Applying Conjoint Analysis to Quantify Customer Preferences for Enhanced Pricing and Product Strategy

PROC 5830 – Pricing

Academic Research Paper

DATE: 10 October 2025

Student Name: Aashish Paudel

Introduction:

Every business today experiences immense pressure in an environment consisting of intense competition and proliferation of products with much more knowledgeable consumers who have more complex demands. To optimize their pricing strategy and product offerings is what it is all about. The conventional market research methods often fail to expose the compromises made by consumers when buying products with multiple features. To such a problem, conjoint analysis turns to be a very effective quantitative approach. It breaks down the consumer preferences to the relative importance of individual product attributes and their levels (Green & Srinivasan, 1978). Applying this method, companies can know which existing product features/attributes are wanted most by the customers and which of them customers consider the most valuable. Along with these, it is revealed to what extent customers are ready to pay for giving a product certain specific feature, which are very important in terms of product pricing.

For instance, this study refers to the automotive industry as a perfect example where it could apply conjoint analysis. When thinking of buying a car, consumers look at a lot of things like the car brand, whether the car is eco-friendly, the price, the safety features, the car's performance, engine performance, technology, and design (Orme, 2010). Consumers in the car market always buy a car that suits their wants, needs, and budget. The companies dealing in the automotive sector need to figure out these preferences so that they can either optimize or restructure their offerings with the right configurations for the different types of consumers that they are targeting and at the same time, set up competitive pricing that takes cost allocation for all of this into consideration.

This paper aims to show methodical steps of the use of conjoint analysis to quantify the customers market research survey question preferences and then to use these insights for price and product strategy creation. The research that is done here answers three insightful research questions. The first one is that what car attributes do buyers value most and thus, how much importance do they assign to them? The second question is that, how customer preferences change under the influence of various market segments. The last and third one is that, how can we use these consumer preferences for forming new pricing and product development strategies?

Literature Review

Foundations of Conjoint Analysis:

Conjoint analysis starts from mathematical psychology and from random utility theory. The theory claims that a shopper judges a product by adding up the separate values he places on each feature (Lancaster, 1966; McFadden, 1974). The method rests on the idea that any product splits into a list of attributes and that the total value of the product equals the sum of the part worth values attached to each attribute level. The approach builds the total score from the parts, whereas older preference tools record a single overall score without breaking it into features.

The rules behind conjoint analysis match the rules that explain how people buy and choose. The first rule is compensatory choice where a buyer will accept a product that scores low on one feature if it scores high on another (Payne et al., 1993). The second rule is diminishing marginal utility where each extra unit of a feature adds less extra value than the unit before it. The third rule is preference heterogeneity where different groups of buyers rank the same features in different orders - the market must be split into segments (Wedel & Kamakura, 2000).

Applications in Marketing Research

The use of conjoint analysis has spread through many industries and research settings. In the car industry, many studies show that conjoint analysis helps to learn which vehicle features, fuel types and mobility services people prefer (Eggers & Eggers, 2011). Brownstone besides Train (1999) ran a choice based conjoint study to measure how much extra money consumers would pay for cars that run on alternative fuels where the data showed large differences among age, income plus other groups. Helveston et al. (2015) applied conjoint analysis to electric vehicle choices in China and found the main blocks to purchase and the mix of features that buyers valued most.

Conjoint Analysis Methodology

Types of Conjoint Analysis

Choice-Based Conjoint (CBC) Analysis: The most popular and common type of conjoint analysis, where it recognizes how a respondent evaluates combination of features.

Adaptive Conjoint Analysis (ACA): Depending on how each respondent answers the preliminary questions, this type of analysis tailors their survey experience. It is frequently used to expedite the process and obtain the most insightful information from each responder in studies that analyze many aspects or traits

Full-Profile Conjoint Analysis: It will showcase the respondent with proper description of a product and make them select the product that would be the best suited for them and are most inclined to buy.

MaxDiff Conjoint Analysis: Here the respondents are given multiple options and they organize all the options from most likely to buy to least likely to buy.

Design Considerations:
Multiple considerations that influence data quality and analytic validity must be carefully considered for a conjoint study to be constructed appropriately. Selecting attributes is the first major decision that must be made because having too few attributes will oversimplify the context of the decision, while more than one could be too much for respondents to handle and will diminish the reliability of the data. While it is reasonable for investigators to adjust these guidelines based on their goals for the study and the characteristics of the population being studied, best practices suggest studies are limited to 5-8 attributes each with 3-5 levels (Orme, 2010).

