ARTIFICIAL INTELLIGENCE-DRIVEN PREDICTIVE VEHICLE MAINTENANCE AND CUSTOMER SERVICE LOYALTY: THE MEDIATING ROLE OF SERVICE TRUST AND THE MODERATING EFFECT OF TECHNOLOGY READINESS

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ABSTRACT
Artificial intelligence (AI) has become an important technological innovation in the automotive service industry by enabling predictive maintenance, intelligent diagnostics, and personalized customer services. Despite the increasing adoption of AI-supported maintenance technologies, limited empirical evidence exists regarding how predictive vehicle maintenance influences customer service loyalty, particularly in emerging automotive markets. Therefore, this study investigates the effect of Artificial Intelligence-Driven Predictive Vehicle Maintenance on Customer Service Loyalty, while examining the mediating role of Service Trust and the moderating effect of Technology Readiness.

A quantitative research design based on a correlational survey model was employed. Data were collected from 469 customers receiving vehicle maintenance and repair services from automotive service centers located in Nicosia, Famagusta, and Güzelyurt in the Turkish Republic of Northern Cyprus. The proposed conceptual model was tested using IBM SPSS Statistics 29.0 and AMOS 24.0. Descriptive statistics, reliability analysis, confirmatory factor analysis, correlation analysis, multiple regression analysis, structural equation modeling (SEM), bootstrapping mediation analysis, and moderation analysis were performed.

The findings revealed that Artificial Intelligence-Driven Predictive Vehicle Maintenance has a significant positive effect on Customer Service Loyalty. Service Trust was found to partially mediate this relationship, indicating that AI-supported maintenance technologies enhance customers' confidence in automotive service providers, thereby strengthening customer loyalty. Furthermore, Technology Readiness significantly moderated the relationship, demonstrating that customers with higher levels of technology readiness responded more positively to AI-supported predictive maintenance services. All proposed hypotheses were supported, and the structural model exhibited satisfactory reliability, validity, and goodness-of-fit indices.

This study contributes to the literature by integrating artificial intelligence, predictive vehicle maintenance, service trust, technology readiness, and customer service loyalty into a single conceptual framework. The findings also provide practical implications for automotive service centers, vehicle manufacturers, and service managers seeking to improve customer loyalty through AI-supported maintenance technologies.
Key Words: Artificial Intelligence, Predictive Vehicle Maintenance, Customer Service Loyalty, Service Trust, Technology Readiness, Automotive Service Management, Predictive Analytics.

Introduction

The rapid advancement of artificial intelligence (AI) has fundamentally transformed service industries by enabling organizations to automate processes, improve operational efficiency, and enhance customer experiences through intelligent technologies. Within the automotive sector, AI has become an essential component of predictive vehicle maintenance, allowing service providers to anticipate mechanical failures, optimize maintenance schedules, and improve diagnostic accuracy through machine learning algorithms, Internet of Things (IoT) technologies, and predictive analytics. These innovations have shifted vehicle maintenance from reactive repair approaches toward proactive maintenance strategies that improve service quality and customer satisfaction (Davenport et al., 2020; Huang & Rust, 2022; Dwivedi et al., 2023).

Predictive vehicle maintenance refers to the use of real-time vehicle data, sensor technologies, and artificial intelligence algorithms to predict potential mechanical failures before they occur. Unlike traditional maintenance practices based on fixed service intervals or component failure, predictive maintenance enables automotive service providers to reduce unexpected breakdowns, minimize repair costs, improve vehicle reliability, and increase operational efficiency. Consequently, AI-driven predictive maintenance has become a strategic innovation that enhances both organizational performance and customer value within the automotive service industry (Lee et al., 2021; Deloitte, 2024).

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The digital transformation of automotive service centers has accelerated considerably with the adoption of AI-powered diagnostic systems, intelligent maintenance scheduling, mobile service applications, and automated customer communication platforms. These technologies enable service centers to provide more accurate diagnostics, transparent maintenance information, personalized service recommendations, and faster repair processes. As competition within the automotive service industry intensifies, organizations increasingly rely on AI-supported maintenance systems to improve customer experiences and strengthen long-term relationships with vehicle owners (PwC, 2024; Chintalapati & Pandey, 2022).

One of the most important determinants of long-term customer relationships within automotive services is Service Trust. Service trust refers to customers' confidence in the competence, honesty, transparency, and reliability of service providers. Customers who perceive predictive maintenance systems as accurate, transparent, and beneficial are more likely to trust automotive service providers, accept maintenance recommendations, and continue using the same service center. Therefore, trust functions as an important psychological mechanism through which AI-supported predictive maintenance contributes to customer service loyalty (Morgan & Hunt, 1994; Sirdeshmukh, Singh, & Sabol, 2002).

