



Analysis Of Selling Price Of Used Cars

¹Kunal Bhidonia, ²Kartik Gaur, ³Naman Yadav, ⁴Mrs, Chhaya Sharma

¹Scholar Final B. Tech, ²Scholar Final B. Tech, ³Scholar Final B. Tech,

¹Computer Science Engineering (CSE),

¹Raj Kumar Goel Institute of Technology, Ghaziabad, U.P., India.

Abstract: The used car market has expanded rapidly over the last decade, driven by rising new car prices, improved vehicle durability, digital marketplaces, and changing consumer preferences. This paper analyses the determinants of the selling price of used cars using insights from existing empirical studies and typical datasets collected from online classified platforms and dealer inventories. Key explanatory variables considered include vehicle age, mileage, brand category, model type, fuel type, transmission, vehicle condition, service history, accident history, and cosmetic attributes such as colour and optional features. Prior research consistently shows that mileage and age are the dominant price drivers, while brand reputation and vehicle class exert substantial additional influence; cosmetic factors such as colour typically have limited but sometimes locally relevant effects. Multiple linear regression and machine learning models, such as random forest regression and neural networks, are commonly used to model the relationship between vehicle characteristics and selling price, achieving reasonably low prediction errors suitable for pricing support in practice. The findings discussed in this paper highlight that:

- Price declines non-linearly with age and accumulated mileage, with sharper depreciation in early years.
- Premium and reliable brands command persistent price premiums, even after controlling for age and mileage.
- Good vehicle condition, documented service history, and clean accident records substantially raise achievable selling prices.
- Machine learning models can improve prediction accuracy compared with simple linear models but at the cost of interpretability.

These insights can help consumers make more informed purchase and sale decisions, and assist dealers and platforms in setting optimal prices, managing inventory, and designing data-driven pricing tools.

Index Terms - Used car price, Resale value, Depreciation, Mileage, Vehicle age, Brand effect, Regression analysis, Machine learning etc.

INTRODUCTION^{1,2,3}

The used car sector represents a significant share of overall automotive transactions in many countries, often exceeding new car sales in unit volume. Used vehicles serve as an affordable mobility option for households that cannot or do not wish to purchase new cars, and they also form a key channel through which fleets, leasing companies, and first-hand owners dispose of vehicles. The proliferation of online marketplaces and valuation tools has increased transparency, but price formation remains complex because it depends on numerous interacting vehicle attributes and market conditions. Understanding the determinants of used car selling prices is therefore important for individual buyers and sellers, finance providers, insurers, and dealers who must decide how to value trade-ins, set asking prices, and manage residual value risk. Prior studies and industry analyses identify several recurring factors as central to pricing, including age, mileage, brand, segment, condition, and history. This paper synthesizes these insights and outlines an analytical framework to study used car prices using standard statistical and machine learning methods.

LITERATURE REVIEW⁴

Several empirical studies have modelled used car prices using regression-based approaches. One line of research uses multiple linear regression to relate selling price to a small set of explanatory variables such as age, mileage, brand category, and colour, often finding that age and mileage have strong negative effects on price, while higher-tier brands exhibit positive coefficients. Studies using datasets with hundreds to thousands of vehicles have shown that mileage and model year explain a substantial portion of price variation, with brand also statistically significant and colour often insignificant or weakly associated with price. Another strand of work applies machine learning techniques, including random forest regression, gradient boosting, and neural networks, to improve predictive accuracy for pricing tools. In these studies, additional variables such as fuel type, transmission, engine power, and body type are incorporated, and results indicate that ensemble and neural models can achieve lower mean absolute percentage errors than traditional linear models in forecasting used car prices. Methodological research has also explored survival analysis for price optimization, focusing on how list price affects time on market rather than just the final transaction price. Overall, the literature converges on a core set of factors and shows that data-driven models can support more precise pricing decisions.

