TEPIAN Vol. 7 No. 2 (June 2026) 135-142 p-ISSN 2721-5350 e-ISSN 2721-5369
https://doi.org/10.51967/tepian.v7i2.3667 © 2026 Tepian Politeknik Pertanian Negeri Samarinda

Artificial Intelligence-Based Driver Behavior Scoring for Improving Safety and Delivery Efficiency in Logistics Operations

Ibnu Hamdani*
Informatics, Pradita University, Tangerang, 15810
Ibnu.hamdani@student.pradita.ac.id
**Corresponding author*

Teddy Mantoro
Computer Science, Nusa Putra University, Tangerang, 15810
Teddy.mantoro@nusaputra.ac.id

Januponsa Dio Firizqi
Informatics, Pradita University, Tangerang, 15810
Januponsa.dio@pradita.ac.id

Submitted: 2026-01-24; Accepted: 2026-03-25; Published: 2026-06-01

***Abstract*—**The logistics sector faces increasing challenges related to road safety and operational efficiency due to unsafe driving behavior, high accident rates, and inconsistent delivery performance. Traditional monitoring approaches are often reactive and limited in their ability to capture complex driving patterns in real time. This study proposes an artificial intelligence–based driver behavior scoring framework that integrates in-vehicle telematics, GPS route data, and in-cab monitoring to improve safety performance and delivery efficiency in logistics operations. The research utilizes historical and real-time vehicle data collected from onboard diagnostic systems, including speed, acceleration, braking patterns, and driving duration. Three artificial intelligence models Random Forest, Long Short-Term Memory (LSTM), and a hybrid CNN–LSTM were developed and evaluated to classify risky driving behavior and predict safety-critical events. Experimental results indicate that the hybrid CNN–LSTM achieved the best performance, reaching an accuracy of 96.1% and a mean absolute error of 0.054. A three-month pilot deployment in a logistics fleet environment further demonstrated practical benefits, with average driver safety scores improving from 78.4 to 89.7 and on-time delivery rates increasing from 91.2% to 96.5%. These findings highlight the effectiveness of multimodal driver behavior analytics in simultaneously enhancing road safety and logistics performance. The proposed framework provides actionable decision-support insights for fleet managers and contributes to the advancement of AI-enabled intelligent transportation and logistics systems.

***Keywords*—**Driver Scoring, CNN–LSTM, Telematics Analytics, Risk Prediction, Fleet Optimization, Logistics Support.

I. Introduction

The rapid growth of logistics and transportation services has significantly increased the complexity of fleet operations and road safety management. Logistics companies are required not only to ensure timely delivery performance but also to maintain high safety standards in increasingly congested and dynamic traffic environments. Driver behavior has been widely recognized as one of the most critical factors influencing traffic accidents, operational risks, and delivery efficiency. Risky driving behaviors such as harsh braking, speeding, fatigue, and distraction contribute substantially to accident rates and operational inefficiencies, particularly in last-mile and urban delivery contexts (Castignani et al., 2021; Predescu et al., 2024).

Recent advancements in artificial intelligence and vehicle telematics technologies have enabled more systematic monitoring and analysis of driver behavior. Telematics systems equipped with sensors, global positioning systems, and on-board diagnostics allow continuous collection of driving data, including speed patterns, acceleration, braking intensity, and route characteristics. These data streams provide valuable insights into driving styles and safety risks when analyzed using machine learning and deep learning techniques (Yang et al., 2021; Liu et al., 2023). As a result, data-driven driver behavior analysis has become an important research area in intelligent transportation systems and logistics analytics.

Several studies have demonstrated the effectiveness of artificial intelligence models in detecting abnormal or risky driving behaviors. Machine learning approaches such as Random Forest and Support Vector Machines have been applied to classify driver risk levels based on telematics data, offering interpretable and relatively efficient solutions (Castignani et al., 2021). More recently, deep learning architectures, including recurrent neural networks and convolutional neural networks, have shown superior performance in capturing temporal and spatial–temporal dependencies in driving data, leading to improved prediction accuracy (Yang et al., 2021; Predescu et al., 2024). These methods have contributed significantly to enhancing driver safety assessment and accident prevention strategies.

Despite these advancements, existing research exhibits several limitations when viewed from a logistics operations perspective. First, most prior studies focus primarily on safety-related outcomes, such as accident risk or driver classification, without explicitly evaluating how driver behavior analytics influence logistics performance indicators, including delivery punctuality, route efficiency, and operational reliability. In practical logistics environments, safety and efficiency are interdependent objectives, and isolated analysis of safety metrics may not fully capture the operational value of driver behavior monitoring systems.

