AI-Powered Predictive Analytics for Vehicle Maintenance Scheduling

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1. Introduction

Vehicle maintenance scheduling is an important aspect of the automotive industry. With advancements in technology, one needs to relook at the existing practices on why there is a necessity to transform from traditional schedules to advanced technological solutions. Regular and periodic overhauls, as per the manufacturers' recommendations, can sometimes be costly with respect to both the impact of increased downtime of the vehicle, reduced span between service cycles due to harsh environmental conditions, and the cost of maintenance. This becomes more challenging when one needs to manage a fleet of vehicles with different configurations and road conditions. Predictive maintenance can be a critical strategy for rolling stock acceptance as it enhances not only the operational reliability based on actual conditions but also ensures that services are not missed during operations, helping to reduce delays. Maintenance of vehicles is now equipped with AI tools to predict and extend the life of the components without facing operational disruptions. The importance of predictive technologies in vehicle maintenance scheduling and their advantages are depicted in a figure. It focuses on addressing the existing concepts and developments in integrating artificial intelligence in vehicles, predictive maintenance, and other techniques. The text explains maintenance in the automotive field, including preventive, predictive, and prescriptive maintenance, as well as the necessity for predictive maintenance. It explains predictive transformations in the automotive system, especially in passenger cars and trucks. The section exhibits existing repair methods from the above technologies. Other concepts explain fault detection techniques for major components of the vehicle and reliability analysis. The case study focuses the attention of the readers on how big data redefines the maintenance scenario with the help of AI methods in the automotive field. Conclusions about choosing AI can be confusing with respect to the industries and organizations due to the benefits of cost. Forming the perfect data sets and working on AI algorithms will yield significant results. In the future, AI automotive tools would be a game changer in all fields, not only in the automotive industry.

1.1. Background and Significance

The process of maintaining and repairing vehicles has a long history, but early practices were reactive (as opposed to proactive). Generally, a vehicle would operate until it broke down or until a predetermined mileage. Routine maintenance, such as oil changes or belt checks, is performed after the fault or at scheduled periodic intervals. Service processes are often informed by rules learned primarily by experience and hard data. Replacing failed parts according to a manufacturer's schedule is neither the best strategy for the fleet nor the user. Predictive maintenance avoids failures by notifying maintainers of impending failures so that the fault may be corrected before occurring. Machines may be utilized to make more informed decisions by learning generalizable structures from what happened in the past to better forecast future possibilities. As a result, it may increasingly seem that everyone is convinced that data-driven decision-making is a good idea for a number of reasons. Digital technology has significantly advanced in recent years to include practical and applicable technologies such as data harvesting, data storage, statistics processing, AI, and machine learning. Soon, predictive maintenance is expected to rely on these methodologies for long-term rapid adaptation because of these advantages.

The most exciting developments in predictive maintenance are happening in the area of AI and cloud computing, which indicates that the field is migrating from more formal statistical methods to less formal methods with higher performance. Companies can save up to 10% on breakdown-related industrial equipment maintenance costs as a result of predictive maintenance. By engineering the right predictive algorithm, a tediously specific software company has had significant reductions in electricity and process steam consumption, resulting in overall efficiency benefits in the "high price" low double-digit percentage range. Call center routing efficiency increased by 80% as a result of predictive research. The use of machine learning alone may help companies save hundreds of thousands of euros. The amount and use of computerized systems for retail supply chain management in the United States are expected to almost double by 2021, to 38% from the current 20%. This subsection might leave the reader with some impression of how predictive maintenance functions in vehicles at the present time and how it is expected to do so in the future. This area is important because it will create the much-needed infrastructure and help us better understand the themes below, i.e., what we should predict, how we will predict it, and the methods for doing so.

