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Towards a Resilient Automotive Industry: AI-Driven Strategies for Predictive Maintenance and Supply Chain Optimization

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Abstract: This paper discusses strategies for the automotive industry derived from maintenance and supply chain optimization technology. It emphasizes the potential of AI systems and includes a survey-based study on adopting these solutions by auto parts manufacturers globally. The strategies provided offer long-term solutions and show the importance to manufacturers worldwide. The study predicts that AI-driven solutions will soon become necessary in the industry, providing credibility to the suggested strategies. This work provides insights into adopting AI-driven systems in today's scenario.

Keywords: Supply Chains, Predictive Maintenance, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML)

I. INTRODUCTION

Predictive maintenance for equipment aims to preserve reliability by monitoring conditions and predicting failures. It reduces costs and prevents unexpected failures. Failure mode and effect analysis is a standard method for assessing maintenance needs. The automotive industry began in 1769 with the first self-propelled vehicle. Wars caused a dip in development, but post-WWII led to advancements. Today, technology drives the industry, impacting cost and leading to predictive maintenance. The automotive industry is vital to the economy, providing jobs and influencing supporting industries. Cars have become essential in people's lives.

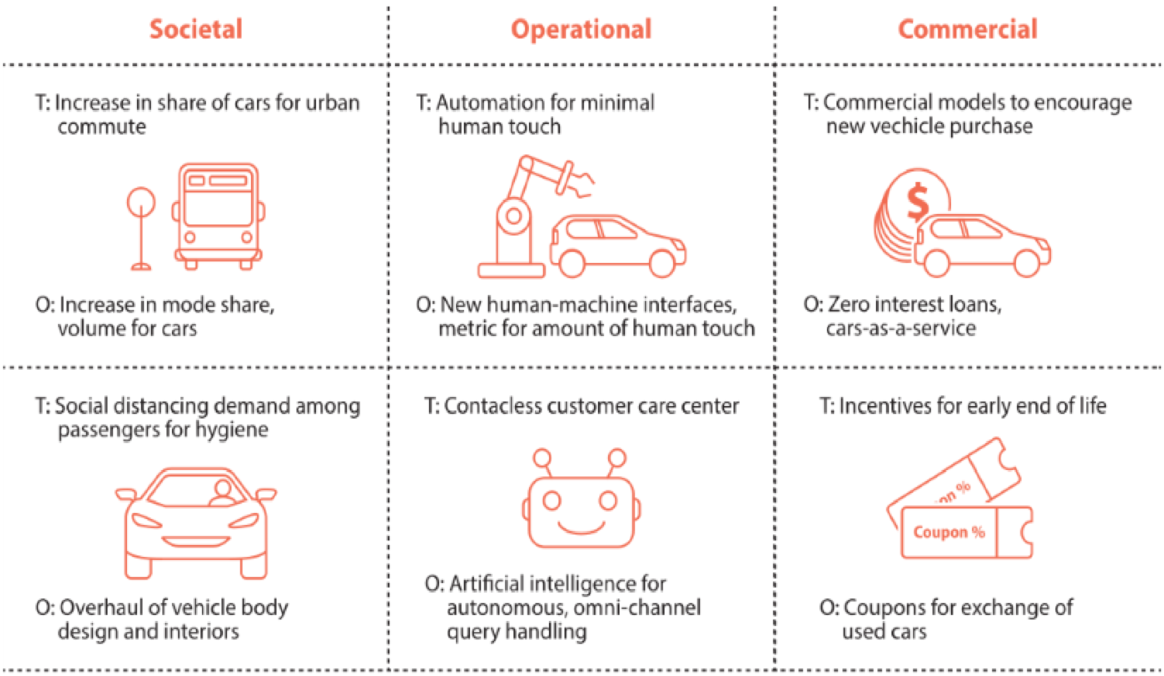

FIGURE 1. Transformation in the Automotive Industry

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1.1. Background

The predictive maintenance concept provides a technique to detect equipment failure before it happens, prevent unscheduled downtime, improve system productivity, plan maintenance activity, extend machinery life, and save costs. Winandyo, P. (2011) refers to predictive maintenance as a maintenance activity that prognosticates the probability of equipment failure to plan the maintenance activity. There are many ways to predict equipment failure; one of the most common is equipment condition monitoring. In the best scenario, condition monitoring is implemented online with monitoring and online analysis methods such as vibration monitoring and analysis, motor current signature, oil, and infrared thermography. If an abnormal trend of a specific equipment condition is noticed, one can then plan a scheduled maintenance activity before the equipment fails. Online condition monitoring is very powerful, but it is quite an expensive implementation. The alternative way to condition monitoring is through offline analysis, where the monitoring itself can be more straightforward than online monitoring, and the analysis can be performed at another time and place using historical data. Another way to implement predictive maintenance is through technical expert system analysis and equipment reliability testing analysis, but both are more complex than condition monitoring.

