Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 10s (2025)

Machine Learning-Based Data Strategies in Automotive After-Sales Services: Systematic Literature Review

Yuly Kridiawan[1], **Harco Leslie Hendric Spits Warnars**[1], **Harjanto Prabowo**[2], and **Sfenrianto**[3]

[1]Computer Science Department, BINUS Graduate Program - Doctor of Computer Science, Bina Nusantara University, Jakarta, Indonesia. {yuly.kridiawan, spits.hendric}@binus.ac.id

[2] Management Department, BINUS Business School Undergraduate Program Bina Nusantara University, Jakarta, Indonesia. harprabowo@binus.edu

[3] Information Systems Management Department, BINUS Graduate Program – Master of Information Systems Management, Bina Nusantara University, Jakarta, Indonesia. sfenrianto@binus.edu

Article History:

Received: *12-01-2025*

Revised: *15-02-2025*

Accepted: *01-03-2025*

Abstract:

This study presents a systematic review on machine learning-based data strategies available in the automobile after-sales service research area to offer insights about currently published studies, their predominant trends, related challenges and their future directions. Using systematic literature review (SLR) methodology, 508 articles were initially sourced from Scopus, with 23 articles selected as meeting the inclusion criteria for deeper analysis. This paper aims to look into machine learning making methods and tools, datasets and their applicability in fostering data strategies for after sales service. Results show that supervised learning techniques such as Support Vector Machines, Random Forests and Neural Networks are especially useful for predictive maintenance and demand forecasting. On the other hand, it is utilized on data without labeled output by unsupervised and reinforcement learning for anomaly detection and decision making too. This also contributes towards enhanced efficiency, better utilization of resources, and higher overall customer satisfaction in automotive after-sales services through deep learning via TensorFlow, Keras, and MATLAB, along with diverse data sets. The elevated application of the ways to manipulate data aspire for a better approach to achieve increasing operational efficiency, improved customer satisfaction and agile solutions in real-time. Variety of data, privacy challenges and a lack of better standards, however, are limiting wider usage. Further studies in particular concerning real-time data and holistic studies, especially covering dealers as representative of after-sales service, shall be at the forefront of future studies. This study bridges the gap by synthesizing the machine learning applications in automotive after-sales services to establishing valuable insights that will guide academia and praxis in applying more practices and methods based on data and prediction of customers to boost the sustainability of after-sales services in the automotive sector.

Keywords: Automotive Industry, After-Sales Services, Machine Learning, Data Strategies, Predictive Maintenance

1. Introduction

The automotive sector continues to be a key contributor to the global economy, adding to both Gross Domestic Product and jobs. In fact, over the last few decades, the industry has seen a metamorphosis due to many factors including the COVID-19 pandemic and the shift towards electrification[1]. These changes create new challenges to automotive manufacturers from all around the world, not only while dealing with the volatility of new vehicle sales while having to face falling margins, but also while having to cope with the growing complexity of vehicles and changing customer expectations.

Consequently, automobile manufacturers have been focusing on the more resilient and a major revenue and client retention contributor avenue of after-sales services. Automotive after-sales service has seen a transition over the years that has led to the emergence of several innovative data-driven strategies to improve efficiency and customer-centeredness.

Faced with these challenges, automotive manufacturers have turned their attention to after-sales service, which has proven to be more recession-resistant and a key contributor to maintaining customer loyalty. Data-driven strategies and the application of technologies such as machine learning are considered crucial in improving the efficiency and quality of after-sales services.

This leads automotive manufacturers to turn to after-sales service that has become a key contributor to improved loyalty with far greater recession resistance. So improving the efficiency and quality of after sales services is regarded as being feasible with data-driven strategies and application of technologies such as machine learning.

Serving this up is not only significant for customer retention in order to produce profit per customer, it is also an innate requirement of the automotive sector, as most of these after-sales services, such as repairs, maintenance, parts sales and much more, can only be handled by willing suppliers automotive manufactures have to rely on. According to [2] report from Allied Market Research the global automotive aftermarket was valued at $438.7 billion in 2021, and is projected to reach $828.2 billion by 2031, highlighting the critical importance of leveraging advanced technologies to optimize service delivery, reduce costs, and enhance customer satisfaction. Additionally machine learning based solutions can mitigate this challenge through predictive analytics, automating repetitive tasks, personalized service recommendations etc.

Machine learning offers several advantages, but its implementation in automotive after-sales service is not without challenges. The inability to manage data quality and integration, issues around privacy and the need for specialized skills are major impediments to this technology being adopted. Moreover, the fast pace of technology development across a wide range of machine learning applications has proven to be burdensome for stakeholders to pinpoint the most applicable and useful solutions.

Though there is a growing interest in applying machine learning in after-sales service, the existing literature is limited to specific applications with relatively few studies providing a comprehensive overview. This leads to gaps in knowledge, hampering researchers, practitioners and policymakers to make evidence-based decisions when developing and/or implementing machine learning strategies within the automotive after-sales sector.

To note, this Systematic Literature Review is an attempt to overcome this gap by providing a broad perspective on the existing machine learning applications in automotive after-sales service. It aims to offer practical utilities for researchers, industry executives, and policymakers by synthesizing study results between January 2019 and October 2024 to foster data-based decision-making and establish actionable policies to improve the competitive advantage and sustainability of the automotive after-sales service industry.

To reach this goal, this systematic literature review pursues various essential research questions. The response will be based on findings of bibliometric studies which, in turn, will help to deliver an overview of the emerging concepts of machine learning in the field of automotive after-sales services, providing the current trends and gaps in this domain. It will review different types of machine learning methods, tools and datasets and identify the most commonly applied algorithms and their role in improving the provision of after sales services. Further in the review, we analyze the goals of employing machine learning algorithms that enhance data approaches in the automotive after-sales field, emphasizing its potential as a tool to make processes more efficient, mitigate risks, and generate practical knowledge. Moreover, this study will provide key performance indicators associated with these type of applications and explore emerging trends and future research directions for advancing automotive after-sales machine learning-based data strategies.

The goal of this systematic literature review is to give an overall perspective of the impact of machine learning in automotive after-sales service and to identify gaps in the literature and paths for future research on such a dynamically growing field.

2. Theoretical Foundations

2.1 The Automotive Industry

The automotive industry is a key economic aide that covers the engineering, manufacturing, distribution, and repair of personal and commercial automobiles[3]. Many changes have gone in the industry over the last few decades with technology improvements, trend variations, and environmental constraints. Automobile industry involves different stages of a complete life cycle, including design & production, after sales services and end-of-life[4]. Each stage is essential to maximizing its economic, social, and environmental value. A framework commonly used to measure the cumulative impact of these stages is the life cycle assessment framework, which enables the manufacturer to make sustainable decisions.

- Design and Planning: The first phase is all about research of the market, designing a concept and prototyping. It also employs eco-design strategies to maximize energy efficiency and use recyclable materials. Eco-design integrates sustainability at an early stage for the design of products, thus minimizing their impact on the planet.
- Production and Manufacturing: This stage assembles the vehicle itself, using the latest technologies. The incorporation of both industrial internet of things (IIOT) and machine learning improves the production efficiency. While this contributes toward improving product quality, real-time data coming from sensors also makes predictive maintenance and early fault detection possible and minimizes downtime.
- Usage Phase: In the usage phase, vehicles are being used by customers. This stage has a major environmental impact in terms of carbon emissions and fuel consumption. To lessen the impact of such technologies, we promote the use of electric and hybrid vehicles. Moreover, in order to sustain a vehicle's performance during its lifecycle, the demand for predictive maintenance services and after-sales technical assistance by manufacturers is also fuelling the market growth.
- End-of-Life Vehicle Management: This is the last step to guide through the safe recycling of vehicles once they are out of action. End-of-life vehicle rules in areas like Europe encourage

higher recycling percentages and reduce the need for toxic materials, aligning with worldwide sustainability goals.

With the industry constantly evolving, automotive manufacturers have identified a strategic after-sales service system as being instrumental when it comes to customer loyalty, market share and competitive advantage. In [5], Gopalakrishnan et al. Through new tech's, like machine learning and industrial internet of things, it drives business outcome of optimizing both operational efficiency and sustainability. By leveraging data-driven after-sales services, companies can quickly and accurately fulfill customer requirements, which serves as a competitive edge in the global marketplace.