CONCEPTUAL FRAMEWORK AND HYPOTHESES^{5,6,7}

The selling price of a used car can be viewed as the outcome of interaction between vehicle-specific characteristics and broader market forces. Vehicle attributes reflect the remaining useful life, perceived reliability, and desirability of the car, while market conditions shape demand for specific segments, fuel types, and brands. Based on prior evidence and industry practice, the main explanatory variables can be grouped as follows:

- Depreciation variables: age (years since first registration) and mileage (kilometres or miles driven).
- Brand and model: manufacturer reputation (e.g., economy, mainstream and premium) and model segment (e.g., compact, SUV, luxury sedan).
- Mechanical and cosmetic condition: documented service history, accident/damage history, visible wear, and interior/exterior state.
- Technical specifications: engine size or power, fuel type (petrol, diesel, hybrid, electric), transmission type, and drivetrain.
- Features and options: safety and comfort features, infotainment systems, and other extras.
- Market and contextual factors: region, fuel price environment, and current demand for certain body types.

From this structure, typical hypotheses include:

- H1: Selling price decreases with vehicle age, holding other factors constant.
- H2: Selling price decreases with mileage, holding other factors constant.
- H3: Vehicles from higher-reputation brands have higher prices than those from lower-tier brands, after controlling for age and mileage.
- H4: Good condition, clean accident history, and complete service records increase the selling price relative to similar vehicles without these attributes.
- H5: Certain body types (e.g., SUVs and trucks in some markets) and fuel-efficient models command price premiums when market demand and fuel prices favor them.

These hypotheses guide the choice of variables and the interpretation of statistical results.

DATA AND VARIABLES (CONCEPTUAL DESCRIPTION)⁸

A typical dataset for analysing used car prices can be assembled from online listings or dealer stock records, where each observation represents a single sold or listed vehicle. For a research-oriented analysis, it is common to restrict attention to actual transactions, but list prices can be used as a proxy where transaction data are unavailable. The core dependent variable is the selling price (or list price) in local currency. Key independent variables may include:

Age: difference between the year of sale and year of manufacture or registration.

Mileage: odometer reading at sale.

Brand category: categorical variable distinguishing economy, mainstream, and premium brands.

Model and body type: sedan, hatchback, SUV, MPV, pickup, etc.

Fuel type: petrol, diesel, CNG, hybrid, or electric.

Transmission: manual or automatic.

Engine power: horsepower or kilowatts

Colour: grouped into neutral (white, black, grey, silver) versus non-neutral

Condition index: derived from inspection scores, number of recorded damages, or service history completeness.

Pre-processing steps usually include removing duplicate entries, handling missing values, and converting categorical variables into dummy (indicator) variables for regression or appropriate encodings for machine learning methods.

METHODOLOGY^{9,10,11}

The most straightforward modelling approach is multiple linear regression, where selling price is expressed as a linear combination of explanatory variables plus an error term. In such a model, coefficients measure the expected marginal effect of each variable on price, holding other factors constant. For example, the coefficient on mileage indicates the average change in price associated with an additional thousand kilometres driven, and the coefficient on age captures annual depreciation effects. Because the relationship between age, mileage, and price can be non-linear, transformations such as logarithms or polynomial terms are often introduced to better capture diminishing value over time. In addition to linear regression, studies have applied machine learning methods to capture complex, non-linear interactions among variables. Random forest and gradient boosting models can automatically discover interaction effects (e.g., how age and brand jointly influence price) and often yield lower prediction errors in held-out test data. Neural network-based approaches have also been explored, sometimes optimized with meta-heuristics to minimize pricing errors in dealership settings. Model performance is typically assessed using metrics such as mean absolute error, root mean squared error, and mean absolute percentage error, alongside cross-validation to avoid over fitting.

KEY DETERMINANTS OF USED CAR PRICE^{12,13,14,15,16,17}

1. AGE AND MILEAGE

Age and mileage consistently emerge as the most influential determinants of used car prices. Empirical models show that price declines as vehicles get older and accumulate more distance, with the steepest depreciation usually occurring in the first few years and at lower mileage ranges. One study using several years of data found that increasing mileage and vehicle age were strongly and negatively associated with price, confirming theoretical expectations about wear and reduced remaining life. Industry practitioners also emphasize that, for two similar vehicles, the one with lower mileage will almost always command a higher price, reflecting buyer preferences for cars with less wear and perceived mechanical reliability.

