



# Sales Forecasting in Automobile Industry Using Data Analytics

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## Abstract

The Indian used automobile market has emerged as one of the fastest-growing pre-owned vehicle segments globally, yet the determinants of resale pricing remain fragmented and inadequately examined through large-scale empirical analysis. This study investigates the key factors that influence used car resale prices in India using a dataset of 140,904 vehicle listings sourced from secondary automobile platforms. Employing exploratory data analysis (EDA), descriptive statistics, Pearson correlation, segmental cross-tabulation, and temporal depreciation modelling, the research examines the impact of brand equity, vehicle age, kilometres driven, fuel type, transmission, ownership history, and geographic location on resale value. Findings reveal that the market is positively skewed, with a mean resale price of ₹7.62 lakh against a median of ₹6.83 lakh, reflecting a volume-dominant affordable segment inflated by a premium luxury tail. Maruti Suzuki commands 38% of market share, underpinning an affordability-driven demand structure. Vehicle age and kilometres driven demonstrate strong negative correlations with price ( $r = -0.404$  and  $r = -0.214$  respectively), while ownership history exerts a pronounced 'ownership penalty', with resale prices declining from ₹8.78 lakh for first-owner vehicles to ₹3.86 lakh for third-owner or beyond. SUVs, though representing only 24.9% of listings by volume, contribute disproportionately to market value.

Accidental history and geographic factors further moderate pricing. These results offer actionable insights for buyers, sellers, dealers, and policymakers, and lay the groundwork for predictive modelling incorporating macroeconomic variables.

**Keywords:** *Used automobile market; resale price determinants; vehicle depreciation; exploratory data analysis; brand equity; ownership penalty; Indian automotive sector*

## 1. Introduction

The automobile industry constitutes one of the most economically significant sectors in both developed and emerging economies, contributing substantially to GDP, employment, and technological progress. Within this sector, the used car market has witnessed exponential growth, driven by escalating new vehicle prices, intensifying fuel costs, and a growing consumer preference for cost-effective mobility solutions. In India specifically, the used car market is projected to surpass the new car market in volume terms within the current decade, catalysed by the proliferation of digital automobile platforms, standardised certification mechanisms, and deeper financial inclusion (SIAM, 2023).



Despite this rapid expansion, the market remains characterised by significant information asymmetry. Buyers frequently struggle to evaluate whether a listed price reflects fair market value, while sellers and dealers lack data-driven benchmarks to formulate competitive pricing strategies. This opacity creates market inefficiencies that disadvantage both transacting parties. The absence of a transparent, analytically grounded pricing framework has consequently attracted growing academic attention to the empirical study of used vehicle valuations.

Resale pricing in the used automobile market is a multi-dimensional phenomenon influenced by a confluence of intrinsic vehicle attributes and extrinsic contextual factors. Intrinsic determinants include brand reputation, model variant, year of manufacture, fuel type, transmission, total kilometres driven, and ownership history. Extrinsic factors encompass geographic market conditions, prevailing economic sentiment, fuel price trajectories, and government regulatory policies such as emission norms. Understanding the relative weight and interaction of these variables is crucial for constructing robust pricing models and informing stakeholder decisions.

The present study addresses this gap through a rigorous exploratory data analysis of 140,904 used vehicle listings drawn from the 'Mugil' secondary dataset, which represents a broad cross-section of the Indian used car market spanning multiple states, brands, fuel types, and price segments. By applying descriptive statistics, correlation analysis, segmental cross-tabulation, and temporal depreciation modelling, the study seeks to identify the principal determinants of resale value, characterise market structure, and derive actionable strategic insights.

## 1.1 Research Objectives

The study is guided by the following specific objectives:

- To analyse the distributional properties and central tendency of resale prices across the dataset.
- To examine the impact of vehicle age, kilometres driven, and ownership history on resale valuation.
- To evaluate the influence of brand, fuel type, car type, and transmission on price retention.
- To identify geographic and temporal patterns in listing density and transaction prices.
- To derive data-driven strategic recommendations for market participants.

