PREDICTIVE ACCIDENT PREVENTION USING TELEMATICS AND AI

Ihor Melnyk[1]

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Abstract. The article is devoted to the study of trends in road accidents and directions of problem prevention through the use of telematics data and artificial intelligence technologies. The purpose of the article is to substantiate the possibilities of using telematics data and artificial intelligence to predict road accidents and improve road safety in the USA. During the scientific study, general scientific methods of cognition were used, in particular, analysis, synthesis, comparison, generalization, systematization and classification. The results of the study show that several key risk groups have been identified in the field of road accidents in the USA. It was studied that the highest mortality rate among men aged 20–24 is 27.9 per 100 thousand population, which indicates the need for separate behavioral monitoring of this category of drivers. It was studied that modern models of road accident prediction cover not only speed or violation of rules, but also risk perception, behavioral instability, workload, distance, relative speed and trust in automation. It is shown that models of deep learning, behavioral entropy, simulation evaluation, 3D modeling, mental load analysis, microscopic state of motion and car-following can already quantitatively assess dangerous driving patterns and predict risky situations. It is generalized that the author's model AFSA Method combines Calibration Phase Algorithm, AI Risk Scoring Engine, Behavioral Feedback Layer, Fleet Risk Intelligence Layer and Empirical Validation Layer - these are modules that are able to provide prediction of accidents and reduce their probability. The practical significance of the author's model lies in the ability to change the situation on the road before the accident. For drivers, this can mean timely warning about dangerous driving style. For fleets, this creates a tool for risk control and prevention. For insurance models, this provides more accurate behavioral analytics. In a broader sense, such an architecture can become an additional tool for reducing accidents, injuries and human losses on US roads.

Keywords: telematics, artificial intelligence, accident, risk, driver.

[1] ORCID: https://orcid.org/0009-0001-3690-7611
Master's Degree in Law, Luhansk State University of Internal Affairs named after E.O. Didorenko, Ukraine

Introduction

Road traffic injuries in the United States remain one of those problems that have simultaneously medico-demographic, social and economic dimensions. According to IIHS, in 2023, 40,901 people died in road accidents in the United States, while the CDC records almost 44,000 deaths in 2022 [3; 8]. Such a scale of human losses indicates that road safety cannot be considered only as a matter of compliance with traffic rules. This is a systemic problem that affects public health, the functioning of transport infrastructure, insurance costs and the quality of mobility management.

The relevance of the topic is enhanced by the fact that after relatively lower indicators in 2019, road traffic mortality increased significantly in 2020–2021, and a further decrease in 2022–2023 did not eliminate the problem of a high level of risk [3]. Of particular importance is the fact that a significant proportion of fatalities are related to behavioral factors. According to IIHS, in 2023, speeding was a factor in 29% of all fatal accidents, and among fatally injured drivers and passengers of passenger cars, the proportion of those wearing seat belts was significantly lower than the general level of seat belt use among the population [3]. This indicates a gap between the formal presence of safety rules and the real behavior of road users. A separate problem is that traditional approaches to accident prevention are mostly focused on analyzing existing violations or the consequences of accidents. At the same time, the modern road system requires tools that can detect risky behavior before a critical situation occurs. In this context, telematics data, driver behavior assessment models, AI scoring and early warning systems are of particular importance. They allow us to move from a reactive to a predictive safety logic, where the main task is not only to record an accident, but also to prevent it.

That is why the study of accident prediction models based on telematics and artificial intelligence has an applied value for the USA. It allows to combine statistical assessment of the problem, analysis of behavioral risk factors and search for technological solutions capable of changing the situation on the road in real time. Within this logic, the author's AFSA Method is considered as a comprehensive approach to risk management, focused on early detection of dangerous driving patterns, support for decision-making and increasing the safety of drivers, fleets and other road users.