When assigning levels to attributes, realism and strategic relevance must be struck. Levels will highlight strategically relevant differences, while also covering the range of values possible for each attribute. Levels for price attributes should delineate all competitive products and pricing strategies being considered. Research shows that the offering of additional information about preference structures, dominated alternatives (profiles that are obviously inferior) can improve the efficiency of estimates (Huber & Zwerina, 1996).

The specific combinations of attribute levels presented to respondents depend on the experimental design. D-efficient designs optimize design information and maximize statistical efficiency based on expected parameter values, whilst orthogonal designs ensure statistical independence among the attributes. To ensure adequate coverage of design space, modern conjoint studies often rely on fractional factorial designs that present the respondent with a limited subset of possible profiles. The specific profiles differ across respondents (Kuhfeld et al., 1994).

Application to Automotive Industry

Research Design:

For demonstrating the practical application of conjoint analysis, investigation of consumer preferences in the mid-size sedan segment for the auto-industry is done in this study. Choice-based conjoint analysis methodology is used here due it's realism and capacity for market share prediction. This study emphasizes the intentions to purchase for the participants who are among the ones that are actively considering a vehicle purchase within the next twelve months. All the survey data displayed here is hypothetical for this study.

Attribute Selection and Level Definition

Six key attributes were selected for investigation. These attributes represent the primary decision criteria identified from a survey amongst prospective vehicle buyers. The table below presents the complete attribute structure with corresponding levels.

Table 1 Conjoint Analysis Attribute Structure for Mid-Size Sedans

Attribute	Levels	Rationale
Base Price	• $24,000.00 • $28,000.00 • $32,000.00 • $36,000.00	Spans competitive price range for mid-size sedans; includes both value and premium positioning options
Fuel Efficiency	• 25 MPG • 32 MPG • 40 MPG	Represents conventional gasoline, efficient gasoline, and hybrid technology performance levels