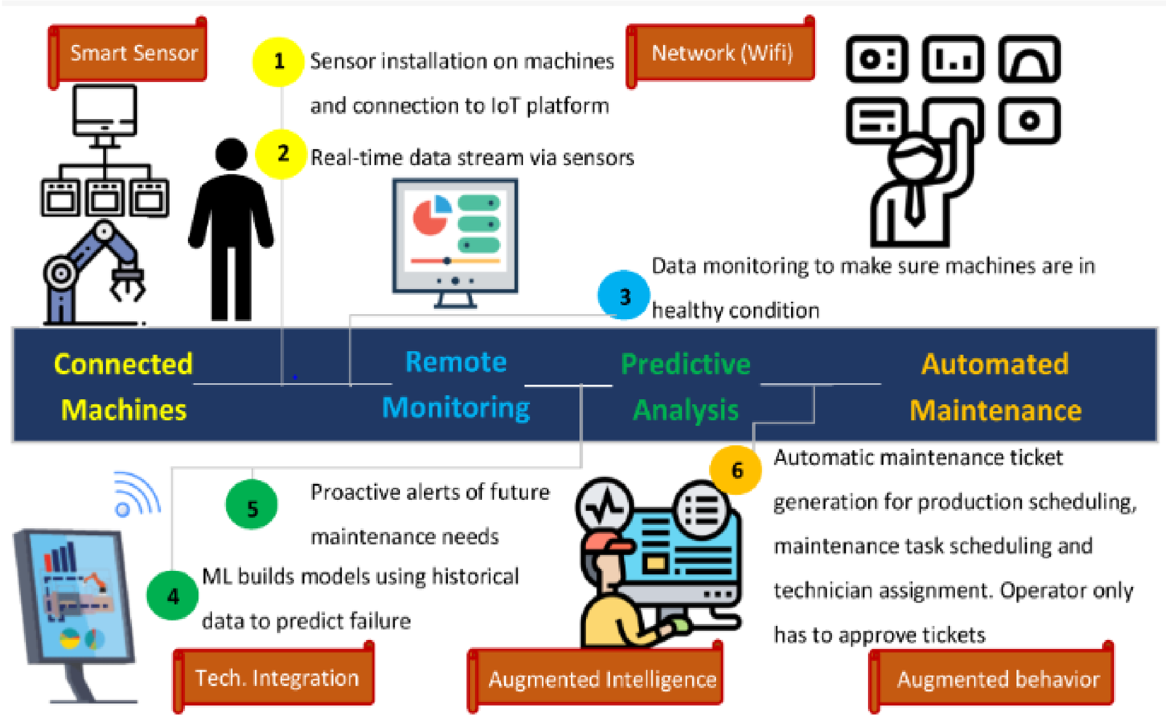

FIGURE 1.1 Process and technologies to drive

1.2. Problem Statement

The problem for this paper is the downturn in the automotive industry and the need for new technologies to compete in an aggressive market. Trends include high costs, short lead times, customized production, flexibility, product quality, inventory reduction, and sustainability. Testing and validation are crucial for product success. These challenges are seen in multiple industries, but the automotive industry considers them crucial for survival. Economic conditions have led to consumers holding onto their vehicles longer, creating a market for high-quality aftermarket parts for OEMs.

1.3. Objectives

The car industry is seeking ways to maintain global competitiveness and sustainability amidst the COVID-19 crisis, which has brought about significant changes. The crisis highlights the need to assess the industry's resilience and global supply chain strength. AI and machine learning can improve industry resilience and reshape global supply chains. While the automotive sector has limited AI applications in production and distribution, it excels in data analytics and ML for after-sales services and spare parts logistics. This paper examines the current landscape and explores how AI can enhance industry resilience, particularly in supply chain flexibility and risk management.

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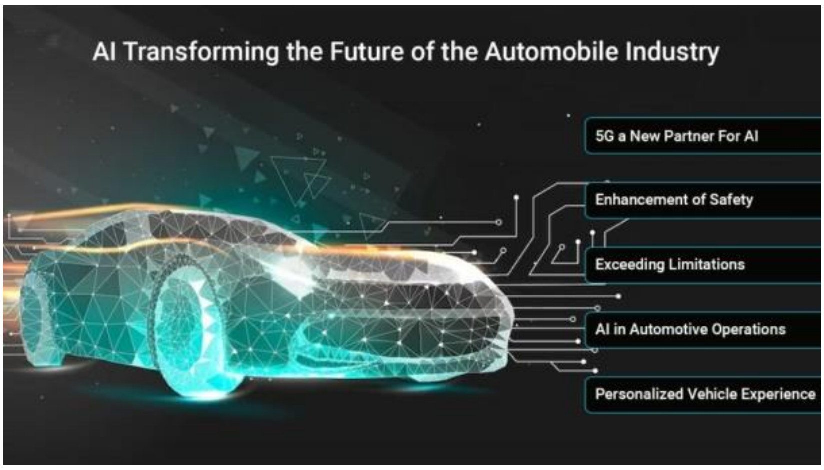

