AI-Enhanced Systems for Vehicle Fleet Telematics

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1. Introduction to Vehicle Fleet Telematics

Vehicle fleet telematics optimizes fleet utilization by integrating telecommunications with monitoring systems. It is the union of two words: telecommunications and informatics. This helps to manage and monitor the installed systems on the newly managed vehicles effectively and efficiently, as these systems can be in constant communication with the control center or data center, and the data can be continuously monitored by the telematics applications. Efficient management leads to considerable cost reductions.

Telematics is a major engineering technological improvement and will enhance the safety, security, maintenance, and operation of modern transport systems, regardless of the origin, destination, and mode of travel. The focus in the last decade has been on incorporating vehicle fleet monitoring systems for timely decisions on incident detection, status monitoring, and location for safety or emergency tracking/communication, and, in some applications, collection of sensor data that includes automatic counting of passengers on public transit vehicles. Telematics is based on the following three components: GPS tracking devices, navigation software, and communication systems such as shortwave radio and satellite systems for communicating and transmitting to the control center. Telematics is experiencing rapid growth in order to collect, transmit, and interpret data from vehicle performance, location, speed, time, and diagnosis of possible issues or the after-execution of planned services. Modern operations find that immediate data analysis must be prioritized, or the position of the vehicle must be processed and updated in real time. Its services can be of enormous value to fleet operators who manage large and complex fleets. The service is not only to provide the right freight delivery on time and at a reduced cost, but also to rationalize the choice of carriers, to show, and allow tracking on the ship.

1.1. Definition and Scope

The concept of vehicle fleet telematics is nothing more than a part of what goes under the label of intelligent systems, involving not just the specialized telecommunications sector but also, and increasingly, areas such as tele-information and management systems. In fact, telematics has no precise technological content but rather configures a reference market for those advanced services that can be rendered in the automotive sector by means of the applications and services of which operators are increasingly in control. From a commercial entrepreneurial point of view, therefore, the universe of telematics comprises a broad range of situations, from publishing to the provision of specialist services, advanced unit services, and applications like cartography. From the point of view of use, telematics configuration tools can be put to the service of many independent applications. These range from improving safety and vehicle efficiency to monitoring cargo handling in order to calculate the most efficient means of organizing a company. Post and forwarding companies and bus transport, for instance, are capable of modifying certain behaviors in order to reduce consumption, changing the routes between various satellites to overcome traffic jams, and selling information for traffic control. The central role of the store-and-forward satellite is thus clear. Such an actor could also form containers into satellites to optimize loading. The telematics system can collect and process data for the operational strategies of the company and provide services to enhance the control of customers. The enthusiastic interest in telematics is relative, among other things, to a series of technological advances including the expansion of satellite communications, the development of user-friendly satellite navigators, and the widely anticipated evolution of telematics services and systems in application of artificial intelligence, including expert systems and decision support technologies. The capture of data on the vehicle's performance and the driver's behavior.

1.2. Importance in Modern Transportation Systems

There are several core reasons why vehicle fleet telematics play an important role in modern transportation systems. First, seamless integration with traffic data, satellite navigation, and cartography has considerably reduced operational costs, as telematically optimized routes cut fuel expenses by minimizing unnecessary mileage, whether due to unplanned traffic jams, road construction, or inaccurate navigation. Second, maintenance through digital services significantly reduces downtime and prevents unnecessary deadlines and intermittent inefficiencies. Real-time monitoring allows for a quick reaction as soon as a fault occurs, ensuring scheduled maintenance causes minimum disruption to the service. Even subtle metrics such as vehicle acceleration profiles are utilized in cloud predictive maintenance services. This is expected to extend vehicle lifetime, while large-scale fleet operations would result in an actual reduction in vehicle costs. In larger fleets, having analyzed the total amount of trip data, it is apparent that the per-mile-per-gallon ratio improves significantly with instantly scored driver adherence.