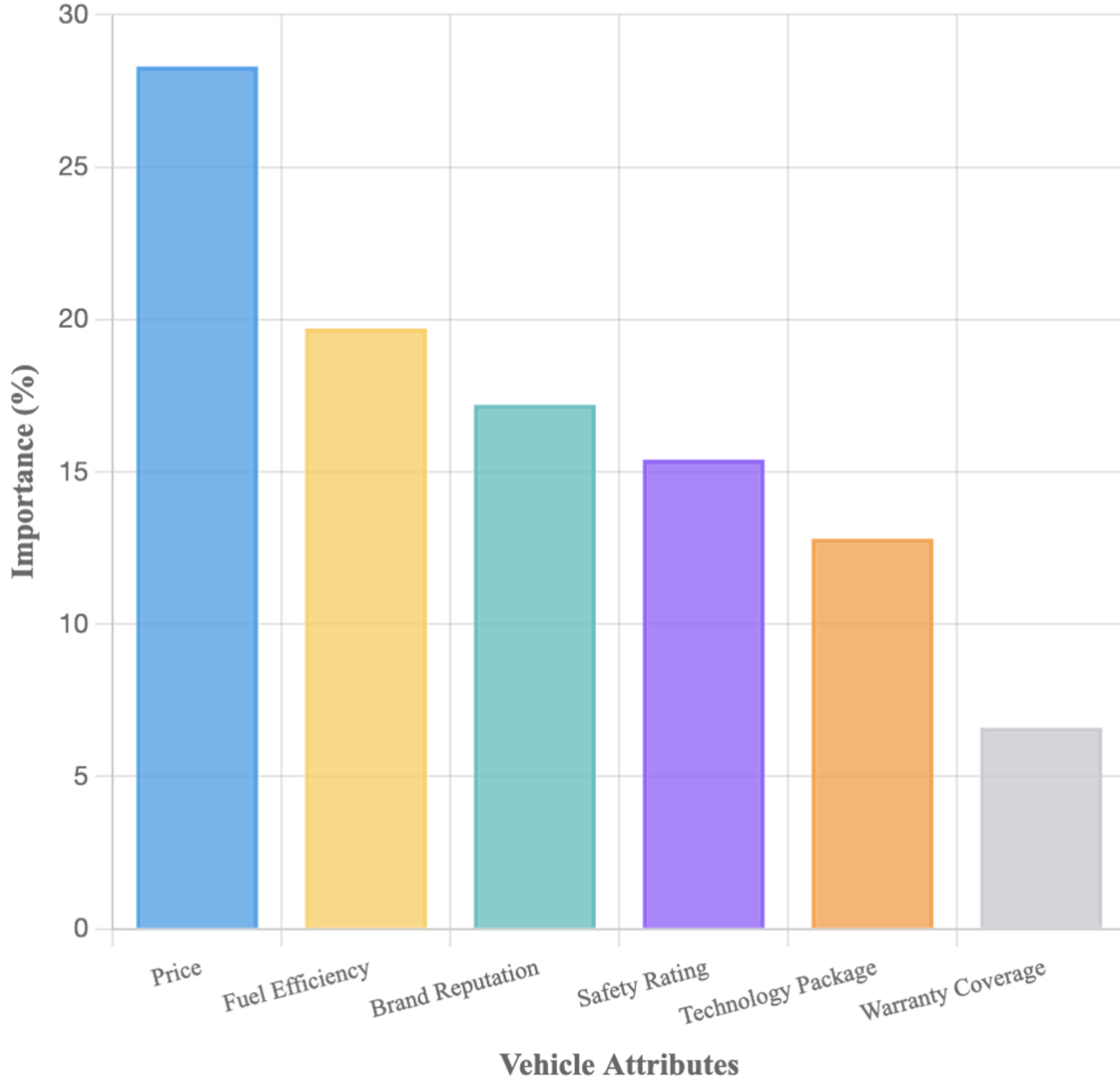
Safety Rating	• 4/5 star • 5/5 star • 5/5 star + Advanced	NHTSA ratings with highest level including autonomous emergency braking and blind-spot monitoring.
Technology Package	• Basic (USB, Bluetooth) • Standard (+ 8" screen Apple CarPlay) • Premium (+ 10" screen, Navigation, WiFi)	Reflects increasing levels of connectivity and infotainment sophistication.
Brand Reputation	• Economy Brand • Mainstream Brand • Premium/ Luxury Brand	Captures brand equity effects across typical market positioning strategies.
Warranty Coverage	• 3 years / 36,000 miles • 5 years / 60,000 miles • 10 years / 100,000 miles	Represents typical, competitive, and exceptional warranty offerings in the market

Sample and Data Collection:

This is a hypothetical data collection scenario where 800 responses are taken; a proper demonstration of real-world data collection is tried to be done for this paper. Screening criteria for this would be that the all the participants are currently in the market for a vehicle purchase or are planning to purchase it within the next 12 months. Each respondent evaluated 14 choice tasks, with each task presenting three vehicle profiles plus a “none of these” option.
So, for realistic approach, out of the 800 responses around 44 responses were removed as in reality some data is removed during the data cleaning phase. Which brings us to 756 complete responses which were retained for analysis, yielding 10,584 total choice observations.

Results and Findings:
Analysis was performed using hierarchical Bayes estimation. Respondent-level utility estimation is possible with hierarchical Bayes estimation while sharing information across the sample to improve estimate stability. Hierarchical Bayes estimation is especially useful for applications such as market segmentation and market simulation analysis, as it produces preference parameters at the individual-level which facilitate analyzing patterns of heterogeneity (Lenk et al., 1996). Results at the aggregate level indicate the mean importance weights consumers assign to each attribute. As illustrated in the bar graph below, price is the most important consideration, representing 28.3% of the entire utility range when assessing vehicles. This is consistent with economic theory and previous vehicle research, which suggests price is a key constraint in vehicle purchase decisions. Nonetheless, the large amount of importance assigned to the optional attributes (over 70% total utility) suggests consumers are concerned about the overall vehicle evaluation instead of simply making decisions based primarily on price

Figure 1: Average relative importance of vehicle attributes



Fuel efficiency can be seen as the second most important attribute with 19.7%, which shows the growing concern of fuel costs and environmental impact from fossil fuel. The part-worth utility for fuel efficiency levels shows almost linear preferences where the 40 MPG level has a significantly greater utility than the baseline of 25 MPG. This shows that customers are willing to pay premiums for fuel efficiency.