## 1.2 Scope and Delimitations

The study is delimited to the Indian used car market as represented in the dataset. It employs purely secondary data and cross-sectional analysis without real-time market data integration or predictive modelling. Macroeconomic variables such as inflation, interest rates, and government policy are acknowledged as influential but are reserved for future research extensions.

## 2. Literature Review

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### 2.1 Empirical Studies on Used Vehicle Pricing

Academic inquiry into used car pricing has evolved considerably over the past two decades, transitioning from hedonic pricing models to machine learning-augmented frameworks. Ashenfelter and Genesove (1992) provided foundational hedonic regression evidence that vehicle age and mileage account for the majority of price variation in used car auctions. Subsequent work by Hall (2000) extended this framework to incorporate make and model effects, demonstrating that brand-level fixed effects explain a substantial share of residual price variance beyond observable vehicle characteristics.

In the Indian context, empirical evidence on used car pricing determinants remains comparatively sparse relative to developed markets. Anand and Annamalai (2018) employed ordinary least squares (OLS) regression on a sample of Indian used car listings, finding that car age ( $\beta = -0.38$ ,  $p < 0.001$ ) and kilometres driven ( $\beta = -0.21$ ,  $p < 0.001$ ) were the strongest predictors of price, consistent with international findings. Brand dummies for premium manufacturers yielded significant positive coefficients, confirming brand equity as a pricing premium in the Indian context.



## 2.2 Machine Learning Approaches to Price Prediction

The growing availability of large-scale listing data has stimulated the application of machine learning methods. Qu et al. (2022) employed Support Vector Regression optimised via the Grey Wolf Optimizer algorithm for automobile sales forecasting, demonstrating significant improvements in MAPE over conventional time-series models. While primarily a forecasting study, their feature importance analysis corroborated the primacy of economic indicators and product attributes in driving price variation.

Ou-Yang, Chou, and Juan (2022) augmented traditional sales forecasting with online sentiment data using a CNN-LSTM hybrid model for the Taiwanese market, achieving accuracy improvements from 41.67% to 69.45%. Their finding that sentiment variables capture consumer preference dynamics underscores the potential value of integrating digital platform data with structured listing attributes in future pricing models.

Zhang et al. (2024) proposed a hybrid model combining SARIMA, Polynomial Regression, and Gradient Boosting Decision Trees for automobile demand forecasting across multiple brand datasets, achieving superior predictive performance through a weighted-average ensemble strategy. Their work highlights the non-stationary and nonlinear nature of automobile market data, reinforcing the importance of robust analytical frameworks.

## 2.3 Supply Chain Dynamics and Brand Efficiency

From a supply-side perspective, Tripathi and Talukder (2020) examined supply chain performance and profitability across Indian automobile segments using a panel data fixed-effects model, finding that distribution inefficiency—rather than inventory turnover or asset utilisation—constitutes the principal drag on profitability. Their segmental analysis of commercial vehicles, passenger vehicles, and two/three-wheelers reveals distinct performance profiles that carry implications for pricing and dealer strategy in the secondary market.

Chou, Hung, and Lu (2021) applied Data Envelopment Analysis within a metafrontier framework to evaluate competitive efficiency across automobile categories, demonstrating that general cars outperform sports cars on cost efficiency and fuel economy, while sports cars exhibit within-category efficiency advantages. The implication for the used market is that fuel efficiency and total cost of ownership are key determinants of broad consumer uptake and consequently resale liquidity.

## 2.4 Research Gap

Despite the breadth of existing literature, several gaps remain. First, most empirical pricing studies are predicated on relatively small datasets or confined to Western or East Asian markets, limiting generalisability to the heterogeneous Indian context. Second, the interaction effects among multiple pricing determinants—particularly ownership history, accidental status, and brand equity—have received limited integrated treatment. Third, geographic heterogeneity in Indian used car pricing has not been systematically characterised through large-scale analysis. The present study addresses these gaps by deploying EDA on a dataset of 140,904 observations across multiple states, brands, and vehicle categories.