2. BRAND AND MODEL SEGMENT

Brand reputation and model segment play a substantial role in determining resale value. Research that groups brands into categories such as economy, mid-range, and premium has found that vehicles from higher brand categories are associated with higher used car prices, even after controlling for age and mileage. This pattern aligns with consumer perceptions of reliability, build quality, and status associated with certain manufacturers. Market analysis also show that popular models within specific segments retain value better than niche products, as they attract a larger pool of potential buyers in the used market

3. VEHICLE CONDITION AND SERVICE HISTORY

Condition indicators significantly modify the price that buyers are willing to pay. Well-maintained vehicles with regular service records and no major accidents often sell for noticeably higher prices than similar vehicles with poor maintenance or prior damage. Industry sources suggest that a documented service history can increase resale value by a meaningful percentage, reflecting buyer confidence in the car's mechanical state. Conversely, accident and damage history lowers value, particularly when major structural repairs or insurance write-offs are recorded, because buyers associate such histories with higher future repair risk.

4. TECHNICAL SPECIFICATIONS AND FUEL TYPE

Technical features such as engine size, power output, and transmission type influence price through their impact on driving experience and running costs. Research that incorporates fuel type, engine characteristics, and mileage shows that engines with efficient fuel consumption can enhance value, especially when fuel prices are high and buyers are sensitive to operating costs. In some markets, diesel vehicles historically commanded higher prices for long-distance use, while in others the shift toward petrol, hybrids, and electric drivetrains is increasing their relative appeal and supporting higher resale values. Automatic transmissions also tend to be more valuable in regions where buyers prefer ease of driving, whereas manual transmissions may be favoured where fuel economy and lower purchase cost dominate preferences.

5. BODY TYPE, FEATURES, AND COLOUR

Body type affects price because it reflects functional suitability and lifestyle alignment for buyers. Truck and SUV models often hold value better in markets where utility and higher driving position are valued, while compact cars may be preferred where urban congestion and parking constraints are prominent. Additional features such as advanced safety systems, infotainment, sunroofs, and leather interiors can raise resale values by enhancing perceived comfort and modernity. Colour, while widely discussed, tends to have modest effects relative to mechanical variables; some studies report negligible colour impact on price, while market commentary notes that neutral colours (such as white, black, grey, and silver) are generally easier to sell and can slightly improve resale prospects.

MODELLING RESULTS AND INTERPRETATION (CONCEPTUAL)^{18,19}

In a typical regression model with price as the dependent variable and factors such as age, mileage, brand category, and colour as independent variables, estimated coefficients usually confirm expected relationships. Age and mileage coefficients are negative and statistically significant, indicating that each additional year or unit of distance lowers expected selling price, with the effect size larger in early years and for lower mileage intervals. Brand category coefficients tend to be positive for mid-range and premium brands relative to economy brands, reflecting the price premium associated with perceived quality and desirability. Colour often appears as statistically insignificant when controlling for these other characteristics, supporting claims that its direct contribution to price is limited. Machine learning models trained on broader feature sets generally achieve lower prediction errors than simple linear models, suggesting that interaction effects and non-linearities are important. For example, neural networks and tree-based ensembles have been reported to provide more accurate used car price forecasts than linear regression in data-driven pricing systems implemented by dealers and online platforms.

PRACTICAL IMPLICATIONS FOR BUYERS AND SELLERS^{20,21,22,23,24}

The analytical findings have several practical implications. For sellers, understanding that age, mileage, condition, and brand are core price drivers helps in setting realistic expectations and in identifying which improvements are most cost-effective before listing a vehicle. Investing in professional cleaning, minor cosmetic repairs, and ensuring that service records are complete can increase buyer trust and support higher asking prices, while overstating the value of cosmetic modifications that do not align with mainstream tastes may not yield a return. For buyers, awareness of how these factors interact supports more informed comparisons between vehicles: for instance, choosing a slightly older car from a highly reliable brand with moderate mileage may offer better long-term value than a newer car from a less reliable brand with higher running costs. Dealers and platforms can employ data-driven models to refine list prices, reduce time on market, and design trade-in policies that reflect realistic resale values, ultimately improving market efficiency.

LIMITATIONS AND FUTURE RESEARCH^{25,26,27,28,29}

Although regression and machine learning models capture many determinants of used car prices, several limitations remain. Many datasets rely on listing prices rather than final transaction prices, which can introduce systematic biases if negotiation behaviour or discounting patterns differ across brands and segments. Data quality issues such as misreported mileage, incomplete accident histories, and inconsistent condition grading can also weaken model accuracy. Future research could integrate telematics data, detailed inspection scores, and

real transaction prices to refine models and better capture the true effect of usage and mechanical health on value. Additionally, incorporating dynamic market variables such as fuel prices, macroeconomic conditions, and policy changes (for example, emission restrictions or incentives for electric vehicles) would enable more robust forecasting of how used car prices evolve over time. Finally, combining pricing models with survival analysis or hazard models could jointly optimize price and expected time on market, yielding more comprehensive decision support tools for dealers and platforms.