Brand reputation emerges as the third most important attribute at 17.2%. Customers are making decisions based on brand names, and this shows that this is a substantial value. The part-worth shows it clearly that the premium brands are receiving higher utilities than the other economy brands, even when controlling for functional attributes. We can see here that brands can work on their branding and charge premium for a brand name.

Safety ratings which come after brand names with 15.4% of attribute importance. Highest safety cars which have features like advanced driver assistance systems is a strong preference for most customers. A substantial utility increment from basic 5-star safety to an advanced 5 star safety shows that autonomous safety systems are now expected by customers in normal cars which may not be luxury as well as this is a major factor for their decision making. A great market opportunity for brands who can showcase more safety than others have an edge in the market.

Technology package importance is at 12.8% where premium features of connectivity and advanced infotainment system is a very desirable feature. Also, we can see that part-worth utility increment from basic to standard technology is a bigger gap then from standard to premium. This also shows some level of diminishing returns on higher premium technology investments. This pattern can be taken into consideration for businesses to prioritize more on standard technologies and just not put emphasis on basic technology as there is a very big gap.

Warranty coverage can be seen as being given the lowest importance. It is only at 6.6%, where extended warranty does provide positive part-worth utility increment. Modest importance weight suggests that warranty enhancements alone won't drive the purchasing decisions by that much but extended warranty can play it's part during tie-breaker decision making times for a consumer to choose it over a similar vehicle with less warranty time period.

Table 2: Part- Worth Utilities and Attribute Importance

Attribute	Level	Part-Worth Utility	Attribute Importance (%)
Base Price	• \$24,000 • \$28,000 • \$32,000 • \$36,000	• 1.42 • 0.38 • -0.61 • -1.19	28.3%
Fuel Efficiency	• 25 MPH • 32 MPH • 40 MPH	• -0.89 • 0.24 • 0.65	19.7%
Brand Reputation	• Economy • Mainstream • Premium	• -0.71 • 0.19 • 0.52	17.2%
Safety Rating	• 4-star • 5-star basic • 5-star adv	• -0.67 • 0.15 • 0.52	15.4%
Technology Package	• Basic • Standard • Premium	• -0.48 • 0.11 • 0.37	12.8%
Warranty Coverage	• 3 years/ 36000 miles • 5 years / 60,000 miles • 10 years/ 100,000 miles	• -0.33 • 0.09 • 0.24	6.6%