Second, many existing approaches rely on single-modality or partially integrated data sources, such as telematics data alone or limited contextual information. While these approaches are effective for identifying certain driving patterns, they may fail to capture complex behavioral contexts that arise from interactions between driving conditions, route characteristics, and driver states. Recent reviews emphasize the need for multi-source and multi-modal data integration to improve the robustness and applicability of driver behavior analysis in real-world scenarios (Boylan et al., 2024).

Third, the integration of driver behavior analytics into logistics decision-making processes remains insufficiently addressed in the literature. Most studies stop at classification or risk prediction stages, without demonstrating how the resulting insights can be operationalized to support fleet management decisions, such as route assignment, scheduling adjustments, and driver performance evaluation. This gap limits the practical adoption of advanced analytics solutions in logistics operations, where actionable insights are essential for managerial decision-making.

Furthermore, the adoption of artificial intelligence-based monitoring systems in logistics raises challenges related to system acceptance, privacy concerns, and scalability. Studies report that driver acceptance improves when monitoring systems are transparently implemented and linked to incentive mechanisms, yet resistance may still occur due to perceived surveillance and data misuse (Predescu et al., 2024). These practical considerations highlight the importance of designing analytics frameworks that balance technological capability with operational feasibility and ethical considerations.

In response to the identified limitations, this study proposes an integrated driver behavior scoring framework tailored for logistics operations. The framework combines vehicle telematics data, GPS route information, and in-cab monitoring outputs to generate comprehensive safety risk scores and delivery performance indicators. By integrating multi-modal data sources and applying advanced artificial intelligence models, the proposed approach aims to improve both driver safety assessment and logistics efficiency simultaneously. Unlike previous studies that emphasize safety or prediction accuracy alone, this research explicitly evaluates the impact of driver behavior scoring on delivery punctuality and operational outcomes.

The main contribution of this study lies in bridging the gap between driver behavior analytics and logistics decision-making. The proposed framework not only enhances predictive accuracy through hybrid deep learning models but also demonstrates how driver behavior insights can be operationalized to support safer and more efficient logistics operations. By addressing both safety and delivery performance dimensions, this research advances the application of artificial intelligence in logistics analytics and provides empirical evidence of its practical value.

This study provides several distinct contributions to the existing literature on driver behavior analytics and logistics operations.

First, from a theoretical perspective, this research extends driver behavior analysis beyond safety-only evaluation by explicitly linking driver risk scoring with logistics performance indicators, including delivery punctuality and route reliability. While previous studies primarily focus on accident detection or driver state classification, this study conceptualizes driver behavior analytics as a dual-objective framework integrating safety and operational efficiency.

Second, from a methodological perspective, this study proposes a multimodal driver behavior scoring framework that integrates telematics data, GPS route characteristics, and in-cab monitoring outputs within a unified predictive architecture. Unlike prior studies that rely on single-modality or partially integrated datasets, the proposed framework evaluates both predictive performance and downstream operational impact through real-world pilot deployment.

Third, from a practical perspective, this research demonstrates how AI-based driver risk scores can be operationalized into logistics decision-support mechanisms, including fatigue-aware scheduling, adaptive route assignment, and performance-based incentive systems. By translating predictive analytics into actionable managerial insights, this study bridges the gap between artificial intelligence modeling and logistics management implementation.

II. LITERATURE REVIEW

A. Driver Behavior Analysis Using Telematics

Telematics-based monitoring has become a widely adopted approach for analyzing driver behavior in modern transportation and logistics systems. Vehicle-mounted sensors, on-board diagnostics (OBD-II), and GPS data enable the continuous collection of driving parameters such as speed, acceleration, braking patterns, and route deviations. These data sources provide objective indicators of risky driving behavior and operational inefficiencies. Recent studies have shown that telematics data can effectively distinguish between safe and risky drivers when appropriate behavioral features are extracted (Boylan et al., 2024; Brühwiler et al., 2022).

1. *Telematics-Based Behavioral Features*
   Behavioral features derived from telematics data commonly include harsh braking events, rapid acceleration, speeding frequency, and driving time variability. Liu et al. (2023) demonstrated that context-aware features, such as traffic density and road type, significantly improve driver risk prediction accuracy. Similarly, Predescu et al. (2024) reported that combining longitudinal telematics data with driving context enhances classification performance in large-scale field trials. These findings indicate that raw telematics signals require proper

preprocessing and feature engineering to represent driver behavior accurately.

