Introduction

As the electric-vehicle (EV) landscape accelerates toward mass adoption, manufacturers face a new strategic frontier: the still-forming second-hand EV market. Unlike the tightly orchestrated domain of new-car launches, pre-owned sales unfold through a patchwork of regional dealerships, diverse consumer segments, and rapidly evolving battery tech. To analyze the markets of EV, manufacturers need hard evidence on what really moves a used EV off the lot. The IntelliDrive Automotive Research Institute (IARI) has assembled a 10,000 record dataset from dealerships in five key U.S. states, capturing whether each vehicle sold alongside price, trade-in details, brand, customer demographics, dealership characteristics, and the car features ranging from fast-charging capability to blind-spot monitoring.

The objective is to interrogate IARI's dataset to identify which variables influences a successful sale of a second-hand EV from the manufacturer's point of view. By exploring data quality, modeling purchase likelihood, comparing brand-specific drivers, and quantifying how trade-in valuations shape outcomes, we will translate raw variables into actionable levers. Ultimately, the analysis will recommend which car features, and customer attributes deserve priority investment to maximize the manufacturer's share and profitability in the burgeoning used-EV market.

Literature Review

EV Sales literature review

Battery transparency is now a prerequisite for confidence in the second-hand EV market. A recent industry survey found that 95 % of used-EV shoppers rate a Battery Health Report as critical or impactful, and dealers increasingly price vehicles on this metric rather than mileage (vsNEW, 2025; Seymour, 2025). Technical attributes that shorten charge time or protect range likewise drive demand: choice-experiment evidence shows buyers will pay $425-3,250 for every hour shaved off fast-charging time (Hidrue et al., 2011), while 48% of U.S. intenders say they would pay extra for DC ultra-fast charging (DeGraff, 2023). Experimental road tests record energy-recapture efficiencies of up to 78% from regenerative braking (Valladolid, Calle, & Guiracocha, 2023), and U.S. Department of Energy data confirm that cold ambient temperatures can cut BEV range by 20–40%, underlining the value of sub-zero weather packages (U.S. Department of Energy, 2024).

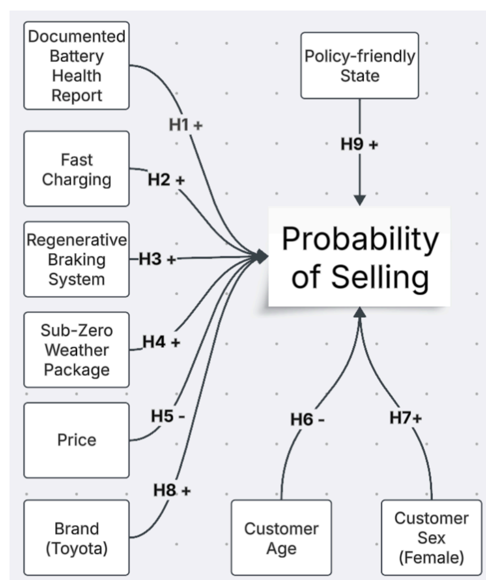

Figure 1

Market response is equally shaped by brand equity, demographics, economics, and geography. Brand-valuation research places Toyota at the top of global automotive rankings and documents Tesla's recent decline, highlighting the reputational lens through which buyers judge used EVs (Brand Finance, 2025). Cross-market survey work shows younger motorists are disproportionately likely to consider an EV for their next purchase (Kantar, 2023), whereas registration data reveal that women constitute only 28% of EV buyers overall and as little as 14% for some startup brands (S&P Global Mobility, 2023).

Price remains the dominant brake on adoption: qualitative interviews indicate cost concerns outweigh environmental motives for most potential buyers (Degirmenci & Breitner, 2017). Finally, state-level incentives and infrastructure matter; a 50-state panel study finds that each additional US $1,000 in tax credits lifts EV registrations by roughly 10%, with California, Oregon and New York persistently leading uptake (Mekky & Collins, 2024). In conclusion, previous studies show the importance of the inclusion of battery health reports, fast charging capabilities, regenerative braking system, subzero weather package, brand, customer age, customer sex, price, and state as variables in predicting EV cars sold in the secondary market. Figure 1 presents the conceptual model incorporating all proposed hypotheses.

