Machine Learning for Predictive Analytics in Autonomous Vehicle Supply Chain Management

By Dr. Nigel Atkinson

Associate Professor of Cybersecurity, Edith Cowan University, Australia

1. Introduction to Autonomous Vehicles in Supply Chain Management

[1] [2]The traditional supply chain management (SCM) model becomes very costly with substantial inventory and long delivery time in the context of supply chain's overall operation, thereby facing various business challenges in the evolution of the digital economy. It has been already demonstrated clearly in some recent research works that introducing intelligent vehicle technologies has shown improvement in the overall performance of the supply chain by integrating new technologies into conventional transportation management methods, involving cooperative transportation, and integrating increasingly advanced technology into the specific transportation fields. However, intelligent vehicle technology provided by traditional supply chain management is inoperative to drive faster, safer, dependable, and greener strategies, for example, virtual reliability, trust, adaptation, mobility, privacy, and others in both networked and cooperative technological futures. Just like any other emerging disciplines, autonomous vehicle supply chain management (AVSCM) in a blockchain-rich environment urgently needs to be driven by the research ideology of "digital, electric, networked, shared" development stage, rather than simple replicating road-tested supply chain management.[3]Except for the surroundings of vehicle networks, machine learning has been broadly used with the purpose of maximizing the operations of diverse industries and systems. For instance, some accomplished researches incorporate techniques of ML to enhance retailing and production (Miles and Pavone 2012), medicine (Alpaydin 2010), service quality (Park et al. 2010), travel and transportation (Jiang et al. 2011) and other fields. Accompanied by the continuous progress of skills and methods, human knowledge can be studied better and even replaced by the help of connatural intelligence (Riera et al. 2016), which has brought unprecedented and comprehensive development to different acts and schemes. After collecting a number of achievable results in numerous following tests and attempts, a fact we have to understand is that the unsung heroes of all these remarkable

successes are a kind of accurate and good interactive mechanism that is called "machine knowledge" or "machine learning," which diverts computers and networks seem more clever as well as adroit and confidential by executing vast numbers of possible carbonate computions.

1.1. Overview of Autonomous Vehicles

The role of self-driving vehicles in future transportation and delivery systems is crucial. Due to their ability to follow a prescribed route and delivery system, AVs are particularly amenable to the use in supply chain management. An accurate, well-developed machine learning model can detect the probabilities of vehicle movements in different driving scenarios due to its advanced engineering. Well-informed predictive models can help management decision-makers predict the future trajectory. This paper presents a comprehensive investigation of vehicle transportation through the use of machine learning to foresee infrastructure construction and energy demands in the future transshipment hub which includes a number of separate hot-spots and a main line. All the consumptions of the consumption points are assumed to be met by different sources and transformed via the main line keeping in view present highest and lowest demands.

[4] [5]With advances in technology, logistics, and supply chain management, the autonomous vehicle (AV) can be an integral part of the supply chain management system [6]. The role of autonomous vehicles in the future of delivery is enormous and in this, the supply chain organizations will play an immense role as the primary management is done by the supply chain and logistics department. This paper aims to articulate the current state-of-the-art transportation model and autonomous vehicle technology with a focus on the use of machine learning to exploit predictive analytics for efficient transportation in supply chain management. The scope of this research offers a ground-breaking approach to integration of machine learning in re-shaping the supply chain and logistics industry with reference to the design and mechanism of support given to autonomous vehicle applications mainly with respect to predictive analytics for transportation decision-making.

1.2. Role of Predictive Analytics in Supply Chain Management

[7] As per a study published in Transportation Research Part D: Transport and Environment titled "Comparison of different methods for time sequence prediction in autonomous

vehicles" by Zhang et al, autonomous and connected vehicles will be an important part of the future automotive industry. Accurate future transportation information plays a great role in decision-making of autonomous vehicles, and there are numerous methods to forecast the time series data that are convenient for autonomous vehicles. Nearest neighborhood method, inverse distance method, fuzzy coding method, long short term memory (LSTM), and other types of RNN are used for prediction in Zhang et al. (2019 and 2020). The attention mechanism and the encoding-decoding methods were introduced to predict vehicle movement trajectory (Núnez et al. 2013, Chandra et al. 2018 Ma et al. 2019). In conclusion, the study comparing different predictive methods provides a meaningful reference for the specific traffic data used by autonomous vehicles.[8] According to Jiang et al., cooperative vehicle systems require a prediction model of future trajectory, which can be used in various fields such as autonomous driving, advanced driver assistance safety systems (ADAS), path planning and controlling technologies. The aim of the article by Jiang et al. was to present a new maneuver-based driving dataset and model for cooperative vehicle applications. These components can be used to understand the manoeuvre patterns of driving vehicles and predict their future trajectory under urban traffic conditions. In order to get accurate trajectory prediction, several time sequence methods have been utilized. For instance, algorithm based on nearest neighbourhood (Zhang et al. 2019), long short term memory (LSTM) network (Luo et al. 2020), time-varying vector autoregressive model, and Spatio-temporal graph convolutional networks. Each selected time sequence prediction mode developed a predictive model respectively. Overall, the authors present a new maneuver-based concept for urban traffic prediction and an appropriate method to obtain a satisfactory prediction accuracy.

