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Identifying and Prioritizing the Role of Artificial Intelligence in Predictive Maintenance and Repairs in the Automotive Industry

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A B S T R A C T

This study aims to identify and prioritize the key roles of artificial intelligence in predictive maintenance and repair processes within the automotive industry from an expert-based decision-making perspective. The study adopts a positivist philosophy with a deductive approach and employs a mixed-methods case-survey design. Initially, a comprehensive review of the relevant literature was conducted to extract the principal roles of artificial intelligence in predictive maintenance and repairs. Based on this review, ten AI-related roles were identified and operationalized into evaluation criteria. Data were collected through structured pairwise-comparison questionnaires administered to a panel of 15 experts drawn from maintenance, research and development, and information technology departments in the automotive sector. To prioritize the identified roles, the Analytical Hierarchy Process (AHP) was applied. The consistency of expert judgments was assessed using the consistency ratio to ensure the reliability and logical coherence of the comparisons. The AHP results indicate that artificial intelligence plays a multidimensional role in predictive maintenance and repairs. Among the identified roles, saving time in the repair and maintenance process achieved the highest priority weight (0.196). This was followed by optimizing vehicle performance (0.185) and improving vehicle availability (0.169). Other significant roles included enhancing predictive accuracy, improving estimation of remaining useful life, reducing overall operational costs, optimizing maintenance schedules, strengthening security and privacy, and increasing customer satisfaction. The consistency ratio confirmed the acceptable reliability of the prioritization results. The findings demonstrate that artificial intelligence is a critical enabler of efficient, reliable, and proactive predictive maintenance in the automotive industry, with its greatest value perceived in reducing maintenance time and enhancing operational performance.

Keywords: *Predictive Maintenance, Artificial Intelligence, Automotive Industry.*

1. Introduction

The rapid advancement of artificial intelligence (AI) technologies has profoundly transformed industrial systems, decision-making processes, and operational strategies across a wide range of sectors. Among these, the automotive industry has emerged as one of the most prominent domains in which AI-driven solutions are reshaping traditional paradigms of production, maintenance, and service delivery. Increasing system complexity, the proliferation of sensor-embedded components, and the growing integration of autonomous and semi-autonomous technologies have rendered conventional maintenance approaches insufficient for ensuring operational reliability and cost efficiency. As a result, predictive maintenance has gained increasing attention as a data-driven and proactive strategy capable of anticipating failures before they occur, thereby minimizing downtime, reducing costs, and enhancing system performance (Daily & Peterson, 2017; Merkt, 2019).

Predictive maintenance represents a significant departure from reactive and time-based maintenance models by relying on continuous condition monitoring, historical data analysis, and predictive analytics to determine the optimal timing of maintenance interventions. In industrial contexts, this shift has been facilitated by the availability of large volumes of operational data generated through sensors, Internet of Things (IoT) infrastructures, and cyber-physical systems. The integration of AI and machine learning algorithms into predictive maintenance frameworks has further strengthened their analytical capabilities, enabling the identification of complex patterns, nonlinear relationships, and early indicators of component degradation that are difficult to detect using traditional statistical methods (Ren, 2021; Sajid et al., 2021). Consequently, AI-enhanced predictive maintenance has become a cornerstone of Industry 4.0 initiatives aimed at optimizing asset management and operational resilience.

Within the automotive sector, the importance of predictive maintenance has intensified due to the increasing sophistication of vehicle architectures and the critical role of reliability in safety-sensitive applications. Modern vehicles incorporate advanced electronic control units, interconnected subsystems, and intelligent sensors that continuously generate high-frequency data streams. While these developments create new opportunities for predictive analytics, they also introduce significant challenges related to data heterogeneity, sensor reliability, and system interoperability (Matos et al., 2024). Studies have shown that failures in sensor systems and data transmission can undermine the accuracy of predictive models, highlighting the need for robust AI-based solutions capable of handling uncertainty and incomplete information (Aissani et al., 2024; Matos et al., 2024).