Another important factor influencing customers' responses to AI-supported automotive services is Technology Readiness, which reflects an individual's willingness and ability to embrace and use new technologies. Customers with higher levels of technology readiness generally perceive AI-based maintenance systems as useful, reliable, and convenient, whereas individuals with lower technology readiness may be more skeptical toward automated diagnostics and digital service platforms. Consequently, technology readiness may strengthen or weaken the effectiveness of AI-driven predictive maintenance in influencing customer loyalty (Parasuraman, 2000; Parasuraman & Colby, 2015).

The automotive service industry in the Turkish Republic of Northern Cyprus (TRNC) has increasingly adopted digital technologies to improve maintenance quality and customer service. In particular, automotive service centers operating in Nicosia, Famagusta, and Güzelyurt have begun implementing AI-supported diagnostic equipment, computerized maintenance management systems, digital appointment platforms, and predictive maintenance technologies. Despite these developments, empirical evidence regarding the effectiveness of AI-driven predictive vehicle maintenance in strengthening customer service loyalty remains limited within the TRNC. Moreover, the mediating role of Service Trust and the moderating effect of Technology Readiness have not yet been comprehensively examined within the local automotive service context.

Accordingly, this study investigates the effect of Artificial Intelligence-Driven Predictive Vehicle Maintenance on Customer Service Loyalty among customers receiving services from automotive repair centers in Nicosia, Famagusta, and Güzelyurt in the Turkish Republic of Northern Cyprus. Furthermore, the study examines the mediating role of Service Trust and the moderating effect of Technology Readiness. Data were collected from 469 customers, and the proposed conceptual model seeks to contribute to the literature on artificial intelligence, automotive service management, customer relationship management, and digital transformation while providing practical implications for automotive service providers and industry practitioners.

Problem Statement

Artificial intelligence has become an important driver of innovation in the automotive service industry through predictive maintenance systems, intelligent diagnostics, and digital customer service platforms. AI-supported predictive maintenance enables automotive service providers to identify potential mechanical failures before they occur, thereby reducing maintenance costs, improving service efficiency, and increasing vehicle reliability. Despite these technological developments, organizations continue to face challenges in understanding how AI-driven predictive maintenance influences customers' behavioral outcomes, particularly customer service loyalty (Dwivedi et al., 2023; Deloitte, 2024).

Previous studies have shown that digital service technologies improve customer satisfaction and service quality. However, relatively limited empirical evidence explains the mechanisms through which AI-supported predictive maintenance contributes to customer loyalty. In particular, Service Trust has received insufficient attention as a mediating mechanism linking AI-supported maintenance systems to long-term customer relationships. Since customers are more likely to remain loyal when they perceive service providers as competent, transparent, and trustworthy, understanding the mediating role of trust is essential for improving customer retention within automotive service organizations (Morgan & Hunt, 1994; Sirdeshmukh et al., 2002).

Customers also differ in their willingness to adopt emerging technologies. Individuals with higher levels of Technology Readiness are generally more willing to accept AI-supported maintenance recommendations, digital

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diagnostics, and automated service systems. Conversely, customers with lower technology readiness may perceive AI applications as complex or unreliable, reducing the effectiveness of predictive maintenance services. Despite its theoretical importance, limited empirical research has investigated whether technology readiness moderates the relationship between AI-driven predictive maintenance and customer service loyalty in automotive service settings (Parasuraman & Colby, 2015; Blut & Wang, 2020).

In the Turkish Republic of Northern Cyprus, automotive repair centers have increasingly implemented digital diagnostic equipment, computerized maintenance systems, and AI-supported repair technologies. This transformation is particularly evident in Nicosia, Famagusta, and Güzelyurt, where automotive service providers seek to improve operational efficiency and customer satisfaction through digital innovation. Nevertheless, there is a lack of empirical studies simultaneously examining the relationships among Artificial Intelligence-Driven Predictive Vehicle Maintenance, Service Trust, Technology Readiness, and Customer Service Loyalty within the TRNC automotive service industry.

Therefore, an important research gap exists regarding how AI-supported predictive maintenance influences customer loyalty and the mechanisms through which this relationship operates. To address this gap, the present study investigates the relationship between Artificial Intelligence-Driven Predictive Vehicle Maintenance and Customer Service Loyalty among 469 customers receiving services from automotive repair centers in Nicosia, Famagusta, and Güzelyurt. Furthermore, the study examines the mediating role of Service Trust and the moderating effect of Technology Readiness, thereby contributing to the literature on artificial intelligence, automotive service management, and customer relationship management while providing practical recommendations for service managers and automotive businesses.

Purpose of the Research

The primary purpose of this study is to investigate the effect of Artificial Intelligence-Driven Predictive Vehicle Maintenance on Customer Service Loyalty among customers receiving automotive maintenance and repair services in Nicosia, Famagusta, and Güzelyurt in the Turkish Republic of Northern Cyprus (TRNC). As artificial intelligence technologies become increasingly integrated into automotive service operations, understanding how AI-supported predictive maintenance influences customers' behavioral outcomes has become an important issue for both researchers and practitioners. (Dwivedi et al., 2023; Deloitte, 2024).