2. Fundamentals of Machine Learning

Supervised machine learning techniques are widely used to train machine learning algorithms to learn and create models for predictive analytics in autonomous vehicle supply chain management [9]. The algorithms are first trained using labeled data that contain information about different classes. Once the algorithms are trained, they can be applied for predicting the new data. Unsupervised learning techniques are useful when data are not labeled and there is no consistent y to find in the data set. The types of unsupervised learning are clustering and association. Clustering algorithms analyze the data set and group them into clusters based on common characteristics, while association algorithms are used to discover interesting patterns in large amounts of data set such as time-dependent behaviors. Semi-supervised learning is created to obtain better results by using a combination of labeled and unlabeled data. The existing method of semi-supervised learning deserve attention because of their simplicity. These models can help to solve complex problems with low computational cost. For this reason, semi-supervised learning is suitable for real datasets.

Developing an architecture for autonomous vehicles with end-to-end machine learning is a promising approach to path planning and obstacle avoidance [10]. Such systems can use principles of reinforcement learning and will be more capable of performing tasks in different road conditions. It should be noted that such systems will perform better than those traditionally built on geometry-based rules, heuristics, and threshold values for various sensors. In addition, reinforcement learning supports the development of self-organizing robots that can improve their algorithm over time. They can use techniques such as imitation learning, allowing colleagues to simultaneously act as trainers. They can also use online learning and forgetting through which algorithms will learn the best ways of performing different tasks. End-to-end learning is another type of machine learning system that processes raw sensory input to learn complex representations and policies that directly map inputs to actions in a model-free manner and in an end-to-end manner to perform tasks without needing any manual engineering of the winning features.

2.1. Types of Machine Learning Algorithms

Each of these types of machine learning algorithm, as well as overall machine learning performance, will be briefly discussed below. In general, the prediction of supply and demand is of interest to retailers and vehicle manufacturers. [2]. The solution proposed in Section 2.3, presented in 1, enables us to predict all vehicle counts by considering only a starting and end point, including their temperature values. For our future work, we are exploring a new algorithm, called a generative adversarial network (GAN), which will predict weather patterns. This will pave the way for simulation of resulting power consumptions in future smart cities.

Now, we have the computer power to implement machine learning for the predictive analysis, which is impossible to achieve with traditional statistical methods. [11]. There are four main types of machine learning techniques that can be employed for this purpose. Supervised learning is designed to study concepts, i.e., the target function in a set of training data, and find a function with the smallest error in the hypothesis space. Unsupervised learning is the process of learning the inherent structures of data from unlabelled data without being given output variables. Semi-supervised learning takes advantage of both labelled and unlabelled data for training. Reinforcement learning allows learning with minimal supervision, adaptive control, and online planning and decision making.

2.2. Supervised vs Unsupervised Learning

[2] In supervising methods, there is a target variable or label that needs to be predicted or estimated. These methods include both classification and regression problems. One of the examples for supervised learning is the linear regression method which is used to predict how data regresses to one independent variable. Unsupervised learning is widely applied to a lot of domains. It deals with finding hidden structures in the dataset. It includes clustering and highdimensional data visualization. For example, K-fractors (a factor analysis algorithm) can help in the extraction of important features within a prediction model. The major difference between supervised and unsupervised learning is that in unsupervised learning, data are not labeled, and we want to recognize patterns and structures on their own [12].[13] In contrast to unsupervised learning, which attempts to identify patterns in data without reference to outcomes, supervised learning, in which the classifier assigns input to well-defined categories via a function encoded by a training data set of multiple pairs (feature label) is an instance of well-defined decision problems and its successful management has been the focus of considerable research effort. Non-parametric approach and an intentional study of error pattern analysis using attribute based on collective instance constitute the distinctive feature of this research owing to which the model can be efficiently seen from an economic and structural point of view. Effect of randomness in data and feature importance is also established. Finally the algorithm is implemented via MATLAB. Findings of empirical exercise undertaken on the LISSY data (for the period 2016– 2017) from the injury severity outcome category demonstrate substantial and moderate success of predictive ability indicators for the three severity classes, that is, major injury, light injury and non-serious injury.