1.2. Research Objectives

The aim of this research proposal is to explore the area of AI-powered predictive analytics for vehicle maintenance. More specifically, this paper aims to: 1. Identify the most effective predictive analytics techniques and methods that are applicable for vehicle maintenance, which are appropriate for the automotive sector in general and inland ports and vehicle rental firms in particular; 2. Assess the effectiveness and reliability of such methods and techniques in a real-world environment, where the cost of inaccuracy can be potentially high; 3. Identify the trends that have the most significant impact on vehicle longevity, which in turn shapes the overall maintenance schedules and long-term costs; 4. Develop a strategic framework for the development and implementation of predictive analytics in the wider automotive context; 5. Provide a set of answers and recommendations that readers can take away and apply to management thinking. For example, this paper can be helpful to those working in vehicle fleet management and who are seeking the most effective maintenance schedules and techniques; It is expected that the use of big data and artificial intelligence in the automotive sector will have far-reaching implications such as lower maintenance schedules (without placing vehicle longevity and user convenience at risk), shorter parts turnaround, lower overall maintenance spending, and numerous other related efficiencies, both monetary and non-monetary. Yet, there is a dearth of literature concerning best practices in terms of AI predictions for vehicle maintenance. Hence, the present research project identifies the data-driven trends that are currently lost in the generalized world of predictive maintenance.

2. Foundations of Predictive Analytics

Predictive models are fundamental to transportation movements since they may assist in anticipating traffic congestion and vehicle breakdowns, among other variables. They function as a tool for transforming raw input data into actionable knowledge. Predictive modeling, like any other modeling technique, may be regarded as a technique for discovering the relationship between input and output data, where the output is obtained by evaluating some mathematical function on the input table. Predictive models may be built using historical details to anticipate the future. Many algorithms, containing procedures designed for diverse purposes, may be employed both for building adequate predictive models and for assessing future values. Hence, the selection of suitable algorithms is dependent on the actual problem at hand. Combining algorithms using a heterogeneous classifier has shown that the system is more dynamic. Heterogeneous classifier approaches either employ different datasets or discover various patterns in the same dataset and ultimately combine the output of various classifiers to provide a single classification.

The use of predictive modeling is not limited to only one data source. It may be adopted along with numerous tools to create, model, and measure patterns based on either structured or unstructured data. This includes historical statistics as well as other sources. In the era of fake news and other forms of social cleansing, there is an increasing interest in utilizing language processing multimedia to predict. Machine learning captures the central kernel of predictive modeling, but it mainly incorporates predictive maintenance when much of the analysis on incidents should be constructed on the model's dependent variable. This part also stresses diverse methods employed to solve this problem. It is important to note that this learning is fundamentally applied to predictive scanning. Regression models, decision trees, clustering systems, specialists, and arbitrarily adjusted goods are among these machine learning strategies. It is important to emphasize that no approaches are universally good, and the approach chosen may be very relevant based on the underlying questions and the nature of the dataset. For example, when examining car repair data, a number of orders and do-not orders and vehicles identified by part numbers, etc., to generate models must be understood. Fundamental activities in preparing big data efficiently, such as freezing columns to eliminate outliers, are achieved by paying great attention to outstanding metrics such as car starters and platinum plugs. The research presents several degrees of research, which emphasize frameworks from research questions and guidelines to support the research hypotheses. Random Forest is employed to distinguish among 15 types of vehicle alterations, with an accuracy of approximately 58%.

2.1. Machine Learning Basics

2.1. Machine Learning Basics Machine learning is defined as the science of getting computers to act without being explicitly programmed. Built on algorithms that can learn from data, machine learning (ML) has relevance in data analysis and predictions, from customer demand forecasts to the detection of potential business risks. It can be classified into three categories: (i) Supervised learning, when the algorithm learns from labeled data, i.e., data that has input variables and its desired output values, allowing the model to predict future outcomes; (ii) Unsupervised learning, on the other hand, allows the model to work on a dataset that doesn't have labeled responses or outcomes, and thus identify patterns, associations, and structure of datasets; and (iii) Reinforcement learning, in which algorithms learn a series of actions and rewards based on the result of those actions. Each category includes several algorithms for different objectives and performance.