<u>Trade-in valuation literature review</u>

A trade-in appraisal hinges on two broad information sets, they are physical attributes of the incoming vehicle and structural attributes of the outlet making the offer. The first screen is odometer, auction evidence shows every additional 1 000 miles (≈1 600 km) knocks roughly 0.5% off a car's wholesale price, even after age and model are held constant (Engers, Hartmann, & Stern, 2009). Furthermore, the appraisers would look at the visible quality, in this case, a single-grade jump on the five-point exterior condition scale lifts expected auction revenue 16–65% by increasing the probability a bidder will step in (Tadelis & Zettelmeyer, 2015). The visible quality for exterior also includes tyre condition, American Automobile Association (AAA) road tests show tread worn to 4⁄32″ boosts wet-road stopping distance by 43%, signalling an imminent reconditioning bill that dealers deduct from the offer (AAA, 2018). Performance indicators also feed directly into valuations; UK hedonic work finds a 10% bump in engine displacement increases used-car asking price by almost 5% (Mandys, 2020).

Power-train choice layers on further price discrimination on used cars. The U.S. resale data show hybrids trade at a premium to equivalent gasoline models once future fuel savings are capitalised (Gilmore et al., 2013), while University of Michigan cost-of-ownership comparisons report diesels retaining 30–50% more value after three years (UMTRI, 2015). By contrast, early-generation battery-electric vehicles with sub-100-mile ranges depreciate faster than internal-combustion cars (Guo & Zhou, 2019). Another example, in Turkey's second-hand market, automatics command a statistically significant premium over manuals (Erdem & Şentürk, 2009).

Dealer characteristics might also affect the offer price for trade in cars. A car enthusiast study tracking 50-mile trading areas found urban dealerships, facing denser competition and deeper buyer pools,

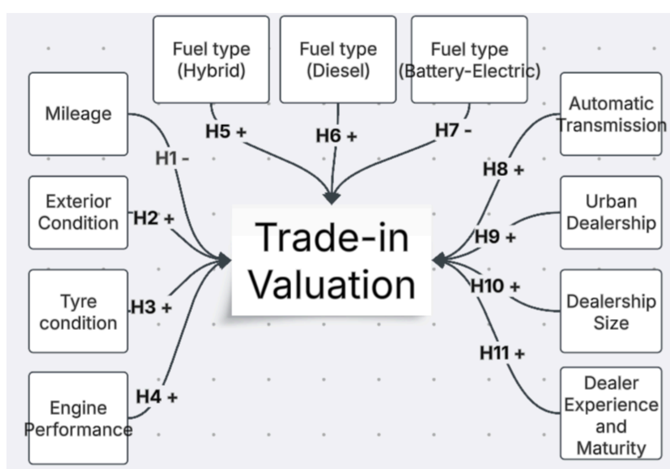

Figure 2

list identical used cars roughly US $345 higher than rural stores (Bond, 2012). Scale seems to cushion offers as well, analyses show larger franchises enjoy lower per-unit reconditioning costs, enabling them to pay more up front (Duman & Taner, 2022). Finally, organisational learning plays a role, production and operations management work links greater dealership tenure and service-quality scores to higher brand sales and profitability, implying experienced outlets can price closer to expected retail and still hit margin targets (Cui, Rhee, & Liu, 2020).

Thus, based on the literature, we formulate our hypotheses as follow: negative effects for mileage, positive premiums for superior exterior and tyre condition, larger engines, hybrids and diesels (relative to gasoline), automatics/CVTs, and for offers originating in urban, large, or highly experienced dealerships, while older short-range Battery Electric Vehicles (BEVs) should trade at a discount. Figure 2 presents the conceptual model incorporating all proposed hypotheses.

Methods

Binary Choice Models with "Sold" as Dependent Variables:

1. Logit model with "sold" as DV and battery_health_report, fast_charging_capabilities, regenerative_braking_system, subzero_weather_package, brand, customer_age, customer_sex, price, and state as IV.
2. Logit model with "sold" as DV and all variables excluding several variables (range_estimator, glass_roof, and trade_in_model) as IV for comparison purposes.

Choice Models with "brands" (Ford, Tesla, and Toyota) as Dependent Variable:

1. Multinomial Logit models with "brand" as DV and battery_health_report, fast_charging_capabilities, regenerative_braking_system, subzero_weather_package, customer_age, customer_sex, price, and state as IV.

Linear Regression Model with "trade_in_value" as Dependent Variable:

1. Tobit type 1 model with "trade_in_value" as DV and trade_in_mileage, trade_in_exterior_condition, trade_in_fuel_type, trade_in_tire_condition, trade_in_transmission_type, dealership_location, dealership_size, and dealership_years_experience.
2. OLS model with with "trade_in_value" as DV and trade_in_mileage, trade_in_exterior_condition, trade_in_fuel_type, trade_in_tire_condition, trade_in_transmission_type, dealership_location, dealership_size, and dealership_years_experience.