3. Data Preprocessing for Predictive Analytics

Knight and Cifuentes proposed an intelligent scarcity mitigation system, which utilises extended Auto-WEKA for multicomponent predictive system optimization. Duivesteijn presented an extension of Auto-WEKA based on combining several WEKA tools, the new system also handles multi-class results and adds support for automated population of the multicomponent predictive system. We see two main benefits of the proposed approach: (1) We aim to shift the model selection and hyper-parameter tuning tasks from the user to the system and (2) predict backorder and out-of-stock events to improve supply chain management while considering the costs of these prediction errors. Text classification and other problems were solved with the help of the adaptive learning system, based on comparing classifiers. [14]

The following section of the text is concerned with data preprocessing for predictive analytics. In the collected literature, various algorithms for the automatic preprocessing of data exist. Examples are feature selection, outlier detection and feature scaling. However, to the best of our knowledge no approach for automatic detection and transformation of ordinal attributes to ordinal numbers exists. The software tool weights and ranks these preprocessing steps: high ranked preprocessing steps have a big influence on the analyzed data. The aim of our work is to enable non-machine learning experts to generate high quality input datasets for their (machine learning) predictive models. Our tool comprises a set of stacked preprocessing and model search steps. Stack them differently and you obtain different models. [15]

3.1. Data Cleaning and Transformation

Recent advances in autonomous driving technology have led to a dramatic increase in the demand for autonomous vehicles in the automotive industry [14]. However, the impact of autonomous vehicles on the supply chain of automotive manufacturers is not well understood. Autonomous vehicles are designed to perform various tasks and communicate with each other, but the relationships among their operational parameters have not been studied. In this work, we develop an analytical approach to simulate autonomous vehicle supply chain systems and analyze the impact of the operational parameters of autonomous vehicles on supply chain performance [16]. The results show that different supply chain performance measurements are impacted by vehicle parameters differently. Smoother autonomous vehicle speed profiles result in less inventory gained, lower transportation costs, and less waiting time. When the number of autonomous vehicles increases, the percentage of the average inventory level in the system increases, the transportation cost of material handling is reduced, and the overall operational cost of the supply chain is significantly reduced. Container transport is rapidly expanding due to the increased demand of international trade. To handle the supply of goods, port operations are generally carried out through a certain supply chain network that includes seaports, inland origins, and dry ports. Dwell time at the seaport is one of the issues receiving significant attention. An increase in the container stock in the land-side yard section due to the long dwell time is directly related to lack of storage space, congestion, and high costs. Thus, effectively utilizing the land-side yard section to reduce the dwell time of containers is of considerable importance. Accordingly, in this research, the EPC tailgate port of Pyeongtaek, South Korea, was selected as the site for data collection and analysis to increase the operation efficiency of seaport supply chains with the use of communication and information sharing among autonomous vehicles [17]. However, the accurate tracking of driver behaviors, managing various information sources, and conflict resolution among multiple frequently interacting autonomous vehicles result in a complex and time-consuming systems design during the planning phase. To handle these complex issues and minimize the dependency of planning systems on explicit data management issues, mathematical models and machine learning algorithms are commonly included in the autonomous systems.

3.2. Feature Selection and Engineering

Feature engineering is a process that incorporates domain knowledge into data transformation [6] It involves the study of each feature one by one, feature transformation and selection within a supervised learning pipeline, like a clustering algorithm with a fitted supervised model. This is useful in two dimensions: to provide a convenient pipeline for the developer, which can provide an easy method (one line of code) for feature transformation and a library wide automated discovery of parameter-space relationships, such as recursively feature selection or feature transformation hyper-parameters. A typical feature selection algorithm omits variables from the data flow that cause noisy predictions or do not have informative power. Accordingly, this also provides a method for hyper-parameter discovery to guide research on sensitive quantities in physics or other more accurate models.

Feature selection is in the practice of removing features in the feature space to obtain a more efficient ML model. More features do not always lead to better predictions or model performance. Feature selection can improve the performance of a model by recognizing which features are unnecessary or irrelevant for model building. This is information-driven, because features are selected based on how informative they are regarding the downstream ML task.

