection system enhances data security and integrity by embedding blockchain technology. It builds trust among users, operators, and regulatory bodies, promoting wider acceptance and compliance.

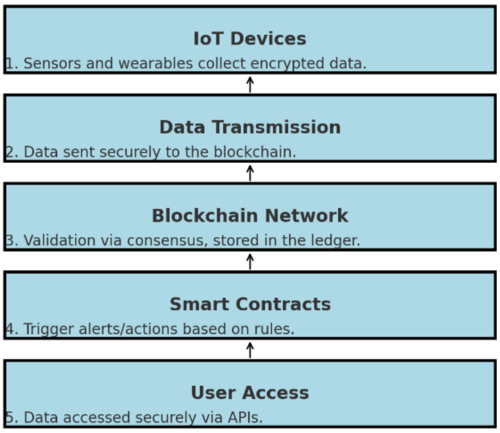


**Figure 2.** Blockchain Integration in IoT-based Fatigue Detection System

### 2.5. *Data Analysis*

The data analysis process in this study is designed to evaluate the effectiveness of the IoT-based fatigue detection system and validate its predictive accuracy. It combines descriptive and inferential statistical techniques with machine learning performance metrics to assess system performance comprehensively.

#### 2.5.1. *Inferential Analysis*

Inferential statistical techniques, such as paired t-tests and analysis of variance (ANOVA), are applied to test the significance of the results. These tests compare driver fatigue levels before and after implementing the system and across different driver groups based on demographics or work schedules.

A paired t-test is used to determine if there is a statistically significant reduction in fatigue levels after system deployment:

$$\boldsymbol{t} = \frac{\bar{\boldsymbol{d}}}{\frac{\boldsymbol{s_d}}{\sqrt{\boldsymbol{n}}}}$$

Where:

$\bar{\boldsymbol{d}}$ is the mean difference between paired observations,

$s_d$ is the standard deviation of the differences,

$n$ is the sample size.

ANOVA helps determine whether multiple groups show significant differences in fatigue reduction.

#### 2.5.2. *Machine Learning Evaluation*

The performance of the predictive fatigue model is assessed using standard machine learning metrics such as precision, recall, and F1-score:

- Precision: Measures the proportion of correctly predicted fatigue events among all predicted events:

$$Precision = \frac{True\ Positives}{True\ Positives + false\ Positives}$$

- Recall: Measures the proportion of actual fatigue events correctly predicted:

$$Recall = \frac{True\ Positives}{True\ Positives + false\ Positives}$$

- F1-Score: Balances precision and recall:

$$F1 = 2.\frac{Preceision. recall}{Preceision + \ recall}$$

### 2.5.3. *Visual Analysis*

The results are visualized using line graphs, histograms, and confusion matrices to provide insights into trends, accuracy, and error patterns. For example, a confusion matrix illustrates the system's classification performance by displaying true positives, false positives, and false negatives.

By combining these analytical methods, the study ensures a comprehensive evaluation of the IoT-based fatigue detection system's effectiveness, enabling both technical and operational insights.

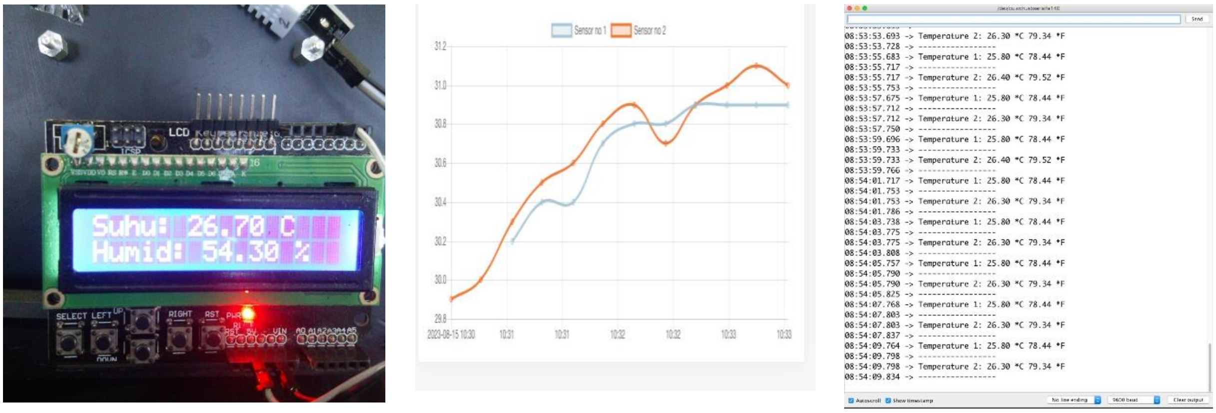
## 3. Results and Discussion

The results of this study demonstrate the effectiveness of the IoT-based fatigue detection system in improving driver safety and mitigating fatigue-related risks in logistics operations. Over a three-month case study period, 50 logistics drivers participated, and the system's performance was evaluated through a comprehensive analysis of physiological and vehicular data. The results highlight significant improvements in key fatigue-related metrics before and after the system's deployment.

