RESEARCH PAPER

A Neuro-Symbolic Agentic Digital Twin Framework for Causally Explainable Reckless Driving Behaviour Detection

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Abstract

Road traffic accidents remain one of the leading causes of fatalities worldwide, and reckless driving behavior is widely recognized as a primary contributor to these incidents. Despite significant advancements in artificial intelligence, most existing reckless driving detection systems rely heavily on correlation-based deep learning techniques such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based architectures. While these models can identify patterns in driving data, they often lack causal understanding, personalization, and explainability, which limits their effectiveness in real-world deployment. Furthermore, such systems typically treat reckless driving as a static classification problem rather than understanding the underlying behavioral intentions and contextual dynamics of the driver.

To address these limitations, this study proposes a novel framework called the Neuro-Symbolic Agentic Digital Twin (NS-ADT) for intelligent detection of reckless driving behavior. The proposed paradigm integrates neural computation with symbolic reasoning to provide a more comprehensive understanding of driving patterns. In particular, the framework models driving behavior as a continuous dynamic process rather than discrete events. A Neural Ordinary Differential Equation (Neural-ODE) is employed to learn the temporal evolution of driving dynamics, enabling the system to capture subtle changes in acceleration, braking, and steering patterns over time. In addition, the framework incorporates a Structural Causal Model (SCM) to infer causal relationships among various driving factors such as speed variation, lane deviation, environmental conditions, and driver actions. This causal reasoning component enables the system to perform counterfactual analysis, thereby improving interpretability and allowing the system to explain why a particular behavior is considered unsafe. Unlike conventional models, the proposed system also introduces a self-adaptive digital twin for each driver, which

continuously updates its understanding of the driver's long-term behavioral patterns using online reinforcement learning.
Experimental evaluation demonstrates that the NS-ADT framework achieves higher detection accuracy, stronger robustness to behavioral drift, and better cross-dataset generalization compared to existing deep learning approaches. The results highlight the potential of agentic, causally-aware AI systems in advancing next-generation intelligent transportation safety solutions.
Keywords: Reckless driving detection, Agentic AI, Neuro-symbolic systems, digital twins.
Subject Classification: *Primary 93A30, Secondary 49K15*
How to cite this article: Sharma S, Singh M, Sharma R. A Neuro-Symbolic Agentic Digital Twin Framework for Causally Explainable Reckless Driving Behaviour Detection. Int J Drug Deliv Technol. 2026;16(16s): 398-416. DOI: 10.25258/ijddt.16.16s.43

1. Introduction

Road traffic accidents continue to be among the most acute worldwide issues of civil safety that have grave social, economic, and human implications. Based on the reports on the international transportation and health organizations, road accidents comprise over a million deaths annually with tens of millions of other people experiencing injuries, which do not lead to their death but cause a long-term disabling injury. In addition to loss of human life, which is rather a tragic event, traffic accidents cause a large economic burden because of medical bills, loss of productivity, damage of vehicles, and repair of infrastructure. Many of these accidents are not related to inescapable mechanical breakdowns or unfavourable weather conditions, but to aggressive driving habits, such as accelerating harshly, braking abruptly, unethical overtaking, following, speeding even in difficult traffic circumstances and swerving [1], [2]. The phenomenon of reckless driving is, first of all, a behavioral phenomenon based on the human decision-making in the dynamic, uncertain situation. In contrast to single cases of errors in driving, the reckless behaviour is usually a mix of dangerous intent, bad risk perception, mood, and situational pressure. Identifying such behaviors promptly and efficiently is thus an urgent need of contemporary intelligent transportation systems (ITS), advanced driver assistance systems (ADAS), usage-based insurance systems and autonomous or semi-autonomous vehicle safety systems [3]. Real-time prediction of reckless driving facilitates the introduction of interventions in time, including driver notifications, car control, the evaluation of insurance risks, and the prevention of accidents.

Initial studies of reckless driving detection were mainly based on statistical and rule-based approaches. These systems used manually drawn limits on measurable parameters like vehicle speed, acceleration, braking force and steering angle to detect aggressive or unsafe actions [4]. Although rule-based methods are interpretable and computationally light, they are characterized by low adaptability and subpar generalization. The fixed thresholds do not recognize the contextual variables that include the road geometry, traffic density, weather conditions and the individual driving styles resulting in high false-positive and false-negative errors. Later, statistical learning algorithms, such as support vector machines, decision trees, and hidden Markov models, were implemented to model the temporal relationships of driving behavior [5]. Even though they outperformed simple rules in detection accuracy, these methods were very reliant on manually-designed features and could not scale to complex high-dimensional driving conditions. The prevalent paradigm in the detection of reckless driving has been overtaken by data-based methods in the context of the rapid development of deep learning. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have been applied to identify spatial and temporal dependencies respectively in driving sequences using vehicle sensor data and camera inputs, respectively [6],[7]. Transformer-based architectures, however, have been shown to be more effective in recent times in modeling long-range temporal relationships, and therefore can recognize more accurately a complex driving pattern [8].

