Computer Science and Information Systems 22(4):1483–1508 https://doi.org/10.2298/CSIS240925058D

Data-Driven Traffic Management: Enhancing Road Safety through Integrated Digital Twin Technology ⋆

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Abstract. This paper proposes a data-driven approach to enhancing traffic safety through the integration of digital twins, in-vehicle monitoring system and machine learning. The main goal is to contribute to solving problems related to driver behavior, inadequate road signage infrastructure, and delayed maintenance by developing a digital twin model that leverages real-time data for predictive analysis, coaching, and maintenance. Using the Prophet algorithm, the model predicts compliance with traffic regulations, identifies frequent driver violations, and highlights deficiencies in road signage, enabling timely interventions. The innovation of this solution lies in its ability to synchronize real-time data from drivers, vehicles and road infrastructure and provide predictive insights, creating a scalable and adaptable framework for traffic management. The proposed model is tested in a proof-of-concept scenario, where it demonstrated significant improvements in road safety.

Keywords: smart mobility, digital twins, machine learning, IVMS, road safety.

1. Introduction

Road safety has been recognized as a critical component of UN Sustainable Development Goals (SDGs). SDG Goal 3 emphasizes ensuring healthy lives and promoting well-being for all, with Target 3.6 specifically aiming to halve the global number of deaths and injuries caused by road traffic accidents by 2030 [35]. Similarly, SDG Goal 11 focuses on making cities and human settlements inclusive, safe, resilient, and sustainable, with Target 11.2 promoting access to safe, affordable, accessible, and sustainable transport systems, with a particular emphasis on enhancing road safety. In addition to these goals, the UN has established five key pillars to further promote road safety. Pillar 1 focuses on Road Safety Management, Pillar 2 emphasizes Safer Vehicles, Pillar 3 targets Safer Road Users, Pillar 4 addresses Post-Crash Response, and Pillar 5 aims to create a Safer Driving Environment [34]. These pillars serve as a comprehensive framework for reducing global road traffic fatalities and injuries worldwide.

⋆ This is an extended version of a conference paper Digital Twins of Road Signage: Leveraging AI and RFID for Improved Road Safety, XIX International Symposium Unlocking the Hidden Potentials of Organization Through Merging of Humans and Digitals, SYMORG 2024

Recent advancements in driving behavior analysis and traffic management have leveraged machine learning (ML), deep learning (DL), Internet of Things (IoT) sensors, and data-driven methods to improve safety and efficiency. Existing research on driving behavior analysis has primarily focused on fuel efficiency [11,28], machine learning classification [30], and behavioral profiling, yet critical road safety factors remain underexplored. Studies on eco-driving have successfully optimized fuel consumption [10], but lack emphasis on broader traffic safety concerns. Similarly, ML/DL-based classification models have achieved high accuracy in distinguishing driving behaviors, yet they face scalability challenges and often fail to integrate real-world environmental data and traffic infrastructure [27]. While these studies demonstrate the potential of ML, IoT, and DL in traffic management, they often lack a holistic approach that integrates real-time data from drivers, vehicles, and road infrastructure into a unified framework. Furthermore, the absence of predictive capabilities for compliance with traffic rules and proactive safety interventions highlights the need for a more comprehensive, scalable solution that addresses both driver behavior and infrastructure management.

To address these gaps, this research introduces a data-driven framework that integrates Digital Twin technology, In-vehicle monitoring system IVMS and ML. The proposed model is designed with the aim to improve compliance with traffic rules, analyze road signage infrastructure, and predict unsafe driving behaviors.

For these purposes, we have posed the following research questions:

- RQ1: How can the DT of road safety identify and mitigate traffic sign non-compliance violations?
- RQ2: How can driving patterns of non-compliance with traffic signage be identified and used to prevent future motor vehicle incidents?
- RQ3: What insights can the DT of Road safety provide for road signage maintenance and infrastructure improvement?

The structure of this paper is as follows. Section 2 provides definitions, background, and related studies relevant to the research problem. Section 3 presents the Road Safety Digital Twin model and its components. Section 4 outlines the experimental research, including data collection and the application of analytical tools and machine learning techniques for predictive modeling. Section 5 discusses the findings in relation to the stated research questions. Finally, conclusions are presented in Section 6.

2. Related Work

This work is based on DT technology, which obtains real-world data through the IVMS system. In this section, we analyze the relevant concepts of digital twins in mobility and IVMSs, and present the analysis of relevant studies that analyze vehicle and driving behavior.

2.1. Digital Twins in Mobility

A Mobility Digital Twin (MDT) framework [36] has been introduced by Wang, characterized as an artificial intelligence (AI)-based data driven cloud–edge–device framework for mobility services.

The MDT framework operates across three distinct planes, as we can see in Figure 1:

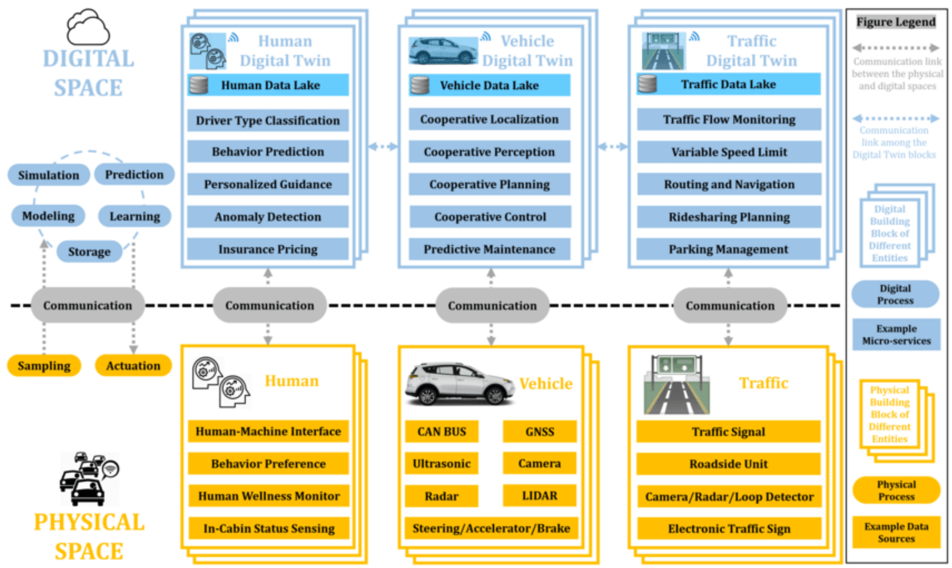

Fig. 1. Illustration of the Mobility Digital Twin framework[36]

1. the physical space, encompassing humans, vehicles, and traffic infrastructure,
2. the digital space, which contains digital counterparts of these physical entities and
3. the communication plane, which facilitates interaction between the physical and digital spaces[36].

This concept is highly significant, enabling functions like monitoring, management, maintenance, optimization, and forecasting. To achieve these goals, physical assets are equipped with RFID and smart sensors, which simplify data capture across the entire product life cycle and transmit real-time data to edge or cloud servers. The more sensors deployed, the more precise insights are obtained. This data is then analyzed and presented to users in an accessible format.

DTs leverage advanced technologies such as IoT for data acquisition, 5G for transmission, and AI/ML for data analysis and prediction. Additionally, tools like Virtual Reality (VR) and Augmented Reality (AR) enhance data representation and provide immersive experiences [18,26].

