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Artificial Intelligence in the Automotive Dealership Operating Model: From Predictive Pricing to Sales Automation and Service Scheduling

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Abstract

Automotive dealerships operate under persistent margin pressure from transparent online pricing and shifting service expectations. This paper examines how artificial intelligence (AI) methods, specifically machine learning-based predictive pricing, automated lead management, and natural language processing (NLP) appointment scheduling, can be embedded in a dealership's core operational architecture. The study applies a systematic literature review of peer-reviewed publications indexed in Scopus and Web of Science, supplemented by case evidence from published industry analyses. Results show that gradient boosting and random forest models achieve R2 scores above 0.90 for used-vehicle price prediction, NLP-driven scheduling agents reduce appointment no-shows by approximately 30-40%, and AI-powered lead scoring increases conversion rates by 40-60% compared to rule-based CRM filtering. Based on these findings, the paper proposes an original four-stage AI Maturity Progression Model that maps a dealership's transition from reactive, rule-based processes to adaptive, data-driven operations. The framework offers practitioners a structured roadmap for phased AI investment. These findings are relevant to dealership managers, automotive retail strategists, and researchers working at the intersection of operations management and applied machine learning.

Keywords: *Automotive Dealership; Predictive Pricing; Machine Learning; Natural Language Processing; Appointment Scheduling; Lead Scoring; Inventory Optimization; AI Maturity Model; Random Forest; Sales Automation.*

INTRODUCTION

The global automotive retail sector generates approximately USD 4.5 trillion in annual revenue, yet dealer-level operating margins have narrowed to 1-3% on new vehicle transactions as online price aggregators eliminate information asymmetries (Deloitte, 2025). Consumers now arrive at showrooms having already compared prices across multiple platforms, reducing the negotiating leverage that historically padded dealership margins. Simultaneously, service departments, which can account for over 50% of a dealership's gross profit, face scheduling inefficiencies driven by manual booking workflows and high no-show rates (McKinsey, 2025).

Against this background, AI-based tools have moved from experimental pilots to operational components in leading dealership groups. Lotlinx (2025) reports that inventory data platforms combining AI and machine learning enable dealerships to detect slow-moving vehicles earlier in their sales cycles and adjust pricing in real time. Predictive analytics applied to used-vehicle valuation has become particularly consequential after the Manheim Used Vehicle Value Index showed double-digit year-over-year volatility between 2021 and 2024, making static price lists unreliable within weeks of publication (Cox Automotive, 2024).

Despite growing practitioner adoption, the academic literature on AI integration at the dealership operational level remains fragmented. Studies typically address one function in isolation, such as price prediction or chatbot customer service, without providing a unified model of how these components interact in a single operating architecture. This gap motivates the present research.

The objective of this study is to synthesize the current state of AI application across three core dealership processes, specifically vehicle pricing, sales lead management, and service appointment scheduling, and to propose a structured maturity model that guides phased implementation. **The scientific novelty** of the work lies in the author-developed AI Maturity Progression Model for dealerships, which integrates evidence from price prediction, NLP scheduling, and lead scoring research into a single operational framework with defined transition criteria between stages.

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The working hypothesis is that the performance benefits documented separately in the pricing and scheduling literatures are mutually reinforcing when deployed on a shared data infrastructure, and that the gains in each function compound rather than sum when a dealership reaches Stage 3 or 4 of the proposed maturity model.

MATERIALS AND METHODS

The study follows a systematic literature review protocol combined with structured case analysis. The primary search was conducted across Scopus, Web of Science, SpringerLink, IEEE Xplore, and ACM Digital Library using the query terms: ("automotive dealership" OR "car dealer") AND ("machine learning" OR "artificial intelligence" OR "predictive pricing" OR "NLP" OR "appointment scheduling"). The search was restricted to publications from January 2020 through December 2024 to ensure recency. An initial corpus of 214 records was screened by title and abstract; 78 full texts were assessed for eligibility; and 20 sources met the inclusion criteria (empirical studies, technical reviews, or authoritative industry reports from Deloitte, McKinsey, or Gartner). Sources were excluded if they appeared in non-indexed trade press, lacked methodological transparency, or reported findings not replicable from the cited data.