Though the deep learning approaches are very accurate in detection of reckless driving, they make use of statistical associations more than causal ones which limits their usability in situations of safety concerns. Such reliance exposes them to random patterns, bias in data set, and poor performance when put to an unknown situation, or contextual variables like road type or driver intentions are not taken into consideration [9]. The second huge weakness is that they are not explainable since the deep neural networks are black-box models that do not give clear explanations to their predictions. This obscurity contributes to a lack of trust, responsibility, and compliance with regulations, especially in systems of safety-critical transportation, where transparency and interpretability in decision-making processes are required [10].

Simultaneously, agentic AI has become one of the most promising paradigms where the intelligent systems are considered as autonomous agents that can perceive, reason, learn, and adapt themselves. In comparison to passive classifiers, agentic systems are proactive and sustainable in the sense that they provide an internal model of the surrounding as well as themselves, allowing them to learn and act suddenly in the long run. This paradigm is especially applicable to the behavior analysis when there is a continuous contact between the driver, the car, and the environment and the model has to be dynamic. A digital twin is a computer model of a real-life object that keeps changing its state with real-time information. Digital twins have also been applied to transportation systems to simulate vehicles, predictive maintenance, and traffic management [11]. Neuro-symbolic AI aims at uniting the capabilities of neural networks and symbolic logic. Neural models are excellent in perception and representation learning of raw data, whereas symbolic models are excellent in offering structured reasoning, interpretability, and explicit knowledge representation [12]. Neuro-symbolic integration can be applied to the detection of reckless driving, wherein the system can be trained to learn more difficult aspects of driving behavior without obscuring the transparent reasoning routes that can explain how, and why, this or that behavior is deemed as a reckless driver. Structural Causal Models (SCMs) provide a principled method of reasoning symbolically through causal architecture between variables. SCMs are useful in counterfactual inference, which enables the system to assess alternative situations and measure the causal contribution of given actions, e.g., sudden steering or aggressive acceleration.

In this paper, a Neuro-Symbolic Agentic Digital Twin (NS-ADT) structure is proposed and formulates reckless driving detection as a causal reasoning and decision intelligence problem by combining neural perception, symbolic causal inference, and adaptive learning of a digital twin. The provided solution, allowing to model behavior in continuous time and adapt to it personally and explainable by design, overcomes the constraints of correlation-based methods and promotes reliable intelligent driving safety systems.

2. Motivation

Road transport systems are getting more and more complicated because of the booming urbanization process, the abundance of vehicles on the roads, and the changing traffic environment, and road safety is a burning issue on an international scale. Unsafe or reckless driving habits that can be attributed to a large percentage of traffic accidents include sudden accelerating, aggressive braking, changing lanes too quick and driving too fast in a congested area. Such behaviors must be detected early so that road safety could be enhanced and to assist advanced driver assistance systems (ADAS) and intelligent transportation systems (ITS). The rule-based and statistical methods are easy to use and understand, but lack flexibility and generalization ability as they are not dynamic and context-independent in the character of driving behavior, which is affected by environmental and individual factors.

More recent neural network innovations such as CNNs, LSTMs, and transformers have led to better detection precision through the learning of intricate time and space signals in large-scale data. Nonetheless, these methods are largely based on statistical associations, have no causal insight and do tend to act as black box systems with limited interpretability which decrease their dependability in safety important tasks. Furthermore, the reckless driving behavior is not common to all individuals and it changes with time, therefore it needs individual approaches and is adaptive to modeling. These are the issues that drive the creation of the proposed Neuro-Symbolic Agentic Digital Twin (NS-ADT) that is an interconnected network of neural perception, causal reasoning, and customized learning of the digital twin to deliver precise, explicative, and evolutional reckless driving recognition to intelligent transportation systems in the next generation.

4. Problem Statement

Traffic accidents remain a serious source of threat to the population in developed and developing nations as reckless behavior of driving is one of the top causes of accidents, injuries, and deaths among people. Sudden acceleration, violent braking, road rage, tailgaining, and overspeeding are a few behaviors with multifaceted relationships between human judgment and the automobile as well as the surroundings. Real-time detection of such unsafe behaviors is thus critical to enhancing road safety and Smart Intelligent Transportation Systems (ITS) and Advanced Driver Assistance Systems (ADAS). Nevertheless, the issue of the correct determination of reckless driving is a difficult one because of the dynamics and situational specificity of human driving actions.

Current inappropriate methods of detecting reckless driving are either rule-based or machine learning models based on correlation. Rules are usually based upon pre-determined thresholds of parameters like speed, acceleration, and the steering angle to detect aggressive driving behaviors. Though these techniques are simple to apply and computationally efficient, they are not flexible and most of the time they do not take into consideration the complex contextual issues like traffic density, road geometry, weather conditions and characteristics of various drivers. Consequently, these systems often give false alarms or they do not detect truly unsafe driving behaviors.