Data Preparation

Prior to the analysis, the data was prepared accordingly by inspecting the missing values, outliers and oddities in the dataset. First, we look at the missing values and oddities, in which we inspect the dataset by using "NA" and "unique" syntax, and later we filter the data to see if there are duplicates. There are no missing values in the dataset, but there are duplicates in the customer ID, in which we analyzed further that the multiple occurrences of customer ID are identical for each observation. There are 530 duplicates, which consist of 1 and 2 duplicate data entries. Thus, we removed the duplicates from the dataset. Furthermore, from the summary of the dataset, we found that Seller's experience can be negative, which in this case the absolute minimum should be 0, not negative. In this case, we decided to treat this by not using it in any of the models; we can do this because we use the focus from the car manufacturer's side and not the dealership's side. Therefore we need the variable dealership years of experience since this is more interesting instead of a specific individual. To gather an overview over the data, boxplots were used to show the data distribution. The boxplots show potential outliers in the Price, Income and Milage variables, however, we decided not to remove this since they possibly reflect true numbers.

A training/test data split is done using an 80/20 split, resulting in a dataset of 8,000 observations for training the model and 2,000 for estimation purposes.

Descriptive statistics

In this data set there are over 20 binary variables available in this data set, with the majority of them being important to test what features a car holds. Despite the sheer amount of these variables, there is also some interesting stuff to find in here. The percentage of customers that come to a dealership and buy a new car is 40.1% and the percentage of customers who visit a dealership to trade in their car is around 55%. For the customers there is no real difference between gender, the average age of a customer is 41.6 years and the mean income is around $93.000. The average price of a car being sold in the dealership is $49.068.

Logit Model

A logistic regression model was estimated to examine the determinants of whether a second hand electric vehicle (EV) was sold, using a binary dependent variable (sold) and a set of vehicle, demographic, and regional variables. The model includes variables for brand, price, technical features, and customer demographics based on the 9 hypotheses outlined above. Results are interpreted in terms of statistical significance and practical implications, with reference to the hypotheses posed.

Hypothesis Testing

The effect of brand on sales probability is statistically significant. Compared to the base category (Ford), Tesla is significantly less likely to be sold ($\beta = -0.511$, $p < 0.001$), whereas Toyota vehicles have a significantly higher likelihood of being sold ($\beta = 0.238$, $p < 0.001$). This implies that, holding all other factors constant, the log-odds of Teslas being sold decreases by 0.511 for Teslas when compared to the baseline category (Ford), while the log-odds increase by 0.238 for Toyota when compared to Ford. When converted to odds ratio, a tesla is 40.0% less likely to be sold while a Toyota is 26.9% more likely to be sold than a Ford, when all other things are held constant. These results fail to reject H8, suggesting that brand identity plays an important role in EV sales outcomes; The results from this model indicate that the relationship between brand and second hand EV sales in this dataset are in line with the expected impact of car brands as outlined in the literature review.

Contrary to expectations, price has a positive and highly significant effect on sale likelihood ($\beta = 2.489e-05$, $p < 0.001$). Each additional dollar raises the log-odds of sale by 0.00002489, or ~0.0025% in odds, holding other factors constant. Though small in magnitude, this suggests higher prices may signal better quality or features. H5 is therefore rejected. These results contradict the broader EV market literature, implying price may have a counterintuitive role in the second-hand segment.

Fast charging capabilities are significantly associated with higher sales likelihood ($\beta = 0.1406$, $p = 0.0093$), increasing the log-odds of sale and making vehicles 15.1% more likely to be sold, all else equal. Regenerative braking shows a weaker effect ($\beta = 0.135$, $p = 0.0886$), increasing odds by 14.5%, marginally significant at the 10% level. In contrast, battery health reports and subzero weather packages are not significant ($p = 0.11$ and 0.25). Thus, H2 and H3 fail to be rejected, while H1 and H4 are rejected.

Customer age is negatively associated with EV purchase likelihood ($\beta = -0.0046$, $p = 0.06$), with each additional year reducing odds by 0.46%, supporting H6 and aligning with the literature. Gender is not statistically significant ($p = 0.201$), providing no evidence of difference in purchasing behavior and leading to rejection of H7. This contradicts prior findings that suggested gender effects.