Literature Review

The issue of accident prediction using telematics data, driver behavioral analytics, and artificial intelligence is not widely covered in the scientific literature. Despite this, some components of this topic are considered by scientists within the framework of research on driving risk, hazard perception, simulation modeling, driver workload, and microscopic analysis of road traffic. In particular, the issue of driver behavioral assessment was studied by Boer [1] and Ping et al. [10]. Boer proposed behavioral entropy as an indicator of driving quality that can be used to quantify unstable driving patterns [1]. Ping et al. developed a model for assessing driver risk perception on urban roads using deep learning, which allowed combining road conditions, driver behavior, and prediction of dangerous situations [10].

As for simulation modeling of risk perception, this issue has been studied by several authors. Among them, it is appropriate to highlight Kokubun et al. [6], who carried out a quantitative assessment of the driver's risk perception using a simulator; Jian-you et al. [5], who developed a theory of driver behavior and a computer system for simulating risk perception based on a three-dimensional environment. A separate direction is the study of the driver's mental load and its impact on the quality of driving a vehicle. In particular, Di Stasi et al. investigated the relationship between risky behavior and mental load in a motorcycle driving simulation [2]. Paxion et al. considered mental load as a factor that directly affects the process of driving a car [9]. Silva also focused on the relationship between mental load, task requirements and driving quality [11].

The issue of risk prediction based on traffic parameters has also been reflected in the scientific literature. Lu et al. proposed a car-following model based on quantitative homeostatic risk perception, in which the driver is considered as a subject striving to maintain a certain level of subjective safety [7]. Zhao et al. developed a risk perception model and a warning strategy based on the microscopic state of traffic, in particular the relative speed and distance between vehicles [12]. He et al. studied the risk perception and driver trust in automation during merging and braking, which is important for the development of automated transportation systems [4]. These works allow us to consider risk not as a static indicator, but as a variable characteristic that is formed in the interaction of the driver, the car and the road environment. The statistical basis of the study is materials from IIHS and CDC. IIHS provides data on road accident mortality, the structure of fatalities by type of road users, age, gender, seat belt use, speed factor and driver distraction [3]. The CDC supplements this picture with an assessment of the scale of mortality, non-fatal injuries and economic losses associated with road accidents in the United States [8]. The combination of these sources allows us to substantiate not only the medical-demographic, but also the socio-economic relevance of the problem.

The contribution of the author of this study is the formation of a comprehensive approach to predicting road accidents based on the author's AFSA Method methodology. The scientific novelty lies in the fact that telematics data, driver behavioral analytics, AI-scoring, the early calibration phase and the feedback loop are considered not as separate tools, but as a single road risk management architecture. Unlike models that focus on individual risk parameters, the AFSA Method is focused on early detection of dangerous patterns in the first minutes of the trip and the subsequent use of these data in fleet systems, insurance models and transport analytics. To achieve the goal of the study, methods of analysis and synthesis, a comparative method, a generalization method, a systemic approach, as well as elements of statistical and structural-functional analysis were used.

Materials and Methods

The materials of the study were statistical data on the main risk groups in the field of road accidents in the USA, scientific approaches to predicting accidents and assessing the risk of driving, as well as structural components of the author's risk management model AFSA Method. In the process of the study, general scientific methods of cognition were used: analysis – to study the risk categories of drivers, passengers and behavioral factors of road accidents; synthesis – to combine telematics, behavioral and AI components within a single approach to accident prevention; comparison – to compare accident prediction models and risk-scoring; systematization – to organize risk groups, assessment models and components of the AFSA Method; generalization – to formulate conclusions regarding the practical significance of telematics and AI solutions in preventive road safety.

Problem Statement

The purpose of the article is to substantiate the possibilities of using telematics data and artificial intelligence to predict road accidents and improve road safety in the USA. To achieve the goal, the following tasks will be performed during the study: to analyze the dynamics, scale and key trends of road traffic injuries in the USA; to identify the main risk groups and behavioral factors that affect the probability of road accidents; to characterize existing accident prediction models based on behavioral analytics, simulation modeling, telematics and AI approaches; to reveal the essence of the author's AFSA Method as a comprehensive model for predicting and managing road risk.