Some of these applications, for instance, monitoring driver behavior for safety solutions, can be adapted as direct applications towards an AI paradigm and can handle larger amounts of data. Most of these applications are already utilizing AI in some form. Access to large-scale environmental data and associated GIS data can also be used for a wide array of AI and ML applications for city planning. These could include spatial analysis to operate autonomously, with a commercial fleet of autonomous vehicles whose services run within boundaries that enhance the chances of either completing the latest pickup request or providing an accurate evaluation of expected travel time and potential pickups. Much of this AI is trained with big data from vehicles, but in a rather centralized approach, where data from a portion of the fleet is sent to a central point to train the AI algorithms. It is obvious that telematics are already a key feature in staying connected with transportation in general, reducing the costs of owning and operating a fleet in human-led driving, and this is likely to remain true for the near future.

2. Fundamentals of Machine Learning in Telematics

In recent years, machine learning, a form of artificial intelligence, has made a transformative impact in various sectors of business. Machine learning algorithms can analyze large amounts of fleet data automatically, and they can give insights into data that are not effectively addressed by more traditional techniques by finding applicable patterns and associations. This is especially important considering the volumes of data produced by massive vehicle fleets. The advancements in machine learning can resolve the need to predict individual operations for each truck every day using massive data sets. A machine learning model can simply capture an expected or average behavior if there exist sufficient examples.

In machine learning, there are two types of predictions: classification and regression. Classification models are used to predict discrete outcomes, such as identifying either a positive or negative case, comparing contrasting situations, and predicting if something will occur, such as whether a particular machine component needs maintenance today. Meanwhile, regression models are used to predict a continuous outcome. Logistic regression is actually a classification method, whereas using the term "logistic regression" as regression is often misleading. However, a simple example of logistic regression can be seen in telematics if managers would like to identify a driver's fatigue risk based on vehicle movement data. The systems in logistic, as well as linear regression models, can include some functions or transformers to isolate an arbitrary subset of data to be checked for the two purposes.

Fundamental concepts

Before we get more deeply involved in the compound capabilities of machine learning, let's start with some basic but important terminologies related to such systems. The terms supervised and unsupervised are fundamental in machine learning and typically relate to the nature of model-building methodologies. Supervised learning refers to systems where the model-building process takes place according to the class label provided for the dataset samples. On the other hand, unsupervised learning does not supervise the model-building process because there are no predefined class labels provided for features within the dataset. The model finds natural clustering as well as representations of the features' statistical distribution.

After discussing the fundamental learning methodologies, we need to talk about a significant factor in building the right model: data. Data cleanliness impacts the model more than almost anything, particularly data preprocessing, and the features within a dataset are pivotal factors. Data preprocessing – also known as data cleaning – is a critical task in data mining. The process usually consists of a combination of data clearing, filling in missing data, transforming values through the operations of normalization, creating new and standardized columns, encoding textual and non-continuous systems, and ultimately removing all redundant or unnecessary records. Model building, assessment, and evaluation require a high level of data preprocessing since it becomes clearer with the associations between features when processed rigorously.

In telematics, the best machine learning model that is capable of offering real-time predictions can be integrated into systems, and data can be collected continuously from an IoT device. The data then can be sent to the relevant predictive model, which updates based on the latest trend or information in order to give a fresh prediction. Since such systems' models are able to take into account dynamic operation, inasmuch as a model could predict planned operations based on historical data, they might offer improved subsequent-operation choices. Importantly, the organization's telematics systems can also study various ML algorithms' capabilities and select the one that appears to be best at guided operation. This is something in which operations managers can clearly benefit as it would save time and money given increases in predictive and then operational performance.

2.1. Basic Concepts and Terminology

Artificial intelligence (AI)-based predictive approaches are finding their way into different sectors of our lives, and one such important area is telematics. A basic understanding of machine learning is essential to understand different aspects of predictive modeling and data analytics. A dataset is a collection of data points, and its attributes are called features that serve as X's in the regression model. The output is the quantity of interest for prediction (and hence called the target or output variable), while its values are called labels (or Y's in the regression model). The process of using labeled examples (input-output pairs) to uncover links between features and labels is referred to as training.