None of the state dummy variables are statistically significant ($p > 0.17$ for all), suggesting that state-level variation does not significantly predict EV sales in this model. We therefore reject H9. In regards to state, the model again contradicts findings outlined in the literature review.

Marginal Effects

Marginal effect analysis of the logistic model quantifies each predictor's impact on sale probability, holding other factors constant. Compared to Ford, Tesla is 11.9 percentage points less likely to sell, while Toyota is 5.7 points more likely. Price has a small but significant positive effect: each unit increase raises sale probability by 0.0006 points, suggesting higher prices may signal desirability. Fast charging raises sale probability by 3.3 points; each additional year of age lowers it by 0.11 points. All are significant at the 5% level, highlighting brand, price, charging, and age as key drivers. Other effects were not statistically significant.

Model Fit

The model's residual deviance is 10,755 on 7,986 degrees of freedom. In comparison to 7,999 degrees of freedom for the intercept only model and a deviance of 13,474, suggesting moderate improvement from the baseline. While the model fits significantly better than an intercept-only model, the relatively small deviance reduction (1.8%) relative to the large sample size (n=8,000) suggests there may be unaccounted predictors or nonlinear relationships. The Akaike Information Criterion (AIC) is 13,270. While the deviance reduction is not substantial, the model successfully identifies several statistically and practically meaningful predictors of EV sales.

Model Validation and Comparison

To assess robustness, we estimated both the logistic regression model (focused on hypothesis testing) and a complex model incorporating all available predictors. Performance was evaluated on the 2,000-observation test set using three metrics:

Hit Rates: Base model accuracy: 61.1%, Complex model accuracy: 62.4%. While the complex model shows marginally better classification, the 1.3 percentage-point improvement suggests diminishing returns from additional predictors.

Lift Curves:

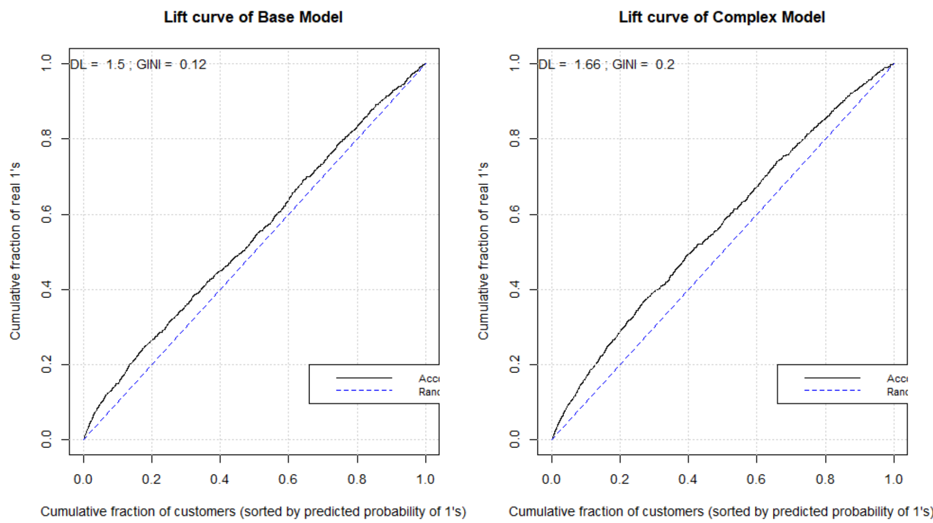

Figure 3

As can be seen in Figure 3, both models perform better than random guessing.

Likelihood Ratio Test: The complex model significantly improved fit over the base model:Chisq =314.44, $p < 0.001$, AIC reduction from 10,591 to 10,350. Despite this statistical superiority, we prioritize the logistic regression base model for hypothesis testing because the marginal predictive gains (1.3% hit rate increase) do not justify the complexity cost. The additional predictors risk overfitting, and the base model offers better interpretability. The scope of this paper was to investigate said hypotheses, which the base model accomplishes.

Results of Multinomial Logit Model

To examine the determinants of consumer brand choice among second-hand electric vehicles (EVs), we estimate a multinomial logit (MNL) model using brand as the dependent variable. The alternatives include Ford, Tesla, and Toyota, with Toyota specified as the reference category. Independent variables include vehicle features (e.g., battery health report, fast-charging capability), customer demographics (e.g., age, sex), price, and state. The analysis was limited to vehicles that were successfully sold.