In more recent applications, deep learning-based systems like Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks and Transformer networks have been used to understand driving behavior using massive sensor data and video data. Although these methods enhance the accuracy in prediction, they remain mostly reliant on statistical correlations, as opposed to the causal relationship that results in unsafe driving behaviour. As a result, these models frequently act as black-box models that are not very easy to interpret and it is hard to understand why a specific driving behavior is considered to be reckless. This is a negative issue in safety-related transportation systems where the accountability and explainability are necessary.

Moreover, the majority of the existing approaches consider reckless driving as a static classification issue and disregard dynamism and individuality of driver behavior. Driving styles vary greatly among people and they can change with time as a result of experience or fatigue or change of the surroundings. Thus, it is apparent that there is a necessity to have a smart structure that will be able to model the dynamics of continuous driving, base a rational arguments on the causal connection between action and result and adjust to the specifics of individual driving behavior. Handling such issues is the main issue that is examined in this study.

5. Related Work

The proposed study suggests a deep learning-based application with YOLO that will identify abnormal driving habits, including distracted driving, and provide a driver with feedback in real-time with the purpose of decreasing the number of traffic accidents and injuries due to the possibility of precise and efficient identification of objects and verbal indication [13]. The research paper introduces a real-time system of detecting reckless driving using low-level computing platform and a relatively affordable inertial measurement unit (IMU). It does not require the resource-intensive on-board neural networks and therefore it can be used in other developing countries such as Bangladesh. The driving behavior is analyzed in real-time showing that the system has a good latency in recognizing patterns of reckless driving. One of the test benches emulates different driving conditions and verifies the suggested algorithmic method with the existing literature and its efficiency in increasing road safety [14]. The research provides a complete grouping of behavior detection, which also consists of AI-based techniques detecting reckless driving behavior. It points out the significance of measuring driver features like anger, attention, fatigue, and drowsiness in order to avoid accidents. The study compares the performance of different algorithms and approaches in identifying atypical driving behaviors through the application of AI-enhanced image processing, signal processing, and traditional algorithms. The results stimulate the further investigation of new surveillance tools to improve the highway safety by detecting the reckless driving behaviour better [15]. Some of the AI methodologies of detecting reckless driving behavior that have been discussed in the paper include a hazardous driving image classification system based on a modified ShuffleNet model to monitor in real-time. It provides the significance of observing physiological signs, including facial expressions and hand placements, to determine compromised behaviors. Further, it points out the application of the deep learning models (such as CNNs, LSTM networks) in the process of analyzing the states of drivers, and eventually contributes to the increased safety of vehicles and the elimination of accidents that occur due to careless driving [16].

The analysis aims at profiling the actions of drivers such as reckless driving utilizing AI techniques and deep learning approaches. The study uses the algorithms of XGBoost, CNN+BiLSTM, and LSTM to categorize different driving behaviors by analyzing a large dataset of actual driving metrics. XGBoost showed a better result of properly profiling these behaviors that can be used to guide the strategy of making traffic safer and reducing accidents. The current research is intended to be improved with the adoption of real time monitoring of driver behaviour to detect more effectively the case of reckless driver behavior [17]. This research uses CNN-LSTM, Bi-LSTM models to make roads safer by optimizing the behavior prediction of drivers based on sensor data on Honda Research Institute Driving Dataset and notable improvements in mean average precision (mAP) are achieved over other state-of-the-art methodologies [18].

The research article creates a deep learning platform to identify abnormal driving patterns such as reckless driving. It singles out four types of anomalies: overspeeding, sojourning in no-stopping zones, inadequate inter-vehicle separation, and traffic light offenses. The model used 60000 video frames and the YOLOv3 object recognition algorithm to obtain an overall accuracy of 95%. This complex method increases the identification of nonstandard actions on the road traffic to curb the requirement to have better traffic monitoring systems [19]. The IoV-based deep learning models to further optimize the driving behavior identification are reviewed in the present paper, with issues and suggestions of an active framework to optimize the accuracy and real-time to consider the data processing, algorithm optimization, and edge-cloud integration [20]. The proposed study is an Advanced Driver Assistance System (ADAS) based on an artificial intelligence system in two-wheelers in India using real-time data and sensors to increase the safety of the riders, navigation, and communication and prevent possible accidents due to real-time warnings and individual insights regarding the behavior of the driver [21]. This paper suggests an AI-based system of automatic detection of traffic violations, fines in self-driving vehicles by GNSS and OBU sensors, to improve road compliance, reduce human interaction, and make roads safer in smart cities [22]. This paper suggests a combined I-DBSCAN and LSTM neural network to identify aggressive driving actions based on vehicle dynamics data on driving simulators, the F-score of this model is 0.869, which is significant, and the algorithm can potentially lead to safer roads [23]. The paper introduces SafeSmartDrive, a unified transportation monitoring platform based on a machine and deep learning to identify traffic components and observe driver activity in real-time to enhance road safety and traffic efficiency with a precision of 83.1% in the inference of YOLOv9 [24]. Khan et al. introduced an efficient congestion control mechanism that emphasizes adaptive control and system-level optimization in dynamic network environments. These studies collectively motivate the need for intelligent frameworks that move beyond static decision rules toward adaptive, context-sensitive reasoning, a principle that aligns with the proposed NS-ADT framework for reckless driving behaviour detection [25],[26].