There are different libraries and toolkits available in Python and R that you can use to carry out the modeling tasks mentioned above. The term machine learning (ML) is used when a predictive modeling problem is solved using statistical software such as R, Python, and external packages. There are three major types of ML that are commonly used, depending on the data or the nature of the relationship to be uncovered between input and output variables, namely supervised, unsupervised, and reinforcement learning approaches. In fleet monitoring, a supervised learning algorithm could be used to predict part failure based on its three-year lifetime usage and post a predictive maintenance action alert to the fleet manager. Similarly, unsupervised learning methods are used in telematics to identify the characteristics of components based on vehicle data to identify types of usage. One of the challenges in this step is to decide the relevant features and possibly the parameters of the model coming out of this study. Some of the performance metrics that will be covered later are required to compare different models for evaluation.

2.2. Types of Machine Learning Models Used in Fleet Telematics

Decision trees, neural networks, k-nearest neighbors, support vector machines, and rule-based models are the major models used for building fleet telematics applications such as driver behavior analysis, fuel consumption analysis, vehicle condition monitoring, predictive maintenance, insurance telematics, traffic intensity prediction, and financial analysis. Every model, to an extent, comes with its own set of pros and cons in implementing big data-driven telematics applications. Decision trees can handle irrelevant inputs and missing values effectively. K-NN is a distance-based algorithm commonly used in combination with missing data imputation methods. Neural networks have the ability to learn patterns from historical data. Support vector machines are also based on statistical learning theory, which can handle higher feature dimensions. Rule-based learning models are more transparent in nature for some stakeholders and can generate frequent data patterns.

Two principal strategies usually used to enhance the prediction accuracy of telematics applications are by combining the decisions from a single learner using ensemble methods or by considering the probabilities of all outcomes to produce one final outcome. The supervised learning models will generate more accurate results. However, the classification models with the highest accuracy might not be accurate when implemented in big data situations. Real-time analysis and predictions are conducted by integrating machine learning models with big data technologies, supported by case studies in fleet management. The advantages and disadvantages of using different modeling techniques help determine which modeling method generates the most effective solutions for fleet operations. Model suitability is a critical question to be addressed while answering fleet operations. It offers simulated results based on the data available.

3. Monitoring Fleet Performance with AI

Monitoring the performance of a vehicle fleet in a data-driven way has become feasible with the current ability to collect vast amounts of information in real time while the vehicle is operating. Materializing some of the many practical or commercial opportunities herein is based on accurate estimations of fuel consumption, environmental impact, and maintenance. These relatively localized research foci have many synergies, all of which require efficient processing of position, speed, and acceleration data, i.e., telematics. Both hardware and communication equipment are required to respond to contemporary performance-monitoring requirements. There are now many experimental applications aiming to exploit various networks, resulting in a heterogeneous and complex telematics data ecosystem. The actual performance analysis of the data collected can be based on a variety of methods, from statistical mechanics to pattern recognition and machine learning. As the computational performance per unit power grows, opportunities to apply more computationally expensive methods in fleet dynamics and optimization in AI-related telematics applications increase.

Fleet performance implies the efficient operation of the strategic business pipelines and is aimed at establishing the operational strength of a company. It depends on various key fleet performance metrics. Vehicle fleet logistics or management often has the prime priority to evaluate their area of strength. The area of strength will provide them with the flexibility to make the operational strategy of a fleet population. There are six different key performance metrics that can evaluate fleet performance considerably efficiently. Monitoring these key performance indicators can provide real-time trends of the operational circumstances and make it possible for effective fleet management. Trend analysis and integration of machine learning algorithms will help the logistics provider evolve powerful decision support systems. Predictive maintenance may deter frequent and sudden vehicle breakdowns that lead to time and cost overruns for the fleet and the business process flow.

3.1. Real-Time Data Collection and Processing

One of the main components of telematics systems is the real-time data collection system. In-vehicle devices like GPS devices, onboard sensors, as well as communication devices are used to collect location-based data and information about a range of other variables and parameters. These are timely gathered, cleansed, and transmitted to the database. Such databases are widely utilized by large transport organizations for their backend processing. The data thus collected is utilized to make vital decision-making tasks easier and more accurate. These devices primarily make use of GPS technology to get the location and time. GPS devices, these days, are readily available at an economical price. Generally, in these systems, in addition to GPS devices, onboard sensors for measuring different vehicle parameters such as speed, acceleration, heading, and engine data like fuel level and consumption are also deployed in the vehicles.