2.2 After-Sales Services in the Automotive Industry

After-sales services in the automotive sector include all activities after the sale of a vehicle. Such providers help vehicle operators to run vehicles smoothly and efficiently, offer satisfaction to users, and retain the loyalty of brand. After-sales services form a strategic element in the value chain of the automotive market, as this is the main way a customer will be supported after purchasing a vehicle. According to Durugbo[6], these services serve many functions designed to ensure the optimum operation of the vehicles over their lifecycle and improve the customer experience. After-sales services consist of the following main activities: field technical assistance, spare parts distribution, customer care, and accessory sales. These activities ensure that customer needs are catered for in prompt and effective manner and are essential for keeping the vehicle performing and creating further revenue stream.

- Field Technical Assistance: Field technical assistance helps to resolve vehicle problems on site at the customer. This includes checks, diagnosis of technical difficulties, and on-site repairs. It plays the critical role of minimizing operational disruption and enhancing customer experience.
- Spare Parts Distribution: Availability of authentic spare parts is an essential component of after-sales services. Efficient distribution can help to ensure repairs and maintenance are done on time. State-of-the-art inventory management systems, powered frequently by machine learning, optimize spare part availability and minimize customer wait times.
- Customer Care: Where customer care deals with inquiries, complaints, and information requests. These include hotlines, apps for feedback, and loyalty programs. Good customer support builds good relationships between organizations and customers, building trust in a brand.
- Accessory Sales: companies also sell vehicle accessories that improve functionality or visual appeal. Selling accessories is a great way to boost revenue at the same time as offering value to the customer. Availability of aftersales services also serves as you très effective way of maintaining and increasing brand and customer loyalty and a sustainable competitive advantage. With new technologies like data analytics and machine learning, companies can now provide increasingly proactive and personalized services

2.3 Machine Learning-Based Data Strategies

Machine Learning (ML) stands for machine leaning, which is part of artificial intelligence (AI) in giving computer systems the ability to automatically learn and integrate without human interference[7]. It also uses data or observations to create computer "models" that analyze and pattern data with the goal of improving operations in technology. Machine learning is mainly aimed at improving results in certain (known) tasks or rendering correct predictions based on existing data. This type of learning is based on so-called "experience," which in the context of machine learning refers to the past data used to build predictive models. Machine Learning is one of the most growing domain of computer science with widespread implementation across disciplines and research areas.

Depending on how data is used in the learning process, ML approaches are classified into the following types:

- Supervised learning: In this type of learning, models are trained on labelled data where the output is already known. The goal is to learn a function from input to output, so that you can predict the right output for new input data.
- Unsupervised learning: In this approach, a model is applied to unlabeled data, and there is a discovery of hidden structures of fit within the data. Algorithms are clustering association rule mining.
- Reinforcement learning: where models learn by interacting with an environment and being rewarded or punished. The objective is to figure out strategies that return maximum rewards over time.

The machine learning (ML) algorithms play a significant role in a wide range of applications. Some of the key algorithms in supervised learning include regression analysis used for predicting certain numeric values, classification algorithms such as k-nearest neighbors (KNN) and Decision trees which are responsible for categorizing data, and last but not least the clustering techniques such as the k-means. artificial neural networks (ANNs) mimic the workings of the brain and can carry out classification as well as regression tasks. It is one of the advanced topics and one of the subfields of artificial intelligence that use deep neural networks and it is the basic technology to solve complex problems such as image recognition and language processing which is called Deep Learning (DL) which is defined as Supervised and Unsupervised Learning.

Technology advancement, especially machine learning(ML), have been the main drive of a seismic shift in automotive industry. By leveraging machine learning-based data strategies, after-sales services can improve customer satisfaction, optimize operations & profitability, etc. This write-up describes different machine learning applications in automotive after-sales services & the approaches companies are taking [8], [9], [10], [11], [12], [13]:

- Predictive Maintenance: Machine learning has became a strong weapon in implementing the intelligent algorithms for prediction. Machine learning-based predictive maintenance is a system that analyzes real-time sensor and equipment data to identify patterns and anticipate potential problems. By being proactive, companies can plan maintenance activities in advance of failures, thus avoiding unexpected downtime and lowering operational expense.
- Resource Utilization Optimization: Data strategies based on machine learning can optimize the utilization of resources, such as spare parts inventory, technician schedules, and logistics. Predictive analytics enable companies to forecast demand for certain parts and keep them in stock to optimal levels while avoiding inventory obsolescence. Likewise, machine learning

algorithms can enhance technician scheduling and routing to increase both productivity and responsiveness to customer demand.

- Service Logistics Optimization: Routing, scheduling, and resource allocation can be optimised with the help of machine learning-based data strategies to improve the efficiency of service logistics. For instance, when machine learning is injected into industrial internet of things frameworks, it allows for real-time monitoring of machinery which in turn informs predictive analytics to enhance operational efficiency
- Anomaly Detection: Machine learning algorithms can be employed to identify anomalies in equipment performance, supply chain data, and customer behavior. Within their data, detecting unusual patterns allows companies to take action before a problem occurs, fixing failures before they happen or improving the customer experience.
- Demand Forecasting: Accurate demand forecasting is very important for after-sales services, as it enables the firms to prepare their stock, labor, and logistics efficiently. Time-series analysis, neural networks, and other machine learning techniques can be utilized to predict demand more accurately, which yields better decisions and optimal resource allocation.
- Supply Chain Optimization: Machine learning-driven data strategies can help optimize several parts of the automotive supply chain, including supplier risk assessment, inventory management, and logistics planning. Predictive analytics helps to predict supply chain disruptions so that proactive steps can be taken to eliminate risks.
- Customer Behavior Modeling: It is very crucial to know how the customer behaves and what are their preferences in order to provide personalized services and targeted marketing. Data-driven focused machine learning models, which are capable of segmenting the customers based on the service interaction data and feedback can analyze the customer data around purchase history, their needs, pain points, goals, etc which helps organizations in making personalized offerings that can lead to better customer satisfaction and loyalty.
- Spare Parts Optimization: Spare parts management can create challenges for after-sales, with implications for both customer satisfaction and operational expense, and developing a strategy to optimize spare parts availability is therefore critical if excessive cost is to be avoided. Machine learning-based data strategies can not only identify and forecast when demand exists for certain parts, but also determine the right levels of inventory to ensure availability, and improve parts procurement and distribution practices to ensure that those parts are available while also minimizing excess inventory.

To summarize, implementation of machine learning driven data strategies in automotive after-sales service can bring a significant boost to operational efficiency, customer satisfaction, and profitability. Companies can enhance their competitiveness and ensure that their products deliver significant value to consumers by making the best use of these advanced analytics tools.

3. Methods

In this paper, a systematic literature review (SLR) approach with strict methods is adopted to review the current status of machine learning-based data strategies in automotive after-sales services. The

SLR method was selected due to its capacity to contribute a repeatable and impartial evaluation of the existing knowledge landscape in the area of automotive industry, including a systematic identification of knowledge gaps and potential avenues for future research. In accordance with the guidelines proposed by Kitchenham and Charters[14], sleep is divided into three stages: planning, conducting, and reporting, and each is divided into detailed steps for a rigorous review process. Fig. 1 shows the systematic workflow applied in this study.