## 3. Research Methodology

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### 3.1 Research Design

This study adopts a quantitative, descriptive-analytical research design grounded in secondary data analysis. The objective is not to test causal hypotheses through controlled experimentation but to characterise the distributional properties and inter-variable relationships within a large observational dataset. This approach is consistent with the exploratory tradition in market structure analysis (Cooper & Schindler, 2014) and aligns with recent large-scale EDA studies in the automotive domain (Zhang et al., 2024).

### 3.2 Data Source and Description

The primary data source is the 'Mugil' used car dataset, comprising 140,904 vehicle listing records sourced from Indian secondary automobile platforms. The dataset encompasses 12 raw features spanning brand, model name, model variant, fuel type, car type, transmission, year of manufacture, kilometres driven, ownership category, state, accidental status, and listed price. Five additional engineered features were derived: car age (2024 minus year of manufacture), kilometres per year (normalised usage intensity), price in lakhs (INR/100,000), owner number (ordinal encoding of ownership category), and accidental indicator (binary flag).



### 3.3 Variable Classification

Variables are classified as follows:

- Dependent Variable: Resale price in Indian Rupee Lakhs (Price\_Lakh).
- Continuous Independent Variables: Kilometres driven, car age (years), KM per year, owner number.
- Categorical Independent Variables: Brand, car type, fuel type, transmission, state, accidental status, ownership category.

### 3.4 Data Cleaning and Pre-processing

The dataset was examined for missing values, duplicate records, and outliers. Vehicles with listed prices below ₹0.50 lakh or above ₹30 lakh were retained as genuine observations representing the budget and luxury extremes of the market. The 'accidental' flag was treated as a nominal binary variable. Categorical variables were encoded ordinally for correlation analysis. No imputation was required owing to the completeness of the dataset.

### 3.5 Analytical Framework

The analysis proceeds through four sequential layers: (i) descriptive statistics to characterise central tendency, dispersion, and distributional shape; (ii) Pearson correlation analysis to quantify bivariate linear relationships among continuous variables; (iii) segmental cross-tabulation to compare pricing patterns across categorical dimensions; and (iv) temporal and geographic analysis to identify depreciation trajectories and regional market heterogeneity. All analyses were conducted using Python (pandas, NumPy, SciPy) and visualised in Microsoft Excel.

## 4. Data Analysis and Interpretation

### 4.1 Descriptive Statistical Profile

Table 1 presents the descriptive statistics for the principal continuous variables in the dataset. The mean resale price of ₹7.62 lakh and median of ₹6.83 lakh indicate a positively skewed distribution (skewness = 0.82), consistent with a market dominated by affordable vehicles but elevated by a premium tail. The standard deviation of ₹4.35 lakh reflects high price dispersion attributable to the coexistence of budget (₹0.50L) and luxury (₹27.44L) segments.

Table 1. Descriptive Statistics of Continuous Variables (N = 140,904)

Variable	Mean	Median	Std. Dev.	Skewness
Price (₹ Lakhs)	7.62	6.83	4.35	0.82 (Right-skewed)
Kilometres Driven	94,702	85,000	28,411	0.00 (Symmetric)
Car Age (Years)	6.61	6.00	4.03	1.04 (Right-skewed)
KM per Year	15,200	13,800	8,520	1.79 (Right-skewed)
Number of Owners	1.42	1.00	0.61	0.72 (Right-skewed)

The car age variable exhibits a mean of 6.61 years with positive skewness (1.04), indicating that the majority of listings correspond to relatively recent vehicles with a long right tail of older models. Kilometres driven displays a symmetric distribution (skewness  $\approx$  0.00) with a mean of approximately 94,702 km, suggesting that listed vehicles span a broad usage spectrum without systematic bias toward high- or low-mileage observations.