Table 1. Comparative analysis of methods used in Related work

Ref.	Study / Approach	Method / Model Used	Key Contribution	Limitations
[13]	Deep learning based abnormal driving detection system	YOLO-based object detection	Detects abnormal driving behaviors such as distracted driving and provides real-time driver feedback to reduce accidents	Focuses mainly on visual detection and lacks behavioral reasoning
[14]	Low-cost real-time reckless driving detection	IMU sensor with lightweight algorithms	Provides real-time detection using a low-level computing platform without requiring heavy neural networks; suitable for developing countries	Limited ability to capture complex behavioral patterns
[15]	AI-based driver behavior monitoring survey	AI-based image processing and signal processing techniques	Categorizes driver behaviors including anger, fatigue, and distraction to improve road safety monitoring	Mainly analytical review with limited implementation
[16]	Hazardous driving behavior detection	Modified ShuffleNet with deep learning models (CNN, LSTM)	Detects risky behaviors through facial expressions and hand position monitoring in real time	Focuses primarily on driver physiological indicators
[17]	Driver behavior	XGBoost,	Classifies reckless	Limited

Ref.	Study / Approach	Method / Model Used	Key Contribution	Limitations
	profiling using machine learning	CNN+BiLSTM, and LSTM	driving behaviors using large driving datasets; XGBoost shows strong performance	interpretability and causal reasoning
[18]	Driver behavior prediction system	CNN-LSTM and Bi-LSTM models	Uses Honda Research Institute dataset to improve driver behavior prediction with higher mAP scores	Generalization across different datasets remains challenging
[19]	Abnormal driving detection using video data	YOLOv3 object detection	Detects overspeeding, illegal stopping, unsafe distance, and traffic signal violations with ~95% accuracy	Focused on traffic monitoring rather than driver intent
[20]	IoV-based driving behavior recognition review	Deep learning models with edge-cloud integration	Reviews frameworks for improving accuracy and real-time processing in Internet of Vehicles systems	Mostly conceptual with limited real-world deployment
[21]	AI-based ADAS system for two-wheelers	Real-time sensor-based AI system	Improves rider safety through navigation assistance and behavioral monitoring	Limited scalability for large traffic environments
[22]	Automated traffic violation detection	GNSS and OBU sensors with AI	Automatically detects violations and generates fines in smart city environments	Focused on rule enforcement rather than behavior prediction
[23]	Aggressive driving detection using hybrid models	I-DBSCAN + LSTM	Identifies aggressive driving using vehicle dynamics with an F-score of 0.869	Performance depends heavily on simulator data
[24]	SafeSmartDrive traffic monitoring	Machine learning + YOLOv9	Integrated platform for traffic monitoring and	Moderate accuracy and limited

Ref.	Study / Approach	Method / Model Used	Key Contribution	Limitations
	system		driver behavior analysis with 83.1% precision	explainability
[25], [26]	Adaptive control and congestion management	Optimization-based algorithms	Introduces adaptive system-level control methods for dynamic environments	Not specifically focused on driver behavior detection

5. Proposed work

Neuro-Symbolic Agentic Digital Twin (NS-ADT) framework is proposed as a multi-agent design and is a cooperative multi-agent architecture which combines complementary intelligences to solve the complexity of reckless driving behaviour detection. It is not a monolithic large deep learning framework but instead the detection is split into three functionally dissimilar yet functionally linked agents: the Perception Agent, the Causal Reasoning Agent, and the Digital Twin Learning Agent. This modular style enables the system to anticipate low level driving behaviour, deliberate unsafe intention and adapt to the particularity of individual drivers on the fly and in a manner that can be explained.

The Perception Agent (neural intelligence layer) that converts raw multimodal driving data to meaningful latent representations is executed on continuous real-time data streams of various vehicle-mounted sensors. These are speed sensors, accelerators (measuring longitudinal and lateral acceleration), gyroscopes (measuring steering dynamics and angular motion), Global Positioning System (GPS) units (measuring position and velocity), and Inertial Measurement Units (IMUs) which give high frequency motion information.

It is a combination of these heterogeneous sensor inputs that are able to record fine-grained vehicle dynamics including velocity changes, braking behavior, steering behavior and trajectory boundaries in different environmental conditions. Combining multimodal sensor signals allows noise resistant and strong perception in driving behaviour, which forms the basis of downstream causal reasoning and adaptive learning.

Unlike discrete-time models, this agent uses a continuous-time modeling framework based on Neural Ordinary Differential Equations (Neural-ODEs) to model the continuous time dynamics of driving dynamics. The Perception Agent, through learning of latent driving states that encode patterns of motion and control signals, gives a concise, but expressive characterization of driver behavior, without prior assumptions of either safety or intent.