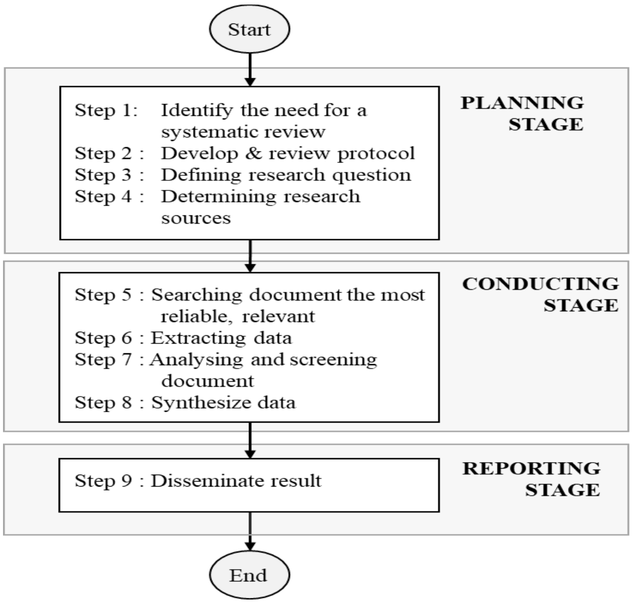

Fig. 1. Workflow Systematic Literature Review

3.1 Planning Stage

The planning stage sets the preliminary roadmap for the review process and other steps, including consensus process, etc. The following measures were carried out:

- Identifying the Need for an SLR: Machine learning applications in automotive after-sales services solutions were identified as paramount to improving operations and customer retention strategies in automotive industries. A systematic literature review (SLR) was performed to aggregate insights from the available research on this topic.
- Developing and Reviewing the Protocol: A comprehensive review protocol was developed to delineate the scope, inclusion/exclusion criteria, and research questions of this review study. To improve its methodological validity, the protocol was subjected to stringent peer review by subject matter experts.
- Defining Research Questions: Questions were created on the functionalities, difficulties, effects, and tendencies of machine learning in automotive after-sale services. These questions helped direct the data collection and synthesis phases.
- Determining Research Sources: Scopus was chosen for use as a database due to its extensive coverage of peer-reviewed literature in pertinent areas. To include high-quality studies, a comprehensive search strategy was developed.

The literature review is grounded on the following research questions, as presented in Table 1.

TABLE I. RESEARCH QUESTIONS

ID	Research Question
RQ1	What is the overview of the included studies and the bibliometric analysis?
RQ2	What machine learning approaches, software, and datasets are discussed in the literature related to automotive after-sales service?
RQ3	What are the objectives of employing machine learning algorithms in the literature to enhance data strategies for automotive after-sales services?

3.2 Conducting Stage

The conducting phase of this systematic literature review (SLR) followed a comprehensive and methodical approach in identifying, screening, and analyzing all relevant literature available on the subject. The search and selection of relevant documents is succinctly shown on Figure 2 that gives an overall but detailed overview of the methodological framework used in this paper. Several critical steps were closely followed in this phase. By following these steps, the research team was able to systematically evaluate the literature available and select the most relevant and significant studies for inclusion in the analysis.

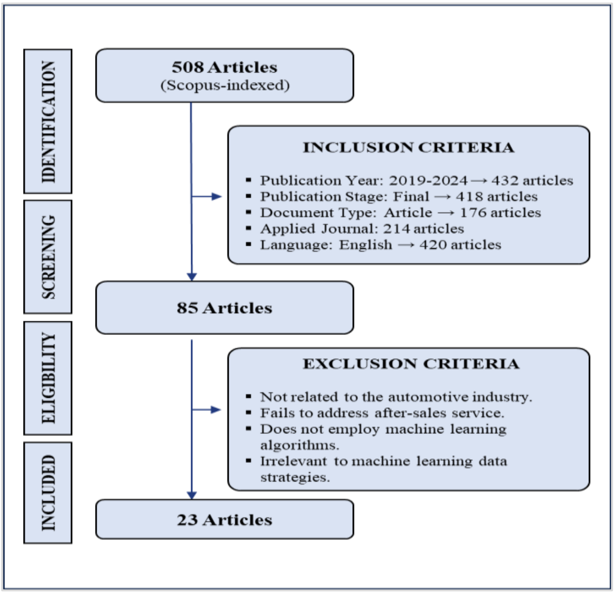

Fig. 2. Search and Selection process research documents

This phase included the following key steps:

- Document Search: A search string *("machine learning" OR "artificial intelligence" OR "data analytics") AND ("automotive" OR "vehicle" OR "car") AND ("after-sales" OR "aftermarket" OR "service" OR "maintenance") AND ("data strategy" OR "data-driven" OR "data analysis")* was used to retrieve 508 articles from Scopus.
- Applying Inclusion Criteria: Articles meeting the following criteria were included: published between 2019 and 2024, written in english, peer-reviewed journal articles, focused on machine learning applications in automotive after-sales services, and at the final publication stage. This reduced the dataset to 85 articles.

- Applying Exclusion Criteria: Articles were eliminated if they lacked relevance to the automotive sector, did not concentrate on aftersales services, failed to incorporate machine learning methodologies, or were unrelated to data strategies. This subsequently refined the dataset to 23 articles.
- Data Extraction: Essential information, encompassing publication year, authors, journal, objectives, methodology, machine learning techniques, application domains, datasets, and findings, was extracted.
- Analyzing and Screening Documents: Each document was assessed to verify its relevance and conformity with the study objectives.
- Synthesizing Data: We conducted a narrative synthesis and theme analysis to amalgamate findings, identifying patterns, trends, and deficiencies. The synthesis was structured in accordance with the research questions and presented the cutting-edge developments in machine learning pertaining to car after-sales services.

TABLE II. SELECTED PAPER

Title	**Research Studies**
Reinforcement learning based optimal decision making towards product lifecycle sustainability	Liu et al. [15]
Machine Learning-Based Fault Detection and Diagnosis of Faulty Power Connections of Induction Machines	Gonzalez-Jimenez et al. [16]
Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry	Theissler et al. [17]
Schedulable capacity forecasting for electric vehicles based on big data analysis	Mao et al. [18]
SVR approach for predicting vehicle velocity for comfortable ride while crossing speed humps	Darwiche et al. [19]
Optimally Tuned Gated Recurrent Unit Neural Network-Based State of Health Estimation Scheme for Lithium Ion Batteries	Rao et al. [20]
Machine Learning Framework for Real-Time Assessment of Traffic Safety Utilizing Connected Vehicle Data	Mussah et al. [21]
Predicting the RUL of Li-Ion Batteries in UAVs Using Machine Learning Techniques	Andrioaia et al. [22]
Improving Lead Time Forecasting and Anomaly Detection for Automotive Spare Parts with A Combined CNN-LSTM Approach	Amellal et al. [23]
Title	**Research Studies**
Machine Learning Approaches for Auto Insurance Big Data	Hanafy et al. [24]
Data-Driven Fault Early Warning Model of Automobile Engines Based on Soft Classification	Li et al. [25]
On-Board Data Management Layer: Connected Vehicle as Data Platform	Benaissa et al. [26]
IIoT Framework Based ML Model to Improve Automobile Industry Product	Gopalakrishnan et al. [27]
Application of Machine Learning Techniques to Predict the Price of Pre-Owned Cars in Bangladesh	Amik et al. [28]
Data-driven optimization for last-mile delivery	Chu et al. [29]
Artificial intelligence based prediction models: sales forecasting application in automotive aftermarket	Türkbayrağí et al. [30]

A Review of the Data-Driven Prediction Method of Vehicle Fuel Consumption	Zhao et al. [31]
A predictive analytics approach to improve the dealers-manufacturer relationship in the after-sales service network; case study in the automotive industry	Ebrahimi et al. [32]
A combined forecasting method for intermittent demand using the automotive aftermarket data	Zhuang et al. [33]
A Machine Learning-Based Robust State of Health (SOH) Prediction Model for Electric Vehicle Batteries	Akbar et al. [34]
A Natural Language Processing and deep learning based model for automated vehicle diagnostics using free-text customer service reports	Khodadadi et al. [35]
A framework for vehicle quality evaluation based on interpretable machine learning	Alwadi et al. [36]
Application of Machine Learning Algorithms in the Development and Consumption Trend of Green and Intelligent Vehicles under the Background of Big Data	Liang et al. [37]

3.3 Reporting Stage

The last phase of this study was organizing and presenting the findings in the most clear, aligned, and accessible way possible. Therefore, the results were grouped by themes, which are directly related to the research questions, namely the machine learning approaches, the data strategies and the applicability in automotive after-sales services. Results associated with profits effectively showed how machine learning-based data methods help in improving after-sales service, solution taking privacy and data administration issues into consideration with practical significance achieved in this essential component. So, this research shows practical implications by providing scalable real-time solutions leading to operational efficiency and customer delight by connecting the dots between theoretical elements and their real life applications in the automobile domain.

3.4 Selected Paper

Table 2 provides a summary of the 23 selected papers that form the foundation of this systematic literature review, drawn from an initial pool of 508 articles sourced from Scopus. The table summarizes the important characteristics, such as titles and citation identifiers. The selected papers show the diversity of research in strategies of automotive after-sales services based on machine learning.