The Digital Twin collects real-time data from sensors [4] and correlates it with historical data previously obtained from the same vehicle, enabling it to make informed decisions and issue alerts for any unsafe conditions.

However, the effective deployment of DTs depends heavily on the advancement of these technologies, which are still maturing. This ongoing evolution limits the ability of DTs to fully realize their benefits. In addition, the implementation of DTs is often impeded by high costs, the complexity of managing numerous interconnected systems, and the necessity for continuous investment to keep up with rapid technological progress. Advancements in simulation and modeling tools, IoT device connectivity, expanded bandwidth, and improved computing architectures [8] will be the key to enabling DTs to become a predominant tool for both companies and governments.

2.2. In-Vehicle Monitoring Systems (IVMS)

IVMS technology offers a comprehensive approach to improving driver safety by leveraging both hardware and software to capture critical vehicle and driving data. Real-time feedback mechanisms, including in-cab warning lights, and auditory alerts, provide drivers with immediate notifications when specific parameters, such as speed limit, are exceeded. This fosters the development of safer driving habits. This data is transmitted via various networks (cellular, Wi-Fi, or satellite) to remote servers, where it is stored for retrospective analysis, coaching, and reporting on driver behavior and vehicle performance. Crucially, IVMS can operate without constant connectivity, synchronizing data once the connection is restored, ensuring that drivers and managers receive consistent feedback [22,25].

IVMS track and analyze vehicle activity to improve road safety and efficiency [12]. These systems are becoming increasingly common, even mandatory in some areas. IVMS, which is accessible for both private and commercial use, can provide valuable insights for young drivers, helping to pinpoint areas where their driving competencies can be enhanced.

In-vehicle monitoring systems consist of five essential layers: the object layer, the sensing layer, the network layer, the data layer, and the application layer, as shown in Figure 2. These layers work together to provide comprehensive monitoring and management capabilities within vehicles [21].

- Object layer: This layer moves beyond traditional license plates by creating a digital information source for each vehicle and driver. This source acts like a digital ID card, containing identification and regulatory data for both machine and human use (think barcode vs. readable text).
- Sensing layer: This layer uses advanced technologies like RFID, GPS, and cameras to collect real-world data about vehicles and drivers. It essentially translates the physical world into a digital one, creating a rich pool of information for analysis.
- Network layer: This layer ensures data collected from various sensors gets transmitted across different regions. It acts like a digital highway, carrying information through wired networks, wireless connections, or even satellites.
- Data layer: This layer acts as the information hub. It stores sensor data, manages system information, and provides tools to analyze and extract insights from the collected data. It can also control sensor devices and provide basic functions like data retrieval to the application layer.
- Application layer: This layer puts the collected information to use. It offers functionalities through various interfaces (large screens, mobile apps, etc.) to manage vehicles and drivers in the real world. This layer essentially builds the foundation for a modern and intelligent transportation system.

Shell (the second-largest investor-owned oil and gas company) presents significant benefits from IVMS, including a 60% reduction in speeding and a major drop in accidents [32]. The system also encourages safer habits like seat belt use and discourages

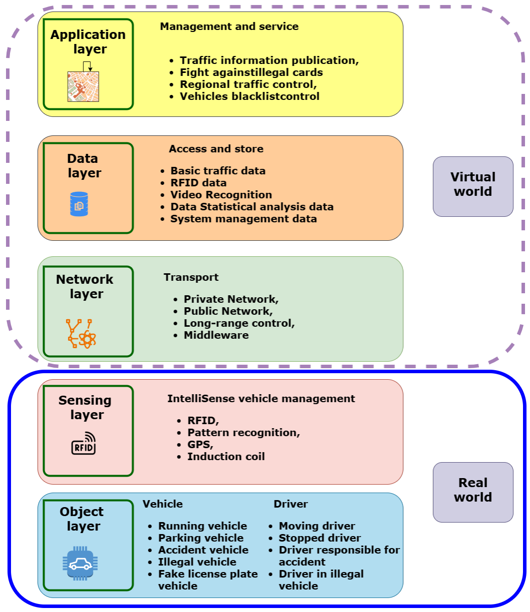

Fig. 2. IVMS 5-layers model [21]

harsh driving behaviors. Beyond safety, IVMS offers cost savings through reduced fuel consumption, less wear and tear on vehicles, and potentially lower insurance premiums.

The International Association of Oil & Gas Producers (IOGP) analyzes studies [22] related to the general usage of IVMS in commercial vehicles. Research has shown that IVMS implementation, combined with tailored driver coaching, leads to significant reductions in risky behaviors like speeding, harsh braking, and cornering, as well as a decrease in motor vehicle incidents (MVIs). IVMS also enhances journey management by providing insights into driving patterns, identifying "hot spots" with frequent incidents, and optimizing routes to avoid high risk areas.

Furthermore, IVMS offers multiple layers of security, including real-time GPS tracking for emergency response, vehicle recovery, and protection against false claims in MVI investigations. As the science of IVMS evolves, best practices continue to be refined, contributing to better driver compliance, improved driving skills, and overall road safety [6,22].

2.3. Related Studies

This research aims to address a critical gap in the existing literature, which is the absence of a DT model capable of integrating data from the all three fundamental entities in traffic and transportation (driver, vehicle and road) to generate actionable insights for enhancing road safety. To bridge this gap, we identified relevant studies that analyze vehicle and driving behavior using onboard diagnostics (OBD) data, apply ML and DL techniques to study vehicle and driver behavior, and leverage RFID technology for road-related applications. Based on our analysis, we categorized the relevant studies into the following three groups: Studies conducted by using Onboard Diagnostics dataset, Studies applying ML and DL techniques, and Leveraging technology for road-related applications.

2.3.1. Studies Conducted Using Onboard Diagnostics Dataset

Existing research has primarily focused on utilizing OBD data and advanced computational models to assess driving patterns and promote eco-friendly driving. Some studies have developed methods to classify safe and unsafe driving behaviors by analyzing key vehicle parameters such as speed, engine RPM, throttle position, and engine load, achieving high classification accuracy through machine learning techniques like the AdaBoost algorithm [11]. Others have proposed eco-driving evaluation models that identify critical fuel-related driving events using statistical approaches such as principal component analysis and multiple linear regression, achieving predictive accuracy of up to 96.72 % [10]. Additionally, some research has explored the integration of IoT vehicle sensors with gamification strategies to encourage fuel-efficient driving, where real-time feedback based on throttle position and engine RPM helps drivers adopt safer and more sustainable driving behaviors [28]. Further advancements include the use of type-2 fuzzy logic models to assess eco-driving skills, incorporating factors such as engine speed, acceleration, and pedal position to evaluate driving style and its impact on fuel consumption, demonstrating the potential for significant fuel savings [38]. While these studies provide valuable insights into vehicle performance and driver behavior, they lack an integrated DT framework that combines real-time vehicle data with road and environmental factors to enhance predictive modeling and adaptive driving recommendations.