FIGURE 1.3 AI transforming the future of the Automobile Industry

II. PREDICTIVE MAINTENANCE IN THE AUTOMOTIVE INDUSTRY

From a simplistic viewpoint, a *maintenance policy* can be defined as a set of rules and actions determining what needs to be done to restore a system to a given condition. These rules and actions are often functions of time T. Maintenance is said to be preventative if actions are taken before the system has failed and corrective if those actions are taken after a failure. The aim of a maintenance policy may be to minimize the downtime of a system, extend the duration of the system in a particular state, or prolong the time until the system reaches a state where the maintenance is more extensive. Maintenance is often considered to minimize the costs of maintenance, lost system performance, and, in some cases, damage due to failures. *Predictive maintenance* is a policy that determines when a device will likely fail so that maintenance can be performed just before this point.

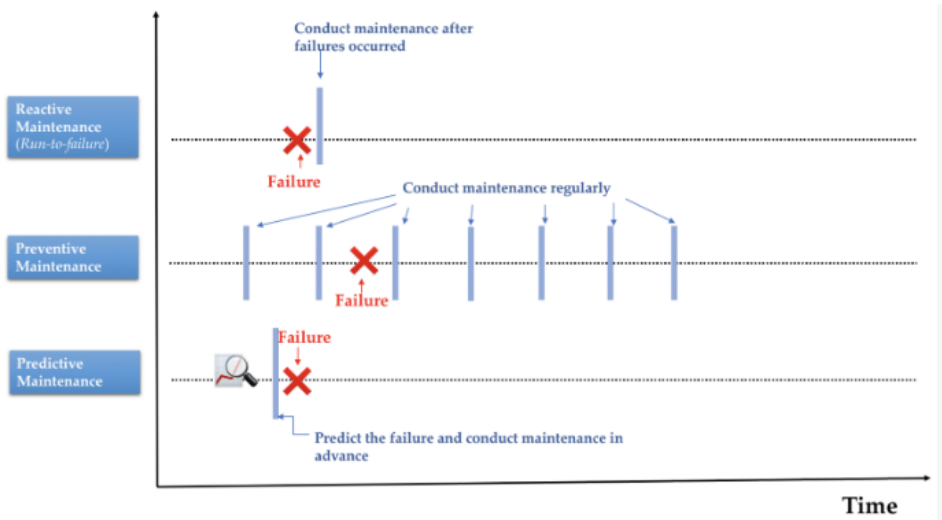

FIGURE. 2 Maintenance strategies

2.1. Definition and Importance

Predictive maintenance, in the simplest of terms, is a method that anticipates and plans repair work for a company's equipment. This is an alternative to a traditional 'run-to-failure' approach. It involves analysis of a piece of equipment and its failure modes. This analysis depends on the specific machinery's cost, function, and criticality. The data collected from this analysis is then converted into useful information so that maintenance work can be carried out more effectively than maintenance tasks at an arbitrary time.

An example of this could be assigning a maintenance worker to lubricate a ball screw on a CNC machine that has been determined to have low lubrication and has a high failure chance concerning the costly ramifications associated with repairing the whole unit if it were to fail. This method can still prove to be difficult because the worker may not recognize

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the specific ball screw in question. This is where the data would be converted to a higher efficiency level, and workers would be notified to carry out this specific task when the machine is not in operation. Predictive maintenance has existed for a long time. However, it has become relevant when utilizing various machine learning methods such as Artificial Neural Networks, Fuzzy Logic, and Proportional Hazards Model.