3.5 Abbreviation of This Studies

The commonly used abbreviation are listed in Tabel 3.

TABLE III. ABBREVIATION USED IN THE PAPER

Abbrev.	**Explanation**	**Abbrev.**	**Explanation**
PdM	Predictive Maintenance	ML	Machine learning
RUO	Resource Utilization Optimization	AI	Artificial intelligence
SLO	Service Logistics Optimization	GAN	Generative Adversarial Networks
AD	Anomaly Detection	GRU	Gated Recurrent Unit
DF	Demand Forecasting	GTB	Gradient Tree Boosting
SCO	Supply Chain Optimization	GNB	Gaussian Naïve Bayes
CBM	Customer Behavior Modeling	HCA	Hierarchical Cluster Analysis
SPO	Spare Parts Optimization	LGBM	Light Gradient Boosting Machine
AC	Agglomerative Clustering	KNN	k-Nearest Neighbors
ANN	Artificial Neural Network	LDA	Linear Discriminant Analysis

BiLSTM	Bidirectional Long Short-Term Memory	HDBSCAN	Hierarchical Density-Based Spatial Clustering of Applications with Noise
BM	Boosting Method	LR	Linear Regression
BNB	Bernoulli Naïve Bayes	LS-SVM	Least Squares Support Vector Machine
CART	Classification and Regression Trees	LSTM	Long Short-Term Memory
CNN	Convolutional Neural Network	MLR	Multiple Linear Regression
DBSCAN	Density-Based Spatial Clustering of Applications with Noise	SMOTE-Tomek	Synthetic Minority Oversampling Technique-Tomek Links
DL	Deep Learning	NLP	Natural Language Processing
DNN	Deep Neural Networks	RF	Random Forest
DT	Decision Tree	RNN	Simulated Annealing
DT-GS	Decision Tree with Gradient Search	SA	Recurrent Neural Network
DTR	Decision Tree Regress	SGD	Stochastic Gradient Descent
EL	Ensemble Learning	NBC	Naïve Bayes Classifiers
ET	Extra Trees	SVM	Support Vector Machine
FCM	Fuzzy C-Means	SVMR	Support Vector Machine for Regression
XGBoost	eXtreme Gradient Boosting	SVR	Support Vector Regression
VAE	Variational Autoencoders	TL	Transfer Learning

4. Results

4.1 Overview of Included Studies & Bibliometric Analysis

A systematic literature review identified 23 studies from 2019 through 2024 in the field of automotive after-sales services that used machine learning (ML)-based data methods. Studies meeting strict inclusion criteria were selected for review based on relevance, rigor, and a contribution to the field. Results Articles are mostly published in high-impact journals (34.8% Q1, 47.8% Q2 and 17.4% Q3 according to the 2023 SCImago Journal Rank [SJR] in Figure 3. Notably, there were no publications in Q4, which highlights the expectation and demand for high-quality research in this sector, noting it as an increasingly vital perspective in academia and industry.

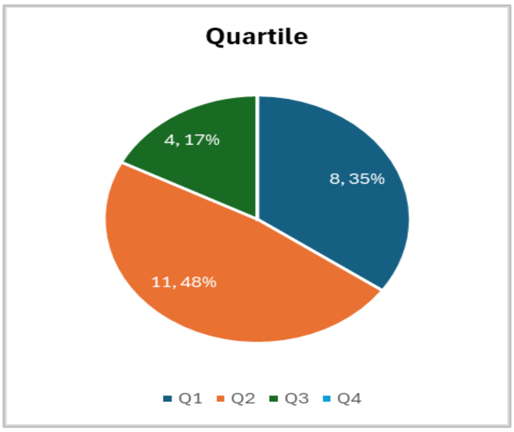

Fig. 3.Quartile (SJR 2023) for Selected Papers

As described in the Figure 4, the distribution of articles published within the past five years was 39.1% for 2022, representing the highest productivity rate of articles among included research. This growth illustrates the increasing interest of academic researchers in utilizing machine learning (ML) for solving problems in the automotive after-sales service domain along with improved analytics, and increased demand for novel approaches. In 2020, the smaller total number of studies may be connected with disruptions from the COVID-19 pandemic.

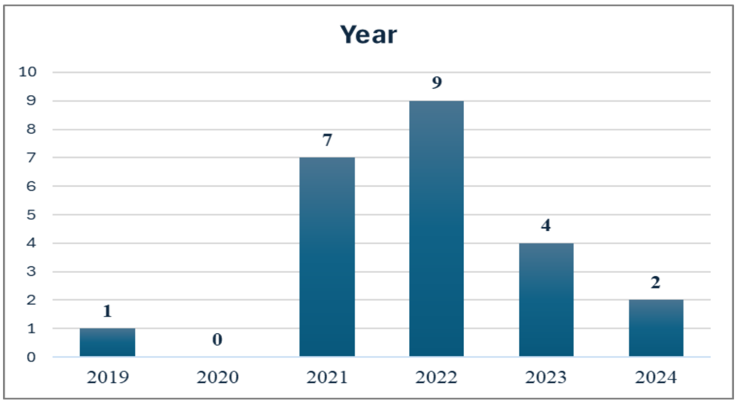

Fig. 4. Year of Publication for Selected Papers

The citation analysis showed variation in studies' impact on the literature. The highest citation paper was published in Reliability Engineering & System Safety (Elsevier) in 2021 with a total of 233 citations, reflecting more predictive maintenance applications. Among the next most impactful studies were on minerals and metals (20 citations), and energy fault detection and diagnosis in Energy (20 citations) and demand forecasting in Complex & Intelligent Systems (35 citations). It can be seen that some like predictive maintenance or inventory optimization or customer behavior models are the topics most commonly discussed in research. Figure 5 shows the VOSviewer visualization that links to other important topics that are relevant for predictive maintenance such as artificial intelligence and big data. Current research focus on relevant topics like state of health, error detection and data-driven techniques, while traditionally important topics like predictive maintenance, big data and artificial intelligence have still high relevance.

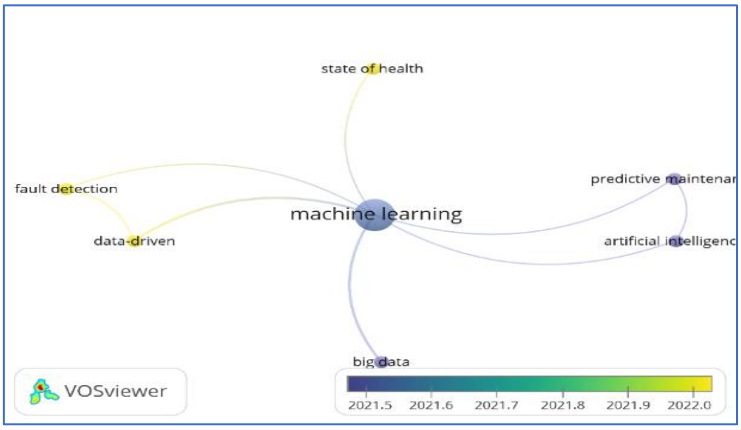

Fig. 5. Year of Publication for Selected Papers

This review of studies highlights trends, challenges and opportunities, providing overview of the current research landscape. While the increase in publication volume reflects the growing academic interest and industry adoption, the variability in citation impact highlights the need for greater standardisation and practical applications.

4.2 Machine Learning Approaches, Tools, and Data in Automotive After-Sales Services

The selected studies that were analyzed demonstrated diverse areas of utilization of machine learning approaches, tools, and datasets in automotive aftersales services. The different machine learning methods, softwares, and datasets used are briefly listed in Tables 4 and 5. Supervised learning is the most prevalent machine learning approach, used in 20 out of the 23 studies. Three studies make use of unsupervised learning, which is used for clustering and anomaly detection, that provides insight without the presence of labeled datasets. Three of the papers leverage reinforcement learning and show its applications for dynamic decision-making problems, used in situations like optimizing product lifecycles and last-mile delivery systems.