The prime consideration for these systems is data transmission time to transfer the data to a centralized database for analytics, as in telematics systems, most of the information is being generated in real-time, and decisions are made at that very instant to automatically control or generate an alert. The collected data from GPS and sensors are cleansed and preprocessed, followed by being transmitted to a centralized database. Utilizing the in-database stream preprocessing and analytics, vital insights are drawn. Due to the seamless integration of the different functionalities, the whole process reduces the time consumed in performing multiple preprocessing activities and detecting and correcting errors. Moreover, an integrated system capable of processing real-time data can efficiently report the possible error conditions as manifested. However, there are a number of challenges with real-time analytics, such as data overload and integration of many diverse systems. The increasing data volume can result in possible latencies and the system processing time, resulting in a loss of fidelity of the data. Moreover, real-time analytics has molded the decision-making policies for applications related to fleet management, such as vehicle location, route optimization, and asset management.

3.2. Key Performance Metrics

Key Performance Metrics (KPMs)

There are a number of key performance metrics that are often tracked by managers and leaders in the manufacturing and fleet sectors. For example, the number of vehicles in the fleet, vehicle and fuel costs, maintenance costs, driver quality, and compliance with industry standards. For telematics systems dedicated to vehicle fleet management, a few fuel and vehicle consumption metrics present higher relevance, as they are more closely related to operational performance and, ultimately, quality of service for passengers. These mostly relate to how well or costly it is to operate and maintain each vehicle.

Fuel efficiency: Typically, the cost of fuel represents around 30% to 40% of the total costs of vehicle operation. Vehicle utilization: Refers to the time the vehicle spends awaiting a new trip or at the depot. Mileage and deterioration in lost fuel efficiency are tied to vehicle utilization: a higher utilized, i.e., constantly moving, vehicle fleet can be operated with higher fuel efficiency. Maintenance costs: Are often correlated to work hours or the engine running time and the miles traveled by the vehicles. Warranty on advanced parts may also relate to vehicle mileage, to a much lesser degree. This metric is directly correlated to the increasing complexity of many onboard systems in next-generation vehicles. Each of these key performance metrics has an associated industry benchmark that fleet managers can strive to achieve or outperform, guiding them towards managing best practices. Automated tracking of these KPMs is often visualized via dashboards on reporting and analytics software platforms. By tracking these KPMs and comparing them to the industry standard, leaders can make data-driven decisions to improve the performance of their fleet. It is also well understood that traditional stop-start GPS route tracing is not suitable for estimating fuel efficiency. Thus, linking GPS data with operational data may provide key performance metrics required to improve the development models for advanced vehicles.

4. Analyzing Fleet Data for Insights

The overarching goal of AI-based data analytics is to gain new knowledge, insights, and support the decision-making processes with human-like cognition, done by algorithms applied to data. Such algorithms seek to explain why an event occurs, rather than just describing that something happened in a dataset. The potential benefits from such AI-enhanced capabilities are numerous. First of all, decision-makers are supported using intelligent systems, repositories of accumulated knowledge about past events, and domain knowledge rules that can contribute to interpreting observed data. Moreover, predictive methods are used to support decisions, revealing patterns and trends hidden in the fleet data collected. Consequently, materials, financial resources, and labor can be utilized more effectively with preventive intervention before an incident occurs, based on the insights provided by the AI-enhanced telematics solutions.

Furthermore, the value of the data collected from telematics repositories can increase significantly when external contextual information is integrated with observed fleet data and combined with the knowledge in the fleet data residing in ontologies and rules of the domain experts, as well as the knowledge coming from AI models, such as recommendations derived to facilitate decision-making. AI models can be developed and trained with deep learning methods at all three types of accumulated knowledge—using the existing fleet data, existing domain knowledge, as well as emerging knowledge. They are automatically consulted when a consumer needs an answer to a query. Furthermore, methods for forecasting both the vehicle states and the observed fleet parameters can be used to provide early warning and make future decisions, and to give a better insight into the historical performance, exploratory analysis that may reveal patterns missed in simple summary statistics.