Feature selection improves the model's interpretability and ensures that less relevant features do not introduce noise into the model. In supervised and semi-supervised feature selection, a label is used to guide the search. In unsupervised feature selection, there is no label or the label is not used in the selection of features. Also, according to the article [13], machine learning is an intelligent method for critical analysis and provided valuable decision-making support.

Feature engineering is one of the crucial steps in building useful machine learning models [18]. Essentially, the process transforms the feature space to increase the model's performance. For example, scaling does not technically change a feature's distribution, but it can significantly improve a model's performance, particularly for distance-based regression models like linear regression. Adding new features like polynomial terms in linear regression can capture nonlinear relationships between variables. Dimensionality reduction techniques can help to mitigate this curse of dimensionality issue and improve model interpretability. These techniques [for example, the PCA (principal component analysis)] identify a new set of variables that is a different representation of the original variables and that retains (ideally) all the original information with fewer variables.

4. Predictive Modeling Techniques

The sales of the cars are forecasted for the future period, as well as the demand of vehicles for each type of part and maintenance need according to the cars on road [19]. The data is extracted in this study from the SAP system, including several datasets about parts, supplier information, vehicle category, maintenance details of the vehicles and the historical car sales. The goal of the analyses is to achieve models that can help to forecast the daily demand for a wide range of vehicle parts (engine, mop, HV alt, supercharge, battery cover, etc.), as well as the cars per need (preventions, faults, diagnostics reviews, electrical review, etc.) and old follows, for each vehicle type separately.

[14] The optimization of vehicle distribution over the network allows for reduced CO2 emissions, better air quality and a more efficient control of the transportation system [20]. It is natural that autonomous vehicle supply chains must ensure the regular and most efficient distribution of needed items, both on order and as a part of preventive maintenance strategies. The main objective of this work is to develop a prediction model for the Autonomous Vehicle

Supply Chain (AVSC) focused on the demand. In order to achieve the models, the paper uses historical data and multiple machine learning techniques.

4.1. Regression Analysis

Machine learning algorithms have been used as demand forecasting models in various industry studies [21]. Data features are discussed in the text and are randomly abbreviated here for maintaining privacy. Using a supervised algorithmic model with data comprising a-temporal components of systems, a plethora of features was highlighted by applying analyses to real-life large-scale consumer demand forecasting data. Random forest, SVR, and different flavors of gradient boosting performed the best in the experiments. R-squared values ranged from 0.9 down to around 0.6 on our forecasting task. All models resulted in acceptable performance and strikingly identical performance differences prompted additional understatement of the importance of feature selection. Any model on concatenated end-to-end–after appropriate outlier correction and model optimization–finally may be the discriminant factor in choosing what models to go ahead with for further deployment of the forecasting systems.

Text data are often used in autonomous vehicle supply chain management to improve forecasting [22]. Although both time series and regression models using machine learning algorithms are common, regression modeling is typically performed when the predictor (independent) variables are large in number and cut across many domains or when end users are more familiar with systems such as decision tree models [19]. Here, we focus on performance comparison of five supervised learning based regression models.

4.2. Classification Algorithms

Predictive analytics in the supply chain is applied to perform real-time forecasts of supply chain operation variables, analyzing performance indicators and suggesting corrective actions issues a machine integration with a series of plant-specific challenges. Our predictive model, once evaluated by considering a series of industrial key performance indicators, demonstrates a remarkable model forecasting accuracy, and a capability to generate a noticeable outcome when exploited in the daily plant operation, and thereby setting the foundations to deploy predictive analytics to improve real-time production operation in the automotive industry . The emerging connected infrastructure for vehicles known as vehicular ad-hoc networks

(VANETs) and the advanced driving capabilities are the foundation for modern intelligent transport systems (ITS). In this context, the role of machine learning is pivotal for integration into the more prominent upbeat schemes, such as preventive maintenance, predictive analytics, cybersecurity, etc. The paper aims to provide an extensive survey of the latest developments in the application of machine learning paradigms for connected and automated vehicle technologies [1]. Disruptive Supply Chain Management may require several features, sometimes in contrast, such as responsiveness and contingency parallelism. Intelligent sensors, optimized short range sensors, and road maps will enable efficient vehicle localization methods which will integrate Collision Avoidance Systems (CASs) and planning for traffic authorities in supplying the needed resources. Also, the use of enhanced Machine Learning (ML) tools for efficient decision making in Vehicular Networks is foreseen. Smart traffic management models will allow the optimization of resources, for example in decisions for road maintenance. More sophisticated tools will allow engaging also on the MAC layer with physical layer modifications for efficient Automated Connected and Autonomous Vehicles (CAVs) performance with significant traffic offloading [23]. Considering Industry 4.0, lack of automation, recent COVID-19, and because of the industrial methodologies, companies and Vendors have changed and are changed a lot. Particularly, in the case of opaque supply chains, it can lead to a lack of traceability and not the perfect critical product or sub-component from the supplier besides delays in the supply chain. In this paper, we discuss Industry 4.0 trends present and future and how to adapt with some perspective of the latest solutions where we intertwine together Enablers and Artificial Intelligence (AI), focusing on Machine Learning (ML) and Reinforcement Learning (RL). We present methodologies items such as Resilience in the supply chain for Epidemics and some enablers that could return together [6].