TABLE IV. MACHINE LEARNING APPROACH AND SOFTWARE

Machine Learning Approach	Research Studies	Software used
Supervised learning	[16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37]	Matlab/Simulink, Amazon Web Services (AWS), AWS SageMaker, Hadoop, Spark, Ubuntu 64-bit operating system, MATLAB, scikit-learn, Python, Pandas, R, ROSE package, Eclipse, Springboot, MyBATIS, Apache Kafka, Maven, MonetDB, Tomcat, Postgres, Anaconda, Web Scraper, Flask, NumPy
Unsupervised learning	[17], [23], [27]	Python, Keras, MATLAB
Reinforcement learning	[15], [29], [30]	TensorFlow, MATLAB

The machine learning methods utilized in the selected papers are:

- Supervised Learning: Supervised learning can be used to different applications through various types of algorithms like support vector machines, random forest, and neural networks. The support vector machines and regression methods are used to implement the predictive tasks vehicle state health estimation and vehicle fault detection.
- Unsupervised Learning: Research using clustering methods such as the K-means method to address issues like spare part segmentation and the detection of anomalies in the supply chain. They provide meaningful information regarding trends and outliers for large data sets, and they do not require any labeled data.
- Reinforcement Learning: whether it is guiding a self-driving car or developing an ideal operational strategy in atmospheres where no decision is independent of previous actions, concepts of this style are rare but critical.

TABLE V. DATASETS USED IN THE ANALYZED STUDIES

Research Studies	Dataset
[15]	Maintenance behavior, state of the product, actions taken, and associated rewards.
[16]	synthetic dataset created via Software-in-the-Loop simulations
[17]	Not mentioned
[18]	operation data from 521 electric vehicles (EVs), collected from their Battery Management Systems (BMS)
[19]	Speed hump profiles, vehicle speed
[20]	voltage, current, and temperature data
[21]	disaggregated vehicle trajectory data, segment-level aggregate speed, travel time data and Historical crash data
[22]	Real-time tracking of voltage, current, and capacity to capture battery degradation
[23]	The ERP dataset contains 51,092 samples and 8 features for forecasting lead time and detecting anomalies in spare parts.
[24]	A dataset comprising 59 variables and 1,488,028 observations, including client details, has been compiled to predict automotive claims.
[25]	engine state features
[26]	vehicle speed, vehicle direction, datasets for connected and autonomous vehicles
[27]	Data from sensor kits, historical data for comparative analysis, product dimensions, and product weights.
[28]	Car name, brand, model, model year, transmission, body type, fuel type, engine capacity, kilometers driven, and price.
[29]	Dataset generated experimentally to simulate conditions relevant to last-mile delivery, including travel time predictions based on contextual information.
[30]	economic indicators, Consumer Confidence Index, Google Search Indices, Brent crude and gas prices, gas consumption, and business ratios, organized into monthly time series for analysis.
[31]	Vehicle inherent variables, driving behavior variables, and driving environment variables are collected through various means, such as onboard sensors and smartphone apps.
[32]	The dataset includes information from 1,368 dealers across 11 columns and 13,515 rows, used to predict dealer cooperation in after-sales service, featuring data from 552 dealers.
[33]	The dataset features 3,089 spare parts SKUs from the XA warehouse and historical sales for 2,167 SKUs from the DS warehouse for transfer learning.
[34]	Driving cycle data, including current, voltage, and capacity metrics for predicting electric vehicle battery state of health (SOH)
[35]	customer service calls over ten years, covering 'Service Department', 'Service Call Log', and vehicle metadata.
[36]	The multivariate car evaluation dataset includes classifications of car acceptability: acceptable, unacceptable, good, and very good
[37]	Not mentioned

The analysis of the selected papers indicates that the software utilized for machine learning implementation encompasses several types, including python-based, matlab, big data frameworks, and cloud platforms.

The datasets of the studies under scrutiny underscore the complexity and diversity of data sources in automotive after-sales services:

- Sensor Data: Numerous studies use data collected from on-board vehicle sensors including metrics of voltage, current and temperature amongst others to predict state of health of batteries, or identify faults.
- Customer and Service Data: Datasets such as customer service logs, spare parts inventory and dealer cooperation metrics help here to analyze operational efficiency and customer behavior.
- Synthetic Data: In situations where real data is not available due to reasons like scarce data points in supply chain optimization or lead time forecasting, synthetic datasets generated from software simulation or experimental setups are used to model the scenario.

It is important to note that the high adoption levels of supervised learning indicate its success, but also highlight the lack of standardization and availability of relevant datasets. Concern about using synthetic data in some studies underscores the importance of availability of larger real-world datasets to further assess the replicability of findings. Finally, the minimal application of reinforcement learning highlights opportunities for future research, especially for applications that demand adaptive approaches for strategic tasks (i.e., real-time decision-making).

Diversity in ML approaches, software tools and datasets have led to tremendous development in automotive after-sales services. In contrast, future work more is probably more focused in building standardised datasets and exploring underused approaches to improve after-sales efficiency and adaptability, like reinforcement learning. We hope this in-depth piece helps readers see just how much ML strategies are influencing the automotive industry and serves as a basis for finding more innovation in this domain.

4.3 Machine Learning Algorithms for Achieving Data Strategy Objectives in Automotive After-Sales Services

In this paper, we provide a summary on how data strategy objectives can be applied using machine learning methods. Table 6 shows how these goals were implemented and assessed in our study. Over the past few years, the automotive after-sales services industry has seen the strategic implementation of machine learning (ML) algorithms across a wide range of domains that aim at improving operational efficiency, optimizing resource utilization, and increasing customer satisfaction.

TABLE VI. DATA STRATEGY OBJECTIVES USING MACHINE LEARNING

Research Studi	**Data Strategy Objective**							
	Predictive Maintenance	***Resource Utilization Optimization***	***Service Logistics Optimization***	***Anomaly Detection***	***Demand Forecasting***	***Supply Chain Optimization***	***Customer Behavior Modeling***	***Spare Parts Optimization***
[15]	**V**	**V**						
[16]	**V**			**V**				
[17]	**V**							
[18]		**V**			**V**			
[19]	**V**							
[20]	**V**							
[21]				**V**				
[22]	**V**							
[23]				**V**		**V**		
[24]							**V**	
[25]	**V**							
[26]			**V**					
[27]	**V**			**V**				
[28]					**V**			
[29]			**V**					
[30]					**V**			

[31]					**V**			
[32]	**V**	**V**		**V**		**V**	**V**	
[33]			**V**		**V**	**V**		**V**
[34]	**V**							
[35]	**V**	**V**	**V**	**V**				
[36]	**V**			**V**			**V**	
[37]				**V**	**V**		**V**	

The following discussion will provide a detailed analysis of each objective accurately based on the table summarized above.

- Predictive maintenance: Table 7 lists 12 papers that applied machine learning algorithms for predictive maintenance like Random Forest, SVM and LSTM. Applications include problem detection in motors, battery health assessment, and anomaly detection in the production line. This means machine learning is dominating the maintenance process, as proven by LSTM and GRU capable of predicting battery State of Health and Remaining Useful Life.

TABLE VII. MACHINE LEARNING IN PREDICTIVE MAINTENANCE

ML Algorithm	**ML Aplication**	**Outcome Measured**	**Research Studies**
Q-learning	Improve product lifecycle sustainability	minimizing failures, increasing product lifetime, reducing costs	[15]
RF, LR, SVM, k-NN	Maintenance tasks and preventing damage, Detects faults	induction motor health status classification, current imbalance, wiring fault	[16]
k-Means, FCM, HCA, BSCAN, HDBSCAN, k-NN, NBC, SVM, ANN, DT, RF, XGBoost, SVR, VAE, GAN, TL	predictive maintenance (PdM) in the automotive industry	Not mentioned	[17]
SVR	Predicts vehicle velocity	acceleration	[19]
LSTM, DNN, GRU	Predicts lithium-ion battery health	State of Health (SOH) estimation	[20]
SVMR, MLR, RF	Predicts Li-ion battery RUL.	Remaining Useful Life (RUL)	[22]
RF, KNN, XGBoost, LSTM, GRU, CNN, LGBM, RNN	Achieves high accuracy for fault detection	accuracy, recall rate, advance time, false positive rate	[25]
K-Means, AC, RF, SVM	Enhances predictive maintenance detection	anomaly detection, machinery effici-ency, sensitivity, specificity, accuracy	[27]
DT, LDA, LR, RF, SGD, SVM, GridSearchCV, SMOTE-Tomek	Forecasts dealer cooperation continuity	dealers' cooperation (continuation or termination)	[32]
CART, LR, ET, BM, DTR, SVM, LS-SVM, ANN, DL, EL	Predicts electric vehicle battery health	State of Health (SOH) of electric vehicle batteries	[34]
NLP, BiLSTM, CNN, SVM, DT, GTB, RF	Improves service request validation	accuracy, sensitivity, specificity, preci-sion, ROC-AUC	[35]
DT-GS, RF, SVM, KNN, BNB, GNB	Predicts vehicle quality	vehicle quality	[36]

- Resource utilization optimization: Table 8 show use of machine learning methods such as Q-learning, gradient boosting decision trees and bidirectional long short term memory to optimize inventory management labor allocation and scheduling efficiency These algorithms improve capacity forecasting and service validation, reducing costs while increasing service reliability. Future study could focus on developing real-time applications. applications of data analysis to improve resource allocation algorithms.