REFERENCES:

1. JOE D'ALLEGRO, KEY FACTORS INFLUENCING YOUR USED CAR'S VALUE, INVESTOPEDIA, NOVEMBER 23, 2025 ([HTTPS://WWW.INVESTOPEDIA.COM/ARTICLES/INVESTING/090314/JUST-WHAT-FACTORS-VALUE-YOUR-USED-CAR.ASP](https://www.investopedia.com/articles/investing/090314/just-what-factors-value-your-used-car.asp))
2. HARI BHUSHAN, WHAT FACTORS AFFECT TRADE-IN VALUE FOR USED CARS?, CLEAR CAR, JULY 9, 2024 ([HTTPS://WWW.CLEARCAR.COM/BLOG/FACTORS-AFFECTING-USED-CAR-TRADE-IN-VALUES](https://www.clearcar.com/blog/factors-affecting-used-car-trade-in-values))
3. Zhengwei Sun, Research on factors affecting second-hand car market prices, Theoretical and Natural Science, EWA Publishing, May 28, 2024 (<https://doi.org/10.54254/2753-8818/36/20240532>)
4. Jiayi Lin, Predicting Used Car Price Based on Machine Learning, 1st International Conference on E-commerce and Artificial Intelligence (ECAI 2024), pages 553-560, (<https://www.scitepress.org/Papers/2024/132705/132705.pdf>)
5. Pallavi Lakra, Top 10 Factors Affecting the Price of a Second-hand Car, Poonawalla Fincorp, Feb 13, 2025. (<https://poonawallafincorp.com/blogs/pre-owned-car-loan/factors-affecting-on-price-of-second-hand-car>)
6. JOE D'ALLEGRO, KEY FACTORS INFLUENCING YOUR USED CAR'S VALUE, INVESTOPEDIA, NOVEMBER 23, 2025 ([HTTPS://WWW.INVESTOPEDIA.COM/ARTICLES/INVESTING/090314/JUST-WHAT-FACTORS-VALUE-YOUR-USED-CAR.ASP](https://www.investopedia.com/articles/investing/090314/just-what-factors-value-your-used-car.asp))
7. HARI BHUSHAN, WHAT FACTORS AFFECT TRADE-IN VALUE FOR USED CARS?, CLEAR CAR, JULY 9, 2024 ([HTTPS://WWW.CLEARCAR.COM/BLOG/FACTORS-AFFECTING-USED-CAR-TRADE-IN-VALUES](https://www.clearcar.com/blog/factors-affecting-used-car-trade-in-values))
8. Zhengwei Sun, Research on factors affecting second-hand car market prices, Theoretical and Natural Science, EWA Publishing, May 28, 2024 (<https://doi.org/10.54254/2753-8818/36/20240532>)
9. Zhengwei Sun, Research on factors affecting second-hand car market prices, Theoretical and Natural Science, EWA Publishing, May 28, 2024 (<https://doi.org/10.54254/2753-8818/36/20240532>)
11. Y. Sudheer and Dr. P. Viswanath, A Study on used Cars Price Prediction using Regression Model with Reference to Cartrade.Com, IJTSRD, Volume-6 Issue-6, and September-October 2022. (<https://www.ijtsrd.com/papers/IJTSRD51956.pdf>)
12. Alexander Born, Nikoleta Kovachka, Stefan Lessmann and Hsin-Vonn Seow, Price Management in the Used-Car Market: An Evaluation of Survival Analysis, ECONSTOR, Reprint December 14, 2018. (<https://www.econstor.eu/handle/10419/230775>)
13. Pallavi Lakra, Top 10 Factors Affecting the Price of a Second-hand Car, Poonawalla Fincorp, Feb 13, 2025. (<https://poonawallafincorp.com/blogs/pre-owned-car-loan/factors-affecting-on-price-of-second-hand-car>)
14. HARI BHUSHAN, WHAT FACTORS AFFECT TRADE-IN VALUE FOR USED CARS?, CLEAR CAR, JULY 9, 2024 ([HTTPS://WWW.CLEARCAR.COM/BLOG/FACTORS-AFFECTING-USED-CAR-TRADE-IN-VALUES](https://www.clearcar.com/blog/factors-affecting-used-car-trade-in-values))
15. TOP FACTORS THAT AFFECT YOUR CAR'S RESALE VALUE, CAR RIGHT BUYING CENTRE, MARCH 4, 2025
16. Zhengwei Sun, Research on factors affecting second-hand car market prices, Theoretical and Natural Science, EWA Publishing, May 28, 2024 (<https://doi.org/10.54254/2753-8818/36/20240532>)
17. JOE D'ALLEGRO, KEY FACTORS INFLUENCING YOUR USED CAR'S VALUE, INVESTOPEDIA, NOVEMBER 23, 2025 ([HTTPS://WWW.INVESTOPEDIA.COM/ARTICLES/INVESTING/090314/JUST-WHAT-FACTORS-VALUE-YOUR-USED-CAR.ASP](https://www.investopedia.com/articles/investing/090314/just-what-factors-value-your-used-car.asp))
18. Zhengwei Sun, Research on factors affecting second-hand car market prices, Theoretical and Natural Science, EWA Publishing, May 28, 2024 (<https://doi.org/10.54254/2753-8818/36/20240532>)
19. Zhengwei Sun, Research on factors affecting second-hand car market prices, Theoretical and Natural Science, EWA Publishing, May 28, 2024 (<https://doi.org/10.54254/2753-8818/36/20240532>)
20. Y. Sudheer and Dr. P. Viswanath, A Study on used Cars Price Prediction using Regression Model with Reference to Cartrade.Com, IJTSRD, Volume-6 Issue-6, and September-October 2022. (<https://www.ijtsrd.com/papers/IJTSRD51956.pdf>)
21. HARI BHUSHAN, WHAT FACTORS AFFECT TRADE-IN VALUE FOR USED CARS?, CLEAR CAR, JULY 9, 2024 ([HTTPS://WWW.CLEARCAR.COM/BLOG/FACTORS-AFFECTING-USED-CAR-TRADE-IN-VALUES](https://www.clearcar.com/blog/factors-affecting-used-car-trade-in-values))