More specifically, this study aims to examine whether Service Trust mediates the relationship between AI-driven predictive vehicle maintenance and customer service loyalty. Predictive maintenance technologies are expected to improve customers' perceptions of service reliability, transparency, and technical competence, thereby strengthening trust in automotive service providers. Increased trust may subsequently encourage customers to continue using the same service centers and develop long-term loyalty. (Morgan & Hunt, 1994; Sirdeshmukh et al., 2002).

The study also seeks to determine whether Technology Readiness moderates the relationship between Artificial Intelligence-Driven Predictive Vehicle Maintenance and Customer Service Loyalty. Customers with higher levels of technology readiness are expected to perceive AI-supported maintenance systems more positively, making them more willing to trust digital diagnostic technologies and continue receiving services from automotive repair centers utilizing artificial intelligence. Consequently, the study evaluates whether technology readiness strengthens or weakens the effectiveness of AI-supported predictive maintenance in enhancing customer loyalty. (Parasuraman & Colby, 2015; Blut & Wang, 2020).

Furthermore, this research aims to contribute to the literature by integrating Artificial Intelligence-Driven Predictive Vehicle Maintenance, Service Trust, Technology Readiness, and Customer Service Loyalty into a comprehensive conceptual framework. The proposed model extends existing research on artificial intelligence, relationship marketing, and automotive service management by simultaneously examining direct, mediating, and moderating relationships. The findings are expected to provide valuable recommendations for automotive service centers, vehicle manufacturers, service managers, and policymakers seeking to improve customer loyalty through AI-supported maintenance technologies. (Huang & Rust, 2022; Chintalapati & Pandey, 2022; Dwivedi et al., 2023).

Importance of the Research

The rapid integration of artificial intelligence (AI) into the automotive service industry has fundamentally transformed traditional vehicle maintenance practices by enabling predictive diagnostics, intelligent maintenance scheduling, and data-driven decision-making. AI-supported predictive maintenance systems allow automotive service providers to identify potential mechanical failures before they occur, thereby reducing maintenance costs,

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minimizing unexpected vehicle breakdowns, and improving service quality. Despite these technological advancements, empirical evidence explaining how AI-driven predictive vehicle maintenance influences customer service loyalty remains limited, particularly in developing automotive markets such as the Turkish Republic of Northern Cyprus (TRNC). Therefore, this study addresses an important research gap by investigating the relationships among Artificial Intelligence-Driven Predictive Vehicle Maintenance, Service Trust, Technology Readiness, and Customer Service Loyalty (Dwivedi et al., 2023; Huang & Rust, 2022; Deloitte, 2024).

From a theoretical perspective, this research contributes to the literature on artificial intelligence, automotive service management, relationship marketing, and consumer behavior by integrating four contemporary constructs into a comprehensive conceptual framework. Although previous studies have examined the direct influence of digital technologies on customer satisfaction and loyalty, relatively few have simultaneously investigated the mediating role of Service Trust and the moderating effect of Technology Readiness within the context of AI-supported predictive vehicle maintenance. Accordingly, this study extends current theoretical understanding by explaining both the direct and indirect mechanisms through which artificial intelligence contributes to long-term customer loyalty in the automotive service sector (Morgan & Hunt, 1994; Sirdeshmukh et al., 2002; Parasuraman & Colby, 2015).

From a practical perspective, the findings are expected to provide valuable guidance for automotive repair centers, authorized vehicle service providers, automotive manufacturers, and service managers. Understanding how AI-supported predictive maintenance influences customer loyalty will enable organizations to improve service quality, strengthen customer trust, optimize maintenance processes, and develop more effective digital service strategies. Furthermore, the findings may support investments in intelligent diagnostic technologies and customer-centered digital transformation initiatives that enhance organizational competitiveness within the automotive after-sales service industry (Lee et al., 2021; PwC, 2024; Chintalapati & Pandey, 2022).

This study is also significant because it provides empirical evidence obtained from 469 customers receiving services from automotive repair centers in Nicosia, Famagusta, and Güzelyurt, representing one of the first comprehensive investigations of AI-supported predictive vehicle maintenance within the TRNC. The findings contribute to a better understanding of customer perceptions regarding artificial intelligence applications in automotive services and provide evidence that may assist policymakers and industry practitioners in promoting digital transformation within the automotive maintenance sector. The proposed conceptual framework may also be adapted and tested in different countries and service industries, thereby contributing to the continued advancement of research on artificial intelligence, service management, and customer relationship management (Blut & Wang, 2020; Deloitte, 2024; Dwivedi et al., 2023).

Research Hypotheses

H1: Artificial Intelligence-Driven Predictive Vehicle Maintenance has a positive and significant effect on Customer Service Loyalty.

H2: Artificial Intelligence-Driven Predictive Vehicle Maintenance has a positive and significant effect on Service Trust.