2.2. AI-Driven Approaches

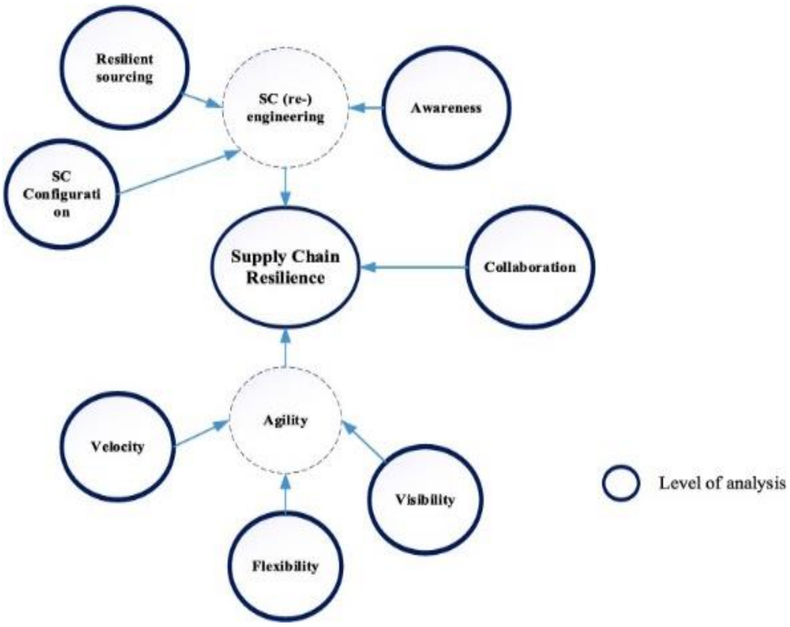

FIGURE 2.1 Artificial intelligence techniques for enhancing supply chain resilience.

Predictive analytics uses data mining, predictive modeling, and machine learning to identify future outcomes based on historical data. It is widely used to predict equipment failures, particularly in the automotive industry. AI techniques play a critical role in predictive maintenance, as they require less prior knowledge and can automatically identify important features from data. Traditional statistical methods and physical models can be complex and require a deep understanding of the equipment. In contrast, machine learning methods, such as support vector machines, can handle complex non-linear relationships and lead to more accurate predictions. Successful case studies demonstrate the potential for AI-driven predictive maintenance to reduce costs by improving accuracy and reducing unnecessary maintenance.

```
# Ploting
plt.figure(figsize=(10 , 5))
plt.bar(range(1, eig_vals.size + 1), var_exp, alpha = 0.5, align = 'center', label = 'Individual explained variance')
plt.step(range(1, eig_vals.size + 1), cum_var_exp, where='mid', label = 'Cumulative explained variance')
plt.ylabel('Explained Variance Ratio')
plt.xlabel('Principal Components')
plt.legend(loc = 'best')
plt.tight_layout()
plt.show()
```

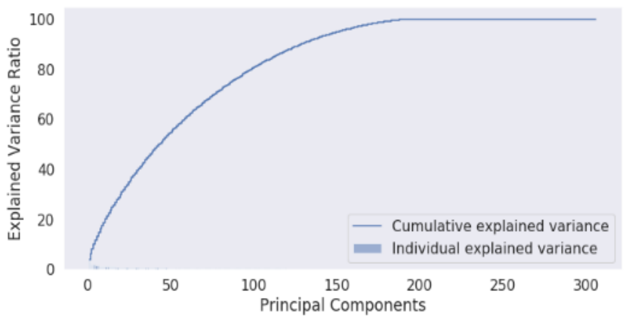

FIGURE 2.2.1. Variance values

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2.3. Benefits and Challenges

Predictive maintenance will bring several benefits to the automotive industry. Firstly, it will help maximize the useful life of factory assets, whether the machines, production line equipment, or facilities. By creating a system that can predict the degradation of parts, there will be savings on costs for replacing the part since it would be done at the most economically viable time, for example, when the car is in for a service, as opposed to replacing it when it has just failed, which could cause a more severe failure in another part and more costly downtime of the vehicle.

This extends to interruptions to the supply chain for automobile manufacturers since, should a part fail and cause production to stop on a vehicle, this vehicle will likely be diverted to the maintenance line and the part replaced there. By predicting part failures and doing maintenance at the opportune time, the carmaker can minimize the impact on production and the need to divert vehicles from their intended destination.

FIGURE 2.2 Artificial Intelligence (AI) in Benefit statistics

2.4. Case Studies

In the first case study, imagery data from transmission oil were analyzed to detect the abnormal wear condition in the bearing and to classify the different stages of bearing failure—the statistical comparison of vibration and image analysis methods results are highlighted.

Detailed analysis and designed experiment provided an optimistic assessment of the bearing condition. It was concluded that the best possible results were obtained from the information fusion of vibration and imagery analysis. The vibration method was also used to provide the maintenance staff with an easily interpreted diagnosis of a fault, its location, and severity.