2.3.2. Studies Applying ML and DL Techniques

These analysis have explored various methodologies, including knowledge-based approaches, classical machine learning, and deep learning techniques, with sensor fusion emerging as a key factor in detecting aggressive, inattentive, and intoxicated driving [1]. Studies utilizing clustering methods have examined driver behavior based on open traffic data, focusing on factors such as the use of safety systems and mobile phone distractions [7]. Other research efforts have leveraged cloud-based machine learning and deep learning systems to classify driving behavior, integrating big data management techniques and clustering algorithms to distinguish between eco-friendly and aggressive driving styles [30]. Additionally, deep learning models have been applied to naturalistic driving data to assess compliance with traffic regulations, demonstrating high accuracy in real-time driver monitoring [2]. These studies provide valuable insights into vehicle and driver behavior analysis, they primarily focus on data processing and classification. The lack of a unified DT framework limits the potential for predictive modeling and real-time interventions, underscoring the need for a more holistic approach to road safety.

2.3.3. Leveraging Technology for Road-Related Applications

The traffic sign detection has explored different approaches, including RFID-based methods and deep learning techniques. Studies have investigated the use of active and passive RFID tags for traffic sign detection, where active tags provide stable detection at speeds exceeding 100 km/h and distances up to 30 m but come with high costs and the need for battery charging, while passive tags offer a more affordable alternative with a limited 5 m range, though they may fail in scenarios like overtaking or roadwork avoidance [27]. Other approaches have focused on computer vision and deep learning, utilizing hierarchical classification models combined with object detection algorithms such as YOLOv5 to enhance traffic sign localization [37]. While these studies contribute significantly to traffic sign recognition, they primarily focus on detection and classification without integrating a DT approach that would connect traffic signage data with real-time road and vehicle conditions. This gap highlights the need for a more holistic DT framework that enhances road safety through predictive analytics and adaptive decision-making.

Since this study builds upon our previous conference paper, ”Digital Twins of Road Signage: Leveraging AI and RFID for Improved Road Safety,”[14] it serves as the foundation for our ongoing research in this field and the expansion of our work. In our previous study, we focused on RFID technology and its potential for recognizing road signage, where RFID-enabled traffic signs collected real-time data on road conditions, which were then compared with values obtained from IVMS reports. Additionally, we introduced a DT model of road signage, which has been further developed for this study. In this paper, we extend our research by utilizing real-world data and incorporating a predictive component for driving behavior analysis.

3. Digital Twin Model of Road safety

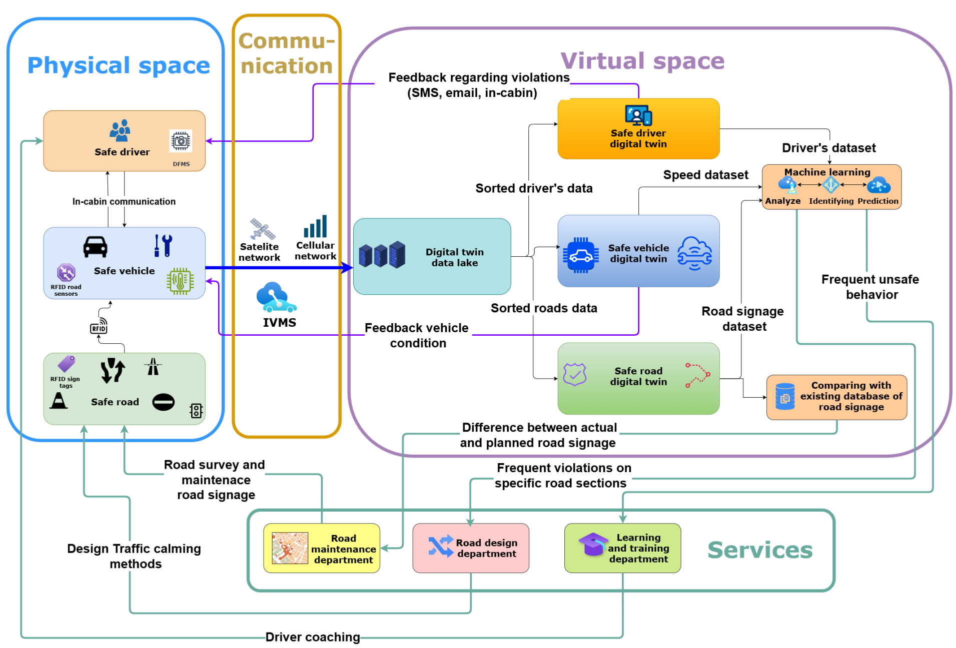

Fig. 3. Digital twin of Road safety

The role of the DT extends beyond simple simulation as it actively interacts with the physical system and adjusts to evolving external circumstances. DT technology heavily relies on data intake and correlation analysis, closely intertwined with data-intensive modeling, driven by advanced Machine Learning and Deep Learning, as well as big data analytics [13]. Our DT model of Road Safety is based on enhancing IVMS using RFID technology and artificial intelligence, as illustrated in Figure 3. In the following sections, we discuss in detail each component of the model we developed.

3.1. Physical Space

The physical space of this model is structured around the three fundamental pillars of road safety: Safe Driver, Safe Vehicle and Safe Road. At the core of this system is the vehicle, which serves as the central element connecting the Safe Road through an RFID-based link and the Safe Driver via in-cabin connectivity. The connection between the Safe Road and the Safe Vehicle is unidirectional, meaning that the vehicle only receives data from the road infrastructure without sending feedback. However, the connection with the Safe Driver is bidirectional, enabling certain driver-related parameters to be monitored and analyzed. This includes data from Driver Fatigue Management systems, as well as vehicle sensor readings influenced by driver behavior, such as speed, engine RPM, harsh braking, and harsh acceleration.

Beyond driver-related parameters, the Safe Vehicle system continuously transmits data regarding of the vehicle's overall condition and reliability. This includes predictive maintenance, utilizing sensors connected to the CANBUS system (Controller Area Network Bus), which facilitates real-time communication between the vehicle's electronic components. Additionally, other distributed sensors within the vehicle contribute to monitoring critical operational aspects, ensuring a comprehensive approach to road safety.

3.2. Virtual Space

In the virtual space, a data lake serves as the central repository where all incoming data is processed and categorized into three DTs entities: DT Safe Driver, DT Safe Vehicle, and DT Safe Road. Each DT is responsible for analyzing data within its specific domain of traffic safety, applying predefined parameters and filters to assess conditions, and either providing feedback or forwarding the information for further processing and analysis.

The DT Safe Driver can detect repeated behaviors through the Driver Fatigue Management System (DFMS) and initiate corrective actions to enhance road safety. These actions may include enforcing a mandatory 20 minute rest break, alerting a supervisor or responsible authority, or even temporarily disabling the vehicle to prevent further driving. Additionally, by combining driver behavior data with road signage information from DT Safe Road and utilizing Machine Learning (ML) algorithms, the system can identify driving patterns and predict potentially unsafe actions that may pose a risk to road safety.

The DT Safe Vehicle continuously monitors the condition of critical vehicle components, providing recommendations for corrective and predictive maintenance based on real-time sensor data collected from the vehicle's internal systems.

The DT Safe Road plays a key role in speed regulation and traffic compliance. By leveraging geolocation data of speed limit signs and stop signs (where a stop sign is technically equivalent to a speed limit of 0 km/h), it can compute speed predictions and alert drivers to reduce speed accordingly. RFID readings of traffic signs act as triggers for these calculations, ensuring that sign data remains accessible even when a vehicle is unable to connect to GPS or GSM servers. Additionally, the RFID reader facilitates real-time traffic sign detection and transmits this information to the DT Safe Road, helping to maintain an updated database of road signage assets and improving overall traffic management.