TABLE VIII. MACHINE LEARNING IN RESOURCE UTILIZATION OPTIMIZATION

ML Algorithm	ML Aplication	Outcome Measured	Research Studies
Q-learning	Improve product lifecycle sustainability	minimizing failures, increasing product lifetime, reducing costs	[15]
PGBDT, PRF, PKNN	Forecasts EV capacity and optimize scheduling and participation	schedulable capacity of electric vehicles (EVSC)	[18]
DT, LDA, LR, RF, SGD, SVM, GridSearchCV, SMOTE-Tomek	Forecasts dealer cooperation continuity	dealers' cooperation (continuation or termination)	[32]
NLP, BiLSTM, CNN, SVM, DT, GTB, RF	Improves service request validation.	accuracy, sensiti-vity, specificity, precision, ROC-AUC	[35]

- Service logistics optimization: Table 9 presents four studies that considered optimizing service logistics using machine-learning techniques, to cite: Artificial Neural Networks Multi-Layer Perception and Light Gradient Boosting Machine. These algorithms provide increased prediction accuracy in predicting spare parts with improved sensitivity, specificity and ROC-AUC performance. These findings highlight the transformative power of machine learning for optimizing logistics operations and represent a significant contribution to our understanding of logistics operations with the challenge being how to address real-time data integration to enhance scalability.

TABLE IX. MACHINE LEARNING IN SERVICE LOGISTIC OPTIMIZATION

ML Algorithm	ML Aplication	Outcome Measured	Research Studies
ANNs, MLP	Predicts traffic flow.	dataset size reduction, traffic flow prediction accuracy	[26]
Mini-batching gradient algorithm, SA, Classical gradient approach, Combined prediction and routing optimization	Optimizes last-mile delivery performance	delivery time, total travel time cost, total operating cost	[29]
IDCF, BTIDCF, TBIDCF, LightGBM, Adjusted TrAdaboost, SBA, Markov chain-model	Enhances spare parts forecasting accuracy.	AUC, MASE, MAAPE	[33]
NLP, BiLSTM, CNN, SVM, DT, GTB, RF	Improves service request validation	accuracy, sensitivity, specificity, precision, ROC-AUC	[35]

- Anomaly detection: As shown in Table 10, Eight studies explore anomaly detection using machine learning approaches, including Random Forest, SVM, k-Means clustering, and CNN-BiLSTM. Used for identifying problems, forecasting lead times, and improving manufacturing line accuracy. The results note a greater sensitivity, specificity, and accuracy, strong lead time estimation, and a larger customer awareness of green vehicles. Future work must focus on the integration of real time anomaly detection.

TABLE X. MACHINE LEARNING IN ANOMALY DETECTION

ML Algorithm	**ML Aplication**	**Outcome Measured**	**Research Studies**
RF, LR, SVM, k-NN	Maintenance tasks and preventing damage, Detects faults	induction motor health status classification, current imbalance, wiring fault	[16]
OLS, Poisson regression, GB, XGBoost, Weighted Ensemble Model	Predicts crash outcomes	crash occurrence	[21]
CNN-BiLSTM, LSTM autoencoder, OCSVM	Lead time forecasting and anomaly detection	lead time forecasting, anomaly detection	[23]
K-Means, AC, RF, SVM	Enhances predictive maintenance detection	anomaly detection, machinery efficiency, sensitivity, specificity, accuracy	[27]
DT, LDA, LR, RF, SGD, SVM, GridSearchCV, SMOTE-Tomek	Forecasts dealer cooperation continuity	dealers' cooperation (continuation or termination)	[32]
NLP, BiLSTM, CNN, SVM, DT, GTB, RF	Improves service request validation	accuracy, sensitivity, specificity, precision, ROC-AUC	[35]
DT-GS, RF, SVM, KNN, BNB, GNB	Predicts vehicle quality	vehicle quality	[36]
SVM, BP Neural Network, MLFFNN, RBFNN, SVR, FIS, ANFIS, Quadratic Relaxation C-SVM, LS-SVM	Shows increasing consumer recognition and acceptance	sales of green intelligent vehicles	[37]

- Demand forecasting: Table 11 shows Six research focuses on demand forecasting with utilizations of machine learning technicals such as Light Gradient Boosting Machine (LightGBM), Random Forest (RF), and hybrid neural networks They improve accuracy of forecasts, in particular related to car fuel consumption and aftermarket sales, reaching high AUC and MAAPE scores. They also show promise in spearing eco-friendly intelligent automobiles. Future research should focus on real-time data integration as well as hybrid models to improve prediction.

TABLE XI. MACHINE LEARNING IN DEMAND FORECASTING

ML Algorithm	**ML Aplication**	**Outcome Measured**	**Research Studies**
PGBDT, PRF, PKNN	Forecasts EV capacity. Optimize scheduling and participation	schedulable capacity of electric vehicles (EVSC)	[18]
LR, LASSO Regression, DT, RF, XGBoost	Predicts pre-owned car prices	price prediction accuracy (R^2 score, RMSE, MAE)	[28]
ANN, MLR	Forecasts automotive aftermarket sales.	sales forecast accuracy (MAD, MAPE, RMSE, RFSE)	[30]
SVM, RF, DT, GBM, LightGBM, LR, ANN, RNN, CNN, MLP, LSTM, Hybrid Models	Predicts vehicle fuel consumption	fuel consumption	[31]
IDCF, BTIDCF, TBIDCF, LightGBM, Adjusted TrAdaboost, SBA, Markov chain-model	Enhances spare parts forecasting accuracy	AUC, MASE, MAAPE	[33]
SVM, BP Neural Network, MLFFNN, RBFNN, SVR, FIS, ANFIS, Quadratic Relaxation C-SVM, LS-SVM	Shows increasing consumer recognition and acceptance	sales of green intelligent vehicles	[37]

- Supply chain optimization: Three articles (Table 12) used machine learning algorithms to improve the supply chain, focusing on lead time forecasting, dealer collaboration and spare parts inventory control. According to the results, predictive accuracy and monitoring of inventory logs can be beneficial in reducing operational risk and improving resilience. Subsequent research should make use of data as it becomes available, ideally in real time, to achieve responsiveness and scalability wherever possible.

TABLE XII. MACHINE LEARNING IN SUPPLY CHAIN OPTIMIZATION

ML Algorithm	ML Aplication	Outcome Measured	Research Studies
CNN-BiLSTM, LSTM autoencoder, OCSVM	Lead time forecasting and anomaly detection	lead time forecasting, anomaly detection	[23]
DT, LDA, LR, RF, SGD, SVM, GridSearchCV, SMOTE-Tomek	Forecasts dealer cooperation continuity	dealers' cooperation (continuation or termination)	[32]
IDCF, BTIDCF, TBIDCF, LightGBM, Adjusted TrAdaboost, SBA, Markov chain-model	Enhances spare parts forecasting accuracy	AUC, MASE, MAAPE	[33]

- Customer behavior modeling: In Table 13, Four studies that used machine learning methods (e.g., Logistic Regression, Random Forest, and Support Vector Machines) for customer behavior modeling. The results show that automobile insurance claims are predicted accurately, breaking the linear property of automobile quality, and the customer living of eco-friendly intelligent automobile is improved. Just as data forms the foundation for machine learning, machine learning works on that data to deliver tailored insights and strategic decision-making, with future plans to integrate behavioral information in real-time.