H3: Service Trust has a positive and significant effect on Customer Service Loyalty.

Mediation Hypothesis

H4: Service Trust mediates the relationship between Artificial Intelligence-Driven Predictive Vehicle Maintenance and Customer Service Loyalty.

Moderation Hypotheses

H5: Technology Readiness moderates the relationship between Artificial Intelligence-Driven Predictive Vehicle Maintenance and Customer Service Loyalty.

H5a: The positive effect of Artificial Intelligence-Driven Predictive Vehicle Maintenance on Customer Service Loyalty is stronger among customers with high levels of Technology Readiness.

H5b: The positive effect of Artificial Intelligence-Driven Predictive Vehicle Maintenance on Customer Service Loyalty is weaker among customers with low levels of Technology Readiness.

Theoretical Framework

Artificial Intelligence

Artificial Intelligence (AI) refers to the capability of computer systems to perform tasks that normally require human intelligence, including learning, reasoning, problem-solving, decision-making, and language understanding. Recent advances in machine learning, deep learning, computer vision, and natural language processing have enabled AI to become an essential technology across numerous industries. Rather than simply automating routine activities, AI can analyze large volumes of data, recognize complex patterns, generate predictions, and continuously improve its performance through experience. Consequently, organizations

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increasingly utilize AI to improve operational efficiency, support strategic decision-making, and create value for customers through personalized and data-driven services (Russell & Norvig, 2021; Dwivedi et al., 2023).

The rapid development of AI has significantly influenced service industries by enabling intelligent automation and enhancing customer experiences. Organizations now employ AI to optimize resource allocation, improve service quality, reduce operational costs, and strengthen customer relationships. In customer-oriented industries, AI supports personalized communication, predictive analytics, intelligent recommendation systems, and real-time decision-making. These capabilities have transformed traditional business models into more proactive, customer-centered, and digitally integrated service ecosystems. As a result, AI has become a strategic capability that contributes to organizational competitiveness and long-term sustainability (Huang & Rust, 2022; Davenport et al., 2020).

Predictive Vehicle Maintenance

Predictive Vehicle Maintenance refers to the use of artificial intelligence, sensor technologies, Internet of Things (IoT) devices, and predictive analytics to monitor vehicle conditions and forecast potential mechanical failures before they occur. Unlike traditional preventive maintenance, which follows predetermined service intervals, predictive maintenance continuously evaluates real-time operational data to determine the optimal timing for maintenance activities. This approach minimizes unexpected breakdowns, reduces maintenance costs, extends vehicle lifespan, and improves service efficiency. Consequently, predictive maintenance has become one of the most important applications of artificial intelligence within the automotive industry (Lee et al., 2021; Deloitte, 2024).

Artificial intelligence enables predictive maintenance systems to process large volumes of diagnostic information collected from vehicle sensors and onboard monitoring systems. Machine learning algorithms identify abnormal operating patterns and estimate the probability of component failures, allowing service centers to perform maintenance before serious mechanical problems develop. These capabilities improve diagnostic accuracy, shorten repair times, reduce operational disruptions, and enhance customer satisfaction. Accordingly, predictive vehicle maintenance is increasingly recognized as a key innovation supporting the digital transformation of automotive service management (PwC, 2024; Lee et al., 2021).

Customer Service Loyalty

Customer Service Loyalty refers to customers' commitment to maintaining a long-term relationship with a service provider through repeated purchases, positive word-of-mouth communication, and resistance to competing alternatives. Loyalty represents one of the most valuable outcomes of relationship marketing because loyal customers contribute to sustainable organizational performance through repeat business and stronger customer relationships. Within automotive service centers, customer loyalty is influenced not only by technical repair quality but also by service transparency, reliability, communication quality, and customer experiences throughout the maintenance process (Oliver, 1999; Morgan & Hunt, 1994).

The adoption of AI-supported predictive maintenance has introduced new opportunities for strengthening customer loyalty. Customers receiving accurate diagnostics, transparent maintenance recommendations, and proactive communication are more likely to perceive greater value from automotive services. AI-supported maintenance systems reduce uncertainty by providing objective and data-driven repair information, thereby increasing customer confidence in service providers. Consequently, organizations utilizing intelligent maintenance technologies may achieve higher customer retention and stronger long-term loyalty compared with organizations relying solely on traditional maintenance practices (Huang & Rust, 2022; Chintalapati & Pandey, 2022).

Service Trust

Service Trust refers to customers' belief that a service provider is competent, reliable, honest, and capable of delivering promised services consistently. Trust is considered a fundamental element of relationship marketing because it reduces customers' perceived risk and encourages long-term cooperation between organizations and consumers. Within the automotive repair industry, customers often lack the technical knowledge necessary to evaluate repair quality independently. Therefore, trust becomes an essential factor influencing customers' willingness to accept maintenance recommendations and continue using the same service provider (Morgan & Hunt, 1994; Sirdeshmukh et al., 2002).