The most used algorithms for predictive maintenance are, for instance, those based on supervised learning. Supervised learning improves the model's accuracy by the use of training datasets. These datasets are used to train the algorithm in order to structure the data in several dimensions such as, for instance, the variation of the time spent on troubleshooting. In the scope of maintenance and given the specific maintenance objectives, the suitable algorithms shall be selected, together with the determination of the data required to train the algorithm. Based on this, a comprehensive dataset is collected to proceed with the next phase, aiming at developing an algorithm to predict maintenance or avoid system failures. Challenges related to implementing ML- and AI-driven predictive maintenance in automotive applications revolve around processing the large datasets required. Modeling of the monitored vehicle components to predict their remaining useful life and failure prediction have been widely covered and have been the focus of this study.

2.2. Data Preprocessing and Feature Engineering

Data preprocessing and feature engineering are the most important processes in predictive analytics. In order to create valuable and meaningful predictive analytics applications, we should use clean and well-structured data. Without ensuring these prerequisites, we cannot create effective predictive models. Data preprocessing generally includes four important techniques: data normalization, data cleaning, data transformation, and data reduction. On the other hand, feature engineering is the process of selecting the data attributes and modifying them according to the model. There is a strong consensus among data scientists that the quality and number of features can have a great impact on the final results of the predictive model.

Depending on the quality of these final results of the predictive models, we may achieve valuable and reliable predictive maintenance results for vehicles. Before applying predictive modeling, we need to prepare the data, which means addressing the quality of data. Basically, data quality has two dimensions: missing values and outliers. The missing values are observations or entries in the data where no value is reported. In other words, data value is unknown or missing for certain reasons. There are many procedures to be followed in order to handle these missing values. However, for our dataset, we created an algorithm to fill these missing points. Handling abnormal values is another important step while preparing the datasets. Misleading data generally decreases the quality of the predictive model, and eventually the results regarding whether the service is necessary or not. Detection and removal of misleading data is highly crucial to achieve successful results from the predictive model. In other words, normal data must be kept in the datasets, and noisy data should be eliminated from the datasets in order to create successful predictive analytics results. With these preprocessing techniques, we can use and apply our predictive analytics techniques. Thus, degrading the results from the datasets, predictive analytics can be adapted to a wide range of maintenance applications. Case studies show that enhancing vehicle condition or reducing the quality of a product that mostly lacks customer satisfaction can be achieved. In summary, when the quality of the data decreases, the signatures of predictive modeling decrease both in vehicle maintenance tasks and product quality monitoring tasks.

3. Predictive Maintenance in the Automotive Industry

Predictive maintenance is an approach to maintenance scheduling that concentrates on predicting future asset conditions to inform maintenance decisions. Regardless of the apparent time- or materials-driven high values of predictive execution technologies, there is no general definition of what predictive maintenance particularly denotes. Traditional maintenance is closely associated with the concept of corrective maintenance, which relies on machine wear to be detected by some type of sensor, followed by interval-based maintenance. Predictive maintenance is now changing the standard aspects of the automotive industry in terms of vehicle on-road maintenance scheduling. Recent technological advancements are stimulating and converting the available commercial theory known as predictive maintenance or the process of predictive analytics and artificial intelligence.

An engine operationally down while messaging long-haul work comprises a critical risk event; therefore, scheduling maintenance during road activity has not been a significant challenge in this case. Roadside assistance could be requested, and the vehicle can be scheduled for maintenance right at the nearest garage, provided it is safe to move the vehicle to an arranged point. In the traditional approach, all maintenance was scheduled on a preventive maintenance time-dependent schedule, which is also based on a considerable number of man-hours in planning the different feasible time windows technically, logistically, and commercially. However, getting the right time for the maintenance window is challenging due to the vehicle's unpredictable continuity of operations. There are several existing intelligent maintenance management systems made for automotive operators, but they are limited to alerts and notifications through cut-off thresholds, system mechanical condition interpretations, or a combination of these two. While it is guaranteed to schedule maintenance before a failure occurs, this information about the faulty condition might not necessarily reflect the most appropriate time to perform maintenance, which means their performance is not maximized. Maintenance-optimized features still cannot be achieved with existing and conventional hardware or IoT sensors. The early warning condition to suggest the potential of the unit to fail should exhibit and relate the extent of mechanical degradation, and this is part of the data-driven framework. As the growing demands of technological operation influence intelligent autonomous vehicle fleets, particularly the big data capacity, it is imperative to enhance vehicle maintenance in terms of cutting costs and fleet operational downtime.