## 4.2 Pearson Correlation Analysis

Table 2 presents the Pearson correlation matrix for key numerical features. Vehicle price exhibits its strongest negative correlation with car age ( $r = -0.404$ ,  $p < 0.001$ ), confirming that temporal depreciation is the dominant quantitative determinant of resale value. The correlation between price and kilometres driven ( $r = -0.214$ ,  $p < 0.001$ ), while statistically significant, is weaker, suggesting that mileage functions as a secondary moderating factor conditioned on vehicle age. Ownership number yields a moderate negative correlation with price ( $r = -0.317$ ,  $p < 0.001$ ), consistent with the ownership penalty hypothesis discussed in Section 5.

Table 2. Pearson Correlation Matrix of Numerical Features

Variable	Price	KM Driven	Car Age	Owner Num
Price (₹L)	1.000	-0.214	-0.404	-0.317
KM Driven	-0.214	1.000	-0.003	0.247
Car Age (Yrs)	-0.404	-0.003	1.000	0.396
Owner Num	-0.317	0.247	0.396	1.000

Notably, car age and year of manufacture are perfectly inversely correlated by construction ( $r = -1.000$ ), confirming the internal consistency of the engineered age variable. The moderate positive correlation between car age and owner number ( $r = 0.396$ ) implies that older vehicles have typically passed through more owners, compounding depreciation effects.

## 4.3 Segmental Analysis: Volume vs. Value

Table 3 summarises pricing by car type, fuel type, and ownership category. Hatchbacks dominate by listing volume (39.7%,  $n = 55,918$ ) but yield a comparatively modest average price of ₹6.83 lakh, reflecting their positioning in the affordable mass-market segment. Conversely, SUVs—representing 24.9% of listings—command the highest average price among mainstream categories (₹8.64 lakh), indicating a value premium consistent with aspirational consumer positioning.

Table 3. Segment-Level Summary Statistics: Price, Volume, and Market Share

Segment / Attribute	Count	Market Share (%)	Avg Price (₹L)	Median Price (₹L)
Hatchback	55,918	39.7%	6.83	6.10
SUV	35,085	24.9%	8.64	7.95
Sedan	25,362	18.0%	6.18	5.60
MPV	9,702	6.9%	7.56	6.78
Luxury	3,358	2.4%	8.49	7.62
Petrol Fuel	79,187	56.2%	7.65	6.86
Diesel Fuel	42,038	29.8%	7.61	6.86
CNG	14,054	10.0%	7.23	6.49
Electric	2,853	2.0%	8.40	7.55
1st Owner	96,210	68.3%	8.78	8.10
2nd Owner	36,483	25.9%	5.42	5.00
3rd+ Owner	8,211	5.8%	3.86	3.50



Electric vehicles, despite their small representation (2.0%,  $n = 2,853$ ), display the highest average resale price (₹8.40 lakh) among fuel categories, potentially reflecting early-adopter premium retention and limited supply. Diesel vehicles (29.8%) and petrol vehicles (56.2%) maintain similar average prices (₹7.61L and ₹7.65L respectively), suggesting fuel-type parity in the mid-range segment, with differential consumer value assigned to running cost and range characteristics rather than purchase price.

#### 4.4 Ownership Penalty Analysis

One of the most pronounced pricing discontinuities in the dataset is associated with ownership history. First-owner vehicles ( $n = 96,210$ , 68.3% of listings) command an average price of ₹8.78 lakh, declining sharply to ₹5.42 lakh for second-owner vehicles and further to ₹3.86 lakh for third-owner or beyond. This represents a cumulative price erosion of approximately 56% from first to third-plus ownership, a decline that substantially exceeds the depreciation attributable to comparable increments in age or mileage. The ownership penalty operates through perceived reliability risk, maintenance history uncertainty, and adverse selection concerns.

#### 4.5 Temporal Depreciation Analysis

Price depreciation over the 2000–2023 manufacturing year cohort follows a non-linear trajectory characterised by rapid initial decline followed by progressive stabilisation. Vehicles aged 0–2 years (2022–2024 manufacture) exhibit median prices of ₹9.73 lakh, declining steeply to ₹9.68 lakh for the 2–4 year cohort and ₹8.04 lakh for the 4–6 year cohort. Beyond six years, depreciation decelerates, with prices stabilising in the ₹4.65–6.67 lakh range for vehicles aged 8–20 years. This inflection pattern suggests that the greatest resale value loss occurs within the first four years, with a more gradual decline thereafter—an insight with direct implications for seller timing strategy.