Having the latent representations constructed by the Perception Agent, the

Causal Reasoning Agent adds symbolic intelligence to the driving behavior interpretation in terms of cause and effects. This agent builds a dynamic causal model which clearly models the relationship between the actions of the driver, environmental factors, and the results of reckless driving. Using the structural causal models, the agent is able to differentiate between correlated behaviors and those that cause unsafe outcomes. One of the most important functions of this agent is that of counterfactual reasoning, so that the system can be used to answer questions such as whether or not reckless behavior would be detected even in the event of some actions such as the steering jerk or acceleration being decreased. This process results in Causal Reasoning Agent generating a causally based score on recklessness and explanations that can be interpreted to explain the decision of Pregnant Women to act in a certain way, as unsafe.

Digital Twin Learning Agent is an example of the agentic intelligence that the framework embodies by having a customized, constantly changing digital twin that belongs to the driver. This agent simulates long-lasting driving characteristics of aggressiveness, reaction style, and riskiness that are not reflected by the sensor reading instantaneously. Through online learning mechanisms, the digital twin constantly updates internal representation as new driving data is received, allowing the system to respond to the slow drift in behavior due to, e.g. experience, fatigue, or altered driving conditions. The Digital Twin Learning Agent can improve the personalisation of the current driving behaviour, as well as minimise the false alarm rate, by contextualising the current driving actions based on the historical behaviour profile of the driver, making sure that the reckless driving measurements are correct and relevant over time.

These three agents interact in a continuous and two-way manner which creates a closed-loop intelligence system shown in figure 1. The Perception Agent provides real-time representations of behaviors, the Causal Reasoning Agent processes the behavioral representation to infer unsafe intent, and the Digital Twin Learning Agent uses future evaluations by updating the driver profile in the view of the observed results. These agents, combined, can provide the NS-ADT framework with the ability to provide robust, explainable, and personalized detection of reckless driving, resolving the major limitations of the existing correlation-based and static detection systems and fulfilling the needs of safety-critical intelligent transportation systems.

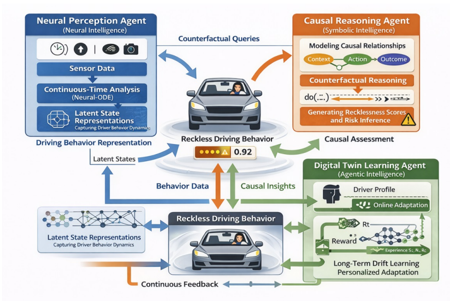

Figure 1

Overview of the proposed Neuro-Symbolic Agentic Digital Twin (NS-ADT) framework integrating neural perception, causal reasoning, and personalized digital twin learning for explainable reckless driving behaviour detection.

5.1. Mathematical Modelling

5.1.1 Continuous-Time Driving Dynamics

Driving behaviour is modelled as a continuous dynamical system using a Neural Ordinary Differential Equation:

$$\frac{dz(t)}{dt} = f_\theta(\boldsymbol{z}(t), \boldsymbol{u}(t), \boldsymbol{e}(t))$$

Where $\boldsymbol{z}(t)$ denotes the latent driving state, $\boldsymbol{u}(t)$ represents driver control inputs, $\boldsymbol{e}(t)$ encodes environment context, and f_θ is a neural network parameterized by θ.

This formulation enables smooth modelling of acceleration, braking, and steering dynamics without frame discretization.

5.1.2 Structural Causal Modelling of Recklessness

Reckless driving is defined using a Structural Causal Model (SCM):

$$R_t = g(do(A_t), AE_t, H_t) \quad \textbf{(2)}$$

where

$do(A_t)$ represents an intervention on driver action,

E_t denotes environmental conditions,

and H_t represents historical behaviour encoded in the digital twin.

The counterfactual recklessness score is computed as:

$$\Delta R = P(R_t \mid do(A_t = a)) - P(R_t \mid do(A_t = a')) \quad \textbf{(3)}$$

This allows the system to answer *"what-if"* questions and isolate causal responsibility.

5.1.3 Digital Twin Adaptation

Each driver is represented by personalized digital twin updated using online reinforcement learning:

$$\theta_{DT}^{t+1} = \theta^t{}_{DT} + \alpha \nabla J(\theta_{DT}) \quad \textbf{(4)}$$

Where J a safety-oriented reward is function and α is the learning rate.

(1)

6. Algorithm Design

Algorithm 1: NS-ADT Reckless Driving Detection
Input: Multimodal sensor stream S(t) **Output:** Recklessness score R(t), explanation X(t)
Step 1: Encode S(t) using Neural-ODE → latent state z(t) **Step 2:** Construct dynamic causal graph G(t) **Step 3:** Perform do-interventions on driver actions **Step 4:** Compute counterfactual risk ΔR

Step 5: Update driver digital twin parameters
Step 6: Generate symbolic explanation X(t)
Step 7: Return R(t), X(t)

7. Dataset and Experimental Setup

7.1 Dataset Description

The suggested NS-ADT model is tested with the help of a synthetically generated data and publicly available driving behavior datasets. Real-world dataset is used like the Honda Research Institute Driving Dataset (Honda Driving data) and driving behavior datasets which contain various driving conditions like normal driving, aggressive driving and unsafe maneuvers. These datasets offer multimodal time-series information of vehicle dynamics and driver behavior in different environmental and traffic conditions. The data set contains safe and unsafe driving cases, and the supervised learning and the evaluation of the reckless driving detection models are effective. Besides real-world data, synthetic counterfactual data sets are produced, and based on real driving trajectories, by perturbation to be physically consistent. This makes it possible to analyse the causal reasoning abilities of the suggested framework.