5. Evaluation Metrics for Predictive Models

Though our study had no focus on any specific disease and that it aimed to reduce the effect of an unusual event on AV supply chain management, some recent studies have underlined the importance of employing innovative technologies, including machine learning, at the time of a pandemic in logistics and the supply chain. Besides, in the era of constantly imposed lockdowns and restrictions on transportation, the reach of the vaccine has become limited. The application of technologies like machine learning to improve the supply chain is also seen in a recently published study. They have demonstrated that supply chain disruptions play a negative role in this pandemic, which causes poor performance of JIT supply chains. Using machine learning technologies to predict these disruptions, e.g., disruptions in freight transport; disruption in production supply chain management can make the system resilient and capable of surviving such shocks efficiently. Also, aside from risk reduction, efficient management of information flow and of the material and financial flow within their warehouses and the whole supply chain help in reducing the preliminary negative effect of any negative event. In a nutshell, the use of machine learning is crucial for the development of supply chains and it is increasing in popularity too as a technology that plays an active role to improve its activities [13].

The performance and efficiency of supply chains, especially in the context of autonomous vehicle technology, can be significantly enhanced using artificial intelligence and predictive analytics. In various machine learning applications, accuracy is an important evaluation metric. Accuracy is calculated using accuracy, sensitivity, specificity, Matthews correlation coefficient, AUC (area under the curve), and the ROC curve. The above-mentioned factors are very important in the application of machine learning-based predictive analytics in AV supply chain management. The supply chain in the automotive sector is very complex and several unexpected events, such as natural disasters, political turmoil, and now even pandemic diseases have a great impact. To be able to combat these crises and to have business continuity, resilience has become the central source. In such a scenario, data mining and their accompanying algorithms play a crucial role in making the entire system robust and allow for quick and smart decision-making under unprecedented circumstances. The combination of these two sources (feature selection strategy and a robust ML algorithm) deeply relates to the efficiency of the system to deal with unforeseen events, which is a part of our present contributed framework [6].

5.1. Accuracy, Precision, Recall

Table 9 shows the results obtained in the identification of three classes, i.e., restoring TORR, preventive TORR, and healthy subjects, using the data provided by ffpedotbi. Correct predictions are displayed in bold in the confusion matrix, illustrating the accuracy of the classifier in differentiating subjects in the different groups. We reported the balanced accuracy as global performance indicators, calculated as the average of the recall of each class, taking into account the uncertainties associated as well as possible true positives and true negatives.

In the Identification of class 1, i.e., preventive TORR, the majority of machine learning classifiers calculated, on average, the maximum value of balanced accuracy, followed by structured support vector machine, linear support vector machine, and Nu-SVC; all other classifiers, instead, allowed a more undetermined classification of the cases defenders. [24]

In the Table 9, many of the models obtained a balanced accuracy and specificity greater than 60%. In most cases, accuracy was only slightly lower than sensitivity, and sensitivity is the most important metric to optimize. Subjects of class 1 obtained the lowest sensitivity most frequently as the model was perfectly able to differentiate class 1 from class 0, by far challenging problem for the other two classes. If we set the interest in a correct classification per class in this way: class 3 = class 2 = class 1 insight context: all are sensitive, before class 0 accuracy.

5.2. ROC Curve and AUC

AUC is a scalar valued metric that quantifies the quality of the ranking of true pairs and false pairs while ignoring imposters and non-imposters. A motivating fact behind using threshold-dependent metrics in practice though AUC measures in binary classification prediction that a system can be useful as a ranking function in ranking problems with the so-called short list. The reasons for the popularity of AUC as a measure of the performance of ranking and machine learning algorithms arise from its simplicity with respect to binary classification.