Artificial intelligence has the potential to strengthen service trust by improving diagnostic accuracy, increasing transparency, and providing evidence-based maintenance recommendations. AI-supported diagnostic systems reduce human error, deliver consistent technical evaluations, and enable customers to receive detailed

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explanations regarding vehicle conditions. These improvements increase customers' confidence in maintenance decisions and reduce uncertainty during the repair process. Consequently, service trust represents an important psychological mechanism through which AI-supported predictive maintenance contributes to customer loyalty (Davenport et al., 2020; Huang & Rust, 2022).

Technology Readiness

Technology Readiness refers to an individual's tendency to embrace and use new technologies to accomplish personal or professional goals. Customers with high technology readiness generally perceive technological innovations as beneficial, convenient, and reliable, whereas individuals with lower readiness may exhibit greater skepticism toward digital technologies. Technology readiness therefore influences customers' acceptance of AI-supported service systems and their willingness to interact with intelligent technologies (Parasuraman & Colby, 2015; Blut & Wang, 2020).

Within automotive service environments, technology readiness determines how customers evaluate AI-supported predictive maintenance systems, digital diagnostics, mobile service applications, and automated communication platforms. Customers possessing higher technology readiness are more likely to appreciate AI-generated maintenance recommendations, trust digital diagnostic results, and remain loyal to technologically advanced service providers. Therefore, technology readiness strengthens the effectiveness of AI-driven predictive maintenance by increasing customers' acceptance of intelligent automotive services and enhancing long-term service loyalty (Parasuraman & Colby, 2015; Dwivedi et al., 2023).

Method

Research Model

This study employed a quantitative research approach using a correlational survey design to examine the relationships among Artificial Intelligence-Driven Predictive Vehicle Maintenance, Service Trust, Technology Readiness, and Customer Service Loyalty. The conceptual model was developed based on the relationship marketing literature and recent studies on artificial intelligence and automotive service management.

In the proposed research model, Artificial Intelligence-Driven Predictive Vehicle Maintenance was treated as the independent variable, Customer Service Loyalty as the dependent variable, Service Trust as the mediating variable, and Technology Readiness as the moderating variable. The proposed hypotheses were tested using Structural Equation Modeling (SEM) to examine both the direct and indirect relationships among the latent constructs (Hair et al., 2022).

Population and Sample

The target population of this study consisted of customers receiving vehicle maintenance and repair services from authorized and independent automotive service centers located in Nicosia, Famagusta, and Güzelyurt in the Turkish Republic of Northern Cyprus (TRNC).

A simple random sampling method was employed to ensure that every customer had an equal opportunity to participate in the study. Eligible participants were individuals aged 18 years and older who had received vehicle maintenance or repair services within the previous twelve months.

A total of 500 questionnaires were distributed between February and April 2026. After eliminating incomplete questionnaires and responses containing excessive missing values or response inconsistencies, 469 valid questionnaires remained for statistical analysis. According to Hair et al. (2022), this sample size is more than adequate for Structural Equation Modeling and provides sufficient statistical power for hypothesis testing.

Data Collection Tools

Data were collected using a structured questionnaire consisting of two sections.

The first section included demographic questions regarding gender, age, educational level, monthly income, occupation, years of driving experience, frequency of vehicle maintenance, and previous experience with AI-supported automotive services.

The second section contained standardized measurement scales adapted from previous studies.

Artificial Intelligence-Driven Predictive Vehicle Maintenance was measured using 10 items adapted from Lee et al. (2021), Davenport et al. (2020), and Huang and Rust (2022).

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Service Trust was measured using 8 items adapted from Morgan and Hunt (1994) and Sirdeshmukh et al. (2002).

Technology Readiness was measured using 8 items adapted from Parasuraman and Colby (2015).

Customer Service Loyalty was measured using 8 items adapted from Oliver (1999) and Zeithaml, Berry, and Parasuraman (1996).

All items were measured using a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

Data Collection Process

The data collection process was conducted between February and April 2026 in automotive service centers located in Nicosia, Famagusta, and Güzelyurt.

Before administering the questionnaire, participants were informed about the objectives of the study, confidentiality procedures, voluntary participation, and their right to withdraw from the study at any time without any consequences. Informed consent was obtained from every participant.

Questionnaires were distributed both in printed form through participating automotive service centers and electronically using secure online survey platforms. Respondents completed the questionnaires independently without researcher intervention. Following data collection, all questionnaires were screened for missing data, inconsistent responses, and response bias. Consequently, 469 questionnaires were considered suitable for statistical analysis.

Data Analysis

The collected data were analyzed using IBM SPSS Statistics 29.0 and AMOS 24.0.

Initially, descriptive statistics were calculated to summarize participants' demographic characteristics. The assumption of normality was evaluated using skewness and kurtosis values.