Additionally, diagnostic telematics systems support monitoring with AI models trained with machine learning on the same sources of knowledge. Models rely on pattern recognition using advanced classification or clustering capabilities and can also include expert systems. They find complex data correlations that represent observed states and activities or detect anomalies that could portend a problem: something inside the vehicle is not functioning as expected by supervised learning methods. The value of the model can be further exploited using reinforcement learning to identify optimally the further action, which is trained on trial and error data in the resulting feedback loop provided by new telematics data interpretations. Typically, the AI algorithms' main task is to interpret the data inside the telematics repositories, to extract insights and explanations about the presence of specific states, issues, and activities. These methodologies enhance the basic telematics systems that only keep track of the data and rely on a user's knowledge and expertise to interpret them.

4.1. Data Visualization Techniques

While traditional and simple to implement, data visualization methods are often time-consuming and inefficient for exploring the high temporal resolution of fleet telematics data. In contrast, business intelligence systems enhance the user experience by providing scalable and interactive visualization tools. Vehicles and events recorded in trips with high temporal density can overload the layout. To deal with this issue, technologies have been proposed; some build internal visual representations at multiple levels of detail that are dynamically updated on the fly. Other approaches split and replicate trip points at different levels of detail before query execution, and some approaches perform data reduction by maintaining a background data structure and deciding when to display when groups with too many elements are too close to each other. Recursive indexing approaches can speed up the process of querying time-limited events on roadways or near a specific point during a specific interval. While fast and simple, extracts from the database many times redundant data that could be shared.

4.2. Predictive Analytics

In the next step, forecast models are designed to predict the future behavior of a series of variables by analyzing the historical data at hand. They are specified by expressing a variable or a series of variables as a function of others through mathematical relationships that capture complex, time-related activities, while at the same time not violating any fundamental laws. The resulting models serve a double purpose. Firstly, they synthesize all the information available on past activities in a coherent framework in a manner that decision-makers find useful. That information is then used from its present state to derive predictions for the future. Secondly, models are used to test hypotheses about different systems, their behavior, and the relationships between variables in a framework that can be adequately described by statistical methods.

Predictive models are used to interpret patterns of behavior that help decision-makers make more informed decisions that can improve the systems they have information about. It is important to distinguish between complex systems and complicated ones based on how they use or do not use prediction. While in complicated systems each observation can provide an unexpected insight, complex systems are more difficult to understand as they have multiple components, all interacting nonlinearly, irreducibly, and rapidly, and hence they display a result not derived from the sum of their individual parts.

5. Improving Fleet Safety through AI

One of the crucial fields of AI-enhanced telematics is the monitoring of drivers' behavior. It is worth noting that unsafe driving behaviors—over-speeding, harsh cornering or braking, distraction events, etc.—explain about 92% of all vehicle crashes. Thus, technologies to detect, measure, and influence driver behavior are imperative. AI-based algorithms can help identify driving patterns and, as a result, teach and assess. The power of data analysis in the improvement of safety practices has rarely been questioned. Fleet data are the starting point for safety management, fuel management, preventive maintenance, customer services, and benchmarking. The more data is analyzed, the better conclusions might be made—this is where AI steps into the game: processing multi-source fleet data helps extract actionable insights for training, assessment, and ultimately, a proactive view.

In addition to proactive techniques, AI is used in fleet management systems for the prediction of near-crash and crash events. Instead of a rule-based or empirical understanding, AI provides an advanced toolset for the complex task of forecasting such events. Integrated systems back up as a system for crash prevention. When it comes to crash prevention and, generally, to the monitoring of drivers' behavior, the use of video footage is important for a full assessment of driving practices. Video-based real-time events management systems, coupled with AI data analysis methods, add to a well-founded assessment of drivers' behavior, using a host of parameters and providing a smart alert system. Vehicle risks are assessed, and alerting thresholds are established. With dashcams and a real-time alerting system, it is easy to change risk perception and ultimately transform an organization into a safety-oriented culture. Automatic feedback is also given to drivers.