Artificial intelligence plays a central role in addressing these challenges by enabling advanced data processing, adaptive learning, and automated decision-making within predictive maintenance systems. Machine learning algorithms, including supervised, unsupervised, and reinforcement learning models, have demonstrated strong potential in predicting remaining useful life, detecting anomalies, and optimizing maintenance schedules in automotive and industrial environments (Achouch et al., 2022; Titus, 2024). By continuously learning from new operational data, AI-driven systems can adapt to changing conditions and improve prediction accuracy over time, thereby enhancing the reliability of maintenance decisions (Ren, 2021).

The application of AI in predictive maintenance is not limited to technical performance improvements but also extends to broader organizational and economic outcomes. Empirical evidence suggests that effective AI-based maintenance strategies can significantly reduce operational costs by preventing catastrophic failures, minimizing unplanned downtime, and optimizing resource allocation (Arena et al., 2022; Merkt, 2019). In the automotive industry, where downtime can disrupt supply chains and compromise customer satisfaction, these benefits are particularly valuable (Nagy & Lakatos, 2024). Furthermore, AI-enabled predictive maintenance supports improved asset availability and lifecycle management, contributing to enhanced competitiveness in increasingly globalized and technologically intensive markets.

The growing reliance on autonomous and intelligent vehicle systems further underscores the importance of predictive maintenance. Autonomous vehicles depend on the seamless interaction of multiple subsystems, including sensors, actuators, communication modules, and control algorithms. Failures in any of these components can have severe safety and performance implications. As highlighted in prior research, AI-based predictive maintenance offers a viable approach to monitoring these complex systems and ensuring their reliability through early fault detection and timely intervention (Aissani et al., 2024; Bathla et al., 2022). By enabling predictive insights across vehicle fleets, AI contributes to safer and more efficient mobility systems.

Beyond technical and economic considerations, the integration of AI into predictive maintenance raises important legal, ethical, and governance-related questions. Issues such as data ownership, algorithmic transparency, accountability, and cybersecurity have become increasingly salient as AI systems assume greater decision-making autonomy. From a legal perspective, the deployment of AI in industrial and automotive contexts necessitates compliance with regulatory frameworks governing data protection, liability, and environmental responsibility (Abdali, 2025). Moreover, ethical concerns related to fairness, responsibility, and trust in AI-driven decisions have been emphasized in recent interdisciplinary research, particularly in safety-critical domains (Zvieriev et al., 2025). Addressing these considerations is essential for ensuring the sustainable and responsible adoption of AI-based predictive maintenance systems.

The sustainability dimension of AI-enabled predictive maintenance has also attracted growing scholarly attention. By optimizing maintenance operations and reducing unnecessary resource consumption, AI can contribute to environmental sustainability goals, including reduced energy use, lower emissions, and extended asset lifespans (Regona et al., 2024). In the automotive industry, where environmental impacts are closely scrutinized, predictive maintenance aligned with sustainability objectives offers a pathway toward greener and more responsible industrial practices. This aligns with broader global efforts to leverage AI technologies in support of sustainable development and responsible innovation (Regona et al., 2024).

Despite the extensive body of literature examining AI applications in predictive maintenance, several gaps remain. Existing studies often focus on specific algorithms, technical architectures, or isolated performance metrics, without providing a comprehensive assessment of the diverse roles and benefits of AI within predictive maintenance and repair processes in the automotive industry. While literature reviews have documented the technological foundations and challenges of predictive maintenance (Achouch et al., 2022; Arena et al., 2022), fewer studies have systematically identified and prioritized the multifaceted contributions of AI from an expert-driven and decision-oriented perspective. This limitation constrains the ability of practitioners and policymakers to make informed strategic decisions regarding AI adoption and investment.

Moreover, the rapid evolution of AI technologies necessitates continuous reassessment of their roles across different industrial contexts. Emerging AI applications in areas such as decision-support systems, value co-creation, and intelligent asset management suggest that predictive maintenance should be examined not only as a technical function but also as an integral component of organizational strategy and innovation (Jalali Filshour et al., 2025). Insights from adjacent domains, including finance, sports, and judicial systems, further demonstrate the transformative potential of AI when integrated with structured decision-making frameworks (Hasan et al., 2026; Volskyi, 2025; Zvieriev et al., 2025). These cross-sectoral perspectives reinforce the need for comprehensive and context-specific analyses of AI roles in predictive maintenance.