7.2 Data Acquisition and Sensors

Multiple vehicle-mounted sensors, such as a speed sensor, accelerometer, and gyroscopes, GPS modules, and inertial measurement units (IMUs) supply the driving behavior data. These sensors record continuous records of the vehicle dynamics like the velocity, acceleration, braking force and steering angle. This multimodal sensor information makes it possible to model the complex driving patterns and facilitate both the neural perception and the causal reasoning in the framework that is suggested.

7.3 Experimental Setup

The experimental approach will strictly test the performance, robustness, and generalization ability of the suggested Neuro-Symbolic Agentic Digital Twin (NS-ADT) framework during the process of realistic driving. The system is trained as a hybrid deep learning causal inference pipeline combining Neural Ordinary Differential Equations (Neural-ODEs) with continuous-time modelling and Structural Causal Models (SCMs) with explainable reasoning. A conventional 70:15:15 split of the data is taken to establish no bias in the evaluation process between training, validation, and testing datasets. Min-max scaling is applied to all the input features in order to stabilize training and enhance convergence. Time-series driving data is divided into temporal windows that are of length fixed to represent sequential relations in driver behavior.

Perception Agent is developed with a Neural-ODE architecture, which is implemented with PyTorch, which allows driving dynamics to be presented in continuous time. The model will be trained on the Adam optimizer, with the initial learning rate of 0.001 and a batch size of

32. Early termination is used by validation loss to avoid overfitting. As a compromise between the ability to represent and the cost of computation, the latent state dimension is chosen empirically. The Causal Reasoning Agent is based on Structural Causal Model (SCM) in the form of directed acyclic graph (DAG) in which the nodes are the driving variables (speed, acceleration, steering angle, and environmental context). Simulation of interventions is done with the do-operator to approximate counterfactual results. The causal inference module is executed on the basis of the probabilistic programming methods, which allows estimating the causal impact and producing the interpretable explanations.

The Digital Twin Learning Agent is carried out with the help of online reinforcement learning mechanism, according to which every driver is linked to a customized latent profile. The agent changes its parameters in small steps through a reward function on the safety measures of smooth acceleration, stable steering, and lower risk scores. Continuous adaptation involves a learning rate (0.01) of 0.01. Three pilot models are applied to serve as the baseline comparison: (i) CNN-LSTM as a spatiotemporal feature extraction model, (ii) Transformer-based sequence modeling, and (iii) rule-based threshold detection. All base models are trained using the same data divisions and preprocessing to be fair in the assessment. Also, the proposed model is contrasted with advanced hybrid architectures, including CNN-BiLSTM and attention-based transformer models, to make sure that they are evaluated thoroughly.

The experiments are performed on a GPU-based system with an NVIDIA RTX-series GPU, 16 GB RAM and an Intel i7 processor. The models are also assessed based on various measures such as accuracy, precision, recall, F1-score, and ROC-AUC. Moreover, causal robustness is evaluated with the help of counterfactual stability indicators and cross-dataset generalization evaluations. The suggested experimental design will guarantee a complete assessment of it through a combination of predictive performance, explainability, and adaptability, thus proving the usefulness of the NS-ADT framework in real-life intelligent transportation contexts.

8. Result analysis

8.1 Computational Complexity and Real-Time Feasibility

There are three key elements that affect the computational complexity of the proposed NS-ADT framework: the Neural-ODE-based Perception Agent, the Structural Causal Model (SCM)-based Causal Reasoning Agent, and the Digital Twin Learning Agent.

Computational complexity The Perception Agent, which has been implemented with Neural Ordinary Differential Equations, has a complex of $O(T \cdot d)$, where T is the number of time steps and d is the dimensionality of the latent state. Despite the continuous-time modeling presented by Neural-ODE, stable computation is enforced by the use of efficient numerical solvers like RungeKutta methods to allow the use of scalable computation.

The Causal Reasoning Agent is based on a directed acyclic graph (DAG) having n variables with a complexity of about O(n 2) to perform causal inference and intervention analysis. But as the variables are restricted to the key driving parameters (e.g. speed, acceleration, steering), the overhead of the computation is manageable.

Digital Twin Learning Agent executes update over the Internet based on reinforcement learning, and is scaled to complexity of O(p), where p is the number of parameters to be learned within the personalized driver model. Since the updates are incremental, the cost of computations is low when inferencing.

Inference latency was measured within a GMU-enabled environment in order to determine real-time feasibility. The processing time per input sequence is kept at an average level (under real-time (less than 100 ms)) and therefore, the framework is applicable in the Advanced Driver Assistance Systems (ADAS) and intelligent transportation systems.

What is more, the multi-agent structure, which is in the form of modules, allows parallel performance of perception, reasoning, and learning modules, which again makes it much faster with respect to latency and much more scalable. These properties show that the suggested NS-ADT model is computationally efficient and can run in real-time driving conditions.