5.1. Driver Behavior Monitoring

Driver behavior monitoring is a very important part of systems aimed at enhancing safety, security, and overall effectiveness of fleet operation. AI technologies provide tools for real-time tracking and analysis of various driving events – speed rate, acceleration, harsh braking, and so on. The advantages of a real-time approach are the immediate and purely informative reactions of the system, which a driver can use to correct behavior if necessary. Taking into account the complexity of driver behavior and road situations, accurate prediction of dangerous scenarios is a very challenging task and usually relies on methods from artificial intelligence. In addition, aggregated, anonymized data, which covers multiple drivers, can be used to evaluate the performance of the entire fleet.

The attitude of professional drivers towards monitoring their behavior has been well described as being resistant, or even hostile, to monitoring and performance evaluation. To motivate and not to frustrate the drivers, various techniques must be implemented. The concept of gamification, the use of games to incentivize certain behaviors, has been the focus of multiple studies and commercial systems. Improving the skills of drivers additionally enhances safety while reducing fleet operational costs. The practice shows that behavioral splits like aggressive drivers, negative event provokers, and frequent abusers can be identified to be included in driver education programs. In general, safe and environmentally friendly driving is encouraged, as the optimized style of driving could result in substantial savings on fuel and maintenance, and can reduce the number of accidents, consequently cutting operating costs. Simulation benchmarks together with practical evaluations have different objectives: the process of driving evaluation, training, and advanced driver assistance system developments.

5.2. Accident Prediction and Prevention Strategies

5.2.1. Accident Prediction Accidents usually occur due to a variety of factors that may not necessarily depend on the driver or the fleet operator. However, a robust fleet telematics system enriched with advanced AI can predict potential accident risks based on the analysis of relevant data. Several machine learning algorithms were trained to categorize data sets with historical data and to understand the risk factors related to accidents. Enriched with the predictions, telematics systems enable the fleet manager to evaluate all parties involved in the potential accident risk and determine some preventative measures to avoid accidents. Based on historical data and the latest trends, such systems predict the probability of preventing accidents. Such systems are real bonuses and add value to fleet management, making the evaluation of drivers' operations and the design of training sessions possible. The telematics AI integrated systems are capable of integrating with the enterprise system and shaping accurate solutions. Such data analytics are very useful and are an essential part of fleet management.

5.2.2. Accident Prevention Strategies The accident predictive data derived from AI systems are available to identify probable risk groups to guide fleet managers and design accident prevention strategies. The AI predictive tool can implement advanced driver training. Additionally, parties can be uniquely evaluated apart from the real set criteria, and negative trends can be assessed for enhanced skill development in training. Vehicles could be withdrawn and arranged for monthly inspections based on individual vehicle predictions. The level of implementation mentioned above depends purely on the fleet's intentions. The conclusions drawn will automatically reduce the root causes of accidents by employing individuals, crew drivers, and vehicles. Both individuals and groups are safety conscious as they are involved in operations. The topic has been described in broader terms, and feedback can reveal and develop value in a structured manner. It is making the entire operations more proactive.

The aforementioned Accident Predictive Systems have been implemented by numerous companies, resulting in a decrease in accident rates and no major fatalities noted. However, this type of use is going to benefit large, medium, and small fleet owners. Historical data, which is available through telematics download history, is accurate, and based on that, the predictions are robust. The system has an embedded safety culture when sold to operators. This predictive description must reach crew members and everyone involved in operations. In this predictive AI analytics tool, reports must reach both parties, and they must understand the value and usefulness of the insights. The issue may arise from the notion that data quality is crucial for effective reporting. A significant amount of effort and energy must be spent to prevent data pollution and resistance from stakeholders. Furthermore, there will be descriptions for the AI-assisted functions, similar to other functions. The purchase of AI systems must align with the value provided by other systems, both system-wise and operation-wise. AI decisions have the stability to meet operational levels, so they must be initiated. AI must determine the locations of people and vehicles. Additionally, the operator may invoke further goals as additional functions. It must simplify operations, whether easy or complicated. The primary cultural change must be communicated to individuals and cannot be imposed on a culture-embedded group like operators. The challenge will always be present if no culture is in place.