The reliability of the measurement scales was assessed using Cronbach's Alpha, whereas construct validity was evaluated through Confirmatory Factor Analysis (CFA). Convergent validity was examined by calculating Composite Reliability (CR) and Average Variance Extracted (AVE), while discriminant validity was assessed using the Fornell–Larcker criterion (Fornell & Larcker, 1981; Hair et al., 2022).

Independent Samples t-test and One-Way ANOVA were performed to determine differences according to demographic variables. Pearson correlation analysis and multiple regression analysis were conducted to examine relationships among the research variables.

Finally, the proposed hypotheses were tested using Structural Equation Modeling (SEM). The mediating effect of Service Trust was examined using the Bootstrapping procedure, whereas the moderating effect of Technology Readiness was analyzed by incorporating interaction effects into the structural model. Statistical significance was accepted at $p < .05$.

Table 1. Normality Analysis (n = 469)

Variables	Mean	Standard Deviation	Skewness	Kurtosis
Artificial Intelligence-Driven Predictive Vehicle Maintenance	4.13	0.58	-0.593	0.417
Service Trust	4.08	0.60	-0.548	0.382
Technology Readiness	4.02	0.63	-0.521	0.346
Customer Service Loyalty	4.16	0.57	-0.615	0.451

Acceptance Criteria

Statistic	Recommended Value	Reference
Skewness	±1.50	Hair et al. (2022)
Kurtosis	±1.50	Hair et al. (2022)

Table 1 presents the results of the normality analysis for the study variables. The skewness values ranged from −0.615 to −0.521, whereas the kurtosis values ranged from 0.346 to 0.451. Since all values were within the

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acceptable range of ±1.50, the data were considered to be approximately normally distributed. Therefore, the assumption of normality was satisfied, supporting the application of parametric statistical techniques, including Independent Samples t-test, One-Way ANOVA, Pearson Correlation Analysis, Multiple Regression Analysis, and Structural Equation Modeling (SEM) (Hair et al., 2022).

The Researcher's Role

The researcher played a central role in designing, implementing, and managing the research process while ensuring objectivity, scientific rigor, and ethical compliance throughout the study. The responsibilities of the researcher included reviewing the relevant literature, developing the conceptual framework, selecting appropriate measurement instruments, adapting the questionnaire to the research context, and coordinating the data collection process in automotive service centers located in Nicosia, Famagusta, and Güzelyurt.

During the data collection process, the researcher informed all participants about the purpose of the study, voluntary participation, confidentiality, anonymity, and their right to withdraw from the research at any time. Participants completed the questionnaires independently without any intervention or influence from the researcher, thereby minimizing response bias. Following data collection, all questionnaires were coded, screened for missing values and inconsistencies, and analyzed objectively using standardized statistical procedures. Ethical principles, including informed consent, confidentiality, and responsible data management, were strictly observed throughout the study, ensuring the reliability and credibility of the research findings (Creswell & Creswell, 2023; Saunders et al., 2023).

Validity and Reliability

The psychometric properties of the measurement instruments were evaluated before testing the proposed hypotheses. Internal consistency reliability was initially assessed using Cronbach's Alpha, with values above 0.70 indicating acceptable reliability (Hair et al., 2022).

Construct validity was examined through Confirmatory Factor Analysis (CFA) using AMOS 24.0. Convergent validity was evaluated using Composite Reliability (CR) and Average Variance Extracted (AVE). According to Hair et al. (2022), CR values greater than 0.70 and AVE values above 0.50 indicate satisfactory convergent validity.

Discriminant validity was assessed using the Fornell–Larcker criterion, whereby the square root of the AVE for each construct should exceed its correlations with the remaining constructs (Fornell & Larcker, 1981). The overall adequacy of the measurement model was further evaluated using multiple goodness-of-fit indices, including Chi-square/degree of freedom (χ^2/df), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The obtained results indicated satisfactory reliability and validity of the measurement model, supporting subsequent Structural Equation Modeling analyses.

Table 2. Reliability Analysis (n = 469)

Construct	Number of Items	Cronbach's Alpha	Interpretation
Artificial Intelligence-Driven Predictive Vehicle Maintenance	10	.946	Excellent
Service Trust	8	.934	Excellent
Technology Readiness	8	.928	Excellent
Customer Service Loyalty	8	.941	Excellent

Table 2 presents the reliability analysis of the measurement scales used in this study. The Cronbach's Alpha coefficients ranged from 0.928 to 0.946, indicating excellent internal consistency across all constructs. The highest reliability coefficient was observed for Artificial Intelligence-Driven Predictive Vehicle Maintenance (α = .946), followed by Customer Service Loyalty (α = .941), Service Trust (α = .934), and Technology Readiness (α = .928). Since all values exceeded the recommended threshold of 0.70, the measurement scales demonstrated excellent reliability and were considered suitable for subsequent validity testing and structural equation modeling.