3.3. Communication

The In-Vehicle Monitoring System serves as a key communicator between the physical and virtual spaces within the DT framework for road safety. It continuously monitors and collects data on vehicle performance and driver behavior, including speed, engine RPM, harsh braking, harsh acceleration, and geolocation, while integrating with RFID technology and CANBUS sensors to support predictive maintenance and traffic sign detection. This data is transmitted to the virtual space, where DT Safe Driver, DT Safe Vehicle, and DT Safe Road process the information and provide feedback for interventions, such as mandatory rest breaks, maintenance alerts, and speed regulation compliance. Each DT entity analyzes the data based on predefined safety parameters, ensuring appropriate real-time corrective measures. By enabling a continuous flow of information, IVMS enhances road safety, vehicle reliability, and overall traffic efficiency within an intelligent transportation ecosystem. Transmission is conducted through cellular and satellite networks.

3.4. Services

Certain services have emerged as a necessary component of the DT framework, as they cannot be strictly classified within either the physical or virtual space. These services are developed based on the 5D Digital Twin model [20] and serve as an added value to the DT system. Their primary objective is to enhance the functionality of each digital entity, ultimately improving the entire road safety ecosystem centered around a specific driver, vehicle, and road network. We have identified three key services, each operating within a dedicated department: Road Maintenance Department, Road Design Department, and Learning & Training Department.

The Road Maintenance Department analyzes data by comparing vehicle records with the existing road infrastructure database and identifying discrepancies based on real-time vehicle inputs. If inconsistencies are detected, the system triggers the Road Survey and Maintenance Road Signage service to assess and address road safety deficiencies. Following this, the Road Design Department utilizes machine learning algorithms to predict driver behavior patterns and detect frequent violations of traffic regulations. This analysis serves as a trigger for implementing traffic-calming measures, aimed at reducing risks on specific road sections. Additionally, the Learning & Training Department focuses on driver coaching, offering targeted safety training in areas where drivers exhibit unsafe behaviors, contributing to a proactive approach in road safety improvement.

4. Experimental Research

The primary goal of the experimental research is to evaluate the DT model in improving road safety. The implementation of the DT of Road safety is based on a layered system architecture comprising edge-level data acquisition and centralized cloud-based processing through the infrastructure of the IVMS service provider. Data collection is carried out using the FMS Fusion 300 IVMS device, which integrates GNSS modules (GPS, GLONASS, BeiDou) and CANBUS connectivity for vehicle telemetry acquisition. Data transmitted via cellular or satellite networks are stored and processed within a centralized Digital Twin data lake hosted on web servers managed by the IVMS provider, where analytics are executed using Python-based geospatial libraries and the Meta Prophet forecasting algorithm. This analytical framework enables the deployment of intelligent DT services, including predictive road maintenance, road signage evaluation, and adaptive driver coaching.

4.1. Context of the Experimental Research

The Digital Twin of Road Safety model served as the foundation for this research. This study involved data collection through IVMS, where historical reports on vehicle movements and the corresponding drivers were generated by the IVMS provider's server. Compared to the model, the research did not implement the RFID component used to confirm the presence of specific traffic signs, but this does not affect the research as a whole. Geospatial data analysis plays a crucial role in traffic monitoring systems, which utilizes

Fig. 4. The FMS Fusion device for collecting data

Python libraries like GeoPandas and Shapely [5] to analyze vehicle behavior around road signs. The central concept behind this script is to evaluate whether vehicles complies with speed limits within specific zones of influence, created around the road signs based on their direction. Using GPS data from both road signs and vehicles, the script transforms this raw input into a GeoDataFrame [5], enabling spatial operations such as determining whether a vehicle falls within the influence zone of a sign. This technique leverages geospatial theory by treating locations as geometric points and constructing directional buffer zones to model the area affected by each road sign. The code further employs spatial joins to analyze the interaction between vehicles and road signs, analyzing whether a vehicle's location is within a sign's zone of influence. Once this spatial link is established, the script compares vehicle speed to the road sign's speed limit to detect potential violations. The theoretical framework here is grounded in spatial data theory, particularly in defining directional influence zones, which are critical for ensuring that only vehicles moving in the direction of the sign are considered. Finally, the system evaluates speed violations within these zones, providing a basis for traffic enforcement and highlighting how geospatial analytics can enhance road safety by ensuring that vehicles adhere to speed limits. The Meta Prophet model (Figure 4.) [29] is a time series forecasting tool that relies on an additive approach to decompose a time series into four primary components: trend, seasonality, holiday effects, and noise. The trend captures the long-term changes in the series, seasonality reflects periodic fluctuations, holiday effects account for the impact of special dates or periods, and noise represents unpredictable random variations [15].

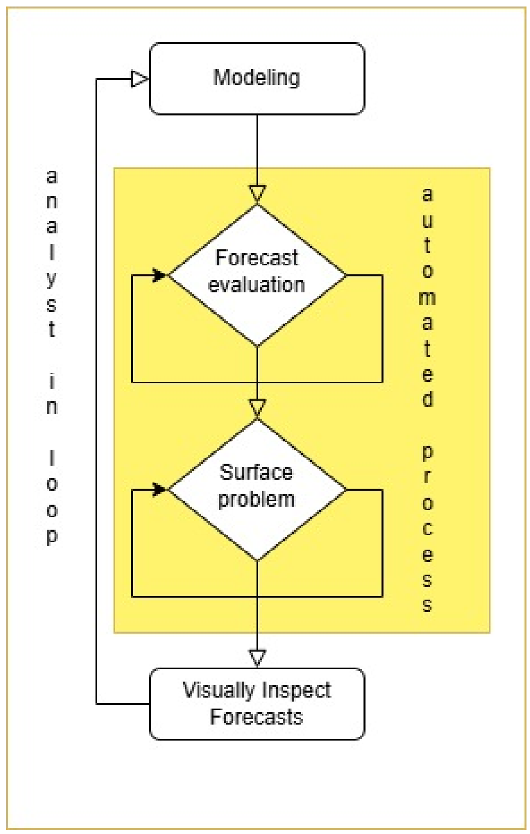

Fig. 5. The Meta Prophet model

The decomposition process in the Prophet model is divided into two parts: trend decomposition and seasonality decomposition. Trend decomposition utilizes a segmented linear function to capture both linear and non-linear components of the trend. Seasonality decomposition employs a Fourier series to break down seasonal patterns into multiple cycles. During parameter learning, the Prophet model estimates regression coefficients using least squares [33].

The overall forecast at any given time t is represented by the equation:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

In this formula, $y(t)$ denotes the predicted value at time t, with each term capturing a different aspect of the time series. The trend, seasonality, and holiday effects are represented by the following equations:

$$g(t) = k + at + \sum_{i=1}^{G} Ci \cdot sigmoid(t - ti)$$

$$s(t) = \sum_{n=1}^{N} (a_n \sin(\frac{2\pi nt}{P}) + b_n \sin(\frac{2\pi nt}{P}))$$

$$h(t) = \sum_{j} KjI$$

The trend component $g(t)$ models long-term changes and can be represented either by a piecewise linear function or a logistic growth model. K is the offset term indicating the overall average, a is the slope of the linear trend, t denotes time, G is the number of inflection points in the non-linear trend, Ci is the growth rate at each inflection point $(t - t_i)$, N is the order of the seasonal pattern, P is the period of the seasonality, and K_j is the effect associated with the $j - th$ holiday. The indicator function I equals 1 if time t is during the $j - th$ holiday and 0 otherwise [3].