TABLE XIII. MACHINE LEARNING IN CUSTOMER BEHAVIOR MODELING

ML Algorithm	ML Aplication	Outcome Measured	Research Studies
LR, XGBoost, RF, DT (C.50), NB, K-NN	Predicts auto insurance claims	prediction of claim occurrence	[24]
DT, LDA, LR, RF, SGD, SVM, GridSearchCV, SMOTE-Tomek	Forecasts dealer cooperation continuity	dealers' cooperation (continuation or termination)	[32]
DT-GS, RF, SVM, KNN, BNB, GNB	Predicts vehicle quality	vehicle quality	[36]
SVM, BP Neural Network, MLFFNN, RBFNN, SVR, FIS, ANFIS, Quadratic Relaxation C-SVM, LS-SVM	Shows increasing consumer recognition and acceptance	sales of green intelligent vehicles	[37]

- Spare parts optimization: In Table 14, we describe an overview of machine learning approaches applied for spare parts optimization to enhance inventory management. The results indicate a major improvement in predictive accuracy, decreasing overstock and stockouts, lower costs and high availability. It also highlights the research gap for integrating real-time information for flexible and on-demand solutions.

TABLE XIV. MACHINE LEARNING IN SPARE PARTS OPTIMIZATION

ML Algorithm	ML Aplication	Outcome Measured	Research Studies
IDCF, BTIDCF, TBIDCF, LightGBM, Adjusted TrAdaboost, SBA, Markov chain-model	Enhances spare parts forecasting accuracy	AUC, MASE, MAAPE	[33]

The broadening scope of machine learning algorithms accounts for a wider range of applications in the automotive after-sale process such as predictive maintenance demand forecasting, anomaly detection and spare parts optimization, among others. It also stresses the importance of integrating standardized data and scalable solutions to maximize the potential of ML and presents key recommendations for prioritizing underrepresented areas for ML-based initiatives.

4.4 Challenges and Limitations

This systematic review based on 23 selected studies highlighted an array of challenges and limitations that undermine the use of machine learning (ML) algorithms in automotive after-sales services. This ranges from issues with what we call data, through the complexity of the algorithms underpinning ML, the infrastructure to support these algorithms and the restrictions on organisations employing them, none of which is unique to ML for this domain.

- Data-Related Difficulties: Data quality and availability is a serious obstacle in many fields such as predictive maintenance, demand forecasting and privacy and security issues. This involves data scarcity and imbalance and advanced preprocessing techniques.
- End-to-End Automotive Dealership Operations Research Gap: The lack of research along the supply chain phases in the automotive aftermarket, especially in automotive dealerships, is identified as a critical gap in the review. The state-of-the-art has focused on predictive maintenance, demand forecasting, and similar techniques which focus on a single operational process while neglecting interconnected operational processes such as service reminders, booking, technician allocation, spare parts management, warranty claims, and others which require integrated solutions. While machine learning is powerful, this withholding of the bigger picture makes it tough to engineer holistic solutions for dealership operations. The research should focus on real-time data processing and scalability of machine learning deployment in future.

4.5 Trends and Future Research Directions

The automotive segment is focused on embedding multiple data sources aiding federated learning/transfer through which model accuracy and decision making can be enhanced. Common practice for complex tasks involve hybrid models that combine standard algorithms with neural networks or deep learning frameworks. In real-time applications they are being used in predictive maintenance and traffic safety testing. They are also developing special algorithms for car dealerships which will increase operational efficiency and customer satisfaction.

Future works should work to develop more complete dealer operation systems with machine learning models, increased robustness and scalability of models, better usage of graph neural networks (GNN) to model more complex supply chain relationships and increased customer engagement with AI models such as these approaches are intended to improve service delivery and overall efficiency at dealerships.

5. Discussion

This paper discusses the integration of machine learning with diverse data sources including IoT data and customer interactions to enhance tactics in the automotive after-sales support. It offers a model that can easily be immediately applied to dealership operations improving spare parts inventory management and forecasting vehicle maintenance requirements. The integration of AI can enhance stakeholder confidence in decision-making systems particularly in safety-critical applications like monitoring the condition of electric vehicle batteries coinciding with the growing advancement of electric vehicles

A thorough examination of several vehicles brands would be quite engaging. This presents a challenge to the dataset as privacy data might offer an interesting perspective on the car industry. Although modern methodologies like federated learning and hybrid models show potential their execution necessitate substantial infrastructure and computational resources, presenting difficulties for small and medium automobile dealers. The advancement of electric vehicles and the integration of autonomous vehicles necessitate the increased use of artificial intelligence technologies in after-sales services.

6. Conclusion

This systematic literature review is providing a comprehensive analysis of machine learning based data strategies in automotive after-sales services addressing critical research questions and offering insights. We perform a systematic review of 23 machine learning-based data strategies in automotive aftermarket services from 2019 to 2024. In our results, the main strategy of predictive maintenance and demand forecasting is supervised learning algorithms such as Random forest, and Neural Networks. Unsupervised learning and reinforcement learning has also been aiding to real-time outlier detection and decision making.

This conclusion highlights the growing imperative that machine learning extends beyond mere data, moving also toward generating actionable information in both theoretical and practical context knowledge, such as predictive maintenance, optimization of energy resources, demand forecasting and load balancing and logistics optimization, spare part management and also, customer behavior modeling. By making use of diverse datasets and tools such as python, matlab, big data frameworks, and cloud platforms, the automotive domain has been able to attain agile and scalable solutions.

Nevertheless, challenges in generalizability issues due to low-resolution and limited data across the board and limited real-time data integrated due to data privatization makes them hard to adapt. Furthermore, the study was limited to functions of dealers and does not discuss real-time data integration, which is an area for future research. Current approaches focus on a single operational process while neglecting others like, here for example, service reminders, service orders, technicians allocation, parts allocation, promo offers and warranty claims.

These limitations need to be explored in other investigation along with further application of different datasets, including instantaneous solutions regarding the decision-making processes in dealerships. These methods enable adaptive and privacy-preserving response in conjunction with a learning algorithm that uses reinforcement learning (RL), enabling it to learn from past experience, and joint learning that combines learning between different sensory modalities. Finally we suggest scalable optimal robust dealer processing systems by ML Models for Robustness and hyper-parameters tuning for Next Level scalability, and utility of graph Neural Network graph for the complex supply chain relations It is expected to strategically optimize service delivery, operational efficiency, and customer engagement, which will certainly lead to an increased positive experience for the automotive industry.

Refrences

[1] D. Harrison, “Global Vehicle Demand Forecast 2020-2030,” Ultima Media Ltd., London, pp. 1–29, Mar. 26, 2020. Accessed: Jul. 02, 2023. [Online]. Available: https://www.automotivelogistics.media/bi-reports/global-vehicle-demand-forecast-2020-2030/40781.article

[2] Allied Market Research, “Automotive After Market : Global Opportunity Analysis and Industry Forecast, 2021-2031,” 2022. Accessed: Dec. 06, 2025. [Online]. Available: www.alliedmarketresearch.com/automotive-aftermarket-market-A17049

[3] M. Hirz and H. Brunner, “ECO-Design in the Automotive Industry-Potentials and Challenges,” 2015. [Online]. Available: https://www.researchgate.net/publication/281633243

[4] R. J. Orsato and P. Wells, “The Automobile Industry & Sustainability,” 2007. doi: 10.1016/j.jclepro.2006.05.035.

[5] S. Gopalakrishnan and M. S. Kumaran, “Iiot framework based ml model to improve automobile industry product,” Intelligent Automation and Soft Computing, vol. 31, no. 3, pp. 1435–1449, 2022, doi: 10.32604/IASC.2022.020660.

[6] C. M. Durugbo, “After-sales services and aftermarket support: a systematic review, theory and future research directions,” Mar. 18, 2020, Taylor and Francis Ltd. doi: 10.1080/00207543.2019.1693655.

[7] M. Mohri, A. Rostamizadeh, and A. Talwalkar, Foundations of Machine Learning second edition, Second edition., vol. second edition. MIT Press, 2018. [Online]. Available: www.dbooks.org

[8] C. Morariu, O. Morariu, S. Răileanu, and T. Borangiu, “Machine learning for predictive scheduling and resource allocation in large scale manufacturing systems,” Comput Ind, vol. 120, p. 103244, 2020, doi: https://doi.org/10.1016/j.compind.2020.103244.