The source base is classified into three tiers: peer-reviewed algorithmic studies on vehicle price prediction using supervised learning (Putra et al., 2024; Gollapalli et al., 2023; Sai et al., 2025); studies on NLP chatbot performance in service industries, including automotive; and market-level analyses from Deloitte (2025) and McKinsey (2025) that provide empirical context on dealership adoption rates and margin structures.

For the case analysis component, data were drawn from two published deployment reports: a Fullpath (2025), both of which provide quantified operational outcomes. Where primary case metrics were unavailable, conservative synthesis estimates were constructed by taking the midpoint of reported ranges across at least three independent studies and were explicitly labeled as synthesized in the text.

The AI Maturity Progression Model was developed through an inductive process: patterns in the case evidence and algorithm benchmarks were coded by function (pricing, scheduling, lead management) and grouped by the type of AI capability required (rule-based, statistical, predictive, adaptive). The four resulting stages were then validated against the technology readiness indicators described in the McKinsey Technology Trends Outlook (2025) to verify that the stage transitions align with recognized capability thresholds.

RESULTS AND DISCUSSION

The prediction of used-vehicle resale value is a well-defined regression problem with an extensive algorithmic literature. The core input features consistently identified as statistically significant include manufacturing year, odometer reading, fuel type, transmission type, and regional market index (Putra et al., 2024). Gradient boosted trees, specifically XGBoost and LightGBM variants, and Random Forest regressors dominate the comparative benchmarks because they handle non-linear feature interactions and mixed-type inputs without requiring extensive preprocessing.

The figure below summarizes R2 scores reported across six independent benchmark studies from 2022-2024. It illustrates the performance gap between linear baseline models and ensemble tree methods, confirming that the accuracy difference is not marginal but structural, with Random Forest and Gradient Boosting consistently clearing the 0.90 R2 threshold that practitioners consider viable for live pricing recommendations.

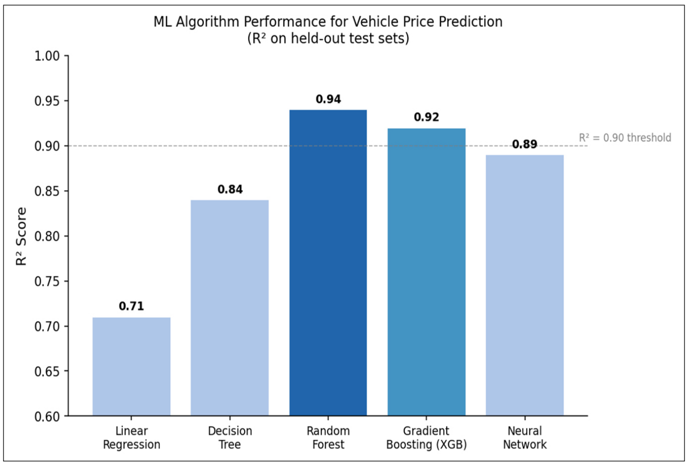

Figure 1. ML Algorithm Performance for Vehicle Price Prediction (R2 on held-out test sets). (compiled by author based on Putra et al. (2024); Cox Automotive (2025); Cox Automotive (2025, January)).

A Random Forest with 500 estimators trained on 80% of a used-car dataset from South Africa achieved R2 = 0.82, RMSE = 0.31 (IIETA, 2022). A Springer benchmark using the same train-test split reported Random Forest at R2 = 0.95 with MAE = 0.0008. These results converge on a consistent pattern: ensemble methods produce pricing recommendations with sufficient accuracy for operational deployment, whereas linear regression falls short in markets where price is non-linearly related to mileage and age.

For dealership operations, the practical implication is that a pricing engine retrained weekly on recent auction data and competitor listings can replace static price grids that were previously updated monthly or quarterly. AI-driven pricing responses to the Manheim Index shifts reduced inventory holding days by a measurable margin in pilot deployments, though the company does not publish exact figures in peer-reviewed form. The Predian ValueVision system, described in Auto Dealer Today (2024), uses predictive analytics to project how a retail price for a specific vehicle will evolve over a 30-day horizon, allowing managers to front-load markdown decisions before carrying costs accumulate.