In light of these considerations, there is a clear need for research that systematically identifies, categorizes, and prioritizes the roles of artificial intelligence in predictive maintenance and repairs within the automotive industry. Such research can provide valuable guidance for managers, engineers, and policymakers seeking to harness AI technologies to enhance operational efficiency, reliability, and sustainability. By integrating insights from existing literature with expert judgment and multi-criteria decision-making approaches, it becomes possible to develop a nuanced understanding of how AI contributes to predictive maintenance outcomes and where its strategic value is most pronounced.

Accordingly, the aim of this study is to identify and prioritize the roles of artificial intelligence in predictive maintenance and repairs in the automotive industry using a structured expert-based decision-making approach.

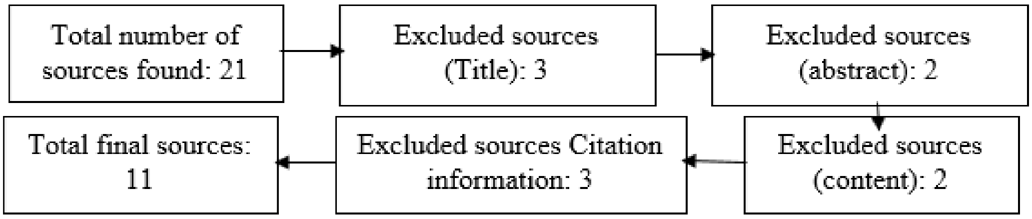
2. Methods and Materials

From the perspective of research philosophy, this study is positivist, as it employs multi-criteria decision-making techniques to prioritize artificial intelligence applications. From the perspective of research approach, it is deductive, using inferences drawn from premises to evaluate the roles of AI in the automotive repair and maintenance sector. From the perspective of research strategy, it is a case-survey that investigates the role of AI in predictive maintenance and repairs using field methods. Finally, from the perspective of method selection, it is a mixed-methods study; a qualitative method was used to identify the roles of AI, while a quantitative method was used to prioritize them.

The Critical Appraisal Skills Program was used to identify articles relevant to the research objectives and title. The results of implementing this program are presented in Figure 1.

Figure 1

Summary of the search and study selection process



The scores assigned to the finally accepted articles are presented in Table 1.

Table 1

The scores assigned to the finally accepted articles

article	Research Objectives	Methodological Rationale	Research Design	Data Collection	Analysis Rigor	Clear of Findings
1	4	3	4	4	5	4
2	5	5	5	5	5	4
3	4	4	4	5	5	5
4	4	4	4	5	4	4
5	5	4	4	5	5	4
6	4	4	4	5	5	4
7	5	4	5	5	5	5
8	5	4	5	5	4	5
9	5	5	4	4	5	4
10	5	4	5	5	4	4
11	4	5	4	4	4	4

Through a review of library studies, ten roles of Artificial Intelligence in predictive maintenance and repairs were identified. These roles and their sources are listed in Table 2.

Table 2

The identified roles of Artificial Intelligence in Predictive Maintenance and Repairs in the Automotive Industry by Literature Review

Role	References
Minimizes unexpected downtime Optimizes vehicle performance	Achouch et al (2022)
Improving vehicle availability Reduces overall operational costs	Merkt (2019)
Optimizing maintenance schedules High predictive accuracy	Titus (2024)
Improving predicting remaining useful life Improving security and privacy	Matos et al (2024)
Customer satisfaction	Nagy & Lakatos (2024)

Saving time consumption	Arena et al (2022)

The factors identified in Table 2 were used to design a questionnaire. The questionnaire's content validity was established using a formal assessment process; as the measured variables were derived from existing research literature, this validity was further confirmed by a panel of academic professors and experts within the research field. In Analytical Hierarchy Process (AHP) questionnaires, reliability is assessed using the consistency ratio (C.R.). This ratio is a mechanism for determining the logical consistency of pairwise comparisons. Empirical evidence indicates that a consistency ratio of less than 0.1 is acceptable, confirming that the comparisons are sufficiently consistent.

The following steps are used to calculate the inconsistency ratio:

Step 1: Calculate the Weighted Sum Vector (WSV)

To do this, multiply the pairwise comparison matrix by the column vector of relative weights. The resulting new vector is called the Weighted Sum Vector (WSV).

Step 2: Divide the elements of the Weighted Sum Vector by the relative priority vector.