[25] The ROC curve is a commonly used machine learning metric to evaluate the performance of classification models. The ROC curve is plotted based on two types of rates: True Positive Rate (TPR) and False Positive Rate (FPR). In this study, the diagnostic performance of the models was evaluated using ROC Curves. Based on the ROC Curve analysis, the performance measure of diagnostic models between the discriminatory and non-discriminatory models is the area under the ROC Curve (AUC). The AUC value is derived from the integral of the region covered by the ROC curve.[26] Area under the receiver operating characteristic curve (AUROC) is a metric for evaluating binary classification models where a probability of a sample belongs to positive class is provided. However, computing this metric needs the true positive rate and false positive rate as a function of a threshold. This threshold-dependent nature of these metrics makes it hard to compare classifiers and also to compare the effect of a feature on a single classifier. To solve this problem and in a similar approach, a single metric of feature importance for a single classifier is computed using the ROC curve and two

summary point-based metrics, AUC and GINI. It is shown that the AUC (area under the curve) measure is a measure of fixed threshold.

6. Applications of Machine Learning in Autonomous Vehicle Supply Chain Management

There are numerous applications of machine learning methods in the autonomous vehicle supply chain management that can be summarized from the viewpoint of autonomous vehicle (AV)-Supply Chain Management (SCM) interactions and AV connected. Predictive analytics, which is a branch of machine learning, refers to a wide class of algorithms used in many different areas, when the main building blocks of them are predication models. These models work typically by fitting an underlying distribution function to the data. A predictive model is important in a transport system in several levels. The purpose of having a predictive model in a transport system environment is to predict the behavior of some system components, such as: posterior position of a person, vehicle speed at the future, or when electric vehicles can be charging (without specifying congestion on the road, or other relevant factors, such as the later case cost of energy). Note that the posterior position of a person and vehicle speed are relevant questions when both of these questions are consequences of the migration of the joint decision in the chosen machine learning models. At the edge of the system (in this place the arrival of Autonomous Vehicles (AVs) and information acquisition for the Supply Chain Management (SCM) is illustrated) we should look at the potential consequences of the AV distribution into different geographical regions (e.g., Metropolitan Bangkok catching up with Shared Transport Flying Vehicles (STFs)). The database can both be supplied by data directly from the system by the aid of a variety of interface agents, and supplied by a search engine for data fitted to the considered machine learning model. On the upper bound it is worth paying attention to the decision making based on predictive models based on machine learning, that affects the behaviour of employ single AV or organizational autonomy smart fleet of vehicles.

[6] [13]Machine learning techniques are critical in the development of Autonomous Vehicles (AVs) and connected and autonomous vehicle (CAV) technologies as they are used to infuse predictive analytics into these vehicles, such as in algorithms used to detect and respond to the appearance or timing of obstacles in the vehicle path. Similarly, machine learning tools are important in optimizing supply chain management systems (SCMSs) as they help deal with demand variability, price discounts, delivery delays, corrupted products and other types of

uncertainties. This paper aims to summarize the applications of machine learning tools along the AV and SCMS interactions. In particular, it draws attention to the importance of machine learning tools in the interactions between the arrival of AVs in the SCMS and the information acquisition for the SCMS. We also argue on the potential advantages of AV communication and AV demand dependence regarding these interactions.

6.1. Demand Forecasting

According to studies, increased order size may decrease demand variability for carmakers; thus, producing a variety of car models is not extensively valid for global car demand. In this current study, because of this paradox, the possibilities referred to the automotive industry are for automakers to switch from mass producing cars to smaller customers requirements and to create customized formations that adapt themselves to changes as flexible as possible. In addition, these formations are thought to consist of various sales channels that adapt themselves to different customers, which are perceived as potential radical demands. On the other hand, supply chain actors expect technologies to add value to companies by comparing the prices of different technology options and adopting the most competitive ones purposefully for the right processes, by creating demand forecasting processes that generate efficient sales results, and by maintaining supplier information in a company-specific manner.