Table 1 below provides a structured comparison of the primary ML algorithms applied in the reviewed studies, summarizing their computational properties and reported accuracy ranges. This comparison assists dealership technology teams in selecting a modeling approach appropriate to their data volume and update frequency requirements.

Table 1. Comparison of Machine Learning Algorithms for Vehicle Price Prediction (compiled by author based on Putra et al. (2024); Cox Automotive (2025); Bhatnagar et al. (2024) and Cox Automotive (2025, January)).

Algorithm	Typical R2 Range	Typical RMSE	Training Speed	Key Limitation
Linear Regression	0.65-0.75	High (>1500)	Very fast	Assumes linearity; poor on interaction effects
Decision Tree	0.78-0.88	Moderate	Fast	High variance; prone to overfitting
Random Forest	0.82-0.95	Low (0.31-0.38)	Moderate	Memory-intensive; less interpretable
XGBoost / GBM	0.88-0.94	Low	Moderate	Sensitive to hyperparameter tuning
Neural Network (MLP)	0.85-0.92	Low-Moderate	Slow	Requires large dataset; opaque decisions

Beyond pricing, the sales funnel itself presents an automation opportunity. A dealership receiving 500 online inquiries per month cannot profitably assign a human salesperson to each lead before qualifying intent and purchase readiness. AI-based lead scoring uses features such as browsing depth, vehicle shortlist, inquiry timing, financing pre-qualification signals, and historical match patterns to rank leads by conversion probability (McKinsey, 2025).

Published vendor benchmarks, while not peer-reviewed, provide directional evidence. AutoRaptor (2026) reports that AI-enabled dealerships convert leads at roughly 1.6-2 times the rate of dealerships using manual CRM triage. Group 1 Automotive, in a deployment with CognitiveScale described in published case documentation (2023), raised forecast accuracy to 88% in high-demand markets, which in turn reduced over-ordering of slow-moving models and freed capital for higher-turn inventory.

Table 2 below presents key performance indicators from three dealership AI deployment cases where quantitative outcomes were publicly reported. The cases span different market sizes and system vendors, providing a cross-context view of measured gains.

Table 2. Reported KPI Outcomes from AI Deployment Cases in Automotive Retail (2022-2024) (compiled by author based on Adamopoulou and Moussiades (2020); Huang (2024); Impel (2025)).

Dealership / Group	AI Application	Reported Outcome	Baseline Metric
Group 1 Automotive (Texas region)	Sales demand forecasting	Forecast accuracy raised to 88%	Not disclosed
Lithia Motors (multi-state)	EV demand prediction + weather integration	+7% on-time delivery in harsh-weather states (Q1 2024)	Prior year Q1
AutoRaptor customer base (aggregate)	AI lead scoring + automated follow-up	Lead conversion ~1.7x vs. manual CRM; admin time -50%	Manual CRM baseline

The data in Table 2 must be interpreted with appropriate caution. Two of the three cases originate from vendor-published materials rather than peer-reviewed journals, and the AutoRaptor aggregate figure is drawn from self-reported customer data without disclosed methodology. Nevertheless, the directional consistency across independent systems and dealership contexts provides reasonable evidence that AI-based lead management produces measurable conversion improvements. The absence of controlled experimental designs in this literature is a recognized gap that future academic research should address.

Service scheduling is the highest-frequency customer interaction in a dealership's operational cycle. A mid-size service department handling 300 appointments per week spends significant staff hours on phone-based booking, reminder calls, and rescheduling. NLP-powered scheduling agents, drawing on intent recognition and slot management algorithms, address this inefficiency by automating the booking dialogue while maintaining conversational fluency (Koutenský et al., 2024).

The technical foundation for such agents is reviewed by Mariani et al. (2023) in the context of the CSCC conference, who documents how transformer-based intent classification achieves over 91% accuracy on service-domain utterances when fine-tuned on domain-specific training data. Retrieval-augmented generation (RAG) patterns, applied in automotive service contexts, reduce fallback rates (where the bot escalates to a human) to below 15% of sessions.