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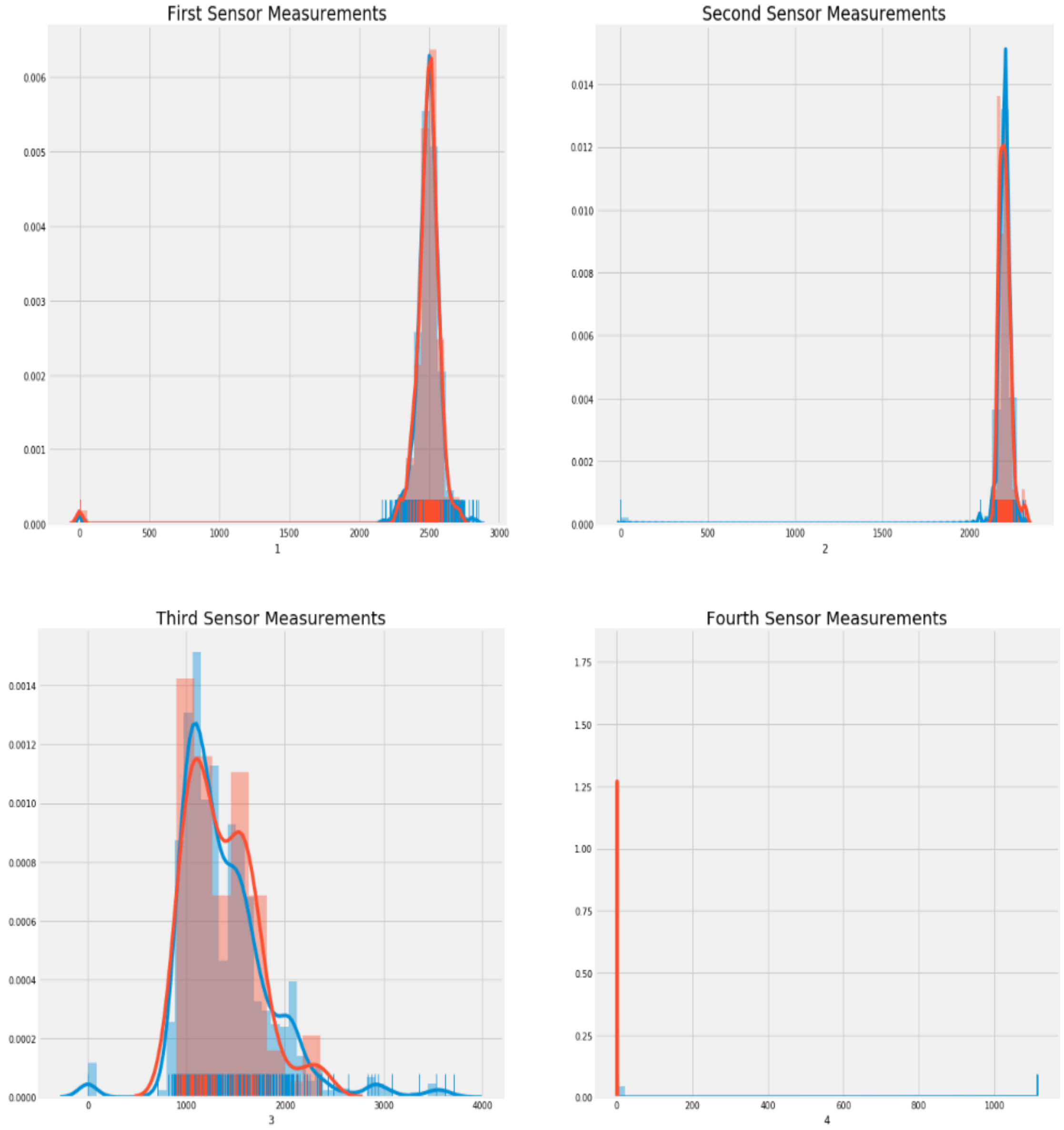

FIGURE 2.4.1 Sensor values

The second case study explores the prognostics of a cooling system's performance of a city bus to move from time-based to condition-based maintenance. Data was collected from buses with various component fault levels and healthy buses.

A model-based method was employed to detect and diagnose losses of cooling system performance, with a staged approach using simple to complex models if a fault is detected. The effectiveness of the developed prognostic indicator for a fault was evaluated using retrospective data from in-service buses. Step-by-step guidelines and lessons learned are provided for applying prognostics to other automotive systems. Significant maintenance cost savings are expected from the results of these case studies.

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III. SUPPLY CHAIN OPTIMIZATION IN THE AUTOMOTIVE INDUSTRY

FIGURE 3. Latest challenges in Manufacturing Segments in the automotive industry

Modern automotive supply chains are highly complex, with lengthy sales predictions, supplier delivery time, and ample storage capacity. The industry faces constant demand changes and strict legislation, creating uncertainty. Supply chain optimization aims to improve coordination and control to increase responsiveness and flexibility and reduce costs. AI technologies offer new opportunities for efficiency in the automotive industry.

AI technologies can gather vast quantities of new data through IoT devices, such as micromachine units, which track parts in real-time. Simulation is a crucial tool for supply chain optimization, and AI-driven simulation, enhanced by machine learning, allows for automatic optimization. AI can automate supply chain decision-making through intelligent agents with autonomy and adaptability. However, effective implementation requires a critical mass of digital supply chain information.

3.1. Overview and Significance

Due to globalization and competitive pressures, the automotive industry operates in an uncertain environment. The industry faces challenges such as technological developments, regulatory policies, consumer demand, reduction of overcapacity, and supply chain risks. Maintenance is crucial for the industry's competitiveness due to high capital intensity, automation, and technical complexity.