Usage band analysis reinforces the age-depreciation relationship. Vehicles with 0–20,000 km driven average ₹9.27 lakh, declining monotonically to ₹6.62 lakh for the 100,000–130,000 km band. This progressive degradation reflects buyer-perceived mechanical wear, diminished reliability expectations, and increasing prospective maintenance costs associated with higher-mileage vehicles.

#### 4.6 Geographic Analysis

State-wise analysis reveals that Maharashtra accounts for the highest listing concentration (approximately 17–18% of total listings), followed by Karnataka, Delhi, and Tamil Nadu. These states correspond to major metropolitan hubs with dense urban populations, high vehicle ownership rates, and mature resale ecosystems. Maharashtra exhibits slightly higher average transaction prices, attributable to elevated per capita income and greater demand for premium and feature-rich vehicles. Tamil Nadu demonstrates a more balanced price distribution, consistent with its mixed urban-semi-urban demand profile and strong preference for fuel-efficient, practical vehicles. The geographic heterogeneity observed implies that pricing models must incorporate state-level fixed effects to account for regional demand-supply dynamics.

## 5. Results and Discussion

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### 5.1 Market Structure: Affordability-Driven with a Premium Tail

The central finding of this study is that the Indian used automobile market is structurally bifurcated: a high-volume, affordability-driven core—anchored by Maruti Suzuki (38% market share) and hatchback body styles—coexists with a lower-volume but high-value premium segment dominated by SUVs, luxury models, and first-owner electric vehicles. The right-skewed price distribution (mean > median) is a diagnostic signature of this structure, wherein the modal transaction occurs at approximately ₹6–7 lakh while a small number of high-value listings disproportionately elevate the mean. This bifurcation has implications for the appropriate analytical treatment of the data: aggregate mean-based statistics obscure segment-specific pricing dynamics, necessitating the segmental approach adopted in this study.

The dominance of Maruti Suzuki—attributable to its ubiquitous service network, established brand trust, and superior fuel economy in the compact segment—creates a structural anchor in the affordable price tier. Hyundai's 15.7% share reflects growing mid-range and crossover demand, while Tata Motors' higher average resale price relative to its market volume signals emerging brand equity gains driven by recent investments in safety, design, and electrification.



## 5.2 Depreciation Dynamics and the Optimal Resale Window

The non-linear depreciation curve identified in this study closely resembles the theoretical depreciation function posited by Hall (2000), characterised by a convex decline that is steepest in the early years and progressively flattens. The practical implication is that vehicle owners seeking to maximise resale return should transact within the 0–4 year ownership window, where residual value remains comparatively high relative to accumulated depreciation. Beyond five years, diminishing marginal depreciation implies that retention for an additional year yields a proportionally smaller price reduction, somewhat mitigating the urgency of early exit.

The usage band analysis further reveals that the transition from the 0–20k km band (average ₹9.27L) to the 40–60k km band (₹8.52L) represents an optimal buyer entry point: vehicles in this range have absorbed the steepest depreciation curve but retain solid operational reliability, offering a value sweet spot for buyers seeking a balance between price and longevity. This finding parallels the 'certified pre-owned' value proposition increasingly exploited by organised players in the Indian used car sector.

## 5.3 The Ownership Penalty and Market Signalling

The ownership penalty—a price discount of approximately 38% between first and second ownership and a further 29% between second and third-plus ownership—is consistent with Akerlof's (1970) classical 'market for lemons' framework, wherein information asymmetry between sellers and buyers about vehicle quality leads buyers to discount prices as a hedge against unknown defect risk. The steepness of the penalty in the Indian context may be exacerbated by limited vehicle history documentation, less prevalent independent pre-purchase inspection services, and lower institutional trust in informal seller claims relative to certified dealership channels.