The resulting vector is called the Consistency Vector (CV).

Step 3: Obtain the maximum eigenvalue (λ_{max}) of the matrix which is equal to the average of the elements of the Consistency Vector.

Step 4: Calculate the Consistency Index (CI), which is defined as follows:

$CI = (\lambda_{max} - n) / (n - 1)$

Where n is the number of alternatives in the problem.

Step 5: Calculate the Inconsistency Ratio (CR).

To obtain this, divide the Consistency Index (CI) by the Random Index (RI):

$CR = CI / RI$

The value of the Random Index (RI) can be obtained from Table 3.

Table 3

Random Index Values

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

If the CR value is less than or equal to 0.1, the consistency of the comparisons is acceptable. Otherwise, the prioritizations should be revised.

The data were analyzed using the Analytical Hierarchy Process (AHP). The problem-solving steps for this technique involve the following four main stages:

Step 1: Modeling

In this step, a hierarchical model for the decision is constructed. The goal is positioned at the top of the hierarchy. The criteria and sub-criteria form the middle levels, and the decision options are located at the bottom.

Step 2: Data Collection and Formation of Pairwise Comparison Matrices

In this step, the decision-maker compares the different options pairwise, each time with respect to a specific criterion. The results of these comparisons are presented in tables known as pairwise comparison matrices. These comparisons use a numerical scale from 1 to 5, developed by Saaty (1990), to compare both criteria and options within the hierarchical system.

Step 3: Calculation of Factor Weights

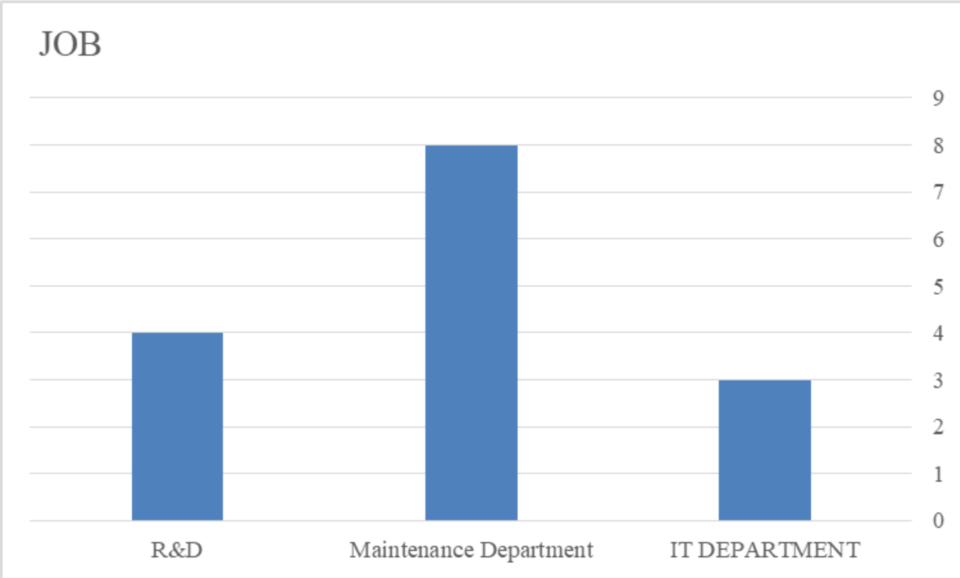
In the third step of the AHP process, the relative weight of the factors at each level is calculated based on the pairwise comparison matrix.

3. Findings and Results

This section is addressed in two parts. In the first part, the characteristics of the respondents are investigated. In the second part, the AHP steps are implemented. According to Figure 2, it was determined that 8 individuals, equivalent to 53.3%, were from the maintenance department; 4 individuals, equivalent to 26.7%, were from the R&D department; and 3 individuals, equivalent to 20%, were from the IT department.