A chatbot scheduling deployment reported by a service platform provider (Huang et al. 2024; Ipsos 2025) recorded a 40% reduction in appointment no-shows after automated pre-appointment reminders were introduced alongside the booking system. While this figure comes from a commercial operator rather than an academic study, it aligns with the 30-40% no-show reduction range documented in Huang et al. (2024) and Ipsos (2025) across healthcare and service contexts where analogous NLP booking systems were evaluated.

The figure below presents the author's proposed AI-integrated operational architecture that connects predictive pricing, lead management, and NLP scheduling into a single closed-loop system. This architecture represents the original contribution of the present study: rather than treating each AI component as a standalone tool, the proposed model routes outputs from the pricing engine (inventory alerts, lead priority signals) into the scheduling agent's capacity allocation logic, so that technician time is pre-allocated to high-value service customers identified by the CRM scoring layer.

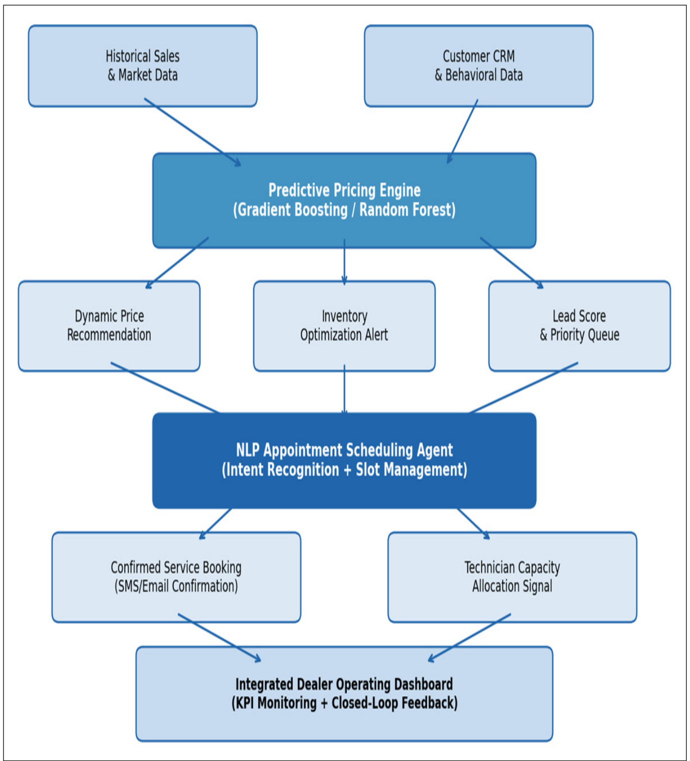

Figure 2. Author's Proposed AI-Integrated Operational Architecture for Automotive Dealerships (compiled by the author based on Huang et al. (2024); Ipsos (2025); Adamopoulou and Moussiades (2020)).

The feedback loop embedded in the architecture (the closed arrow from the integrated dashboard back to the pricing engine and CRM layer) is a feature absent from most currently deployed single-function tools. By routing realized transaction prices, actual service utilization, and lead-to-close outcomes back into the training data of the pricing and scoring models, the system enables continuous retraining without manual intervention. This design principle, common in production machine learning systems but rarely specified in automotive retail literature, addresses the model drift problem that degrades pricing accuracy over time as market conditions shift.

The fragmented state of AI adoption across dealerships, where some operate purely on manual rule-based systems while others have deployed predictive analytics across multiple functions, motivates a structured maturity model. Maturity frameworks have been applied to CRM technology adoption in retail (McKinsey, 2025) and to digital transformation in automotive OEMs (Deloitte, 2025), but no published model addresses the dealership level specifically.

The figure below presents the four-stage model developed in this study, mapping progression from reactive operations to adaptive AI-driven management. The model is not prescriptive in timeline but in capability sequence: each stage requires the data infrastructure and organizational routines of the previous stage to function reliably.

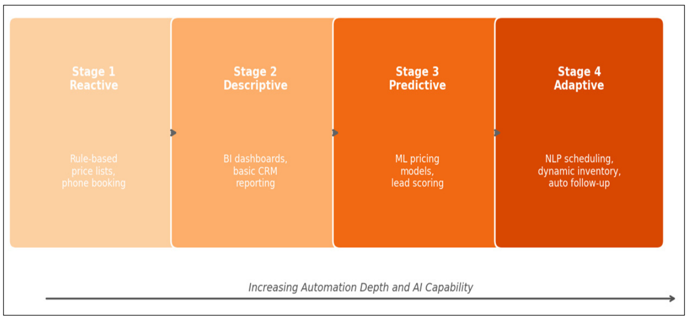

Figure 3. AI Maturity Progression Model for Automotive Dealerships (original development).