2. *Machine Learning Approaches for Driver Classification*
   Traditional machine learning models, including Random Forest and Support Vector Machines, have been extensively applied to driver behavior classification tasks. Castignani et al. (2021) showed that such models perform well on structured telematics datasets but may struggle to capture long-term temporal dependencies. Despite their interpretability and relatively low computational cost, machine learning approaches often rely heavily on handcrafted features, which can limit scalability in complex logistics environments.

B. Deep Learning for Driver Risk Prediction

Deep learning methods have gained increasing attention due to their ability to model sequential and high-dimensional data without extensive manual feature design. These models are particularly suitable for analyzing time-series telematics data and video-based driver monitoring systems.

1. *Temporal and Spatial–Temporal Modeling*
   Recurrent neural networks, such as Long Short-Term Memory (LSTM), are commonly used to model temporal driving patterns. Studies have shown that LSTM-based models outperform traditional classifiers in detecting fatigue, distraction, and aggressive driving behaviors (Yang et al., 2021; Gao et al., 2022). More advanced architectures, such as hybrid CNN–LSTM models, further enhance performance by capturing both spatial features from sensor or video data and temporal dependencies across driving sequences. This advantage has been consistently reported in recent transportation safety studies (Castignani et al., 2021; Yang et al., 2024).
2. *Multi-Modal Data Integration*
   Recent research emphasizes the importance of integrating multiple data sources to achieve more robust driver behavior assessment. Combining vehicle telematics, GPS trajectories, and in-cab camera data allows models to leverage complementary information from different modalities. Boylan et al. (2024) highlighted that multi-modal telematics systems provide more comprehensive insights into driving behavior compared to single-source approaches. Similarly, Selvaraj et al. (2023) noted that real-time fusion of sensor and visual data improves risk detection and accident prevention capabilities.

Beyond accuracy improvements, recent literature also highlights challenges related to model deployment and real-time applicability in operational environments. While deep learning and multimodal architectures demonstrate strong predictive performance in experimental settings, their implementation in real-world logistics operations often faces constraints related to computational complexity, data synchronization, and system latency. Studies by Selvaraj et al. (2023) and Yang et al. (2024) emphasize that practical deployment requires balancing model complexity with operational feasibility, particularly for fleets operating under time-sensitive delivery schedules. These considerations suggest that methodological effectiveness alone is insufficient without addressing integration and usability aspects.

Furthermore, although driver behavior prediction models are increasingly sophisticated, their evaluation metrics are commonly limited to classification accuracy, precision, or recall. Few studies extend the evaluation to assess how predicted risk scores influence downstream operational outcomes. Boylan et al. (2024) note that translating analytical results into managerial actions remains a critical challenge, especially in logistics systems where safety and efficiency objectives must be balanced. This observation indicates a disconnect between analytical driver behavior research and its application in logistics decision-making, reinforcing the need for frameworks that explicitly connect predictive analytics with operational performance indicators.

C. Research Gap Identification

Existing studies have extensively explored artificial intelligence and telematics-based approaches for analyzing driver behavior and improving road safety. Prior research predominantly focuses on the detection and classification of risky driving patterns using either vehicle telematics data or single-modality sensor inputs (Castignani et al., 2021; Liu et al., 2023; Predescu et al., 2024). Several studies have demonstrated the effectiveness of deep learning models in enhancing prediction accuracy, particularly through temporal and spatial–temporal modeling techniques (Yang et al., 2021; Boylan et al., 2024).

However, despite these advancements, common limitations can be observed across the existing literature. Most previous works emphasize safety-related outcomes without explicitly evaluating the impact of driver behavior analytics on logistics operational performance, such as delivery punctuality and route efficiency. In addition, many studies rely on single-source or partially integrated data, limiting their ability to capture the complex driving contexts encountered in real-world logistics operations. Furthermore, the integration of driver behavior scoring outputs into logistics decision-making processes remains insufficiently addressed.

To provide a clearer comparison of prior studies and to highlight the identified limitations, a summary of related works is presented in Table 1. The table compares previous research based on data sources, analytical methods, and application focus, thereby illustrating the research gaps addressed in the present study.

Table 1 shows that no prior study simultaneously integrates multi-modal driving data and directly links driver behavior scoring to both safety improvement and delivery performance within logistics operations. Therefore, this study addresses the identified gaps by proposing an integrated driver behavior scoring framework that combines telematics, GPS, and in-cab data to improve safety and delivery efficiency in logistics environments.