The Meta Prophet model is well-suited for this research due to its advanced time-series forecasting, anomaly detection, and predictive analytics capabilities, which align with the study's goals of improving road safety, traffic compliance, and infrastructure management. Its ability to analyze IVMS data enables accurate predictions of traffic sign violations, identifying high-risk areas and driver non-compliance patterns. By handling complex, multi-variable traffic data, it detects behavioral trends and key compliance factors, enhancing driver monitoring and intervention strategies.

4.2. Data Collection

For the purposes of this study, data was provided by the IVMS provider with the consent of the participating company, ensuring that no personal identifiers were disclosed. The data collection period spanned from January 2023 to May 2024. Additionally, a field survey was conducted to compile a list of traffic signs, including geolocation data and speed limits, covering a total of 25 signs, among which were speed limit signs and stop signs. The research also involved the analysis of data from 22 drivers and two vehicles.

The FMS Fusion 300, presented in Figure 5., is an advanced IVMS device designed for precise data collection and processing related to vehicle and driver activities. It is equipped with an ARM (Advanced RISC Machine) Cortex-A53 Octa-core processor, 16GB eMMC (embedded MultiMediaCard) storage, and 2GB LPDDR3 (Low Power Double Data Rate 3) RAM. The device utilizes GNSS (Global Navigation Satellite System) capabilities, including GPS (Global Positioning System), GLONASS (Global Navigation Satellite System, Russia), and BeiDou (Chinese Satellite Navigation System) to accurately capture and record real-time location data, vehicle speed, and trip duration [16]. IVMS uses cellular or satellite networks to transmit data. This research was conducted in an area without natural or artificial obstacles (such as tunnels or mobile coverage gaps). However, existing studies [9] [23] indicate that cellular signals can be maintained even inside tunnels. After data collection, the IVMS device transmits the information to IVMS provider servers, which, within the DT model, are referred to as the DT data lake. For our research, we extract various types of data from the DT data lake to construct DT Safe Driver, DT Safe Vehicle, and DT Safe Road. Later, this classified data, combined with additional collected inputs, is processed using the Meta Prophet algorithm to generate predictive results. These predictions help in triggering specific DT Services, enhancing road safety and traffic management.

4.3. Results of Experimental Research

This subsection presents the key findings derived from the experimental implementation of the proposed DT of Road Safety. Following data collection within the DT Safe Driver, DT Safe Vehicle, and DT Safer Road components, as an integral part of this research, the focus in the subsequent subsections is placed on the application of analytical tools and machine learning techniques for predictive modeling and dataset comparison, in accordance with the defined research objectives.

4.3.1. Identification of Violations Related to Traffic Sign Non-Compliance

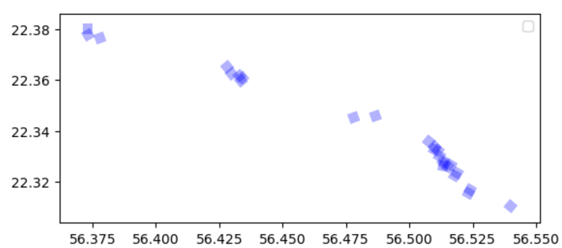

Fig. 6. The position and influence zone of traffic signs

To detect violations associated with traffic sign non-compliance, the analysis began with the integration of a geospatial dataset containing the precise coordinates of all traffic signs. A directional influence zone was then established for each sign by generating a directional buffer aligned with the sign's orientation. The direction, initially provided in degrees (with 0° indicating North), is converted into radians to facilitate the calculation of horizontal and vertical displacements based on trigonometric functions. These displacements outline a line extending from the sign's location in the specified direction.

To represent the influence zone, a buffer is generated around this line, with its width set to half the specified distance, ensuring that the zone accurately captures the sign's directional impact along the road. Additionally, square ends are produced for the buffer to simulate the area affected by the sign. This method is applied to each road sign in a GeoDataFrame, resulting in a new column that contains the directional influence zone for each sign.

The approach ensures that the influence zone is not isotropic but instead follows the direction in which the sign impacts traffic in Figure 6. This method allows for the precise delineation of areas influenced by road signs, improving the accuracy of our model. Afterward, a spatial join is conducted between the driver data and the road sign influence zones to link each driver to the respective zone they are located within. This spatial join matches the driver's position with the influence zone of road signs based on their spatial relationship as shown in Listing 1.

```
# Spatial join to associate driver data with the road sign influence zones
joined_gdf = gpd.sjoin(driver_data_gdf,
road_signs_gdf.set_geometry('influence_zone'),
how='left', op='within')

# Ensure the geometry column is correctly set
# joined_gdf = gpd.GeoDataFrame(joined_gdf,
geometry=driver_data_gdf.geometry.name,
crs=driver_data_gdf.crs)

joined_gdf['geometry'] = joined_gdf['geometry_left']
# or another appropriate column
joined_df = joined_gdf
joined_gdf = gpd.GeoDataFrame(joined_gdf,
geometry='geometry', crs=driver_data_gdf.crs)
# def is_moving_with_sign(vehicle_direction,
sign_direction, tolerance=30):
#     Check if the vehicle's direction is aligned with the road sign's
    direction.
#     Allow some tolerance for slight deviations.
#     diff = abs(vehicle_direction - sign_direction)
% 360
#     return diff <= tolerance or diff >=
(360 - tolerance)

# # Filter based on direction
# joined_gdf['correct_direction'] = joined_gdf.apply(
# lambda row: is_moving_with_sign
(row['vehicle_direction'],row['direction']), axis=1
# )
# valid_vehicles_gdf = joined_gdf
[joined_gdf['correct_direction']]

valid_vehicles_gdf = joined_gdf
#driver_data_gdf = gpd.GeoDataFrame
(driver_data, geometry='geometry')
```

Listing 1.1. Code to associate driver data with sign influence areas

The outcome is GeoDataFrame that initially contains data from both drivers and road signs. To ensure the correct heading (direction) is maintained, the geometry column is explicitly set to the driver's original heading. The final GeoDataFrame is then validated to confirm it has the correct coordinate reference system. Although the commented-out portion of the code provides a method for checking if a vehicle's direction aligns with the road sign's direction ($is\_moving\_with\_signfunction$), this function calculates the angular difference between the vehicle's and the sign's directions, allowing for a tolerance range to account for slight deviations. If needed, the function could be applied to filter out vehicles moving in directions that do not align with the sign's influence, creating a subset of vehicles (($valid\_vehicles\_gdf$) that are correctly oriented relative to the signs. However, in this instance, the script concludes by setting ($valid\_vehicles\_gdf$) to the result of the initial spatial join, effectively retaining all joined records without further directional filtering.