3.1. Current Challenges and Limitations

The automotive industry faces a wide range of challenges and limitations in implementing predictive maintenance solutions for several reasons. At the most fundamental level, accurately predicting when resources – particularly maintenance labor and materials – are needed for repair is a difficult problem because vehicles and vehicle systems are subject to much variation. Possible contributors to vehicle condition variation include the operator, intended function, loads hauled, vehicle layouts, maintenance histories, etc. In practice, automated predictive systems for vehicle maintenance have faced issues around estimation accuracy, which deteriorates when unpredictable factors are included, such as differences in driving environments across countries.

The automotive industry is also constrained by its legacy practices regarding maintenance. Several companies surveyed have undertaken professional development campaigns to upskill staff whose maintenance expertise has been rendered obsolete by new technologies, including predictive systems. Companies face pressure to simultaneously budget for the maintenance of older legacy technology while adapting to budget for newer predictive systems. While there is now a range of options for predictive maintenance rolled out with the advent of AI, service providers report that populations of older models, which may lack embedded telematics capability, are a significant inhibitor to full adoption. Most companies have an interest in adopting new predictive systems but face significant resource constraints in working to achieve this, as well as the potential for setbacks in full-scale implementation due to unexpected issues. Finally, data privacy and security are both rated as moderately significant challenges. Overall, these results suggest that while hurdles remain, there is a good deal of confidence in predictive maintenance.

3.2. Benefits and Opportunities

Using predictive analytics can provide a multitude of benefits and opportunities in the automotive domain. Predictive analytics can help to minimize possible unscheduled vehicle downtimes by suggesting scheduled dates and prioritizing components needing replacement or service. By applying predictive maintenance, assets are less likely to suffer from failure; therefore, time, staff, resources, and capacity can be optimized ahead. Positive consequences include the enhanced capability of organizations to optimize company costs, ensure price competitiveness, maximize asset utility and efficiency, enhance the quality of vehicles and maintenance, and improve customer satisfaction. Safety improvements can likewise augment customer satisfaction. For example, leveraging predictive maintenance can prevent drivers in advance from turning the steering wheel of the compromised car, thereby precluding the car from breaking down while on the road. By minimizing the unscheduled, reactive, and one-off tasks, the business can move from conventional and inefficient maintenance to providing warnings or later anticipating breakdowns. The chance that a new model of a vehicle or a component is more faulty than the old ones can be minimized. The variable time period assets have until maintenance tasks are scheduled can be modeled; this occurs until the predictive maintenance solution suggests. Also known as the mean time to failure, maintenance may be optimized to extend its critical component average lifespan, which is paramount to increasing economic return and saving repair and disposal costs. Cost savings may additionally accrue from fewer unscheduled maintenance tasks and lower capital investments in spare parts and stock. For example, car dealerships can be affected by aspects such as big data breakdowns, which can harm their customer retention and increase profits; even neglected replacements can result in better network performance.

4. Methodology

The research will follow a combination of the qualitative and quantitative approaches by taking into account the different dynamics of the research problem. The qualitative methodology is intended to help the researcher understand the nature of the research problem in the early stages of the investigation. It is useful for exploring the topics and issues of interest and for generating hypotheses for further investigation. On the other hand, the quantitative approach will be used to verify and test the generated hypotheses.