A significant policy implication follows: standardised, accessible vehicle history reporting—analogueous to the CarFax model in North America—could reduce this asymmetry, improve market efficiency, and enhance consumer welfare by enabling first-owner vehicles with demonstrably good maintenance histories to command appropriate premiums while reducing unwarranted discounts on genuine-quality multi-owner vehicles.

## 5.4 Fuel Type Transition and the Electric Vehicle Premium

The finding that electric vehicles command the highest average resale price despite their small volume share (₹8.40 lakh, 2.0% of listings) warrants careful interpretation. This premium likely reflects multiple concurrent factors: the relatively recent vintage of most EVs in the dataset (lower age-related depreciation), restricted resale supply sustaining price levels, early-adopter residual value retention, and government subsidies effectively lowering the buyer's effective acquisition cost on the new-vehicle side while insulating resale prices from downward pressure. As EV penetration deepens and the fleet matures, the premium is expected to moderate, and future studies will need to monitor whether EV depreciation trajectories converge toward or diverge from those of internal combustion vehicles.

## 5.5 Accidental History as a Resale Penalty

Vehicles disclosed as accidental exhibit systematically lower resale prices and reduced buyer pool size, corroborating the risk perception mechanism identified in the qualitative literature on used car markets. Even when repairs are objectively complete, buyer-perceived residual structural risk generates a persistent price discount—a phenomenon termed 'stigma depreciation' in the insurance and vehicle valuation literature (McAlister et al., 2019). This finding underscores the importance of transparency in vehicle condition disclosure for market participants and the potential value of third-party structural integrity certifications in mitigating stigma discounting.

## 6. Conclusion

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This study provides a comprehensive empirical characterisation of pricing determinants in the Indian used automobile market through exploratory data analysis of 140,904 vehicle listings. The findings collectively establish that resale price is a function of a layered hierarchy of determinants: temporal depreciation (car age) and usage intensity (kilometres driven) constitute the primary quantitative drivers, while brand equity, ownership history, car type, and fuel type exert significant categorical premia or penalties that interact with the depreciation baseline.



The market's positively skewed price distribution reflects its structural duality—a high-volume affordable core dominated by Maruti Suzuki and hatchbacks, and a lower-volume premium segment driven by SUVs, luxury models, and EVs. Geographic heterogeneity, particularly the Maharashtra-Tamil Nadu contrast, underscores the importance of regional market calibration for pricing and inventory strategies.

For sellers, the optimal resale window lies within 0–4 years of vehicle age to capture maximum residual value before the steepest depreciation curve has fully elapsed. For buyers, the 40,000–60,000 km usage band represents an optimal value-to-reliability trade-off. Policymakers and industry associations should prioritise standardised vehicle history reporting to reduce information asymmetry and its associated ownership and accidental status penalties.

## 7. Limitations and Future Research Directions

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Several limitations of the present study merit acknowledgement. First, the analysis is restricted to cross-sectional listing data and does not incorporate actual transaction prices, which may deviate from listed prices due to negotiation and seasonal demand dynamics. Second, the absence of macroeconomic variables—inflation, interest rates, fuel price indices, and EV incentive schedules—limits the model's explanatory completeness. Third, the study employs bivariate correlation and segmental analysis rather than multivariate regression, precluding causal inference and interaction effect estimation.

Future research should address these limitations through: (i) multivariate hedonic regression or random forest-based feature importance analysis to isolate the independent contribution of each pricing determinant while controlling for confounders; (ii) integration of macroeconomic and sentiment variables following the approach of Ou-Yang et al. (2022); (iii) longitudinal panel data analysis tracking price trajectories of specific models over time; and (iv) geospatial regression models to decompose regional price variation into its economic, demographic, and infrastructure components. The development of real-time, ML-powered pricing engines that synthesise structured listing attributes with unstructured consumer sentiment data represents a promising frontier for both academic inquiry and industry application.

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