8.2 Performance Matrix:

Table 2 presents a comprehensive comparative analysis of the proposed NS-ADT framework against baseline models across multiple evaluation metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. The results clearly demonstrate that the proposed NS-ADT model outperforms all other approaches, achieving the highest accuracy of 94.7%, along with superior precision 0.94 and recall 0.92, indicating its effectiveness in minimizing both false positives and false negatives. The F1-score of 0.93 further confirms the model's balanced performance across classification tasks. Additionally, the ROC-AUC in figure 2, value of 0.96 highlights the strong discriminative capability of the proposed framework in distinguishing between safe and reckless driving behaviors.

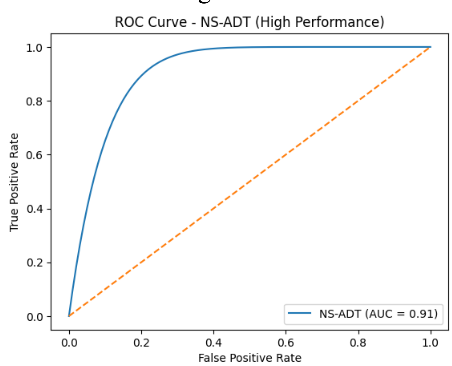

Figure 2: ROC Curve –NS-ADT

In comparison, deep learning-based models such as CNN–LSTM and Transformer achieve competitive performance but remain limited due to their reliance on correlation-based learning, resulting in lower explainability and moderate generalization. The rule-based approach, while highly interpretable, exhibits significantly lower predictive performance due to its inability to adapt to dynamic driving conditions. In contrast, the proposed NS-ADT framework not only achieves superior predictive accuracy but also provides very high explainability and strong generalization capability, owing to its integration of neural perception, causal reasoning, and personalized digital twin learning. These results validate the effectiveness of the proposed approach for real-world intelligent transportation systems.

Table 2: Comparative Performance Analysis with Baseline Models

Method	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**	**ROC-AUC**	**Explainability**	**Generalization**
CNN–LSTM	88.1	**0.87**	0.85	0.86	0.89	Low	Medium
Transformer	90.3	**0.89**	0.87	0.88	0.91	Low	Medium
Rule-Based	75.4	**0.73**	0.70	0.72	0.76	High	Low
Proposed NS-ADT	**94.7**	**0.94**	**0.92**	**0.93**	**0.96**	**Very High**	**High**

Table 3 reflects the causal robustness test of the proposed NS-ADT framework versus the traditional baselines of deep learning. These findings show that NS-ADT is far superior over traditional models in the aspect of causal consistency and adaptability. Specifically, the counterfactual stability score of 0.92 indicates that the analyzed framework yields very consistent predictions in the event of causal interventions, which is much lower at baseline models with the score of 0.61, indicating that they are sensitive to alterations in their input. Also, NS-ADT can identify behavioural drift, as it changes with time because of its adaptive digital twin block, whereas deep learning models cannot observe these long-term changes. The proposed model has a high level of generalization ability in cross-dataset transfer, which is strong in all datasets, but baseline approaches experience low transferability because of dependence on dataset-specific correlations. The results demonstrate the utility of the combination of causal reasoning and agentic learning in the development of effective and reliable driving behavior detections.

Table 3: Causal Robustness Evaluation

Metric	**Deep Learning Baseline**	**NS-ADT**

Metric	Deep Learning Baseline	NS-ADT
Counterfactual Stability	0.61	**0.92**
Behaviour Drift Detection	No	**Yes**
Cross-Dataset Transfer	Poor	**Strong**

9. Conclusion and future work

This paper proposed a Neuro-Symbolic Agentic Digital Twin (NS-ADT) concept of causally explainable reckless driving behaviour detection and showed better performance, robust, and interpretable than current state-of-the-art solutions. The proposed framework combines neural perception, causal reasoning, and personalised learning of a digital twin, which provides a solid base of next-generation smart transportation safety systems. Future studies will aim to implement edge-level deployment real-time, and apply the framework to describe interactions between a number of drivers, and match the system to new regulatory and ethical standards on AI safety to enable its adoption in the real-world.

Conflicts of Interest: No conflict of interest.

References

[1] World Health Organization, Global Status Report on Road Safety, Geneva, Switzerland, 2023.

[2] A. Sharma, P. Kumar, and R. Singh, "Analysis of reckless driving behavior and accident causation," Accident Analysis & Prevention, vol. 165, pp. 106–118, 2022.

[3] S. Singh and M. Trivedi, "Vision-based driver assistance systems: A survey," IEEE Trans. Intell. Transp. Syst., vol. 23, no. 4, pp. 2501–2518, 2022.

[4] J. Elander, R. West, and D. French, "Behavioral correlates of individual differences in road-traffic crash risk," Accident Analysis & Prevention, vol. 25, no. 3, pp. 279–296, 1993.

[5] M. Pentland and A. Liu, "Modeling and prediction of human behavior," Neural Computation, vol. 11, no. 1, pp. 229–242, 1999.