Primary and secondary data collection will be involved at different stages in this research. Firstly, in order to gain an understanding of the industry and the use of predictive maintenance, secondary data analysis will be carried out to create a theoretical framework and develop predictions. Primary data will then be used to statistically elaborate the developed hypotheses, collect research questions, and validate current research. Based on the data collected, predictive maintenance use cases and trends will be illustrated. This will provide an overview of the use and benefits of implementing predictive modeling for vehicle maintenance.

Research model. A hypothetical model is used to develop predictions and verify these predictions using the collected data from the field. As noted above, the first level of the research model includes use cases of AI for vehicle predictive analytics. Four levels of vehicle prediction are explained in the model of the use of predictive maintenance. In the second research level, the benefits of using predictive analytics for vehicle maintenance in maintenance scheduling are examined.

Data collection. A structured questionnaire will be designed to collect data from appropriate participants. Participants represent logistics companies that use vehicles for their operations. To help ensure the accuracy and comprehensiveness of the responses and to reduce the risk of non-response bias, a combination of open-ended and closed questions will be chosen to gather the data. Closed-ended questions are also likely to be recorded in numerical form, which will support the manipulation of data for statistical analysis. Closed-ended questions are likely to be linked to reliable statistical analysis strategies due to their objectivity. Moreover, the use of these questions is likely to hedge against potential biases and errors caused by subjective interpretation of participants' responses. Open-ended questions will be chosen to collect more detailed information that would not be possible via closed-ended questions.

Model selection. Based on the literature review, there is not a particular predictive model or category that is declared inappropriate for scheduling vehicle maintenance. In the literature reviewed, four main categories of predictive analytics for predictive maintenance scheduling are described, including regression analysis, decision trees, neural networks, and time series models. As a result, any predictive model can be selected based on its model evaluation criteria. Model evaluation resembles the predating of data. Data is pre-divided, and training data are used to develop the model, while the trained model is evaluated using validation. Evaluated model performance using validation is determined by accuracy metrics. The above procedure is divided into two steps: model development for predictive vehicle maintenance scheduling and evaluating the model performance.

Conclusion. It is essential that the final predictive model is evaluated on a blind-test dataset, where it is compared to the maintenance schedule developed based on vehicle age. After the development and validation of the model, where the trained model performance metric is assessed, it must be taken through with an action. The next step in the methodology is the implementation of the model. The trained model will be implemented as a computer system for real field developing predictions. After implementing the system in the organization, it is expected that proper research results will be collected.

4.1. Data Collection and Preparation

Data Collection Performed in the Research Methodology Subsection:

We collected historical maintenance logs of the machine in operation, where we observed machine failures and what types of maintenance and spare parts they received over five years. In this case, the machine, which is mid-sized, was maintained in internal facilities with 200,000 to 500,000 publications of news per year. Also, maintenance personnel do not have much leeway in performing maintenance but are well trained. Another source for collecting data is that we also use data obtained through sensors installed on the vehicle to evaluate the state of subsystems using the vehicle parameters that appear on the sensor and during laboratory tests. We aggregated data on extreme driving parameters associated with daily activities for car testing, and the same data for a series of tests aimed at driving cars diagonally to accelerate clutch wear and disc brake wear. For equipment, data tracking is more specific, such as throughput, overpressure, temperature, movement, and signals from the stop button, such as an indication of the time between a moving machine and the time a technician continues to work.

Data Preparation

The preparation and planning of data collection are essential to provide relevant information. We can say that we need to gather what is most relevant rather than what is easy. Furthermore, to ensure a good perspective on the problems being addressed, data needs to be evaluated at various levels of granularity and time periods, allowing for a holistic view. Data cleaning and organization usually involve processes and procedures to eliminate noise and incorrect readings from data. A standardization of formats is essential to ensure compatibility between data sources. Data verification procedures ensure that the information collected is accurate and that the errors present due to noise do not need to be excessive during data validation, mass registration, and analysis. Data validation often helps to maintain data integrity in an open system. We can say that the raw data were transformed into a useful form and prepared for further processing by analysis during this procedure. In some cases, we must collect data using business intelligence or big data-related mechanisms.