It affects equipment failure costs and product quality. AI and data-driven approaches offer cost-effective solutions for maintenance improvement. Maintenance impacts the entire supply chain, affecting production and supply chain performance. However, maintenance has received limited attention in the academic supply chain and risk management literature. This indicates a need for more understanding of its strategic implications.

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3.2. AI-Enabled Techniques

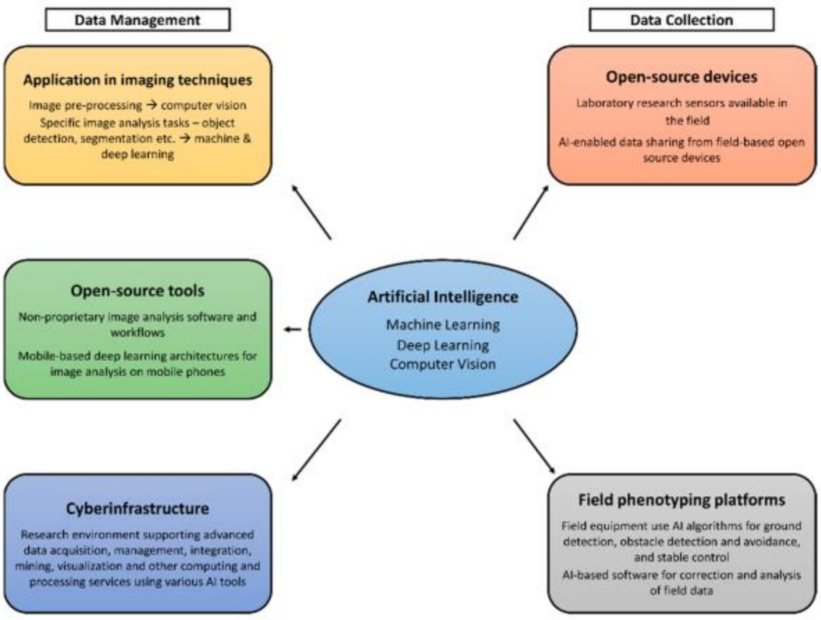

FIGURE 3.1 Applications of AI

AI and predictive modeling are essential for optimizing the automotive industry's complex supply chain. Managing the chain is challenging due to various unpredictable events, like quality issues, capacity shortages, and supply-demand mismatches. The industry needs to reduce costs and enhance efficiency to stay competitive. Improvement opportunities exist due to the significant gap between current supply chain performance and the level required for competitiveness. Predictive modeling extracts knowledge from historical data to predict future events or find hidden patterns. It improves supply chain decision-making by identifying scenario impacts and automating decisions. This is valuable in the automotive industry due to long product life cycles. However, data mining and predictive modeling support decision-making rather than fully automating it.

3.3. Key Factors and Considerations

FIGURE 3.3 Ethical frameworks proposed in this work in the context of sustainable cities

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Predictive systems in automotive companies must address concerns about data accuracy and reliability. Implementations often need more time due to unforeseen data issues. For long-term success, predictive maintenance requires ongoing data collection, quality, and analytics improvement. The cultural shift towards predictive analytics can be challenging. Resistance may arise, mainly when production uptime is considered satisfactory. Efforts must be made to support team members with doubts. Implementing predictive maintenance reas with small pilot projects, critical areas, etc., can demonstrate its value. Decision-makers should be patient, as quick results are unlikely. Cost reductions and time savings may be difficult to accept for those accustomed to traditional methods. Changes in KPIs and a decision-making culture based on predictive output indicate full system acceptance.

3.4. Real-World Applications

Supply chain optimization is critical for efficient production and is especially important in the automotive industry. The need for efficient material flow and aftermarket service, along with the costs and risks associated with inventory and stockouts, have led to a surge of interest in solving this problem using artificial intelligence. Given the size and complexity of supply chains and the fast-paced competitive environment, more than traditional manual methods are required.

Real-world supply chain problems have multiple constraints and objectives, making them complex and challenging for traditional decision-support tools. AI techniques, such as case-based reasoning, genetic algorithms, neural networks, and operations research, can effectively address these challenges and be applied to model building, optimization, and simulation.

FIGURE 3.4 Real-World Applications

Stephane Lepoint discussed how constraint programming in production systems at Ford led to potential savings of 100 million dollars. CP produced nearly optimal plans in a fraction of a human planner's time. Ford also used CP successfully for shipping schedules. AI simulation models are adaptable and learn from experience. Monitoring supply chain situations and automating the supply chain with intelligent agents shows promise and is a growing application for AI techniques.