Table 1. Output table with drivers violations

TachoDate (Date)	TachoDate (Time)	Driver	Speed	Speed limit	Violation
1/2/23	8:09:48	Driver 2	46	50	FALSE
1/2/23	8:09:58	Driver 2	27	50	FALSE
1/2/23	8:10:18	Driver 2	40	30	TRUE
1/2/23	8:10:19	Driver 2	40	30	TRUE
1/2/23	8:10:23	Driver 2	31	30	TRUE
1/2/23	8:10:23	Driver 2	31	30	TRUE
1/2/23	8:10:28	Driver 2	22	30	FALSE
1/2/23	8:10:28	Driver 2	22	30	FALSE
1/2/23	8:10:30	Driver 2	20	30	FALSE
1/2/23	8:10:30	Driver 2	20	30	FALSE
1/2/23	8:10:31	Driver 2	20	30	FALSE
1/2/23	8:10:31	Driver 2	20	30	FALSE
1/2/23	8:10:34	Driver 2	20	30	FALSE

In this research, we identify instances where vehicles exceed the speed limit and count the number of violations in Table 1. A new column, "violation", is created in the dataset by comparing each vehicle's recorded speed against the speed limit specified by the corresponding road sign. This comparison determines whether the vehicle's speed exceeds the limit, with the result indicating a violation if the speed is above the limit. After identifying these violations, the total number is calculated by summing the number of instances where violations occurred. This count represents the total number of vehicles that exceeded the speed limit according to the road signs they encountered. Finally, the total number of speed violations detected within the dataset is displayed, highlighted in red in Figure 7.

4.3.2. Predictions of Driver Behavior

If we examine compliance with traffic regulations, particularly speed limits, we can distinguish between intentional and unintentional driving behavior[31]. Intentional non-compliance may arise due to a lack of knowledge, unawareness of consequences, absence of enforcement or monitoring ("nobody sees me"), or reduced concentration. While occasional instances of such behavior can happen to any driver, the concern arises when these actions become repetitive patterns. Identifying such patterns enables us to anticipate future traffic violations, which could ultimately lead to motor vehicle incidents. This research focuses on predicting potential driver behavior and drawing data-driven conclusions based on these predictions to enhance road safety interventions.

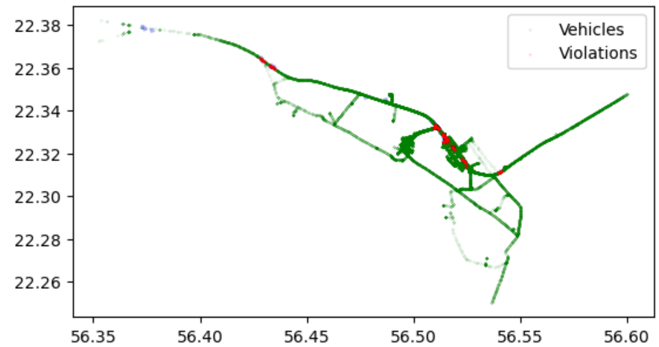

Fig. 7. Spatial join to associate driver violations with the road sign influence zones

Table 2. Output a table with predictions of drivers' behavior

ds	yhat_lower	yhat_upper	trend_lower	trend_upper	yhat	Driver
2024.10.20	-0.142796082	0.832923817	0.115616094	0.115616157	0.341534197	Drv1
2024.10.27	-0.15413158	0.781563299	0.112826379	0.112826445	0.338744484	Drv1
2024.11.03	-0.120619894	0.790254016	0.110036663	0.110036735	0.335954771	Drv1
2024.11.10	-0.093254485	0.806663005	0.107246948	0.107247024	0.333165057	Drv1
2024.11.17	-0.177004874	0.790667688	0.104457232	0.104457312	0.330375344	Drv1
2024.11.24	-0.137346225	0.760633958	0.101667516	0.101667601	0.327585631	Drv1
2024.12.01	-0.138367901	0.805363476	0.098877801	0.09887789	0.324795917	Drv1
2024.12.08	-0.173509915	0.783826341	0.096088085	0.096088179	0.322006204	Drv1
2024.12.15	-0.133032178	0.791374811	0.093298369	0.093298469	0.319216491	Drv1
2024.12.22	-0.134742919	0.783052654	0.090508654	0.090508758	0.316426777	Drv1
2024.12.29	-0.132399781	0.796272074	0.087718938	0.087719047	0.313637064	Drv1
2025.01.05	-0.137950205	0.771677584	0.084929223	0.084929337	0.31084735	Drv1
2025.01.12	-0.165706826	0.790620813	0.082139506	0.082139626	0.308057637	Drv1
2025.01.19	-0.166182664	0.75937172	0.079349791	0.079349916	0.305267924	Drv1
2025.01.26	-0.171092742	0.798246192	0.076560075	0.076560205	0.30247821	Drv1
2025.02.02	-0.168234231	0.784721728	0.073770358	0.073770495	0.299688497	Drv1
2025.02.09	-0.195392163	0.743006299	0.070980644	0.070980783	0.296898784	Drv1
2025.02.16	-0.172924502	0.756590949	0.068190928	0.068191072	0.29410907	Drv1
2025.02.23	-0.16626537	0.755384227	0.065401212	0.065401361	0.291319357	Drv1
2025.03.02	-0.1781599	0.764092547	0.062611495	0.06261165	0.288529644	Drv1
2025.03.09	-0.166079517	0.753248377	0.059821779	0.059821939	0.28573993	Drv1
2025.03.16	-0.159474004	0.772116024	0.057032063	0.05703223	0.282950217	Drv1
2025.03.23	-0.210509577	0.744856374	0.054242347	0.054242519	0.280160504	Drv1
2025.03.30	-0.194617814	0.735365529	0.051452631	0.05145281	0.27737079	Drv1
2025.04.06	-0.186525308	0.727976744	0.048662915	0.0486631	0.274581077	Drv1
2025.04.13	-0.190258675	0.745741923	0.045873199	0.04587339	0.271791363	Drv1

The output dataset shown in Table 2. presents predictions for driver behavior based on time series analysis, with each row corresponding to a specific time-stamped prediction. Key variables in the dataset include the timestamp (ds), the underlying trend component (trend), and the prediction intervals ($yhat\_lower$ and $yhat\_upper$), which indicate the range within which the actual driver behavior is expected to fall. The dataset also provides confidence intervals for the trend component ($trend\_lower$ and $trend\_upper$), as well as additive terms that account for daily and weekly seasonal patterns, along with other influencing factors. The impact of these seasonal patterns is further detailed in the daily and weekly components, while the multiplicative terms are set to zero, indicating no multiplicative effects were considered in this dataset. The $yhat$ value represents the predicted driver behavior at each timestamp, and the $Driver$ column specifies the driver associated with each prediction [29].

The results indicate that the trend component for each driver remains consistent over time, suggesting a stable underlying pattern in their behavior. The prediction intervals, represented by $yhat\_lower$ and $yhat\_upper$, are relatively narrow, which implies a high level of confidence in the predictions. Seasonal effects are evident in the daily and weekly components, with the data indicating variations in driver activity or compliance at different times of the day and across different days of the week [19].