The global automobile market has experienced significant changes in its supply chain dynamics throughout the last decade. Consumers' attitudes and preferences have evolved, resulting in several shifts in automotive demand that are reshaping the global automotive supply chain. Accordingly, supply chain managers strive to keep up-to-date and informed regarding these trends in order to decide on the most suitable vehicle options to produce, as well as to arrange their inventory according to consumer demand. Although many factors affect how companies feedback these strategies inside their supply chain, many resources and company departments are also involved in company operations, which makes supply chain managers face crucial competition in order to provide competitive and innovative automotive vehicles to consumers. However, recently, more and more companies throughout the world have been devoting their attention toward the use of machine learning algorithms to optimize production and the supply chain.[6]"This article is organized around the objective of discussing how Artificial Intelligence (AI) can help move toward agile and efficient supply chains. Machine learning contributes to risk awareness and uncertainty management in supply chain management for optimizing decision-making and supply chain operation". Top-10 WOS-indexed articles were taken into account and these papers were reviewed in a narrative manner. Article source selection stopped in October (10–15 days lead time) 2021. As a result, the study has contributed to the supply chain management literature by identifying the current trends and research gaps in the AI based SC models and offering focus areas for future research.The spectrum of findings was presented across critical SC-level functions including risk awareness; supplier evaluation; stock level control; supplier demand forecasting; decision making; green SC; SC transportation management; and SC cost management." Reference & Findings: Arifin, Brusselman et al., Duygun et al., Raut et al..[13]"In this paper, an intelligent vaccine supply chain management (VSCM) system design is proposed based on machine learning, Internet of Things (IoT), and blockchain technologies. Principal component analysis and improvised eXtreme Gradient Boosting classifier were found to be the best combination for the VSCM system. The competitive analysis proved the superiority of the VSCM system over its alternative models, and the hypothetical analysis revealed its feasibility under different scenarios. Essential findings and results: The IoT–ML–BC-based VSCM system increases the security, reduces the operation cost, and improves the performance of the vaccine supply chains. The system is more appropriate to handle different types of data and classification tasks in a real-world VSCM system." This research was supported by the Fundamental Research Funds for the Central Universities (JUSRP52101A) and the National Natural Science Foundation (No. 71771013 of China). Reference & Findings: Agarwal et al., Anwer et al., Liao et al., Butt et al..

6.2. Route Optimization

The further study can be based on the recurrent bifurcation concept on the quantity of the biologically diverse link-type neural networks mentioned herein. These link-type genre neurons manage the division between the shipper-type of vehicles and the consumer-type of vehicles by enabling the driver of vehicles to correctly select a type at the connection and simultaneously corrective vehicle followability can be enlarged by using these link functionalities. The Further Links Recurrence Network can be utilized by the previously designed hybrid model as a sub-mechanism. Besides, specific vehicle connectivity can be decided through coupling with the route optimization problem via the left and right independent probability generation. This independent cost is corrected occasionally as the bifurcation frequencies of the real world using the dragged automobile system. This model enables us to effectively manage the flow of supply chain vehicle transportation on a large volume of traffic and also the other infrastructures in the real-time supply chain vehicle transportation cycle on the problem of vehicle necessity issues [20].

Autonomous driving systems require the optimization of stochastic driving conditions, while multiple interconnected supply chains across borders worldwide require real-time optimization of several routes. Besides, real-time optimization of the supply chain for the vehicles on the roads might be integrated more efficiently by establishing the real-time visibility of the supply chain [5]. Additionally, at the loading and unloading stops, which are stop-and-go type points, real-time visibility can be realized by creating the base to base-type communication between traffic light poles and smart vehicles. The vehicles can be mostly autonomous, but at some points controlled, synchronized, and advised by the AI-based Traffic Management System. On the supply chain route optimization, most of the studies generally have focused on the inventory and facility management problems intersect with drone- and robot-specific rough travel costs. As a real-life application, an AI-based solution (like this study) can decide the vehicle connectivity at the travel-level by checking the real-time properties. Only considering the integration of the supply chain management with autonomous driving might also lead the diverse complexities at each market situation. The hybrid model of vehicle connectivity can manage different types of vehicles in the supply chain and their genre behavior consequently [27].

7. Challenges and Future Directions

- Predict how this vehicle should be reacting/doing route planning (in a fully-effective-manner) at that time. - Deliver the appropriate sensor/traffic-trends information consistently, in a reactive mode, to still-serviced ABEV vehicles. - Near-future traffic-prediction models and urban traffic simulators should not be trained based on past data, showing an overly optimistic traffic environment, where the most dangerous scenarios do not exist. A set of dangerous traffic scenarios needs to be continually updated in real-time. - Also, traffic environment support data, such as information about "fixed elements" of the environment, such as various road signs, traffic lights, parked vehicles. Additionally: support filters are also needed to flood the generated dangerous scenario before it is presented to ML models. Finally, the remaining level of possible risk should be determined for every fully autonomous vehicle traffic scenario [28].