IV. INTEGRATION OF PREDICTIVE MAINTENANCE AND SUPPLY CHAIN OPTIMIZATION

The automotive industry sees predictive maintenance and supply chain strategy as separate cost centers. However, integrating the two is essential as their impacts on each other are becoming more apparent. The recent downturn in automotive sales highlights the importance of supply chain efficiency and its relationship to demand-pull production.

A reliable predictive maintenance system reduces spare parts inventory and improves supply chain efficiency. Research at The University of Nottingham focuses on scheduling methods for predictive and condition-based tasks to minimize maintenance costs without increasing equipment failure risk. This approach also has implications for optimizing a multi-echelon supply chain. A holistic approach to maintenance and supply chain strategy is best achieved through integration.

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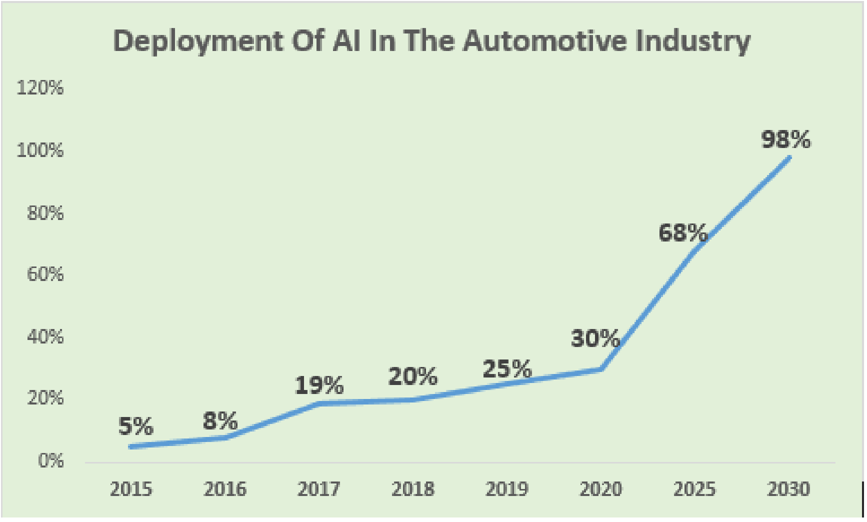

FIGURE 4. AI In Automotive Industry Examples of AI in Auto Industry

4.1. Synergies and Interactions

In a supply chain, a failure anywhere can affect the availability of finished vehicles. Supply chain disturbances impact production schedules and equipment maintenance. Conversely, production equipment affects lead time and flexibility. For example, if a paint shop conveyor fails, redirecting bodies to another shop increases flexibility. Understanding the relationship between maintenance and the supply chain can reduce the impact of disturbances. Integrating predictive maintenance and supply chain optimization is a crucial area of future research. Decision-makers need a method for determining the best actions based on predictive information and heuristics.

4.2. AI-Based Strategies

Predictive maintenance (PdM) involves determining when equipment will fail to prevent costly damages. AI techniques, such as anomaly detection and machine learning models, can be used to predict the equipment's remaining useful life (RUL). This requires a large dataset or example data from similar equipment. ML models should use features that are easily obtainable from online sensors. Integrating the RUL prediction model with scheduling software can optimize maintenance. A case study in the electricity supply industry exemplifies the combination of PdM and AI for maintenance scheduling.

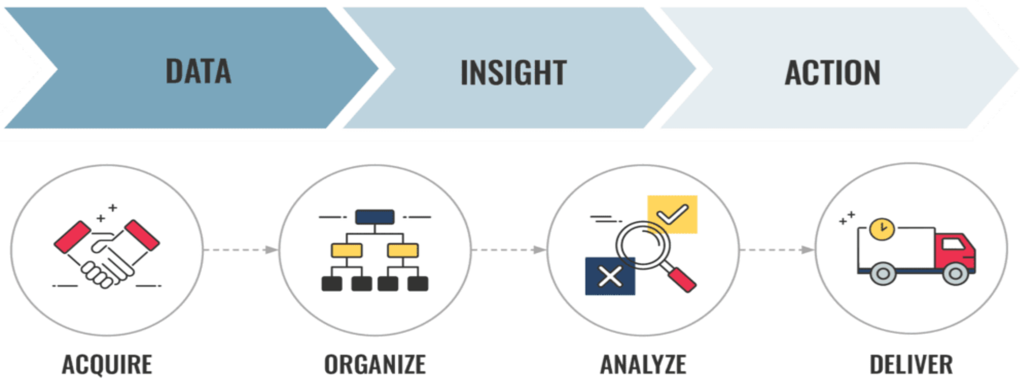

FIGURE 4.2 AI-Based Strategies

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4.3. Impacts on Efficiency and Resilience