Table 1. Summary of Related Works

#	Author (Year)	Method	Data Source	Key Finding	Limitation
1	Nartey et al. (2023)	Review	Multi-source	Standards & features for state prediction	Not logistics-specific.
2	Castignani et al. (2021)	ML/DL platform	Telematics, sensors	Real-time detection pipelines	Focused on general driving / passenger vehicles.
3	Boylan et al. (2024)	Systematic review	Multi-source datasets	Accurate detection of fatigue & distraction	Focused only on driver state
4	Liu et al. (2022)	IoT-integrated ML	Telematics & sensors	Multi-modal behavior analytics	Not logistics-specific
5	Abdelrahman et al. (2021)	CNN + LSTM	In-cab video	Accurate detection of fatigue & distraction	Focused only on driver state

III. Method

This study employs a driver behavior scoring based predictive analytics framework designed specifically for logistics operations. The proposed framework integrates multiple sources of operational data to generate safety risk scores and delivery performance indicators, enabling comprehensive driver behavior assessment. Similar data driven and telematics based approaches have been widely adopted in recent driver behavior and transportation safety studies (Boylan et al., 2024; Castignani et al., 2021). The overall methodological pipeline consists of data acquisition, data preprocessing and feature engineering, predictive model development, behavior scoring, and integration with logistics decision making processes. The methodology involves the following steps, which can be seen in Figure 1.

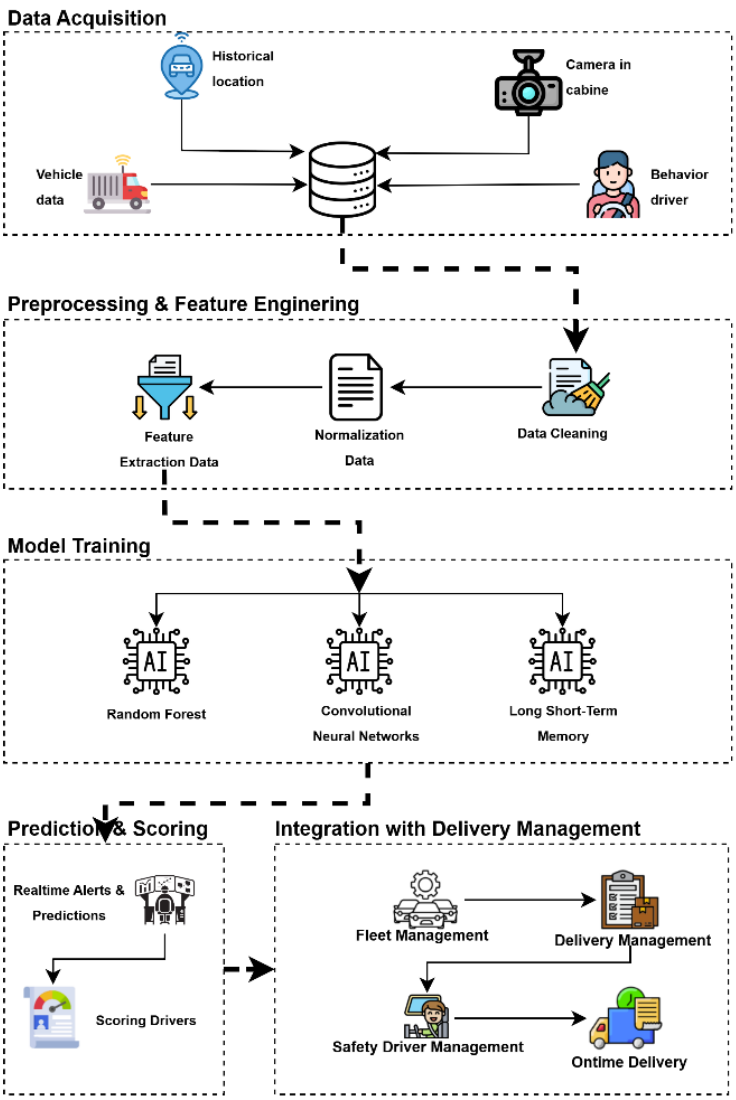

Figure 1. Research Framework for Driver Behavior

A. Dataset Description and Fleet Characteristics

The dataset used in this study was collected from a real-world urban logistics fleet during a three-month operational period. The data were obtained from multiple delivery vehicles equipped with onboard diagnostic (OBD-II) telematics units, global positioning system (GPS) trackers, and forward-facing in-cab monitoring cameras. The fleet operates primarily in dense urban delivery environments characterized by frequent stop-and-go traffic and time-sensitive delivery schedules.