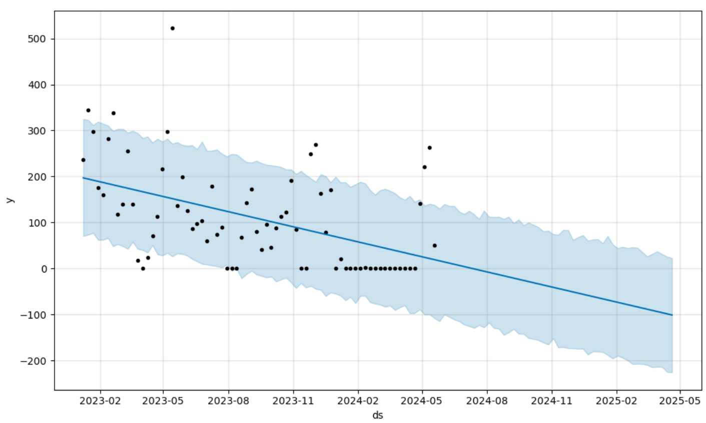

Fig. 8. Forecast trend of traffic rules violations

The plot in Figure 8. shows the predicted trend of traffic rule violations associated with posted traffic signs from 2023 until mid-2024. It suggests that traffic rule violations are expected to decrease significantly over time. This could be due to various factors, such as better enforcement, increased driver awareness, or changes in traffic management policies. However, the confidence interval indicates some uncertainty, and the model's performance should be closely monitored to ensure it continues to provide reliable forecasts. In our research, we analyzed historical driving data to forecast future behaviors, focusing on the likelihood of violations and changes in habits. This methodology enables the identification of key behavioral trends, seasonal variations, and anomalies at the individual driver level, thereby offering valuable insights for targeted safety improvement and performance management.

In Figure 9, we present forecasts for four drivers, each representing a typical driving behavior pattern identified among the 22 analyzed driver behaviors in this study. For

Driver 1, the forecast indicates a slight decline in violations, suggesting a potential improvement in adherence to traffic regulations over the analyzed period. However, the wide prediction interval suggests significant uncertainty, possibly due to inconsistent driving patterns. The data shows noticeable seasonal patterns, with some recurring peaks and dips, and violations clustered around certain values. The forecast for Driver 2 shows a relatively stable trend with a slight upward movement towards the end of the forecast period, suggesting a steady but slightly increasing rate of violations. The prediction interval is moderately wide, indicating some uncertainty but less variability compared to Driver 1. The pattern of violations is more consistent, with fewer fluctuations, indicating more stable driving behavior. The forecast for Driver 3 indicates a slight upward trend in violations, pointing to a possible increase over time. The prediction interval is wide, especially in the middle and towards the end of the forecast, reflecting high uncertainty and potentially erratic driving behavior. The pattern shows pronounced spikes and dips, suggesting more irregular behavior or external influences. The forecast for Driver 4 (driving during maintenance) exemplifies how predictions should ideally appear for all drivers, reflecting stable driving patterns with minimal fluctuations and promoting good driving behavior. In contrast, Driver 1 shows a downward trend but with high variability, Driver 2 exhibits a more stable pattern with slight increases, and Driver 3 displays an upward trend with considerable uncertainty.

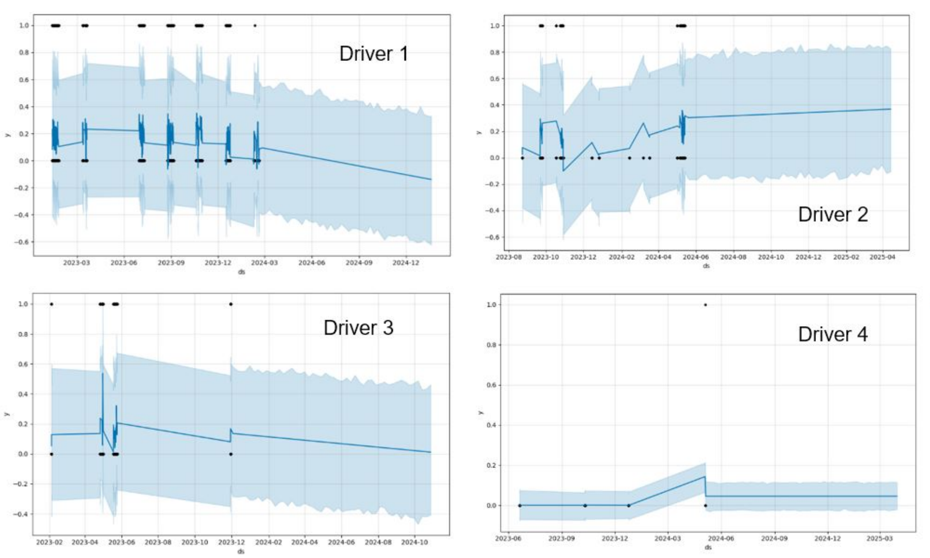

Fig. 9. Forecast for driving behaviors of selected drivers 1, 2, 3 and 4

4.3.3. Forecasting Compliance with Road Signage as Part of Maintenance and Infrastructure Improvements

The following analysis presents forecasts of driver compliance with various traffic signs, including speed limits and stop signs on both main and side roads, as illustrated in Figure 10. The results identify distinct behavioral patterns, ranging from consistent adherence to fluctuating violations, emphasizing critical areas for traffic management intervention. The forecast for the ”Speed Limit 40 km/h” sign on the main road indicates a generally

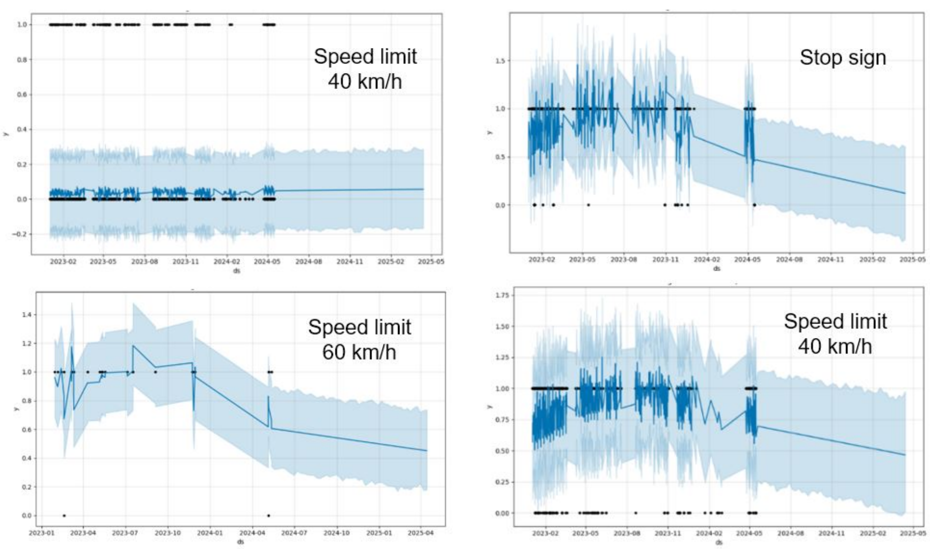

Fig. 10. Prediction of compliance with traffic signs

stable trend, with minimal fluctuations around the posted speed limit. The prediction interval remains narrow, signifying a high level of confidence in the projected values. This consistency suggests that drivers largely comply with the speed limit, with only occasional deviations observed. The stability in adherence implies that existing traffic control measures are effective in maintaining compliance at this location.

In contrast, the forecast for the ”Stop Sign” on the side road reveals significant variability in driver behavior, with widening fluctuations, particularly from mid-2023 onward. The prediction interval expands, reflecting greater uncertainty and an increased frequency of violations. A downward trend in compliance beginning in early 2024 raises road safety concerns, indicating a potential decline in driver awareness or enforcement effectiveness. This suggests the need for targeted traffic interventions to enhance compliance at this intersection.