Hypothesis Testing

The MNL model shows that brand choice is significantly influenced by both vehicle features and customer characteristics. Price has a statistically significant positive impact on the likelihood of choosing both Ford and Tesla over Toyota (β_{Ford} = 8.12e-05, $p < 0.001$; β_{Tesla} = 2.45e-04, $p < 0.001$), suggesting that higher-priced vehicles are associated with higher probabilities of being Tesla or Ford rather than Toyota. This contradicts conventional expectations and fails to reject H5, suggesting instead that higher prices may signal superior quality or performance for those specific brands.

Battery health reports are a key determinant in distinguishing Tesla from Toyota, with a large and highly significant positive coefficient ($\beta = 4.5716$, $p < 0.001$), translating into an odds ratio of

96.7. This indicates that vehicles with a battery health report are overwhelmingly more likely to be Teslas, supporting the notion that Tesla buyers prioritize battery-related information. In contrast, this feature is not significant for Ford ($p = 0.396$), indicating brand-specific valuation. Thus, we fail to reject H1, but only for the Tesla segment.

Subzero weather packages also play a significant role in predicting Tesla selection ($\beta = 1.1255$, $p = 0.030$), with an odds ratio of 3.08. This implies vehicles equipped with this feature are over three times more likely to be Tesla rather than Toyota. The feature is not significant for Ford, again highlighting a brand-specific effect (for Tesla) and providing partial support for H4.

Other technical features such as fast-charging capabilities and regenerative braking are not statistically significant predictors of brand choice for either Ford or Tesla ($p > 0.13$ for all), failing to reject H2 and H3. While these features may influence overall sale probability (as seen in the logistic model), they do not appear to significantly differentiate between brand selections in the used EV market.

Demographics also yield insightful patterns. The coefficient on sex for Tesla is marginally significant and negative ($\beta = -0.3227$, $p = 0.0668$), implying male customers are somewhat less likely to choose Tesla over Toyota, though the effect size is modest. Age is not a statistically significant determinant of brand selection ($p > 0.50$), suggesting no clear demographic segmentation among brands, thus leading to the rejection of H6 and H7.

Geographic indicators (state dummies) do not significantly predict brand outcomes across the board ($p > 0.10$ for all), failing to support H9. This again suggests that while state-level EV incentives may shape adoption overall, they do not substantially influence brand choice in the second-hand market.

Marginal Effects

Marginal effects further clarify how predictors influence the probability of selecting a particular brand. A one-unit increase in battery health report score increases the probability of choosing Tesla by 6.3 percentage points and decreases the likelihood for Ford and Toyota by 4.5 and 1.8 percentage points, respectively. Similarly, the presence of a subzero weather package increases the probability of selecting Tesla by 16.8 percentage points while reducing Ford and Toyota probabilities by 14.8 and 2.0 percentage points, respectively. These directional effects align with the coefficient results, underscoring brand-specific differentiation tied to select features.

Model Fit and Predictive Performance

The model demonstrates strong statistical performance, with a McFadden pseudo-R^2 of 0.487 and a likelihood ratio test yielding $\chi^2 = 3411.4$ ($p < 0.001$), indicating substantial improvement over a null model. The predicted brand shares from the model align exactly with the observed market shares (Toyota: 33.35%, Ford: 33.01%, Tesla: 33.64%), indicating excellent in-sample calibration. A likelihood ratio test comparing the full model to a restricted model with only price yields $\chi^2 = 1062.3$ ($p < 0.001$), indicating a highly significant improvement in model fit. This result confirms that the inclusion of additional product and demographic attributes substantially enhances explanatory power beyond price alone. Out-of-sample validation on the 2,000-observation test set shows a hit rate of 68.6%, meaning the model correctly predicted the brand chosen by consumers in nearly 7 out of 10 cases. This predictive accuracy is substantially higher than random chance (33.3%) and supports the model's practical applicability for forecasting and strategic planning.

Results of Tobit Model

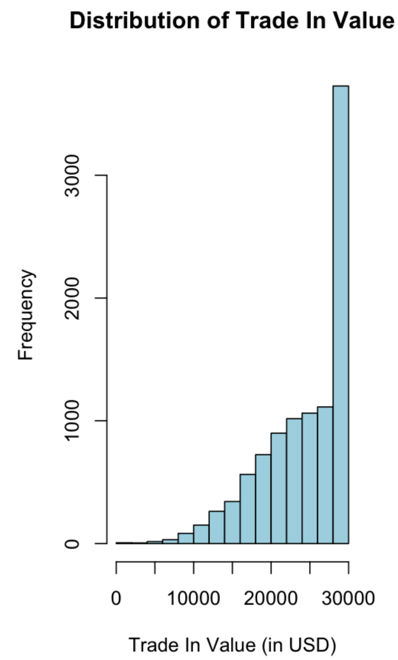

Figure 4

For the hypotheses of the trade-in valuation we decided to use a tobit type 1 model, this is because dealerships have only reported a trade-in value up to \$30.000 as can be seen Figure 4. What this means is that if a dealer has offered a client more, we only know that the client has at least gotten \$30.000. This means that some of the data has been censored which means that we have to use a tobit type 1 model to account for this censoring. Among the 8,000 observations, 2,172 were censored at the upper limit.