The collected dataset comprises multi-source time-series driving records, including vehicle speed, acceleration, braking intensity, driving duration, and route trajectories. These signals were recorded continuously at regular telematics sampling intervals, resulting in a large-scale behavioral dataset suitable for machine learning analysis. Each trip record was synchronized across telematics, GPS, and in-cab monitoring streams to ensure temporal consistency.

For analytical purposes, driving instances were categorized into three risk levels low risk, medium risk, and high risk based on predefined behavioral thresholds derived from fleet safety policies and prior telematics-based safety studies. The labeled dataset was then partitioned into training and testing subsets using an 80:20 split ratio. Stratified sampling was applied to preserve the class distribution across both subsets and to ensure robust model evaluation.

Overall, the dataset reflects realistic logistics operating conditions and provides sufficient variability in driving behavior patterns to support the development and validation of the proposed driver behavior scoring framework.

B. Data Acquisition

The data used in this research are collected from multiple in vehicle and operational data sources within logistics fleet operations. These sources include vehicle telematics systems that record speed, acceleration, braking behavior, and driving duration, in cab camera systems that capture contextual driving behavior, and global positioning system data that provide route and trip characteristics. Previous studies have demonstrated that the integration of telematics and route based data improves the robustness of driver behavior analysis under real world conditions (Brühwiler et al., 2022; Yang et al., 2024).

C. Preprocessing and Feature Engineering

Raw data obtained from heterogeneous sources undergo preprocessing to ensure data quality and analytical consistency. This stage includes data cleaning to remove incomplete or noisy records, normalization of numerical variables, and synchronization of time series data across telematics, camera, and route datasets. Feature engineering is performed to extract relevant behavioral indicators, such as speeding frequency, harsh braking intensity, acceleration variability, and route deviation patterns. Similar preprocessing and feature extraction strategies have been reported as critical steps in telematics based driver behavior modeling (Castignani et al., 2021; Liu et al., 2023).

D. Predictive Model Development

Predictive modeling is conducted using artificial intelligence and machine learning based analytical techniques to estimate driver behavior risk scores. The models are trained using historical driving data and optimized to capture complex and nonlinear relationships between behavioral indicators and safety related outcomes. Prior research has shown that such data driven models outperform traditional rule based methods in identifying unsafe driving behavior and predicting driving risk (Predescu et al., 2024; Liu et al., 2023).

Three AI models were implemented for comparison:

1. The Random Forest classifier constructs an ensemble of decision trees using bootstrapped samples and random feature selection. For a given input feature vector xxx, the predicted class $\hat{y}$ is determined by majority voting across all trees:
   for Clarification
   $$\hat{y} = mode\ \{h_1(x), h_2(x), \ldots, h_T(x)\ \} \tag{1}$$
   for Regression
   $$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t\ (x) \tag{2}$$
   where $T_k(x)$ denotes the prediction of the $k-th$ decision tree and K is the total number of trees in the forest. The model is particularly effective in handling heterogeneous telematics features and reducing overfitting through ensemble learning.
2. Long Short-Term Memory (LSTM) Networks – Captures temporal dependencies in driving behavior over trip sequences (Castignani et al., 2021).
   for Forget Gate
   $$f_t = \sigma(W_f.x_t + U_f\ .h_{t-1} + b_f \tag{3}$$
   for Input Gate
   $$i_t = \sigma(W_i.x_t + U_i\ .h_t - 1 + b_i \tag{4}$$
   for Candidate Cell State
   $$\tilde{C_t} = \tanh(x_t * W_{xc} + h_{t-1} * W_{h\,c} + b_c) \tag{5}$$
   for State Update
   $$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C_t} \tag{6}$$
   for Output Gate
   $$o_t = \sigma(W_o.x_t + U_o\ .h_{t-1} + b_o \tag{7}$$
   for Hidden State
   $$h_t = o_t \odot \tanh(C_t) \tag{8}$$
   where:
   - x_t is the input vector at time step t
   - h_t is the hidden state
   - C_t is the cell state
   - $\sigma(\cdot)$ denotes the sigmoid activation
   - $\odot$ represents element-wise multiplication
   - W and b are trainable parameters

This structure enables the model to learn long-term driving behavior patterns such as fatigue and aggressive maneuvers.