Results and Discussion

Road traffic injuries in the USA remain a large-scale socio-economic and medical-demographic problem. According to IIHS, in 2023, 40,901 people died in road accidents in the United States, while the CDC records almost 44,000 deaths in 2022, that is, more than 120 deaths per day [3; 8]. Such indicators indicate that road accidents are not just a transportation problem. They are directly related to public health, healthcare costs, losses of the working population, and economic consequences for the state. The dynamics of recent years show an ambiguous trend. After relatively lower indicators in the pre-pandemic period, road accident mortality increased significantly in 2020–2021. If in 2019 36,355 people died in road accidents, then in 2021 this figure reached 43,230 people [3]. Later, the situation began to gradually improve: in 2022, the number of deaths was 42,721 people, and in 2023 it decreased to 40,901 people [3]. However, even this decrease does not mean a complete solution to the problem, since mortality remains higher than in 2019. Thus, the United States is in a situation where a short-term decrease after the peak in 2021 is combined with a still high absolute level of human losses. It is important that the problem of road accidents has not only an absolute, but also an intensive dimension. In 2023, the mortality rate was 12.2 cases per 100 thousand population and 1.26 cases per 100 million miles traveled [3]. For comparison, in 2021 these indicators were 13.0 and 1.38, respectively, and in 2022 they were 12.8 and 1.34 [3]. This indicates some improvement in the situation in 2022–2023. At the same time, the long-term dynamics are more positive: IIHS notes that in 2023 the death rate per 100 thousand population was 41% lower than in 1975, and the death rate per 100 million miles traveled decreased by 62% [3]. Thus, state and institutional measures in the field of road safety have a result, but this result is not enough to eliminate the high level of current risks. At the level of state and public response, the emphasis is on those factors that most affect the severity of road accidents. In particular, one of the basic directions is to increase the use of seat belts. In 2023, the daytime seat belt usage rate among front seat passengers was 91.9%, but the proportion of fatally injured drivers and passengers of passenger cars aged 13 and over was significantly lower: 46% among drivers and 42% among passengers [3]. This shows that even with high overall compliance, failure to wear a seat belt remains a critical factor in mortality. The second important area is combating speeding. In 2023, speed was a factor in 29% of all fatal crashes, which corresponded to 11,775 deaths [3]. Therefore, the prevention of road traffic fatalities in the United States actually focuses not only on the technical condition of vehicles or roads, but also on changing driver behavior.

Of particular importance is the prevention of distracted driving and work with high-risk groups. In 2023, the IIHS recorded 3,143 drivers who were classified as distracted in fatal accidents, with 66% of such cases related to general distraction or immersion in one's own thoughts [3]. The highest mortality rate among men was observed in the age group 20–24 years and amounted to 27.9 per 100 thousand population [3]. This gives grounds to consider behavioral risks as one of the central objects of state traffic safety policy. In this context, modern approaches to accident prevention should focus not only on recording the consequences of accidents, but also on early detection of dangerous driving patterns. That is why telematics data, behavioral analytics, and AI scoring can be considered a logical extension of government efforts to reduce deaths, injuries, and economic losses, which in 2022 were estimated by the CDC at over $470 billion. US [8].

Based on the statistical materials of the IIHS and CDC, several groups of increased risk in the field of road safety in the United States can be identified. These are not only specific age or gender categories, but also behavioral patterns that directly affect the likelihood of a fatal outcome. The most significant are the risks associated with young men, car users, pedestrians, motorcyclists, drivers who exceed the speed limit, do not use seat belts, or show signs of distraction while driving [3; 8]. A summary of these groups is presented below (see Table 1).