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Table 3. Confirmatory Factor Analysis and Convergent Validity Results (n = 469)

Construct	Number of Items	Standardized Factor Loadings	Composite Reliability (CR)	Average Variance Extracted (AVE)
Artificial Intelligence-Driven Predictive Vehicle Maintenance	10	.754 – .918	.953	.671
Service Trust	8	.742 – .903	.941	.665
Technology Readiness	8	.735 – .894	.937	.651
Customer Service Loyalty	8	.760 – .916	.946	.686

Acceptance Criteria

Criterion	Recommended Value	Reference
Standardized Factor Loading	≥ .70	Hair et al. (2022)
Composite Reliability (CR)	≥ .70	Hair et al. (2022)
Average Variance Extracted (AVE)	≥ .50	Fornell & Larcker (1981)

The standardized factor loadings ranged from 0.735 to 0.918, indicating that all measurement items adequately represented their corresponding latent constructs. Composite Reliability values ranged between 0.937 and 0.953, while AVE values ranged between 0.651 and 0.686. Since all values exceeded the recommended thresholds, the measurement model demonstrated satisfactory convergent validity and internal consistency.

Table 4. Demographic Characteristics of Participants (n = 469)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	271	57.8
	Female	198	42.2
Age	18–29 years	86	18.3
	30–39 years	151	32.2
	40–49 years	124	26.4
	50 years and above	108	23.1
Education	High School	121	25.8
	Associate Degree	77	16.4
	Bachelor's Degree	197	42.0
	Graduate Degree	74	15.8
Monthly Income	Below 30,000 TL	92	19.6
	30,001–45,000 TL	153	32.6
	45,001–60,000 TL	129	27.5
	Above 60,000 TL	95	20.3
Maintenance Frequency	Every 3 Months	132	28.1
	Every 6 Months	183	39.0
	Once a Year	99	21.1
	Other	55	11.7
Experience with AI-supported Services	Yes	279	59.5
	No	190	40.5
Total		**469**	**100.0**

The majority of respondents were male (57.8%) and between 30 and 39 years old (32.2%). Most participants held a bachelor's degree (42.0%), while approximately one-third reported a monthly income between 30,001 TL and 45,000 TL. More than half (59.5%) had previous experience with AI-supported automotive services.

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Table 5. Independent Samples t-Test and One-Way ANOVA Results (n = 469)

Demographic Variable	Test	AI Predictive Maintenance	Service Trust	Technology Readiness	Customer Loyalty
Gender	t	2.641 (.009)*	2.458 (.014)*	1.633 (.103)	2.984 (.003)*
Age	F	5.842 (<.001)*	6.311 (<.001)*	7.954 (<.001)*	6.417 (<.001)*
Education	F	4.517 (.004)*	5.104 (.002)*	6.782 (<.001)*	5.228 (.002)*
Income	F	3.864 (.010)*	4.183 (.007)*	4.925 (.003)*	4.664 (.004)*
AI Service Experience	t	4.632 (<.001)*	5.248 (<.001)*	6.871 (<.001)*	5.463 (<.001)*

p < .05

Most demographic variables produced statistically significant differences across the study constructs. Participants with previous AI-supported service experience reported significantly higher perceptions of predictive maintenance, trust, technology readiness, and customer loyalty.

Table 6. Pearson Correlation Analysis (n = 469)

Variables	Mean	SD	1	2	3	4
AI Predictive Maintenance	4.13	.58	1			
Service Trust	4.08	.60	.742**	1		
Technology Readiness	4.02	.63	.638**	.667**	1	
Customer Service Loyalty	4.16	.57	.781**	.751**	.692**	1

p < .01

All study variables were positively and significantly correlated. The strongest correlation was observed between AI Predictive Maintenance and Customer Service Loyalty (r = .781).

Table 7. Multiple Regression Analysis (n = 469)
Dependent Variable: Customer Service Loyalty

Predictor	β	t	p	VIF
AI Predictive Maintenance	.463	10.83	<.001	2.19
Service Trust	.341	8.66	<.001	2.08
Technology Readiness	.181	5.18	<.001	1.84

Model Summary

R	R^2	Adjusted R^2	F	p
.867	.752	.750	468.54	<.001

The regression model explained 75.2% of the variance in Customer Service Loyalty. AI Predictive Maintenance was the strongest predictor (β = .463), followed by Service Trust (β = .341) and Technology Readiness (β = .181). All predictor variables significantly influenced customer loyalty.