[9] S. F. Chevtchenko et al., “Anomaly Detection in Industrial Machinery Using IoT Devices and Machine Learning: A Systematic Mapping,” IEEE Access, vol. 11, pp. 128288–128305, 2023, doi: 10.1109/ACCESS.2023.3333242.

[10] S. Kim, “Innovating knowledge and information for a firm-level automobile demand forecast system: A machine learning perspective,” Journal of Innovation and Knowledge, vol. 8, no. 2, Apr. 2023, doi: 10.1016/j.jik.2023.100355.

[11] A. Brintrup et al., “Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing,” Int J Prod Res, vol. 58, no. 11, pp. 3330–3341, Jun. 2020, doi: 10.1080/00207543.2019.1685705.

[12] M. Mustak, H. Hallikainen, T. Laukkanen, L. Plé, L. D. Hollebeek, and M. Aleem, “Using machine learning to develop customer insights from user-generated content,” Journal of Retailing and Consumer Services, vol. 81, Nov. 2024, doi: 10.1016/j.jretconser.2024.104034.

[13] A. M. Khedr and S. R. S, “Enhancing supply chain management with deep learning and machine learning techniques: A review,” Dec. 01, 2024, Elsevier B.V. doi: 10.1016/j.joitmc.2024.100379.

[14] B. Kitchenham and S. Charters, “Guidelines for performing systematic literature reviews in software engineering,” Technical report, EBSE Technical Report EBSE-2007-01, 2007.

[15] Y. Liu, M. Yang, and Z. Guo, ‘Reinforcement learning based optimal decision making towards product lifecycle sustainability’, Int J Comput Integr Manuf, vol. 35, no. 10–11, pp. 1269–1296, 2022, doi: 10.1080/0951192X.2022.2025623.

[16] D. Gonzalez-Jimenez, J. Del-Olmo, J. Poza, F. Garramiola, and I. Sarasola, ‘Machine learning-based fault detection and diagnosis of faulty power connections of induction machines’, Energies (Basel), vol. 14, no. 16, Aug. 2021, doi: 10.3390/en14164886.

[17] A. Theissler, J. Pérez-Velázquez, M. Kettelgerdes, and G. Elger, ‘Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry’, Reliab Eng Syst Saf, vol. 215, Nov. 2021, doi: 10.1016/j.ress.2021.107864.

[18] M. Mao, S. Zhang, L. Chang, and N. D. Hatziargyriou, ‘Schedulable capacity forecasting for electric vehicles based on big data analysis’, Journal of Modern Power Systems and Clean Energy, vol. 7, no. 6, pp. 1651–1662, Nov. 2019, doi: 10.1007/s40565-019-00573-3.

[19] M. Darwiche and O. Mokhiamar, ‘SVR approach for predicting vehicle velocity for comfortable ride while crossing speed humps’, Alexandria Engineering Journal, vol. 61, no. 8, pp. 6119–6128, Aug. 2022, doi: 10.1016/j.aej.2021.11.045.

[20] K. D. Rao, N. V. Anand, T. K. S. Pandraju, F. Alsaif, and T. S. Ustun, ‘Optimally tuned gated recurrent unit neural network-based state of health estimation scheme for lithium ion batteries’, IEEE Access, vol. 12, pp. 58597–58607, 2024, doi: 10.1109/ACCESS.2024.3392432.

[21] A. R. Mussah and Y. Adu-Gyamfi, ‘Machine learning framework for real-time assessment of traffic safety utilizing connected vehicle data’, Sustainability (Switzerland), vol. 14, no. 22, Nov. 2022, doi: 10.3390/su142215348.
[22] D. A. Andrioaia, V. G. Gaitan, G. Culea, and I. V. Banu, ‘Predicting the RUL of li-ion batteries in UAVs using machine learning techniques’, Computers, vol. 13, no. 3, Mar. 2024, doi: 10.3390/computers13030064.
[23] A. Amellal, I. Amellal, H. Seghiouer, and M. Rida Ech-Charrat, ‘Improving Lead Time Forecasting and Anomaly Detection for Automotive Spare Parts with A Combined CNN-LSTM Approach’, OPERATIONS AND SUPPLY CHAIN MANAGEMENT, vol. 16, no. 2, pp. 265–278, 2023.
[24] M. Hanafy and R. Ming, ‘Machine learning approaches for auto insurance big data’, Risks, vol. 9, no. 2, pp. 1–23, 2021, doi: 10.3390/risks9020042.
[25] X. Li, N. Wang, Y. Lyu, Y. Duan, and J. Zhao, ‘Data-driven fault early warning model of automobile engines based on soft classification’, Electronics (Switzerland), vol. 12, no. 3, Feb. 2023, doi: 10.3390/electronics12030511.
[26] K. Benaissa, S. Bitam, and A. Mellouk, ‘On-board data management layer: connected vehicle as data platform’, Electronics (Switzerland), vol. 10, no. 15, Aug. 2021, doi: 10.3390/electronics10151810.
[27] S. Gopalakrishnan and M. S. Kumaran, ‘Iiot framework based ml model to improve automobile industry product’, Intelligent Automation and Soft Computing, vol. 31, no. 3, pp. 1435–1449, 2022, doi: 10.32604/IASC.2022.020660.
[28] F. R. Amik, A. Lanard, A. Ismat, and S. Momen, ‘Application of machine learning techniques to predict the price of pre-owned cars in bangladesh’, Information (Switzerland), vol. 12, no. 12, Dec. 2021, doi: 10.3390/info12120514.
[29] H. Chu, W. Zhang, P. Bai, and Y. Chen, ‘Data-driven optimization for last-mile delivery’, Complex and Intelligent Systems, vol. 9, no. 3, pp. 2271–2284, Jun. 2023, doi: 10.1007/s40747-021-00293-1.
[30] M. G. Türkbayrağí, E. Dogu, and Y. Esra Albayrak, ‘Artificial intelligence based prediction models: Sales forecasting application in automotive aftermarket’, Journal of Intelligent and Fuzzy Systems, vol. 42, no. 1, pp. 213–225, 2022, doi: 10.3233/JIFS-219187.
[31] D. Zhao et al., ‘A review of the data-driven prediction method of vehicle fuel consumption’, Energies (Basel), vol. 16, no. 14, Jul. 2023, doi: 10.3390/en16145258.
[32] A. Ebrahimi, P. Bakhshizadeh, and R. Varasteh, ‘A predictive analytics approach to improve the dealers-manufacturer relationship in the after-sales service network; case study in the automotive industry’, International Journal of Management Science and Engineering Management, vol. 18, no. 3, pp. 225–235, 2023, doi: 10.1080/17509653.2022.2116733.
[33] X. Zhuang, Y. Yu, and A. Chen, ‘A combined forecasting method for intermittent demand using the automotive aftermarket data’, Data Science and Management, vol. 5, no. 2, pp. 43–56, Jun. 2022, doi: 10.1016/j.dsm.2022.04.001.
[34] K. Akbar, Y. Zou, Q. Awais, M. J. A. Baig, and M. Jamil, ‘A machine learning-based robust state of health (SOH) prediction model for electric vehicle batteries’, Electronics (Switzerland), vol. 11, no. 8, Apr. 2022, doi: 10.3390/electronics11081216.
[35] A. Khodadadi, S. Ghandiparsi, and C.-N. Chuah, ‘A natural language processing and deep learning based model for automated vehicle diagnostics using free-text customer service reports’, Machine Learning with Applications, vol. 10, p. 100424, Dec. 2022, doi: 10.1016/j.mlwa.2022.100424.
[36] M. Alwadi, G. Chetty, and M. Yamin, ‘A framework for vehicle quality evaluation based on interpretable machine learning’, International Journal of Information Technology (Singapore), vol. 15, no. 1, pp. 129–136, Jan. 2023, doi: 10.1007/s41870-022-01121-6.
[37] B. Liang, J. Yang, Y. Guo, and X. Guo, ‘Application of Machine Learning Algorithms in the Development and Consumption Trend of Green and Intelligent Vehicles under the Background of Big Data’, Wirel Commun Mob Comput, vol. 2022, 2022, doi: 10.1155/2022/4436016