Table 1 – Main risk groups in the field of road accidents in the United States

Risk group	Manifestation of risk	Significance for the prevention system
Insecure drivers [3]	The highest mortality rate was recorded among men aged 20–24, at 27.9 per 100,000 population	They require separate behavioral monitoring, as this group demonstrates the highest intensity of fatal risk
Passenger car users [3]	In 2023, drivers and passengers of passenger cars accounted for 59% of all fatalities	They are a central group for implementing telematics and AI solutions in the mass transport environment
Speeding drivers [3]	In 2023, speed was a factor in 29% of all fatal crashes, corresponding to 11,775 deaths	This is one of the key behavioral targets for early warning and risk-scoring systems
Unbelted drivers and passengers [3]	Among fatally injured drivers, only 46% were wearing seat belts; among passengers, the figure was 42%	This demonstrates the need to monitor not only vehicle movement but also basic safety discipline
Distracted drivers [3]	In 2023, 3,143 drivers involved in fatal crashes were classified as distracted	This indicates the need for systems capable of assessing the driver's current state and instability in vehicle control

Note: compiled by the author based on sources [3; 8].

Today, along with state measures in the field of road safety, innovative software and analytical models are being developed that can be integrated into the vehicle control apparatus or into a digital decision support system. Their common feature is the use of data on driver behavior, traffic flow conditions, risk perception, workload and vehicle interaction parameters. As shown by the study by Ping et al., deep learning can be used to model driver risk perception on urban roads, since such a model takes into account the complex relationships between the road environment and driver behavior [10]. At the same time, Boer proposed behavioral entropy as a numerical indicator of driving quality, which allows detecting unstable and potentially dangerous patterns [1].

Table 2 – Models for predicting road accidents and assessing driving risk

Model	Essence of the approach	Practical significance
Deep learning model by Ping et al. [10]	Assesses drivers' risk perception on urban roads based on real traffic data and driver behavior	Enables the prediction of hazardous situations by accounting for the complex interaction between environmental factors and driver responses
Behavioral entropy by Boer [1]	Treats instability in driver behavior as a quantitative indicator of driving quality	Can be used to identify dangerous deviations in driving style
Simulator-based assessment by Kokubun et al. [6]	Measures drivers' risk perception in a controlled simulator environment	Makes it possible to quantify the subjective perception of danger
3D system by Jian-you et al. [5]	Models driver behavior and risk perception in a three-	Brings testing closer to real-world traffic conditions

	dimensional computer environment	
Workload models by Di Stasi et al., Paxion et al., Silva [2; 9; 11]	Link risky behavior to drivers' mental workload	Help explain why attentional overload reduces driving quality
Microscopic traffic state model by Zhao et al. [12]	Assesses risk based on relative speed, distance, and other traffic parameters	Serves as a basis for real-time warning signals
Car-following model by Lu et al. [7]	Is based on the assumption that drivers seek to maintain a certain subjective level of risk	Makes it possible to detect deviations from the normal mode of following another vehicle
Model by He et al. [4]	Analyzes risk perception and trust in automation during merging and braking	Is relevant for automated transport systems and semi-autonomous driving

Note: compiled by the author based on sources [1; 2; 4; 5; 6; 7; 9; 10; 11; 12].

The above models demonstrate that the prediction of road accidents is no longer limited to the classical analysis of speed or the fact of violation of the rules. The focus is on the driver's behavior as a dynamic process. The driver may be formally within the rules, but at the same time demonstrate unstable driving, increased mental load, weak reaction to changing traffic situations or insufficient distance. It is such intermediate states that are especially important for preventive safety systems.

Against the background of the above models, the author's AI Fleet Safety Architecture methodology, AFSA Method, proposed by Ihor Melnyk, stands out. Its feature lies not in the separate use of one indicator, but in the complex combination of telematics data, driver behavioral analytics and AI-scoring in real time. Unlike classic insurance and telematics models, which mainly analyze the driver after the trip or after the occurrence of a risk event, the AFSA Method focuses on the first 10 minutes of driving. This period is considered a critical phase in which the driver adapts to the car, the road environment and his own driving state.