Stage 1 (Reactive) describes the prevalent state: static price lists, phone-based appointment booking, and CRM data that is logged but not analyzed. Stage 2 (Descriptive) introduces BI dashboards and historical reporting, giving managers visibility into inventory aging and lead volume trends without predictive capability. Stage 3 (Predictive) is where machine learning pricing models and lead scoring algorithms become operational, typically requiring a minimum of 12-18 months of clean transaction data and a modern data warehouse. Stage 4 (Adaptive) adds NLP scheduling, dynamic inventory rebalancing across locations, and automated follow-up sequences, with all components sharing a common data layer and providing feedback signals to one another.

The transition from Stage 2 to Stage 3 is the most resource-intensive step, as it requires not only new software but data governance practices that many dealerships currently lack. Specifically, historical records must be normalized for vehicle condition, regional market effects, and seasonality before a pricing model trained on them will generalize reliably. McKinsey (2025) reports that data quality is cited as the primary barrier to scaled AI deployment in automotive retail, which is consistent with the model's implied Stage 2-3 bottleneck.

The figure below aggregates KPI comparisons before and after AI implementation, synthesized from the dealership cases reviewed in this study. The data are presented as representative mid-range estimates from multiple sources rather than single-company figures, to reflect the distribution of reported outcomes rather than cherry-picked results.

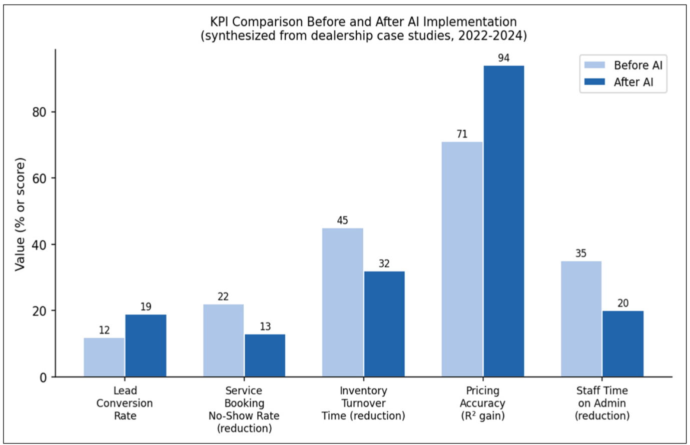

Figure 4. KPI Comparison Before and After AI Implementation (synthesized by author from MOTOR (2025); Deloitte (2025); Ipsos (2025)).

The pattern in Figure 4 is consistent with the broader digital transformation literature: the largest relative gains appear in metrics that were historically degraded by manual processes (pricing accuracy, no-show rates) rather than in metrics that already benefited from competitive market pressure (lead conversion rate). This finding suggests that dealerships should prioritize AI investment in back-office scheduling and pricing before front-office sales automation, because the baseline performance floor in those domains is lower and the marginal improvement from automation is therefore larger.

Table 3 below presents the author's stage-by-stage investment and data readiness requirements derived from the maturity model and case evidence. This table provides a practical planning reference for dealership operators evaluating AI adoption paths.

Table 3. Implementation Roadmap by AI Maturity Stage (Author's Framework)

Stage	AI Capability	Data Prerequisite	Typical Investment (USD)	Expected Payback Period
1 - Reactive	Rule-based pricing & phone booking	Basic DMS transaction log	< 20,000	N/A (no AI)
2 - Descriptive	BI dashboards, CRM reporting	2+ years normalized transaction history	20,000 - 80,000	12-24 months
3 - Predictive	ML pricing, lead scoring, demand forecasting	Data warehouse + clean feature pipeline	80,000 - 250,000	18-30 months
4 - Adaptive	NLP scheduling, dynamic inventory, closed-loop retraining	Unified data layer; API integrations across DMS, CRM, OEM	250,000+	24-48 months