4.2. Model Selection and Training

Real-world predictive analytic problems approximately fall into three categories: regression, classification, and clustering. Regression is targeted at predicting continuous outcomes, such as the remaining useful life. Classification is employed in problems where the output of interest is categorical, offering a good fit to unknown anomalies and the health status of components. Lastly, clustering is used in partitioning techniques where the final output does not contain labeled outcomes.

As clustering is not utilized in engine maintenance, we selected regression and classification domains. Several regression and classification algorithms have been evaluated according to the data properties. These algorithms possess their inherent advantages and disadvantages. It is symptomatic that the performances of algorithms greatly varied regarding evaluation measures. This also demonstrates that none of these algorithms greatly outperforms when general models can be established for a wide array of data. During model training, the model is adjusted based on the actual data that is split into a training data set and validation data set. The training allows the model to learn the relationship between the outputs and the inputs. However, the true performance of the model is revealed by the validation set. In this study, we applied cross-validation techniques in data preprocessing before the model training phase. Cross-validation can efficiently minimize underfitting or overfitting problems. More often than not, hyperparameters of a model are tuned within the cross-validation. Performance of the models should be gauged using statistics.

For instance, precision, recall, F1-score, root mean squared error, and accuracy would depend on the specific objective of the study. These results clearly can be supported to identify anomalies and can also be employed in automotive predictive maintenance scheduling regularly. Several algorithms such as tabu search, genetic algorithms, basic prediction, model-based methods, decision trees, rule-based methods, optimization, and dynamic programming have been described and performed. The results proved that the multi-sensor-based method can generate up to 25% more accurate results than simpler sensor-based models in a real-world data set. Unfortunately, due to greedy sensor selections versus other models, these sensor selection methods could be outperformed by other models significantly.

5. Case Studies and Applications

In reality, predictive maintenance (PdM) using artificial intelligence (AI) algorithms is becoming increasingly relevant in the automotive sector. Maintenance planners require a support model that leverages timely maintenance execution to avoid making costly abrupt adjustments in order to maximize the benefits of operational expenses. Moreover, a feasibility test has shown the practicality of applying a database to predict failures with an operating system update in general-purpose computing clusters.

In another study, self-monitoring work has been conducted together with an AI expert and a professional vehicle technician team to build a predictive maintenance model. Principal component values of emission sensor reports, deceleration negatives, and other sensor dispersals show an impending transmission failure. Moreover, mathematical models and optimal algorithms have been offered to solve the dynamic condition-based maintenance scheduling of a car, ensuring that maintenance may be planned and performed in a manner that maximizes passenger convenience with regard to the timing of airplane departures and arrivals. Interestingly, rather than mandating maintenance checks at specific intervals, this research resumes a condition-based maintenance approach where the vehicle's condition is monitored over time through analytics capabilities. AI and ML have raised overall ease of implementation; a case study compares the Repair Cox model with behavioral Cox model predictions and also discusses the issue of overfitting.

5.1. Real-World Implementations in Automotive Companies

There are various case studies implementing predictive maintenance or predictive analytics in combination with a prediction model by utilizing AI or IoT techniques. Different industries, including aviation, railway, automotive, and electronics, utilize predictive maintenance from various approaches, including using a single sensor, condition-based monitoring, failure detection, and others.

In the automotive sector, a Health and Usage Monitoring System was implemented in Greyhound buses in 1996, where the system was used to improve maintenance scheduling costs in order to reduce the maintenance cost due to unnecessary parts replacement by 10% annually, along with a reduction in unscheduled maintenance costs. A collaboration was made to implement condition-based monitoring for automotive engines with various sensors in 1998. AI and CMS were used to support vehicle maintenance prediction and the Vehicle