Figure 2

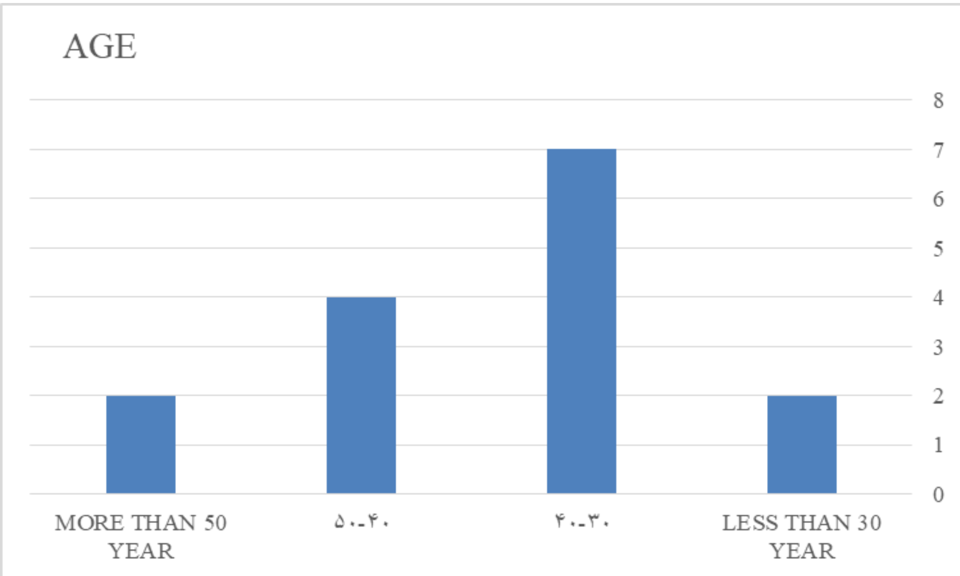
Frequency distribution of respondents' place of employment



According to Figure 3, the age distribution of the respondents was as follows: 7 individuals (46%) were between 30 and 40 years old, 4 individuals (26%) were between 40 and 50 years old, 2 individuals (14%) were under 30 years old, and 2 individuals (14%) were over 50 years old.

Figure 3

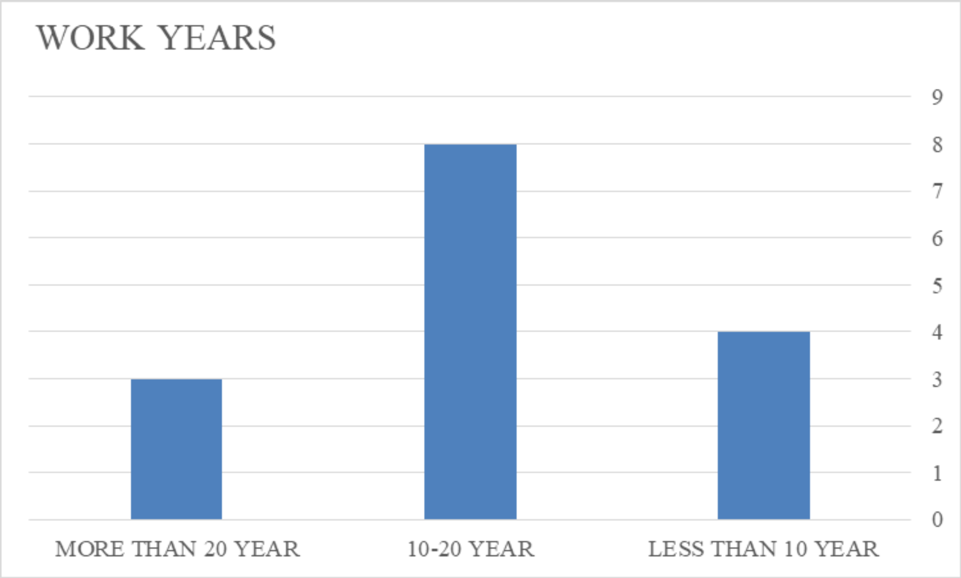
Frequency distribution of respondents' age



According to Figure 4, 8 individuals (54%) had between 10 and 20 years of work experience; 4 individuals (26%) had less than 10 years; and 3 individuals (20%) had more than 20 years of work experience.