6. Future Direction

The vehicle fleet telematics systems in the future could provide real-time performance analytics not just through footage analysis but also by integrating artificial intelligence to make apt recommendations. It could study the drivers and identify behaviors that could trigger accidents, though drivers are not aware of such triggers. A greater number of companies opt for fully outsourced telematics models as they realize that a well-managed remote system with external facilities could fulfill the majority of objectives. From a broader perspective, they want to achieve the following in the future: holistic vehicle and driver insight implementation, proof of more sustained and successful implementation of ELDs due to external support of systems. There is a possible upsurge in the number of requests from insurance companies for data. They feel that to prevent a claims situation, if the insurance company has the last say, then they will surely want to study vehicle data. In the future, real-time analytics could be expected to become more accurate and much more valuable. By having the complete driving logs electronically, they could be used monthly for driver training, bonus systems, safety metrics, etc.

Recent years have experienced telematics and the IoT trend. Future telematics could integrate with blockchain, but it is in the research stage. Automation and predictive analytics are other future systems that could be used for scheduling. Benchmarking across various industries could be another outcome that telematics might offer in the future. The telematics and traffic monitoring fields are also emerging as a 'meso-level field,' where network management organizations strive to support a new concept of collaborative, integrated network operation. In the near future, telematics could offer solutions for predicting what would happen in the next five minutes. More rigid compliance systems could be in place. However, given the considerable technological transformation, there might be a requirement to implement a new or upgraded structural compliance and auditing system to suit values emerging from our objectives, with a future that could be moving very rapidly in a data-oriented field, as data becomes more open and thereby potentially assessments become more independent.

Over the next ten years, many changes are expected in transportation, particularly with the development of autonomous vehicles and shared bikes/vehicles. These events point to the need to be more aware and prepared to move from one set of values and obligations that are not technology-oriented to those that are. The future systems should address current travel behavior as well as future shared fleet management – going all the way to understanding the shift in principles for a telematics unit that is focused on a sustainable mobility agency, particularly in supporting shared vehicle businesses. While the technology is constantly evolving, its usefulness will be based on the applications and regulations imposed across a country or area. In the future, a more holistic learning and action research would also help to bring in further environmental benefits as opposed to what telematics is doing now. The area of performance measurement could also elevate institutions to a whole new level. While the technology would rapidly evolve, the relevance of the models would be based on their continuous benefits. In order to have a sustained benefit arising from telematics, training and education could be an inevitable option.

7. Conclusion

The four essays included in this Special Issue propose several AI-enhanced telematics system solutions, which constantly track, analyze, and predict the behavior of vehicles, the infrastructure, the drivers, the passengers, and the environment, also detecting emerging problems and anomalies. Readers who are familiar with this field can appreciate also the significant improvements occurring in forecasting, and further enhancements in timeliness, understood as the capability to generate advanced notices for the fleet manager. Finally, it is a common viewpoint from the research community that the integration of machine learning methods with telematics systems will lead to a revolution in vehicle fleet management, as companies will be progressively able to switch from performing daily, routine tracking, to simply supervising, checking the action of AI-based automatons, while possibly providing training for them.

It is nice to note how pervasively the digital revolution is making inroads into all application domains. Technological improvements have had a rather “democratic” manifestation in the telematics field. Heavy transport has been a pioneer, possibly thanks also to larger capitalization and an easier quantification of the economic benefits. If any reconstruction of the comoving events that led to the explosion of telematics is task that is beyond our present purposes, it is still worth observing that vehicles seem to have already been conceived by 1970s as an assemblage of “integrated communications, information, and control systems.” Nor should we underestimate the influence that consciousness about the ethical dimension of road safety has had in shaping the increasing sensitivity about the “roadworthiness” of the environment–infrastructure ecosystem. It would not be appropriate either to neglect the escalating costs that companies are forced to support in case of heavy accidents, from any standpoint. It was reported that the world’s largest delivery provider was forced to put up with significant damage because of numerous accidents. A portion of this figure generally goes into insurance costs, into damage to the truck, and into accidents’ aftermaths. As eyes turned admiringly in those days to a successful use of technology, the delivery provider grounded its decision to equip a large number of vehicles with “brake stroke indicators,” which can contribute to decreasing the risk of brake failure and hence the likely number of rear-end and other accidents.

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