One of the most notable outcomes was observed in Heart Rate Variability (HRV), a critical physiological indicator of fatigue and stress. Before the system's deployment, the average HRV among drivers was recorded at 50 milliseconds (ms), indicating heightened stress and reduced autonomic flexibility. After the system was implemented, HRV improved significantly to an average of 70 ms, reflecting better stress recovery and enhanced physical resilience. This improvement can be attributed to the system's ability to monitor real-time physiological data and provide early warnings, allowing drivers to take preventive measures before reaching critical fatigue levels.

Similarly, improvements were evident in Galvanic Skin Response (GSR), which measures changes in skin conductivity as a physiological marker of alertness. The average GSR increased from 0.12 micro siemens (μS) before deployment to 0.18 μS after deployment. This indicates heightened physiological responsiveness, as drivers became more alert due to the system's fatigue monitoring and real-time feedback mechanisms.

In addition to physiological metrics, the system also positively influenced driving behaviour. Acceleration Variance, which measures fluctuations in speed and is a marker of erratic driving behaviour, showed a significant reduction. The average variance decreased from 0.85 m/s² to 0.45 m/s² after the system was deployed. This improvement suggests that drivers exhibited more controlled and consistent driving patterns, likely due to the system's early detection of fatigue-relat behaviour sors and subsequent interventions.