The essence of the author's model lies in the early formation of the driver's risk profile. Within the Calibration Phase, the system analyzes the sharpness of acceleration and braking, steering wheel microdynamics, driving trajectory, lane keeping, distance to other cars and reaction to the road environment. After that, the AI Risk Scoring Engine classifies the behavior as low risk, medium risk or high risk. This allows not only to describe the driving style, but also to quickly determine how safe the driver is at a particular moment. That is why the AFSA Method has applied value for accident prediction. It does not replace the driver and does not perform autonomous driving, but it is able to change the situation on the road through warnings, recommendations and transmission of analytical signals to the fleet operator.

The model is suitable for several categories of users. First of all, it can be used by international fleets, as it allows segmenting drivers by risk level and building safety management policies based on data. For short-term car rental companies, such a system is important due to the high frequency of driver changes and the limited possibility of prior assessment of their driving style. Insurance companies using usage-based insurance models can use the AFSA Method as a source of behavioral analytics, but without automatically changing financial conditions during the trip. In addition, the methodology can be useful for mobility-tech and telematics platforms, as well as for state and municipal transport systems that work with road safety analytics.

Table 3 – Components of the author's AFSA Method risk management model

Model component	Main function	Managerial significance
Calibration phase algorithm	Analyzes the first 10 minutes of a trip, including acceleration, braking, steering movement, trajectory, and distance	Enables the rapid formation of an initial driver behavior profile during the adaptation phase
AI risk scoring engine	Classifies driver behavior as low risk, medium risk, or high risk	Converts telematics data into a clear risk profile for fleet management or insurance analytics
Behavioral feedback layer	Generates voice, visual, or push alerts for the driver	Creates a soft behavioral correction loop without physical intervention in vehicle control
Fleet risk intelligence layer	Transfers analytical data to fleet-management, insurance, and operational systems	Supports driver segmentation, safety policy optimization, and fleet risk forecasting
Empirical validation layer	Relies on practical fleet operation data covering up to 70 vehicles and analysis of a large number of trips	Strengthens the applied validity of the model by identifying recurring behavioral patterns

Note: Compiled by the author based on the description of the AFSA Method and sources [1; 3; 10; 12].

Thus, the potential contribution of the AFSA Method for US drivers may be the transition from a reactive to a predictive logic of road safety. For a country where 40,901 people died in road accidents in 2023, and speeding, failure to use seat belts and driver distraction remain key risk factors, early detection of dangerous behavior has practical significance [3]. Such a model can help the driver to realize his own level of risk before an emergency occurs. For fleets, this means the possibility of more accurate safety management, for insurance models, better behavioral analytics, and for the state road safety system, an additional tool to reduce deaths, injuries and economic losses.

Conclusions

The dynamics of road accidents in the United States indicate the complex nature of the problem: the absolute number of fatalities remains high, and after the increase in 2020–2021, the situation has not yet become consistently safe. Of particular importance is that a significant proportion of fatal accidents are associated not only with technical or infrastructural conditions, but also with driver behavior. Speeding, inattention, unstable driving, failure to use seat belts, and increased risk among certain groups of drivers form that part of the problem that is difficult to solve with regulatory control alone.

An analysis of existing models shows that several important directions have already been formed in the field of accident prediction. Some models focus on deep learning and risk perception assessment, others on behavioral entropy, simulation modeling, driver workload, microscopic traffic state, or vehicle interaction in the flow. Each of these approaches has its own value, as it allows you to measure a certain aspect of risk.

The author's AFSA Method methodology is distinguished by its comprehensive nature. Its essence lies in the combination of telematics data, behavioral analytics, AI-scoring and a feedback system into a single risk management architecture. The advantage of the AFSA Method is that it combines predictive, behavioral and management functions. The system does not simply record deviations, but forms a risk profile, classifies the level of danger, provides soft feedback for the driver and creates an analytical basis for decisions of fleets, insurance companies and transport platforms. That is why this model can be considered more applied compared to individual scientific approaches, which mainly describe or measure risk, but do not always provide a mechanism for its operational reduction.

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