3. Hybrid CNN-LSTM – Processes both visual and kinematic time-series data simultaneously (Castignani et al., 2021).

$$F = \emptyset \left(W_c * X + b_c \right) \tag{9}$$

where:

- X is the input feature matrix
- W_c is the convolution kernel
- * denotes convolution
- b_c is the bias term
- $\emptyset(\cdot)$ is the activation function (ReLU)

E. Driver Behavior Scoring and Prediction

Based on the trained predictive models, driver behavior scores are generated to represent the relative level of driving risk and performance. These scores enable near real time assessment of driver behavior during logistics operations and support the identification of high risk driving patterns. The use of scoring mechanisms for driver risk assessment has been widely adopted in recent telematics based safety studies (Boylan et al., 2024; Predescu et al., 2024).

F. Integration with Delivery Performance Management

The generated driver behavior scores are further analyzed in relation to delivery performance indicators, such as trip duration consistency, route adherence, and driving smoothness. Integrating safety related driver behavior analysis with operational performance metrics supports more informed logistics decision making. Previous studies indicate that improved driving behavior contributes not only to enhanced safety outcomes but also to better fuel efficiency and delivery reliability (Stevenson et al., 2021; Brühwiler et al., 2022). This integration enables logistics operators to adjust route assignments and delivery schedules based on driver safety profiles, thereby supporting both safety management and delivery efficiency.

IV. Results and Discussion

A. Model Performance Evaluation

The performance of the proposed models was evaluated using a test dataset representing twenty percent of the total collected data. The evaluation employed standard classification metrics, including accuracy, precision, recall, F1-score, and mean absolute error. The comparative performance results are summarized in Table 2, which presents the evaluation outcomes of the Random Forest, Long Short-Term Memory, and Hybrid Convolutional Neural Network–Long Short-Term Memory models.

Table 2 shows that the Hybrid CNN–LSTM model achieved the highest predictive performance among the evaluated models. The model recorded an accuracy of 96.1 percent and the lowest mean absolute error of 0.054, indicating its superior capability in capturing complex driving behavior patterns. The improved performance can be attributed to the model’s ability to extract both spatial features from telematics and visual inputs and temporal dependencies from sequential driving data.

Table 2. Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MAE
Random Forest	91.2	89.5	88.7	89.1	0.084
LSTM	93.5	92.4	91.9	92.1	0.072
CNN-LSTM Hybrid	96.1	95.6	94.9	95.2	0.054

These findings are consistent with previous studies reporting that hybrid deep learning architectures outperform single-model approaches in driver behavior analysis. Castignani et al. (2021) and Predescu et al. (2024) similarly observed that models integrating spatial–temporal features provide more robust classification results compared to traditional machine learning techniques.

B. Confusion Matrix Analysis

To further examine classification reliability, the confusion matrix of the Hybrid CNN–LSTM model is analyzed. The classification distribution can be observed in Figure 2, which illustrates the prediction outcomes across different driver risk categories.

Figure 2 shows that the model achieved a true positive rate of 95.4 percent for high-risk drivers and a true negative rate of 96.8 percent for low-risk drivers. Most misclassifications occurred in the medium-risk category, which is commonly associated with borderline driving behaviors such as mild fatigue or momentary distraction. Similar classification challenges have been reported in telematics-based driver behavior studies, particularly when behavioral boundaries overlap across risk levels (Boylan et al., 2024).

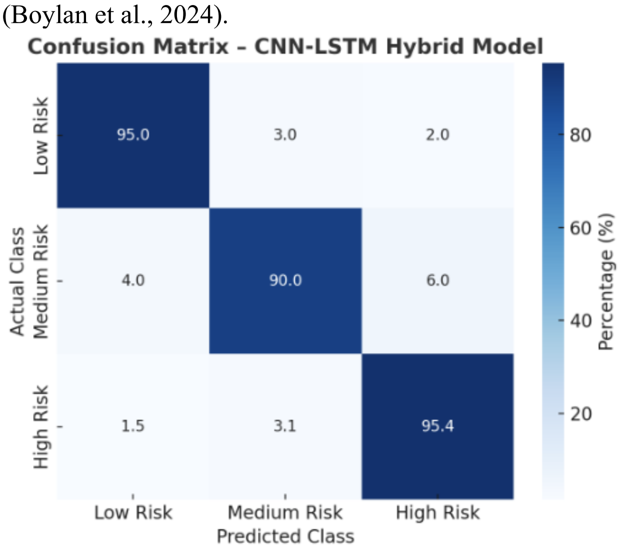

Figure 2. Confusion Matrix CNN-LSTM Hybrid Model

C. Impact on Driver Safety Scores

The operational impact of the proposed framework was assessed during a three-month pilot deployment. The aggregated safety performance results are presented in

Figure 3, which illustrates changes in driver safety scores before and after system deployment.