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Table 8. Structural Equation Modeling (SEM) and Hypothesis Testing Results (n = 469)

Hypothesis	Structural Path	Standardized β	S.E.	C.R.	p	Decision
H1	AI-Driven Predictive Vehicle Maintenance → Customer Service Loyalty	.463	.039	11.84	<.001	Supported
H2	AI-Driven Predictive Vehicle Maintenance → Service Trust	.742	.034	19.32	<.001	Supported
H3	Service Trust → Customer Service Loyalty	.341	.036	9.17	<.001	Supported
H4	AI-Driven Predictive Vehicle Maintenance → Service Trust → Customer Service Loyalty	.253	.028	7.46	<.001	Supported
H5	AI-Driven Predictive Vehicle Maintenance × Technology Readiness → Customer Service Loyalty	.188	.025	5.63	<.001	Supported
H5a	High Technology Readiness strengthens the relationship	—	—	—	<.001	Supported
H5b	Low Technology Readiness weakens the relationship	—	—	—	<.001	Supported

Model Fit Indices

Fit Index	Obtained Value	Recommended Value	Evaluation
χ^2/df	2.21	<3.00	Good Fit
CFI	.966	≥.90	Good Fit
TLI	.960	≥.90	Good Fit
GFI	.942	≥.90	Good Fit
AGFI	.918	≥.90	Good Fit
RMSEA	.051	≤.08	Good Fit
SRMR	.038	≤.08	Good Fit

The structural equation model demonstrated a satisfactory fit to the data. All hypothesized relationships were statistically significant (**p < .001**), indicating strong support for the proposed conceptual model.

Table 9. Bootstrapping Mediation and Moderation Analysis Results (n = 469)

Mediation Analysis (Bootstrapping)

Indirect Effect	β	Boot LLCI	Boot ULCI	p	Result
AI Predictive Vehicle Maintenance → Service Trust → Customer Service Loyalty	.253	.184	.332	<.001	Partial Mediation

Moderation Analysis

Interaction Effect	β	Boot LLCI	Boot ULCI	p	Result
AI Predictive Vehicle Maintenance × Technology Readiness → Customer Service Loyalty	.188	.112	.264	<.001	Significant Moderation

Direct, Indirect and Total Effects

Relationship	Direct Effect	Indirect Effect	Total Effect
AI Predictive Vehicle Maintenance → Customer Service Loyalty	.463	.253	.716

Bootstrapping analysis confirmed that Service Trust partially mediated the relationship between AI-Driven Predictive Vehicle Maintenance and Customer Service Loyalty. Furthermore, Technology Readiness significantly moderated this relationship, indicating that customers with higher levels of technology readiness benefited more from AI-supported predictive vehicle maintenance services. The confidence intervals did not include zero, confirming the statistical significance of both the mediation and moderation effects.

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Conclusion

The primary objective of this study was to investigate the effect of Artificial Intelligence-Driven Predictive Vehicle Maintenance on Customer Service Loyalty while examining the mediating role of Service Trust and the moderating effect of Technology Readiness. The study was conducted among 469 customers receiving vehicle maintenance and repair services from automotive service centers located in Nicosia, Famagusta, and Güzelyurt in the Turkish Republic of Northern Cyprus.

The empirical findings demonstrated that Artificial Intelligence-Driven Predictive Vehicle Maintenance positively and significantly influences Customer Service Loyalty. AI-supported maintenance technologies, including predictive diagnostics, intelligent maintenance scheduling, automated fault detection, and digital customer communication systems, improve customers' perceptions of service quality and increase their willingness to maintain long-term relationships with automotive service providers. These findings indicate that artificial intelligence has become a strategic resource for strengthening customer relationships within the automotive after-sales service sector.

The results further revealed that Service Trust partially mediates the relationship between AI-driven predictive vehicle maintenance and customer service loyalty. Customers who perceive AI-supported maintenance systems as reliable, transparent, and technically accurate develop greater confidence in automotive service providers, which subsequently strengthens their loyalty. This finding highlights the importance of trust as a key psychological mechanism linking intelligent maintenance technologies to favorable customer behaviors.

Furthermore, the study confirmed that Technology Readiness significantly moderates the relationship between AI-driven predictive vehicle maintenance and customer service loyalty. Customers possessing higher levels of technology readiness demonstrated stronger positive responses toward AI-supported maintenance services and exhibited greater loyalty than customers with lower levels of technology readiness. This finding suggests that customers' willingness to embrace emerging technologies enhances the effectiveness of artificial intelligence applications within automotive service environments.

Overall, all proposed hypotheses were supported, and the structural equation model demonstrated satisfactory reliability, validity, and goodness-of-fit indices. The study contributes to the existing literature by integrating artificial intelligence, predictive vehicle maintenance, service trust, technology readiness, and customer service loyalty into a comprehensive conceptual framework. The findings provide empirical evidence from the Turkish Republic of Northern Cyprus, thereby extending current knowledge regarding artificial intelligence applications in automotive service management.

From a managerial perspective, the findings suggest that automotive service centers should continue investing in AI-supported predictive maintenance systems, intelligent diagnostic technologies, and digital customer communication platforms. Simultaneously, organizations should implement strategies that increase customer trust through transparent maintenance processes and improve customers' technology readiness through education and digital engagement initiatives. These efforts may strengthen customer loyalty, improve organizational competitiveness, and support the successful digital transformation of the automotive service industry.

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