22. TOP FACTORS THAT AFFECT YOUR CAR'S RESALE VALUE, CAR RIGHT BUYING CENTRE, MARCH 4, 2025
23. Pallavi Lakra, Top 10 Factors Affecting the Price of a Second-hand Car, Poonawalla Fincorp, Feb 13, 2025. (<https://poonawallafincorp.com/blogs/pre-owned-car-loan/factors-affecting-on-price-of-second-hand-car>)
24. JOE D'ALLEGRO, KEY FACTORS INFLUENCING YOUR USED CAR'S VALUE, INVESTOPEDIA, NOVEMBER 23, 2025 ([HTTPS://WWW.INVESTOPEDIA.COM/ARTICLES/INVESTING/090314/JUST-WHAT-FACTORS-VALUE-YOUR-USED-CAR.ASP](https://www.investopedia.com/articles/investing/090314/just-what-factors-value-your-used-car.asp))
25. Zhengwei Sun, Research on factors affecting second-hand car market prices, Theoretical and Natural Science, EWA Publishing, May 28, 2024 (<https://doi.org/10.54254/2753-8818/36/20240532>)
26. Alexander Born, Nikoleta Kovachka, Stefan Lessmann and Hsin-Vonn Seow, Price Management in the Used-Car Market: An Evaluation of Survival Analysis, ECONSTOR, Reprint December 14, 2018. (<https://www.econstor.eu/handle/10419/230775>)
27. Jiayi Lin, Predicting Used Car Price Based on Machine Learning, 1st International Conference on E-commerce and Artificial Intelligence (ECAI 2024), pages 553-560, (<https://www.scitepress.org/Papers/2024/132705/132705.pdf>)
28. Y. Sudheer and Dr. P. Viswanath, A Study on used Cars Price Prediction using Regression Model with Reference to Cartrade.Com, IJTSRD, Volume-6 Issue-6, and September-October 2022. (<https://www.ijtsrd.com/papers/IJTSRD51956.pdf>)
29. Zhengwei Sun, Research on factors affecting second-hand car market prices, Theoretical and Natural Science, EWA Publishing, May 28, 2024 (<https://doi.org/10.54254/2753-8818/36/20240532>)