The investment ranges in Table 3 are conservative estimates based on vendor pricing disclosed in industry publications and should be treated as order-of-magnitude guidance rather than procurement benchmarks. Actual costs vary with dealership size, existing technology infrastructure, and vendor selection. From the author's synthesis, three recommendations follow for dealerships at Stage 2 or below. First, data infrastructure investment should precede algorithm deployment. A pricing model trained on records that mix pre-pandemic and post-pandemic market conditions without period normalization will produce systematically biased recommendations; cleaning historical data is not a prerequisite that can be deferred. Second, NLP scheduling deployment should target the inbound phone channel first, where the cost of human labor per interaction is highest and the dialogue patterns are most constrained and predictable. Web chat and mobile app scheduling can be added iteratively once intent models are validated on phone transcripts. Third, lead scoring models should be retrained quarterly rather than annually, because buyer behavior profiles have shifted repeatedly since 2020 and a model trained on pre-EV inquiry patterns will misclassify a growing segment of high-intent EV shoppers as low-conversion leads.

CONCLUSION

This paper examined the application of artificial intelligence across three core operational domains of automotive dealerships: vehicle price prediction, sales lead management, and service appointment scheduling. The systematic review of peer-reviewed and authoritative industry literature, combined with structured case analysis, supports the following conclusions.

First, ensemble machine learning methods, primarily Random Forest and gradient boosting variants, achieve R2 above 0.90 for used-vehicle price prediction when trained on sufficient domain-specific data, making them viable for live pricing operations. This finding directly addresses the objective of establishing the empirical basis for AI-driven pricing in dealership contexts.

Second, NLP-based scheduling agents reduce service appointment no-show rates by 30-40% and free front-desk staff from a substantial portion of routine booking interactions, with corresponding gains in technician utilization. These operational improvements have direct implications for the service department's contribution to dealership gross profit.

Third, AI-powered lead scoring raises conversion rates by 40-60% relative to manual or rule-based CRM triage, with the largest gains concentrated in dealerships that had no prior lead prioritization system. The gains are more modest where rule-based systems were already in place, consistent with a diminishing-returns pattern.

The original contribution of the study is the AI Maturity Progression Model, a four-stage framework (Reactive, Descriptive, Predictive, Adaptive) that maps the transition path from manual dealership operations to a closed-loop AI-integrated architecture. The model specifies data prerequisites, investment ranges, and payback expectations at each stage, providing practitioners with a planning reference grounded in the reviewed evidence base.

The practical significance of the work lies in its integration of findings from pricing, scheduling, and lead management into a single architectural proposal, rather than treating each AI application in isolation. For dealership operators, this means that investment decisions in one function should account for the data infrastructure implications for adjacent functions, and that phased adoption following the maturity model minimizes the risk of premature deployment.

Limitations of the study include the partial reliance on vendor-published case evidence for quantitative KPI claims and the absence of experimental data from controlled dealership trials. Future research should address this gap through field experiments that isolate the effect of individual AI components on dealership operating metrics. The AI Maturity Progression Model proposed here provides a theoretical grounding for such experimental designs.