The Tobit results show that trade-in mileage and exterior condition are the most significant predictors of trade-in value. The model showed similar findings to the existing literature, mileage has a strong negative effect, meaning cars with higher mileage tend to have lower trade-in values. In contrast, better exterior condition is associated with significantly higher trade-in values. These findings are both highly statistically significant ($p < 0.001$). This means that H1 & H2 are confirmed.

Other variables such as fuel type, tire condition, dealership location and years of experience were not statistically significant in this model. However, the variable for the CVT transmission and dealership size category are also statistically significant at the 5% level, which suggests a positive effect on the trade-in price, just like the literature suggested. This means that H8 and H10 are also validated.

<u>Model fit</u>
The Wald test was conducted to evaluate the explanatory power of the selected variables in the tobit model. The test showed a Wald statistic of 2248 with 14 degrees of freedom, where the p-value is less than 0.05 therefore being significant. This result shows that, together, the independent variables can significantly explain variation in the trade-in value, even after accounting for the censoring at the upper limit of \$30,000.

<u>Comparison to OLS</u>
We also created an OLS model for the same data, an OLS model does not account for censoring and therefore may underestimate or misrepresent the true effects of the when the data on trade in-values is capped. The results are somewhat similar: mileage and exterior condition remain highly significant, while dealership size category 4 and CVT transmission also show statistical significance and the other variables show no or weak statistical significance. The model fit of the OLS model is also weak, with R-squared being 0.22 which means that 22% of the variance in trade-in price is explained by the OLS model. Overall, the Tobit model shows better performance and a more accurate picture of how trade-in prices are influenced.

Advice

The findings from this study offer concrete, actionable insights for manufacturers. First, brand identity plays a critical role. Toyota leads in resale likelihood, while Tesla dominates brand choice when vehicles include features like battery health reports and subzero weather packages. This suggests manufacturers should tailor certified pre-owned programs by brand emphasizing reliability for Toyota and technological features for Tesla. For Tesla in particular, maintaining transparency on battery condition and climate adaptability can help sustain appeal. Bundling or prominently marketing these features in used listings may further boost brand-specific demand.

Second, price does not deter buyers in the used-EV market, unlike in new-EV sales. Higher prices are positively associated with sales, signaling better battery quality, features, or longevity. This supports premium certified resale strategies, enabling manufacturers to help dealers justify higher prices, especially when paired with battery diagnostics and charging upgrades.

Third, fast-charging capability boosts sales likelihood, confirming the importance of convenience. Manufacturers should document, verify, and highlight this feature in dealer marketing. Upgrading or certifying older models with modern charging ports may yield strong returns.

Fourth, younger buyers are more likely to purchase, making age a key predictor. Targeted strategies like digital outreach and financing may boost conversions. Gender showed no consistent effect, supporting gender-neutral messaging by default.

From a trade-in perspective, mileage and exterior condition are strong value predictors. This underscores the manufacturer's role in promoting regular maintenance to boost resale value and loyalty. Transmission type and dealership size also matter, suggesting benefits in routing trade-ins to larger dealerships better equipped to assess and resell vehicles.

Finally, while policy-friendly states were not statistically significant in the sale likelihood or brand models, this should not be interpreted as a dismissal of state-level EV policy. Rather, manufacturers should focus on consistent value communication and nationwide readiness, especially given the volatility and variability in local EV infrastructure.

Limitations and Future Research

Limitations in this research lies in the data, we can only know what people have bought but we do not know why. People might be interested in a secondhand EV because of environmental motives or less noise from the engine. For this data set we only know what people have bought but not *why*, this is something future research can look into. Additionally, having a time dimension and attribute specific characteristics (ASCs), as the current dataset only provides user specific characteristics, would ultimately boost the model's story power, steady the coefficients, and give us cleaner, more dependable forecasts of the second-hand EV market.

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