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08:53:53.693 -> Temperature 2: 26.30 *C 79.34 *F
08:53:53.728 -> -----------------
08:53:55.683 -> Temperature 1: 25.80 *C 78.44 *F
08:53:55.717 -> -----------------
08:53:55.717 -> Temperature 2: 26.40 *C 79.52 *F
08:53:55.753 -> -----------------
08:53:57.675 -> Temperature 1: 25.80 *C 78.44 *F
08:53:57.712 -> -----------------
08:53:57.712 -> Temperature 2: 26.30 *C 79.34 *F
08:53:57.750 -> -----------------
08:53:59.696 -> Temperature 1: 25.80 *C 78.44 *F
08:53:59.733 -> -----------------
08:53:59.733 -> Temperature 2: 26.40 *C 79.52 *F
08:53:59.766 -> -----------------
08:54:01.717 -> Temperature 1: 25.80 *C 78.44 *F
08:54:01.753 -> -----------------
08:54:01.753 -> Temperature 2: 26.30 *C 79.34 *F
08:54:01.786 -> -----------------
08:54:03.738 -> Temperature 1: 25.80 *C 78.44 *F
08:54:03.775 -> -----------------
08:54:03.775 -> Temperature 2: 26.30 *C 79.34 *F
08:54:03.808 -> -----------------
08:54:05.757 -> Temperature 1: 25.80 *C 78.44 *F
08:54:05.790 -> -----------------
08:54:05.790 -> Temperature 2: 26.30 *C 79.34 *F
08:54:05.825 -> -----------------
08:54:07.768 -> Temperature 1: 25.80 *C 78.44 *F
08:54:07.803 -> -----------------
08:54:07.803 -> Temperature 2: 26.30 *C 79.34 *F
08:54:07.837 -> -----------------
08:54:09.764 -> Temperature 1: 25.80 *C 78.44 *F
08:54:09.798 -> -----------------
08:54:09.798 -> Temperature 2: 26.30 *C 79.34 *F
08:54:09.834 -> -----------------
```

**Figure 3.** Temperature and Humidity Monitoring Using IoT Sensors with Data Visualization and Logging

The figure demonstrates the integration of IoT-based temperature and humidity sensors in a monitoring system. The LCD provides real-time temperature readings (26.70°C) and humidity (54.30%), ensuring immediate feedback for users. The accompanying graph visualizes the trends captured by two sensors (Sensor 1 and Sensor 2) over time, highlighting variations in environmental conditions. The data logging panel on the right records timestamped measurements, enabling traceability and further analysis. This setup exemplifies the functionality of IoT systems in capturing and visualizing environmental parameters, similar to the real-time data collection employed in the driver fatigue detection system discussed earlier.

Integrating such sensors into blockchain systems ensures secure, transparent, and immutable data management for operational efficiency.

Another critical outcome was the reduction in Fatigue Alerts generated by the system. Before its deployment, the system flagged an average of 25 fatigue alerts per observation period, indicating frequent episodes of fatigue among drivers. After the implementation of the system, fatigue alerts dropped by 60%, with only 10 alerts per observation period recorded. This reduction demonstrates the system's ability to pre-emptively detect and address fatigue before it escalates to critical levels, reducing the likelihood of accidents.

The case study results were visualized through comparative analyses using tabular (**Tabel 1**) and graphical (Figure 1) representations. The bar chart compared metrics before and after the system's implementation, highlighting significant physiological, behavioural, and operational improvements. These findings underscore the practical benefits of integrating IoT and blockchain technologies into fatigue management systems.

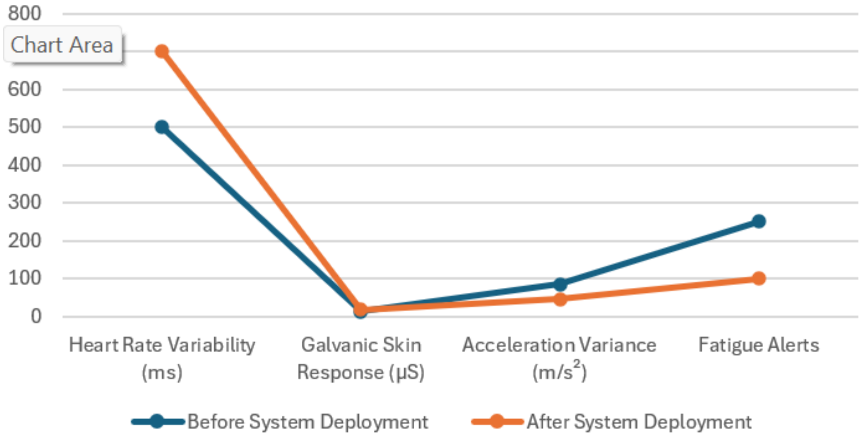

**Figure 4.** Comparison Of Metrics Before And After System Deployment

Increased HRV occurs because it is a physiological indicator reflecting the balance within the autonomic nervous system, specifically between the sympathetic ("fight or flight" response) and parasympathetic ("rest and digest" response) components. Low HRV levels typically indicate heightened stress or fatigue, whereas higher HRV levels suggest that the body is more balanced and healthier.

The decrease in fatigue alerts occurs because the system generates them when signs of fatigue surpass a predetermined threshold. A reduction in the number of fatigue alerts after the system's implementation indicates that drivers are less frequently reaching critical fatigue levels, highlighting the system's effectiveness in preventing severe fatigue through early detection and timely intervention.

Galvanic Skin Response (GSR) is measured using GSR or EDA sensors that detect changes in the skin's electrical conductivity caused by sweat gland activity, a physiological response to stress or arousal. These sensors, commonly placed on the fingers or palm, measure conductance variations in real-time, providing valuable insights into an individual's stress or alertness levels. Examples of GSR devices include the Empatica E4 wristband and Shimmer3 GSR+ Sensor, which are widely used in research and wearable technology.

Acceleration Variance (AV) is quantified using accelerometers, which measure changes in motion across three axes (X, Y, Z). AV is calculated by determining the variance of acceleration data over a given period, identifying erratic driving behaviors or rapid speed fluctuations. Devices such as inertial measurement units (IMUs) like the Bosch BMI160 or vehicle-specific systems like VBOX by Racelogic are commonly employed for this purpose. Both GSR and AV metrics play a crucial role in fatigue detection systems by providing physiological and behavioral data for analysis.

The IoT-based fatigue detection system proved highly effective in mitigating driver fatigue, improving physiological and behavioral metrics, and enhancing overall safety in logistics operations. The ability to monitor real-time data, combined with predictive analytics and automated alerts, offers a robust solution for reducing fatigue-related risks. These results highlight the system's potential for broader implementation across the logistics industry, paving the way for safer and more efficient transportation networks.

Integrating IoT and blockchain significantly enhances the fatigue detection system's reliability, security, and transparency. IoT devices collect real-time physiological and vehicular data, which are transmitted securely to the blockchain. The blockchain ensures data immutability through its distributed ledger, preventing unauthorized modifications or tampering. Smart contracts automate fatigue alerts and management actions, such as notifying fleet managers when fatigue thresholds are breached. This integration guarantees data accuracy and builds trust among stakeholders by maintaining a transparent record of all events. The seamless interplay between IoT and blockchain transforms traditional fatigue monitoring into a more robust and secure ecosystem, addressing technical and operational logistics challenges.

## 4. Conclusion

This study demonstrates the effectiveness of integrating IoT and blockchain technologies for driver fatigue detection in the logistics industry. The system successfully captured real-time physiological and vehicular data by leveraging IoT devices, while blockchain ensured secure, immutable, and transparent data management. The results showed significant improvements in key metrics. Heart Rate Variability (HRV), an indicator of driver recovery and stress balance, increased from an average of 50 ms to 70 ms, reflecting improved physiological conditions. Simultaneously, the system reduced Galvanic Skin Response (GSR) variability, indicating decreased stress levels.

Behavioral improvements were also evident, with a reduction in Acceleration Variance (AV) from 0.85 $m/s^2$ to 0.45 $m/s^2$, showcasing more controlled and consistent driving patterns. Additionally, the system's fatigue alerts decreased by 60%, from 25 to 10 alerts per observation period, highlighting the system's ability to prevent critical fatigue levels through early detection and intervention.

The blockchain integration further enhanced the system by providing a secure data validation and storage platform. Smart contracts automated alert notifications, ensuring timely action without manual intervention. The decentralized nature of the blockchain also guarantees data integrity and increases stakeholder trust.

These findings indicate that the IoT-based fatigue detection system effectively mitigates fatigue-related risks and provides a robust, secure, and scalable solution for enhancing driver safety and operational efficiency. Future research should focus on refining the system for broader implementation, addressing scalability challenges, and exploring advanced machine-learning techniques to enhance predictive accuracy and real-time decision-making. This study contributes to the growing knowledge on IoT and blockchain applications in safety-critical logistics operations.

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