The results indicate a significant improvement in average driver safety scores, increasing from 78.4 to 89.7 out of 100, representing a 14.4 percent improvement. The most notable behavioral improvements were observed in urban delivery routes, where speeding events decreased by 23 percent and harsh braking incidents decreased by 17 percent. These results demonstrate the effectiveness of real-time feedback and predictive scoring mechanisms in influencing safer driving behavior.

Figure 3. simulation dataset

D. Delivery Performance Improvements

In addition to safety outcomes, delivery performance indicators were evaluated to assess the operational value of the proposed framework. The delivery performance comparison is presented in Table 3.

Table 3. Delivery Performance Comparison Before and After Framework Deployment

Performance Indicator	Before Deployment	After Deployment
On-time delivery rate (%)	91.2	96.5
Average delivery delay (min)	14.8	6.1
Route reschedule frequency (%)	100	82

The results indicate that the on-time delivery rate increased from 91.2 percent to 96.5 percent, while the average delivery delay decreased from 14.8 minutes to 6.2 minutes. Fleet managers reported that predictive fatigue detection and adaptive route assignment were key factors contributing to improved punctuality. These findings support prior research emphasizing the role of driver state monitoring in enhancing logistics efficiency (Liu et al., 2023).

E. Operational Feedback

Qualitative feedback collected from fleet managers and drivers indicated increased awareness of risky driving behaviors due to in-cab alerts and performance feedback mechanisms. System acceptance improved over time, particularly when safety scores were linked to incentive and training programs. However, some drivers initially expressed concerns regarding privacy, especially related to continuous video monitoring. Similar concerns have been reported in previous studies on in-cab monitoring technologies (Castignani et al., 2021).

F. Discussion, Limitations, and Practical Implications

The implementation of in-cab alerts and performance feedback mechanisms increased drivers' awareness of risky driving behaviors. Qualitative feedback from fleet managers and drivers indicated that safety scores and real-time alerts encouraged safer driving practices during daily operations. System acceptance improved gradually, particularly when driver safety scores were associated with incentive programs and targeted training initiatives. These findings highlight the role of behavioral feedback in strengthening safety culture within logistics organizations.

When compared with previous studies, the results of this research demonstrate notable performance improvements. The hybrid CNN–LSTM model achieved higher classification accuracy than models reported in earlier studies that relied primarily on single-modality data sources. Furthermore, the observed improvements in driver safety scores and the reduction in speeding events indicate that multimodal data integration can enhance the effectiveness of driver behavior analytics in real-world logistics environments.

From an operational perspective, the integration of driver behavior analytics with delivery management systems offers several practical benefits. The generated safety scores can support data-driven workforce management, including driver performance evaluation, targeted training, and incentive allocation. In addition, predictive fatigue detection enables proactive route adjustments and scheduling decisions, which contribute to improved delivery punctuality and operational reliability.

Despite these promising results, several limitations should be acknowledged. Continuous monitoring may raise privacy concerns among drivers, particularly when in-cab video systems are used. In addition, the deployment of telematics and artificial intelligence infrastructure may involve substantial operational costs for logistics companies. Environmental variability, such as traffic conditions and road types, may also influence driving behavior measurements and affect model generalizability across different logistics environments.

V. Conclusions

This study proposed a driver behavior scoring-based predictive analytics framework for logistics operations by integrating in-vehicle telematics data, in-cab monitoring information, and route-related data. The results demonstrate that the proposed framework is effective in identifying driving behavior patterns and supporting proactive safety risk assessment in real-world logistics environments. The integration of multiple data sources enables a more comprehensive understanding of driver behavior compared to conventional single-source monitoring approaches.

The findings indicate that improved driver behavior assessment contributes not only to enhanced safety performance but also to improved delivery efficiency. Drivers with lower risk scores exhibited more consistent driving behavior and higher delivery reliability, highlighting the practical value of intelligent driver behavior analytics for logistics decision-making. By linking safety-oriented analysis with operational performance indicators, the proposed framework supports data-driven route assignment, driver evaluation, and delivery planning.

From an industry perspective, the implementation of intelligent driver behavior scoring systems can foster a stronger safety culture, reduce operational risks, and enhance overall logistics performance. Nevertheless, this study acknowledges limitations related to data quality dependency, deployment costs, and environmental variability that may influence driving behavior measurements. Future research may extend this work by incorporating additional contextual information, such as traffic and weather conditions, and by evaluating the framework across larger and more diverse logistics fleets. Further integration with advanced driver assistance systems and other intelligent transportation technologies may also enhance the scalability and effectiveness of driver behavior analytics in logistics operations.