Figure 4

Frequency distribution of respondents' Work Years



First, an abbreviation is provided for each identified indicator

Table 4

Abbreviation for research indicators

Role	Abbreviation
Minimizes unexpected downtime	A1
Optimizes vehicle performance	A2
Improving vehicle availability	A3
Reduces overall operational costs	A4
Optimizing maintenance schedules	A5
High predictive accuracy	A6
Improving predicting remaining useful life	A7
Improving security and privacy	A8
Customer satisfaction	A9
Saving time consumption	A10

Then, the responses from the collected questionnaires were aggregated using the geometric mean to form a single pairwise comparison matrix

Table 5

Normalized matrix

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	1	0.031	0.011	0.016	0.010	0.054	0.109	0.031	1/38	0/045
A2	2.38	1	2.13	0.71	1.36	2.54	0.49	1.82	1/69	0/029
A3	1.95	0.092	1	3.12	1.15	0.94	0.73	2.19	0/79	1/11
A4	0.59	0.014	0.018	1	2.25	1.17	0.81	0.94	0/92	1/23
A5	0.95	0.030	0.073	0.048	1	0.013	0.011	0.025	2/24	0/02
A6	3.24	0.022	1.06	0.064	0.74	1	2.84	1.27	1/39	0/025
A7	1.73	0.020	0.013	0.012	0.89	0.014	1	1.75	1/58	0/015
A8	2.11	0.013	0.063	0.010	1.43	0.047	0.014	1	2/03	0/033
A9	0/029	0/015	0/0127	0/010	0/05	0/028	0/018	0/4	1	1/298
A10	1/24	1/37	0/9	0/81	1/55	2/47	1/69	1/33	0/77	1

The columns of integrated values in Table 6 are added together to form the matrix of pairwise comparisons of factors.

Table 6

Sum of index columns

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
Sum	15/22	2/61	5/37	5/80	10/43	8/27	7/71	10/75	13/79	4/80

The values of the pairwise comparison matrix are normalized by dividing each matrix value by the sum of the corresponding column

Table 7

Normalized matrix of indices

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	0/065	0/012	0/002	0/002	0/001	0/006	0/014	0/002	0/100	0/009
A2	0/156	0/383	0/396	0/122	0/130	0/307	0/063	0/169	0/122	0/006
A3	0/128	0/035	0/186	0/537	0/110	0/113	0/094	0/203	0/057	0/231
A4	0/038	0/005	0/020	0/172	0/215	0/141	0/105	0/087	0/066	0/256
A5	0/062	0/011	0/013	0/008	0/095	0/001	0/001	0/002	0/162	0/004
A6	0/212	0/008	0/197	0/011	0/070	0/120	0/368	0/118	0/101	0/005
A7	0/113	0/007	0/002	0/002	0/085	0/001	0/129	0/162	0/114	0/003
A8	0/138	0/005	0/011	0/001	0/137	0/004	0/001	0/093	0/147	0/006
A9	0/001	0/006	0/002	0/001	0/004	0/003	0/002	0/037	0/072	0/270
A10	0/081	0/524	0/167	0/139	0/148	0/298	0/219	0/123	0/055	0/208

Finally, the weight of each factor is obtained by taking the arithmetic average of each row.

Table 8

Final prioritization of indicators

	Role
A1	0/021
A2	0/185
A3	0/169
A4	0/110
A5	0/036
A6	0/121
A7	0/062
A8	0/054
A9	0/040
A10	0/196

Step 1: Weighted Sum Vector (WSV)

First, the normalized matrix is multiplied by its relative weight vector.

Table 9

Weighted Sum Vector (WSV)

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	W	WSV
A1	1	0.031	0.011	0.016	0.010	0.054	0.109	0.031	1/38	0/045	0/021	1.230
A2	2.38	1	2.13	0.71	1.36	2.54	0.49	1.82	1/69	0/029	0/185	0.992
A3	1.95	0.092	1	3.12	1.15	0.94	0.73	2.19	0/79	1/11	0/169	0.896
A4	0.59	0.014	0.018	1	2.25	1.17	0.81	0.94	0/92	1/23	0/110	0.547
A5	0.95	0.030	0.073	0.048	1	0.013	0.011	0.025	2/24	0/02	0/036	0.159
A6	3.24	0.022	1.06	0.064	0.74	1	2.84	1.27	1/39	0/025	0/121	0.542
A7	1.73	0.020	0.013	0.012	0.89	0.014	1	1.75	1/58	0/015	0/062	0.225
A8	2.11	0.013	0.063	0.010	1.43	0.047	0.014	1	2/03	0/033	0/054	0.198
A9	0/029	0/015	0/0127	0/010	0/05	0/028	0/018	0/4	1	1/298	0/040	0.318
A10	1/24	1/37	0/9	0/81	1/55	2/47	1/69	1/33	0/77	1	0/196	1.099

At this stage, the Weighted Sum Vector (WSV) is divided by the relative weight vector.