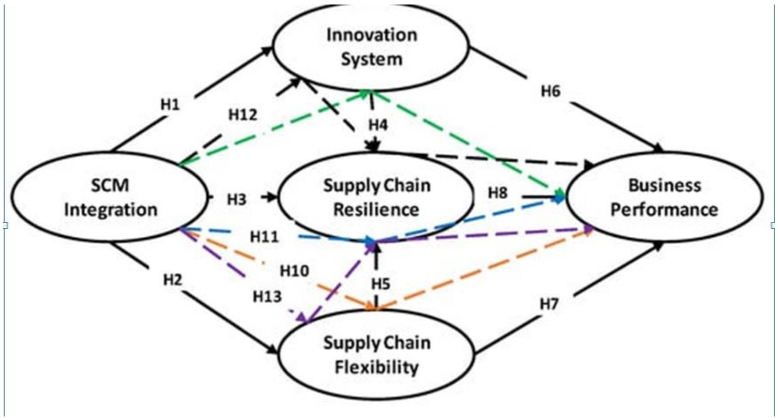

FIGURE 4.3. Impacts on Efficiency and Resilience

Predictive maintenance and supply chain optimization are crucial for efficiency and resilience. They prevent disruptions, enable alternative sourcing during disruptions, and capitalize on market dips for competitive advantage. These technologies impact efficiency by allowing better planning and execution of production activities, reducing overtime and rushed production. In a case study, scheduling stability from effective maintenance increased average output by 10%. It also reduces inventory and back orders for maintenance-critical parts. Proper maintenance timing prevents secondary equipment damage, saving maintenance costs. Predictive maintenance extends the life-cycle output of a manufacturing system by minimizing time-based maintenance, offsetting the effects of increased automation.

4.4. Future Directions and Research Opportunities

FIGURE 4.4. Key Drives AI in Automotive

The first direction is to extend optimization models for dynamic and stochastic formulations in predictive maintenance. This includes multi-period maintenance scheduling and maintenance/inventory control under uncertainty. Research in this area is still in its early stages, offering opportunities for future work. The second direction combines operations research and AI techniques for practical impact in supply chain management and maintenance scheduling. Empirical validation through industry case studies is necessary to bridge the gap in the market for predictive maintenance technologies. Collaboration between the research community and industry is essential for accessing realistic data and assessing practical impact.

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```
Recall = np.array([84.4, 87.9, 81.3,9.4,0,0,0])
label = np.array(['Isolation Forest', 'Local Outlier Factor', 'Elliptic Envelop',
                  'Logistic','XGBoost','Random Forest','Lasso'])
indices = np.argsort(Recall)
color = plt.cm.rainbow(np.linspace(0, 1, 9))

plt.rcParams['figure.figsize'] = (18, 7)
plt.bar(range(len(indices)), Recall[indices], color = color)
plt.xticks(range(len(indices)), label[indices])
plt.title('Recall Accuracy - Normal Data', fontsize = 30)
plt.grid()
plt.tight_layout()
plt.show()
```

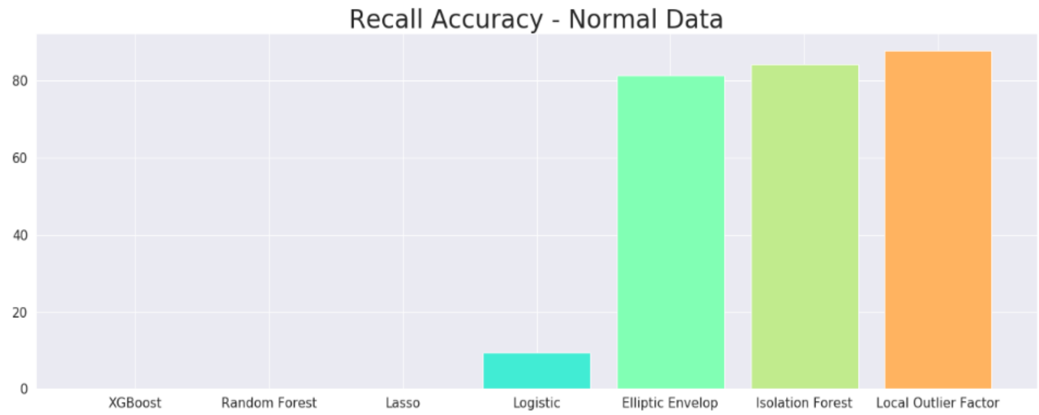

FIGURE 4.5. Algorithm comparisons

V. CONCLUSION

The automotive industry has changed rapidly in the past two decades due to the rise of the Internet era. AI technologies are playing a significant role in this progress. The industry now includes various markets and complex procedures. Maintenance and supply chain are crucial components. Predictive maintenance strategies benefit consumers and providers by anticipating issues and providing solutions. AI technologies can also simulate supply and demand scenarios, helping manufacturers make informed decisions. Implementing these strategies will result in efficient services and lower operations costs. The industry will become more adaptable to technological change.

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BIOGRAPHY

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