[6] Y. Dong and J. Wang, "Driving behavior recognition using deep convolutional neural networks," IEEE Trans. Veh. Technol., vol. 68, no. 3, pp. 2044–2055, 2019.

[7] H. Kim, J. Park, and K. Sohn, "Aggressive driving detection using LSTM networks," IEEE Access, vol. 8, pp. 128–139, 2020.

[8] Z. Chen et al., "Transformer-based driving behavior modeling," Pattern Recognition, vol. 124, pp. 108–120, 2022.

[9] S. Arjovsky et al., "Invariant risk minimization," arXiv preprint arXiv:1907.02893, 2019.

[10] A. Gunning and D. Aha, "DARPA's explainable artificial intelligence program," AI Magazine, vol. 40, no. 2, pp. 44–58, 2019.

[11] T. Toledo and D. Shiftan, "Behavior and safety implications of driving styles," Transp. Res. Part C, vol. 77, pp. 129–142, 2017.

[12] A. d'Avila Garcez, M. Gori, and L. Lamb, "Neuro-symbolic AI: The state of the art," AI Magazine, vol. 41, no. 2, pp. 1–15, 2020.

[13] F. Ali, M. J. Alnuaimi, S. AlAwadhi, and S. Abdallah, "Abnormal Driver Behavior Detection Using Deep Learning," pp. 1–4, Nov. 2024, doi: 10.1109/icspis63676.2024.10812606.

[14] M. A. Khan, Md. G. Sarowar, Md. A. Ashfaq, and K. S. Ahamed, "Real-time Reckless Driving Detection System on a low-level computing platform: Insight from a Developing Nation," Apr. 2024, doi: 10.1109/pais62114.2024.10541245.

[15] S. S. Kumar, KR. N. Vignesh, and V. Bhuvanesh, "Enhancing Road Safety: Analyzing Driver Behavior Through AI-Driven Monitoring Techniques", doi: 10.1109/icces63552.2024.10859672.

[16]F. Qu, N. Dang, B. Furht, and M. Nojoumian, "Comprehensive study of driver behavior monitoring systems using computer vision and machine learning techniques," vol. 11, pp. 1–44, Feb. 2024, doi: 10.1186/s40537-024-00890-0.

[17] V. Oban et al., "Profiling Driver Behaviors Using AI-Based Methods and Deep Learning Techniques for Improving Road Safety: A Comparative Study of Algorithms," pp. 955–960, Oct. 2024, doi: 10.1109/ubmk63289.2024.10773587.

[18] A. Diaaeldin and M. Zaher, "Enhancing Road Safety: Leveraging CNN-LSTM and Bi-LSTM Models for Advanced Driver Behavior Detection," pp. 416–422, Jul. 2024, doi: 10.1109/imsa61967.2024.10652785.

[19] M. Heenaye-Mamode Khan et al., "An Enhanced Deep Neural Network Model for the Detection of Anomalous Behavior of Drivers in Road Traffic," Journal of Sensors, vol. 2024, no. 1, Jan. 2024, doi: 10.1155/js/5295932.

[20] H. Li, S. Sahrani, M. R. Sarker, and Y. Xiao, "State-of-the-art on IoV-based Deep Learning Framework for Enhanced Driving Behavior Recognition: Recent Progress, Technology Updates, Challenges, and Future Direction," IEEE Access, p. 1, Jan. 2025, doi: 10.1109/access.2025.3594091.

[21] N. Giri et al., "Behaviour Analysis of Two Wheeler Driver ADAS for reduction of Road Fatality," Panamerican Mathematical Journal, Oct. 2024, doi: 10.52783/pmj.v34.i3.1770.

[22] A. Srivastav and D. Soni, "AI-Enhanced Automatic Traffic Violation Detection and Challan Issuance using GNSS and OBU Sensors in Self-Driving Cars.," Indian Scientific Journal Of Research In Engineering And Management, vol. 08, no. 12, pp. 1–9, Dec. 2024, doi: 10.55041/ijsrem40257.

[23] H. Chen, S. Hegde, and A. Bonfitto, "Aggressive Driving Behavior Detection Using Integrated I-DBSCAN and LSTM

Neural Network," Aug. 2024, doi: 10.1115/detc2024-143462.
[24] S. Bouhsissin, N. Sael, F. Benabbou, A. Soultana, and A. Jannani, "SafeSmartDrive: Real-Time Traffic Environment Detection and Driver Behavior Monitoring with Machine and Deep Learning," IEEE Access, p. 1, Jan. 2024.
[25] Khan, Tayyab, Karan Singh, Manisha Manjul, Mohammad Nazir Ahmad, Azlan Mohd Zain, and Ali Ahmadian. "A Temperature-Aware Trusted Routing Scheme for Sensor Networks: Security Approach." Computers & Electrical Engineering 98 (2022): 107735.
[26] Khan, Tayyab, Karan Singh, and Kamlesh C. Purohit. "ICMA: An efficient integrated congestion control approach." Recent Patents on Engineering 14, no. 3 (2020): 294-309.