Table 10

Consistency Vector

	CV
A1	10/095
A2	10/362
A3	10/301
A4	10/972
A5	10/416
A6	10/479
A7	10/629
A8	10/666
A9	10/95
A10	10/607

Step 3: Calculation of the Matrix's Maximum Eigenvalue

The λ_{max} value is obtained from the average of the dimensions and factors of the Consistency Vector (CV).

λ_{max} =10.648

Step 4: Consistency Index Calculation

$$CI = [\frac{10.648 - 10}{10 - 1}] = 0.072$$

Step 5: Inconsistency Ratio Calculation

$$\mathrm{CR} = \frac{0.072}{1.49} = 0.048$$

4. Discussion and Conclusion

The findings of the present study provide empirical support for the growing strategic importance of artificial intelligence in predictive maintenance and repair activities within the automotive industry. Using a structured multi-criteria decision-making approach, the results demonstrate that AI contributes to predictive maintenance through multiple interrelated roles, with varying levels of perceived importance among industry experts. The prioritization outcomes reveal that *saving time in the repair and maintenance sector* constitutes the most critical contribution of AI, followed by *optimizing vehicle performance* and *improving vehicle availability*. These results reflect a pragmatic industry perspective that emphasizes operational efficiency, system reliability, and responsiveness to maintenance demands.

The highest-ranked role—saving time in maintenance and repair processes—highlights the operational urgency faced by automotive organizations in managing increasingly complex vehicle systems. AI-enabled diagnostics, automated fault detection, and real-time decision support significantly reduce the time required to identify failures and initiate corrective actions. This finding aligns with prior research emphasizing that AI-driven predictive maintenance minimizes diagnostic latency and accelerates maintenance workflows by replacing manual inspections with automated data-driven insights (Arena et al., 2022). Similarly, studies on AI-based maintenance systems indicate that reduced intervention time directly translates into lower downtime and improved service continuity, particularly in environments where vehicle availability is critical (Titus, 2024).

The prioritization of optimizing vehicle performance as the second most important role underscores the close relationship between predictive maintenance and overall system efficiency. AI algorithms enhance performance optimization by continuously monitoring operational parameters and detecting deviations from optimal functioning before they escalate into failures. This result is consistent with findings demonstrating that AI-supported predictive maintenance enables fine-grained performance tuning and adaptive maintenance scheduling, thereby enhancing system output and energy efficiency (Achouch et al., 2022; Ren, 2021). In the automotive context, where performance degradation can compromise safety and customer satisfaction, this role assumes particular significance (Nagy & Lakatos, 2024).

Improving vehicle availability, ranked third, reflects the industry's emphasis on maintaining continuous fleet operability. AI-driven predictive maintenance supports higher availability by preventing unexpected breakdowns and enabling proactive interventions based on real-time condition monitoring. This result aligns with analytical reviews indicating that predictive models significantly improve asset availability by shifting maintenance decisions from reactive to condition-based strategies (Merkt, 2019). The integration of AI further enhances this effect by improving prediction accuracy and reducing false alarms, which can otherwise lead to unnecessary maintenance actions (Sajid et al., 2021).

Another notable finding relates to the role of AI in reducing overall operational costs. Although not ranked among the top three, cost reduction remains a central benefit of AI-enabled predictive maintenance. By minimizing unplanned downtime, extending component life, and optimizing spare parts management, AI contributes to long-term cost efficiency. This finding is consistent with prior evidence showing that predictive maintenance strategies supported by machine learning significantly reduce lifecycle costs compared to traditional preventive maintenance models (Daily & Peterson, 2017; Merkt, 2019). In automotive manufacturing and service operations, these savings are particularly relevant due to high capital intensity and competitive cost pressures.