The forecast for the ”Speed Limit 60 km/h” sign on the main road exhibits moderate variability, with the prediction interval widening over time, reflecting increasing uncertainty in driver behavior. A downward trend in compliance is observed starting from early 2024, suggesting a decline in adherence to the speed limit. The growing volatility in driver behavior may indicate inconsistent enforcement or changing driving patterns, necessitating further analysis and possible intervention to ensure traffic safety at this location.

Similarly, the forecast for the sign ”Speed Limit 40 km/h” on the main road highlights high variability in driver compliance, characterized by frequent fluctuations in the number of violations. The confidence interval remains wide throughout the forecast period, indicating substantial uncertainty in future trends. Although a slight decrease in violations is projected over time, irregular driving patterns persist, emphasizing ongoing challenges in maintaining compliance with posted speed limits. These findings suggest a need for further monitoring and potential traffic calming measures to improve speed regulation and overall road safety.

4.3.4. Potential Validity Issues

While it may appear that the volume of collected data is a limitation for a comprehensive experimental analysis, our DT of Road safety, although tested on a limited dataset, is inherently scalable and can be effectively extended to larger geographic areas, encompassing a greater number of vehicles, road segments, and traffic signs. This aspect will be explored in future research.

5. Discussion

This section provides a comprehensive discussion of the principal findings derived from the experimental investigation, aligning them with the previously formulated research questions. Each part is dedicated to one question, drawing connections between the results and the research aims. By combining insights from data analytics, user behavior patterns, and interactive vehicle system responses modeled through the Digital Twin environment, the discussion explores the DT of Road Safety capacity to support data-driven road safety improvements.

5.1. How Can the Digital Twin of Road Safety Identify and Mitigate Traffic Sign Non-Compliance Violations?

The DT model, specifically the DT Safe Road, in this research utilizes real-world data collected from the physical environment combined with existing traffic signage records to identify all instances of traffic non-compliance. This serves as the initial step toward the ultimate goal of mitigating traffic sign violations and enhancing compliance.

Our finding provides an answer to RQ1 by establishing a method for identifying traffic sign violations and gaining an initial insight into potential black spots [24] within the road network. To address this issue, we identify two key factors influencing non-compliance. The first factor is driving behavior, particularly human errors, which can be intentional or unintentional [31]. The second factor relates to Safe Road infrastructure, where addressing this challenge involves implementing traffic calming measures to reduce speed and enhance compliance. This can be achieved by activating Road Maintenance Department services within the Digital Twin model, ensuring timely interventions and improvements in road safety. These measures will be explored in more detail through RQ2 and RQ3.

5.2. How Can Driving Patterns of Non-Compliance with Traffic Signage Be Identified and Used to Prevent Future Motor Vehicle Incidents?

If we examine compliance with traffic regulations, particularly speed limits, we can distinguish between intentional and unintentional driving behavior[31]. Intentional non compliance may arise due to a lack of knowledge, unawareness of consequences, absence of enforcement or monitoring ("nobody sees me"), or reduced concentration. While occasional instances of such behavior can happen to any driver, the concern arises when these actions become repetitive patterns. Identifying such patterns allows us to anticipate future traffic violations, which could ultimately lead to motor vehicle incidents. This research focuses on predicting potential driver behavior and drawing data-driven conclusions based on these predictions to enhance road safety interventions. By analyzing recurrent behaviors, the model aims to predict and mitigate potential violations before they escalate into safety-critical events.

This study reveals intentional non-compliance with speed-related traffic regulations and identifies behavioral patterns where drivers improve or deteriorate their driving habits over time. By utilizing predictive tools, we can anticipate that certain behaviors may lead to motor vehicle incidents, including asset damage and injuries to pedestrians and other road users. These risk patterns trigger one of the DT services within the Learning & Training Department, which then delivers targeted awareness programs and knowledge-based interventions to enhance driver safety and compliance. When discussing unintentional driving behavior, we will explore this aspect further in response to RQ3 in the next chapter.

5.3. What Insights Can the Digital Twin of Road Safety Provide for Road Signage Maintenance and Infrastructure Improvement?

The DT Safe Road is designed as a key component of road infrastructure, aimed at enhancing road signage maintenance and infrastructure improvements. Communication within road networks, encompassing interactions among vehicles and between vehicles and infrastructure, has begun to garner interest within the traffic engineering community [17].

Fig. 11. Road signage survey after analysis

In our post-analysis of certain graphs, we gained key insights that significantly impacted the graphical representation, underscoring the importance of this type of analysis. In particular, we found that the stop sign had no recorded values despite being located on a secondary road, where violations should have been more frequent. Interviews with drivers and data from the road maintenance department revealed that the stop sign had been damaged (knocked down), and one of the 40 km/h signs had been rotated by the wind, showing the speed limit in the opposite direction, as shown in Figure 11. These issues were rectified before our field data collection, but it is important to note that two months passed between the initial occurrence and the repair. In the context of road safety, such delays are unacceptable given the potential consequences of these events. Furthermore, some traffic signs were incorrectly positioned or had faded to the point of being barely legible, a fact that we were aware of during data collection. Our graphical analysis confirmed that a portion of traffic violations could be attributed to these specific issues.

6. Conclusions

In conclusion, mitigating traffic incidents caused by sign disobedience requires a multi-faceted approach that considers the interdependent relationship between drivers, roads, and vehicles. By synchronizing these elements and leveraging technological advancements, significant progress can be made toward enhancing road safety. The integration of IVMS and DT offers a transformative opportunity to complement traditional road safety strategies and foster a safer, more efficient transportation ecosystem.

This research proposes a DT model that integrates all three pillars of traffic safety: Safe Driver, Safe Vehicle, and Safe Road, by combining IVMS data with machine learning techniques. The model presents a comprehensive traffic safety approach, facilitating detailed vehicle data collection and enabling real-time traffic sign recognition. By analyzing this data, the system can predict driver behavior, monitor compliance with speed limits, and provide proactive warnings, thereby promoting adherence to traffic regulations.

The research findings highlight the ability to identify drivers in need of additional coaching, evaluate the effectiveness of safety interventions, and ensure long-term improvements in driving behavior. The focus remains on promoting consistent, safe driving habits, with forecasting models ideally showing stable, low-violation patterns. Additionally, classifying violations by traffic sign type and predicting trends in non-compliance rates allow for targeted road surveys and the implementation of traffic-calming measures to enhance safety.

Future research should focus on scaling the DT road safety model across broader geographical areas and a diverse range of vehicles. Expanding its application would enable better validation of its effectiveness across various road networks and traffic environments, providing critical insights into cost-effectiveness, scalability, and the potential for widespread adoption. Furthermore, integrating additional sensor technologies, such as LiDAR (Light Detection and Ranging) and camera-based systems, alongside IVMS would enhance traffic sign detection accuracy and data collection reliability under diverse road conditions.

Advancing machine learning techniques remains crucial for improving predictive capabilities related to driver behavior and traffic management. Incorporating external factors such as weather conditions, time of day, and traffic density could increase forecasting accuracy and enable more dynamic safety interventions. Additionally, future research should focus on real-time applications of the model, offering immediate feedback to drivers and ensuring proactive traffic management. As the adoption of DT technology in smart city traffic systems continues to grow, this model holds significant potential to contribute to data-driven traffic management solutions and enhanced road safety outcomes.

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Received: September 25, 2024; Accepted: June 25, 2025.