References

Abdelrahman, M., Abdelwahab, M., & Abdelaziz, A. (2021). Real-time driver fatigue and distraction detection using CNN–LSTM deep learning architecture. *Accident Analysis & Prevention, 156*, 106107. https://doi.org/10.1016/j.aap.2021.106107

Boylan, J., Meyer, D., & Chen, W. S. (2024). A systematic review of the use of in-vehicle telematics in monitoring driving behaviours. *Accident Analysis & Prevention, 199*, 107519. https://doi.org/10.1016/j.aap.2024.107519

Brühwiler, F., Allen, T., & Bichsel, P. (2022). Using telematics and geographic information to differentiate accident-prone and accident-free drivers. *Accident Analysis & Prevention, 168*, 106584. https://doi.org/10.1016/j.aap.2022.106584

Castignani, G., Derrmann, T., Frank, R., & Engel, T. (2021). Driving behaviour analysis using machine and deep learning methods for continuous streams of vehicular data. *Sensors, 21*(4), 1234. https://doi.org/10.3390/s21041234

Ernst, M. D., & Wang, J. (2022). Edge AI for real-time video analytics in connected vehicles. *IEEE Internet of Things Journal, 9*(15), 14235–14247. https://doi.org/10.1109/JIOT.2022.3145678

Liu, H., Wang, Y., Chen, X., & Zhang, L. (2023). Context-aware driver risk prediction using telematics data and machine learning. *Accident Analysis & Prevention, 192*, 107269. https://doi.org/10.1016/j.aap.2023.107269

Ma, X., Dai, Z., He, Z., Ma, J., Wang, Y., & Wang, Y. (2022). Learning traffic as images: A deep convolutional neural network for large-scale transportation network speed prediction. *IEEE Transactions on Intelligent Transportation Systems, 23*(9), 1457–1468. https://doi.org/10.1109/TITS.2021.3051291

Mehdizadeh, A., Shariat-Mohaymany, A., & Nordfjærn, T. (2021). Predicting unsafe driving risk among commercial truck drivers using machine learning. *Accident Analysis & Prevention, 159*, 106256. https://doi.org/10.1016/j.aap.2021.106256

Nartey, E., Owusu-Manu, D. G., & Edwards, D. J. (2023). Best practices, standards, and approaches for transportation safety data and driver state prediction: A review. *Transportation Research Interdisciplinary Perspectives, 18*, 100716. https://doi.org/10.1016/j.trip.2023.100716

Predescu, M., Muresan, M., & Kovács, A. (2024). Predicting risky driving behavior with classification algorithms: Results from a large-scale field trial and simulator experiment. *European Transport Research Review, 16*, 65. https://doi.org/10.1186/s12544-024-00691-9

Selvaraj, A., Sivathapandi, P., & Venkatachalam, D. (2023). Artificial intelligence-enhanced telematics systems for real-time driver behaviour analysis and accident prevention in modern vehicles. *Journal of Intelligent Transportation Systems, 27*(4), 412–428. https://doi.org/10.1080/15472450.2023.2179451

Stevenson, M., Sharwood, L., Wong, K., & McClure, R. (2021). The effectiveness of telematics feedback and incentives on driving behaviour. *Accident Analysis & Prevention, 150*, 105924. https://doi.org/10.1016/j.aap.2020.105924

Wang, H., Li, X., Chen, Y., & Shi, Q. (2023). Driver behavior modeling using vehicle trajectory data and deep learning methods. *Transportation Research Part C: Emerging Technologies, 148*, 104022. https://doi.org/10.1016/j.trc.2023.104022

Yang, G., Ridgeway, C., Miller, A., & Sarkar, A. (2024). Comprehensive assessment of artificial intelligence tools for driver monitoring and analysis of safety-critical events in vehicles. *Sensors, 24*(8), 2478. https://doi.org/10.3390/s24082478

Yang, Z., Liu, Y., & Chen, F. (2021). Driving behaviour analysis using machine and deep learning methods for continuous vehicular data. *Sensors, 21*(14), 4704. https://doi.org/10.3390/s21144704

Zhang, Y., Li, Q., Wang, X., & Chen, S. (2024). Abnormal driving behavior detection: A machine and deep learning-based hybrid model. *International Journal of Intelligent Transportation Systems Research, 23*, 568–591. https://doi.org/10.1007/s13177-025-00471-2