The role of AI in optimizing maintenance schedules also emerged as a meaningful contributor to predictive maintenance effectiveness. AI systems dynamically adjust maintenance timing based on actual equipment condition rather than fixed intervals, reducing both over-maintenance and under-maintenance risks. This result is supported by earlier studies demonstrating that AI-enhanced scheduling improves maintenance efficiency by balancing reliability and cost considerations (Bouabdallaoui et al., 2021; Titus, 2024). In automotive environments characterized by variable usage patterns and operating conditions, such adaptive scheduling capabilities are essential for maintaining reliability without incurring unnecessary costs.

High predictive accuracy and improved estimation of remaining useful life (RUL) were also identified as important, though relatively lower-ranked, roles of AI. These findings suggest that while technical accuracy is fundamental, industry practitioners prioritize tangible operational outcomes over purely analytical performance. Nonetheless, prior research has established that accurate RUL prediction is a core enabler of effective predictive maintenance, as it underpins timely decision-making and resource allocation (Ren, 2021). Challenges related to sensor reliability, data quality, and environmental variability may explain why these technically critical roles received lower relative priority (Aissani et al., 2024; Matos et al., 2024).

The identification of security and privacy enhancement as a distinct role of AI reflects growing awareness of cyber risks in data-intensive maintenance systems. AI-based security mechanisms can detect anomalous behavior, prevent unauthorized access, and safeguard sensitive operational data. This finding is consistent with recent research emphasizing the importance of integrating cybersecurity considerations into AI-driven industrial systems (Matos et al., 2024). Moreover, from a legal and ethical standpoint, ensuring data protection and responsible AI use is increasingly recognized as a prerequisite for sustainable AI adoption in industrial and transportation sectors (Abdali, 2025; Zvieriev et al., 2025).

Customer satisfaction, although ranked lower than operational factors, remains an important outcome of AI-enabled predictive maintenance. By reducing breakdowns, improving service reliability, and shortening repair times, AI indirectly enhances customer trust and satisfaction. This result aligns with findings showing that predictive maintenance improves perceived service quality and reduces customer dissatisfaction associated with unexpected failures (Nagy & Lakatos, 2024). In highly competitive automotive markets, these customer-centric benefits can translate into long-term brand loyalty and market advantage.

Taken together, the results demonstrate that the value of AI in predictive maintenance extends beyond technical performance improvements to encompass strategic, economic, and organizational dimensions. The prioritization pattern observed in this study suggests that industry experts place greatest emphasis on AI capabilities that deliver immediate and measurable operational benefits, such as time savings and availability enhancement. This pragmatic orientation complements broader academic perspectives that view AI as an enabler of intelligent, adaptive, and sustainable maintenance systems (Regona et al., 2024). Furthermore, insights from related domains—including finance, sports, and governance—underscore the transformative potential of AI when embedded within structured decision-making frameworks (Hasan et al., 2026; Volskyi, 2025).

Overall, the findings reinforce the argument that successful implementation of AI in predictive maintenance requires not only advanced algorithms but also alignment with organizational priorities, regulatory considerations, and sustainability objectives. By systematically identifying and prioritizing AI roles, this study contributes to a more nuanced understanding of how AI-driven predictive maintenance can be strategically leveraged within the automotive industry.

Despite its contributions, this study has several limitations that should be acknowledged. First, the analysis is based on expert judgments drawn from a limited sample within a specific organizational and industrial context, which may constrain the generalizability of the findings. Second, the use of a single multi-criteria decision-making technique emphasizes relative prioritization but does not capture dynamic interactions among the identified roles. Third, the study focuses on perceived importance rather than direct performance outcomes, which may introduce subjective bias into the results.

Future research could address these limitations by expanding the sample to include experts from multiple automotive firms and geographical regions. Longitudinal studies could examine how the prioritization of AI roles evolves as technologies mature and organizational experience increases. Additionally, integrating complementary analytical methods, such as causal modeling or simulation-based approaches, may provide deeper insights into the interdependencies among AI-enabled maintenance functions and their long-term impacts.

From a practical perspective, automotive managers should prioritize AI applications that deliver immediate operational value, particularly those that reduce repair time and improve vehicle availability. Investment decisions should be guided by a clear understanding of organizational needs and readiness for AI adoption. Moreover, successful implementation requires not only technical capability but also workforce training, data governance frameworks, and alignment with regulatory and ethical standards to ensure sustainable and responsible use of AI in predictive maintenance.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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