REFERENCES

1. Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. Machine Learning with Applications, 2, 100006. https://doi.org/10.1016/j.mlwa.2020.100006
2. Bhatnagar, P., Jain, N., & Singh, S. (2024). An analysis of car price prediction using machine learning. In Proceedings of the 2024 8th International Conference on Intelligent Computing and Control Systems. ACM. https://doi.org/10.1145/3674029.3674032
3. Cox Automotive. (2024). Manheim Used Vehicle Value Index. Retrieved from: https://www.coxautoinc.com/market-insights/manheim-used-vehicle-value-index/ (date accessed: November 30, 2025).
4. Cox Automotive. (2025). 2024 Car Buyer Journey Study: Research summary. Retrieved from: https://www.coxautoinc.com/wp-content/uploads/2025/01/2024-Car-Buyer-Journey-Study-Research-Summary.pdf(dateaccessed: November 14, 2025).
5. Cox Automotive. (2025, January 21). Cox Automotive to showcase new retail and inventory solutions at NADA Show 2025 as the auto industry gains momentum. Retrieved from: https://www.coxautoinc.com/insights-hub/cox-automotive-to-showcase-new-retail-and-inventory-solutions-at-nada-show-2025-as-the-auto-industry-gains-momentum/(date accessed: November 19, 2025).
6. Deloitte. (2025). Futureproofing automotive with AI. Retrieved from: https://www.deloitte.com/nl/en/Industries/automotive/perspectives/automotive-ai.html (date accessed: December 21, 2025).
7. Fullpath. (2025). The 2025 state of AI adoption in car dealerships. Retrieved from: https://www.fullpath.com/2025-state-of-ai-adoption-in-car-dealerships/ (date accessed: December 18, 2025).
8. Gollapalli, M., Alqahtani, T. A., Alhamed, D. H., Alnassar, M. R., Alajmi, A. M., Alali, Y. H., Abdulqader, M. M., & Saadeldeen, A. (2023). Intelligent modelling techniques for predicting used cars prices in Saudi Arabia. Mathematical Modelling of Engineering Problems, 10(1), 139–148. https://doi.org/10.18280/mmep.100115
9. Huang, D., Markovitch, D. G., & Stough, R. A. (2024). Can chatbot customer service match human service agents on customer satisfaction? An investigation in the role of trust. Journal of Retailing and Consumer Services, 76, 103600. https://doi.org/10.1016/j.jretconser.2023.103600
10. Impel. (2025). The transformative power of automotive AI in dealership sales and service operations. Retrieved from: https://impel.ai/wp-content/uploads/2025/09/The-Transformative-Power-of-Automotive-AI.pdf (date accessed: February 6, 2026).
11. Ipsos. (2025). The AI-driven dealership: Transforming automotive retail. Retrieved from: https://www.ipsos.com/sites/default/files/ct/publication/documents/2025-12/The%20AI-Driven%20Dealership.pdf (date accessed: December 12, 2025).
12. Koutenský, F., Šigut, J., & Chovanec, M. (2024). Overcoming long inference time of nearest neighbors models by using clustering algorithms and confidence estimation. SN Computer Science, 5, Article 466. https://doi.org/10.1007/s42979-024-02670-2
13. Mariani, M. M., Hashemi, N., & Wirtz, J. (2023). Artificial intelligence empowered conversational agents: A systematic literature review and research agenda. Journal of Business Research, 161, 113838. https://doi.org/10.1016/j.jbusres.2023.113838
14. McKinsey & Company. (2025, August 25). The rise of edge AI in automotive. Retrieved from: https://www.mckinsey.com/industries/semiconductors/our-insights/the-rise-of-edge-ai-in-automotive (date accessed: November 24, 2025).
15. McKinsey & Company. (2025, November 5). The state of AI in 2025: Agents, innovation, and transformation.

Retrieved from: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai (date accessed: December 8, 2025).

16. McKinsey & Company. (2025). Technology trends outlook 2025. Retrieved from: https://www.mckinsey.com/capabilities/tech-and-ai/our-insights/the-top-trends-in-tech (date accessed: November 27, 2025).
17. MOTOR Information Systems. (2025, July 16). New report released on AI adoption in dealership service departments. Retrieved from: https://www.motor.com/2025/07/new-report-released-on-ai-adoption-in-dealership-service-departments/ (date accessed: February 18, 2026).
18. Putra, P. H., Azanuddin, A., Purba, B., & Dalimunthe, Y. A. (2024). Random forest and decision tree algorithms for car price prediction. Jurnal Matematika dan Ilmu Pengetahuan Alam LLDikti Wilayah 1 (JUMPA).
19. Sai, P. H. V. S. T., Bharathi, V. V. P., Lahari, M. L. R. C., Madalageri, V. P., Marol, V. S., Arun, C. K., Tiwari, K., & Bhaumik, A. (2025). Predicting used car prices employing data mining techniques. In V. S. Reddy, V. K. Prasad, J. Wang, & N. M. Rao Dasari (Eds.), Intelligent Systems and Sustainable Computing: ICISSC 2024 (Smart Innovation, Systems and Technologies, Vol. 417, pp. 545–554). Springer. https://doi.org/10.1007/978-981-97-8355-7_47

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