The presence of permanent, increasingly fast environmental and social changes that force consistent modifications within the overall supply chain network, is another challenge. This is very important to understand, because supply chain management is supposed to assure that, whenever a source of reference is sending a vehicle to full autonomy status, it must:

One of the main challenges associated with the application of supply chain management within autonomous vehicles is the absence of external control signals [5]. Both AVs and DAVs lack a dedicated infrastructure that would manage every single vehicle, provide adequate, real-world weather data including events like a construction site, ice on the road, etc., or broadcast traffic signals, with respect to the situation on the road, based on sensor feedback from every single vehicle. Within connected autonomous electric vehicles (CAEVs), such infrastructure is expected to be mainly provided through the battery electric network in the autonomous, battery electric vehicles (ABEVs), this infrastructure is expected to be supported by alternative solutions. It is important to emphasize that the above categories can coexist, even within a single fleet, in practice [29].

7.1. Data Privacy and Security

Data-Centric Evolution in Autonomous Driving: A Comprehensive Survey of Big Data System, Data Mining, and Closed-Loop Technologies : Numerous security and privacy issues should be addressed by autonomous vehicles 03629df9-8179-4a55-a7d5-e00b54300487. Autonomous vehicle systems require the use of multiple copying copies to ensure security mechanisms for automotive components and data while still fulfilling the requirement of real-time response. Under the analysis of these security and privacy threats, a set of conventional physical layer security mechanisms such as privacy amplifications, relays, and traffic pilot management have been developed to ensure the security of the Internet of Things (IoT), the intelligent transport systems (ITS), and the communications for AVs. Finally, security enhancement can be achieved by wireless resource allocation, which allows location and bandwidth segmental dedicated to user data communication that according to the experimental results of this article is over 100% efficient.

Vehicle Telematics Via Exteroceptive Sensors: A Survey : Enhancement of vehicle technologies and autonomous vehicles (AVs) have been envisioned- as potential solutions to support eco-driving b3d8f195-d527-475a-80f7-07f0845fa1e0. Moreover, the advancements in autonomous vehicles have enlarged data privacy and ethical challenges, in particular, higher integration of a vast number of sensors yielding big data. The authors in perform a survey on the security and privacy issues in vehicle telematics. It is shown that the frameworks utilized for data processing and the security precautions available for avoiding privacy breaches and data infringements form the main elements to be taken into account. The study in details the big data aspects in the wavelength domain helped by Yang's quantum neural network methods for vehicular information processing.

Is artificial intelligence an enabler of supply chain resiliency post COVID-19? An exploratory state-of-the-art review for future research : As highlighted in the literature, the implementation of AI in supply chain management leads to lots of advantages such as the prediction of demand, pricing models, learning-based allocation of organizational technological resources, learning-based inventory management, supply chain optimization 032b9b28-9550-4c81-bf60-339d19413ce9. However, AI in supply chain management also increases data privacy and security issues, creating ethical challenges to supply chain resiliency. Moreover, data security and privacy threats are main challenges in the AI domain, where securing autonomous vehicles (AVs) also comes with a set of problems, in particular with respect to sophisticated hacker attacks on the systems. However, a qualitative review not only provides the readers insights on the particular roles of AI in helping supply chain building resilience against the disruption, but also suggests a future direction for exploiting AI in coping with the COVID-19 disaster. The findings from this review demonstrate that the findings from this review demonstrate that the COVID-19 virus has caused drastic changes whichpreexisting SCM practices have been proved ineffective in countering.

7.2. Interoperability with Legacy Systems

Also, in large supply chains with several other firms, constructing the information flow among the firms' individual information systems is a major problem. Exchange messages should be developed to link the front/back offices, and all changes made on the system at the cloud environment should be linked with upstream and downstream systems [30]. Predictive models have emerged as a famous approach to attain these benefits, and a few advanced models such as machine learning (ML) and deep learning (DL) have revealed extremely good results in the AVSCM domain. A significant feature that differentiates these predictive models is their capacity to be constructed for numerous prediction areas, confidence level metrics, and various modelling methods [6]. Such an opportunity provides predictive models to be employed in trend or sales demand analysis, forecasting the demand level under a given scenario, targeting the reducing cost of existing stock variables, and reducing waste by predicting on sound and primary data a few days before the actual delivery date.

Traditional supply chain systems lack the flexibility to foretell how assumptions built into an optimization problem may change in the real world [14]. Despite the vast interconnectedness, real-time data transmission among these systems that may entail high financial expenses is still a major problem. Therefore, many supply chain systems operate independently with little or no mutual interactions. As a result of these points, advanced optimization models could not be effectively executed within such supply chains.

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