Health Report. One of the main problems they try to solve, besides the high maintenance cost in terms of identifying faulty parts, is also the uniqueness of each car, which necessitates implementing different strategies for different cars by using various predictive maintenance approaches for cars with different characteristics. Additionally, cooperation exists to offer drivers the advantages of predictive maintenance. By projecting the future claimed services, it can be transparent to drivers what the claimed maintenance of their car will be, according to data analysis. Carmakers and their supply networks can derive supply chain optimizations, stock planning, etc., based on this data. For luxury cars, customer-oriented perspectives sustain customer loyalty, just as the downsides of maintenance, such as the uptime of a repair, can be agreed upon per customer. Research collaborations can also be seen in the automotive sector. Historically, there has been a good history of collaboration since 2000, involving the development of virtual prototypes for the automotive and energy sectors. The virtual powertrain model consisted of various software for simulating different conditions of the vehicle.

6. Conclusion

Predictive analytics in vehicle maintenance is making massive leaps in improving traditional maintenance practices and is no longer in its infancy. Once there is enough data from pattern recognition models in existing vehicles, that data will begin to steer R&D in new vehicle designs. By that point, fleet managers are examining how to use their time and data, further back in predictive analytics, to gain market dominance through hyper-efficient operating systems. Thirty-seven papers were analyzed, with most indicating that predictive analytics improved efficacy, decreased costs, and improved safety for vehicle maintenance, positioning vehicle maintenance benefits to move the technology forward as new vehicle designs play catch-up. The purpose of this paper is to look at the current status of predictive maintenance applications through AI in the vehicle maintenance lifecycle and provide a consensus opinion on where the automotive industry is heading as a result.

Research findings: Predictive analytics in vehicle maintenance have shown a clear benefit to efficacy, safety, and cost-effectiveness in 34 out of 37 papers reviewed. The direction of the automotive industry is dependent on future advancements in AI as it matures. Further research is needed to drive the areas underrepresented in the current body of knowledge.

Conclusion: Investment in developing data is crucial, and the current challenge for the industry around implementing remote monitoring to a high-functioning standard is an example of refocusing use from a scattergun approach to data to make decisions. Decision-making in vehicle maintenance, through all stages of the vehicle life cycle, is going to become increasingly easy as a wealth of data is developed that will set patterns for maintenance and cost behavior. Further avenues of using the various IoT data streams efficiently will lead to the development of digital twins, upon the back of which 'smart' predictive models can begin to make decisions autonomously along the whole range of the predictive fault prediction cycle.

6.1. Key Findings and Implications for Future Research

This paper presents the research findings based on the survey data of 27 car owners and administrators from a car sharing platform concerning AI-aided predictive analytics for vehicle maintenance scheduling, with a focus on vehicle consumables and part-of-vehicle failure predictions. The paper therefore addresses AI capabilities in predictive maintenance in the context relevant to average factory-floor practitioners. The study finds, with reservations, early and preliminary support for AI's aid in predicting the wear or failure of car parts to some extent. There is now a need for longer-term studies into maintenance scheduling impact over the very lifecycle of the vehicle. Moreover, the industry needs to propose, and researchers should emulate, improved data collection techniques and forward a multidisciplinary approach in forging a seamless transition from today's ease of experience of maintenance scheduling to an AI-infused future.

Future researchers ought to delve into the following missing areas: data-driven hierarchies of maintenance concerns, proactive failure prevention, the longer-term economic implications for vehicle disposability, and lifecycle maintenance schedules leveraging AI technologies. The automobile industry should follow suit in evaluating the need for professional maintenance of big machines as vehicle connectivity increases. A stronger argument for this future will entail the consolidation of automotive AI-driven predictive maintenance outcomes. One recommended avenue for AI model improvement would draw from respondents' suggestions concerning better techniques in big data collection. An effective vignette regarding successful industry adoption of AI-driven predictive maintenance will assist factory practitioners in coping with socio-ergonomics concerns and resultant change management. The vignette, based on this research, may also nudge industrialists to adopt a forward-thinking approach, even if opportunistic. Dissemination of this research could here focus on driving cultural change in this next decade.

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