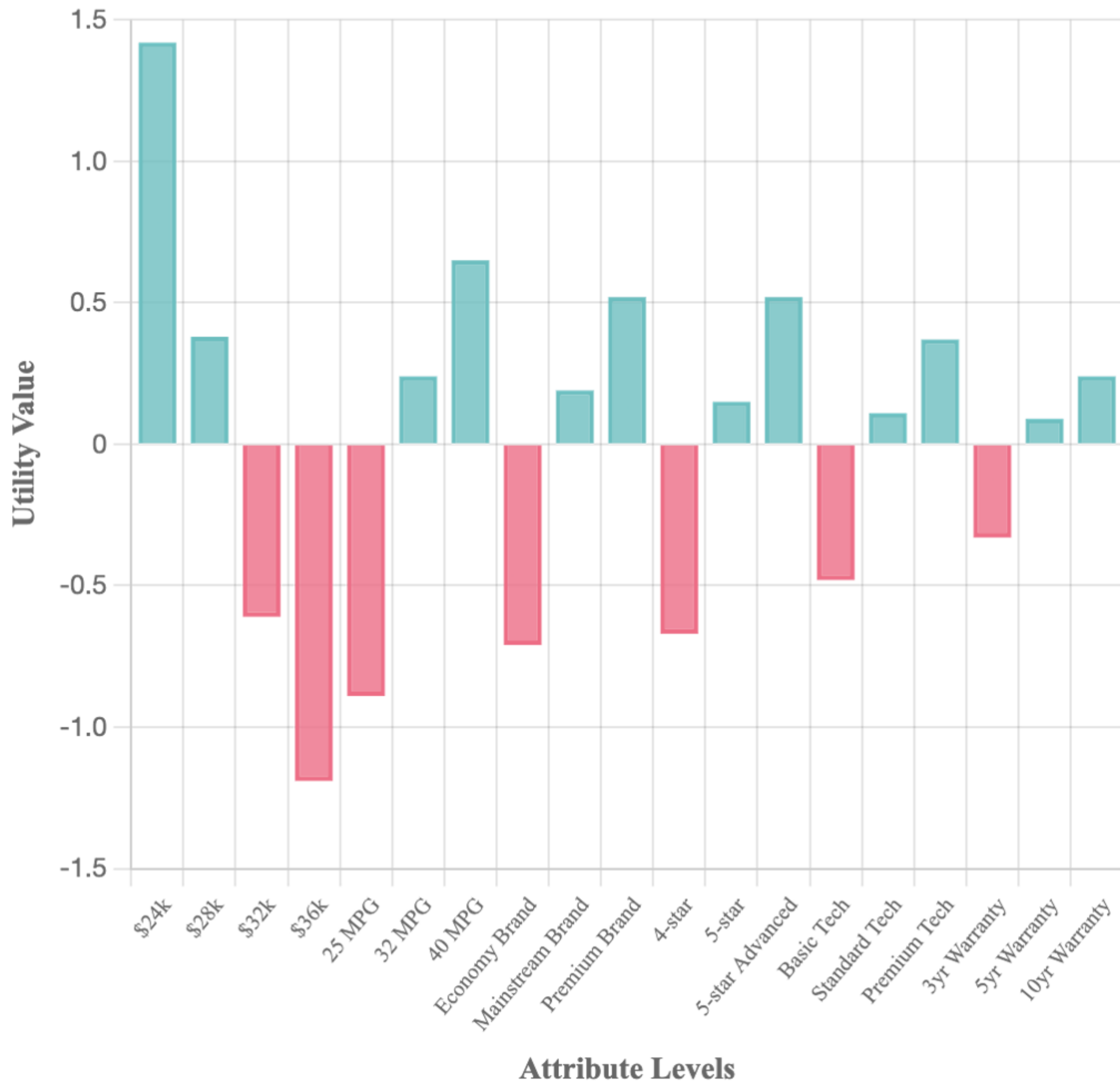


Figure 2 Part-worth utilities by attribute level

Market Segmentation Analysis:
When utilizing latent class analysis of individual-level utilities we can see three distinct consumer segments, each segment having vastly different preference structures. This segmentation method identifies groups of customers with similar utility functions. This is informative for targeting marketing and product decisions (Wedel & Kamakura, 2000).

In this dataset, 38% of the sample falls into Segment 1 which is, "Price-Sensitive Pragmatists." Specifically, price and fuel economy each represent 41 percent and 27 percent, respectively, while brand and technological characteristics have relatively undiscernible preference weights. Customers in this segment may demonstrate the ideal target for value-oriented car models and economy brands that are pragmatic and focus on functionality rather than comfort.

Whereas 35% of people fall into Segment 2, "Safety-Conscious Families," which gives very high priority to technology and safety as it is seen as something that's very useful day to day and keeps you safe from dangers in the road. Price is still a concern (22%) when weighed against high demand for modern safety features (24% importance) and advanced technology packages (18% importance). The largest index for this segment is customers 35-54 years of age with kids under 18 living at home and household incomes of $75,000-$125,000. Messages that they want technology for convenience and family protection will resonate most amongst these customers.

To conclude, Segment 3, "Premium-Seeking Enthusiasts," represents 27% of the sample. Premium-seeking enthusiasts represent a segment that is very brand-oriented and relatively price-sensitive, with price not enhancing their experience. In their decision-making, 18% is based on price and 29% is based on brand reputation. For this segment, technology and performance characteristics also appear highly rated. In terms of demographics, a premium-seeking enthusiast is likely to be an older person (median age 48), and with higher wealth and income (median income above $98,000). Given that they are a premium market for luxury brands, these customers should be the target of brand-building messaging, which showcases superior performance and prestige.

Table 3 Market Segmentation - Attribute Importance by Segment

Attribute	Segment 1	Segment 2	Segment 3
Price	41%	22%	18%
Fuel Efficiency	27%	16%	14%
Safety Rating	9%	24%	16%
Brand Reputation	8%	15%	29%
Technology Package	10%	18%	17%
Warranty Coverage	5%	5%	6%

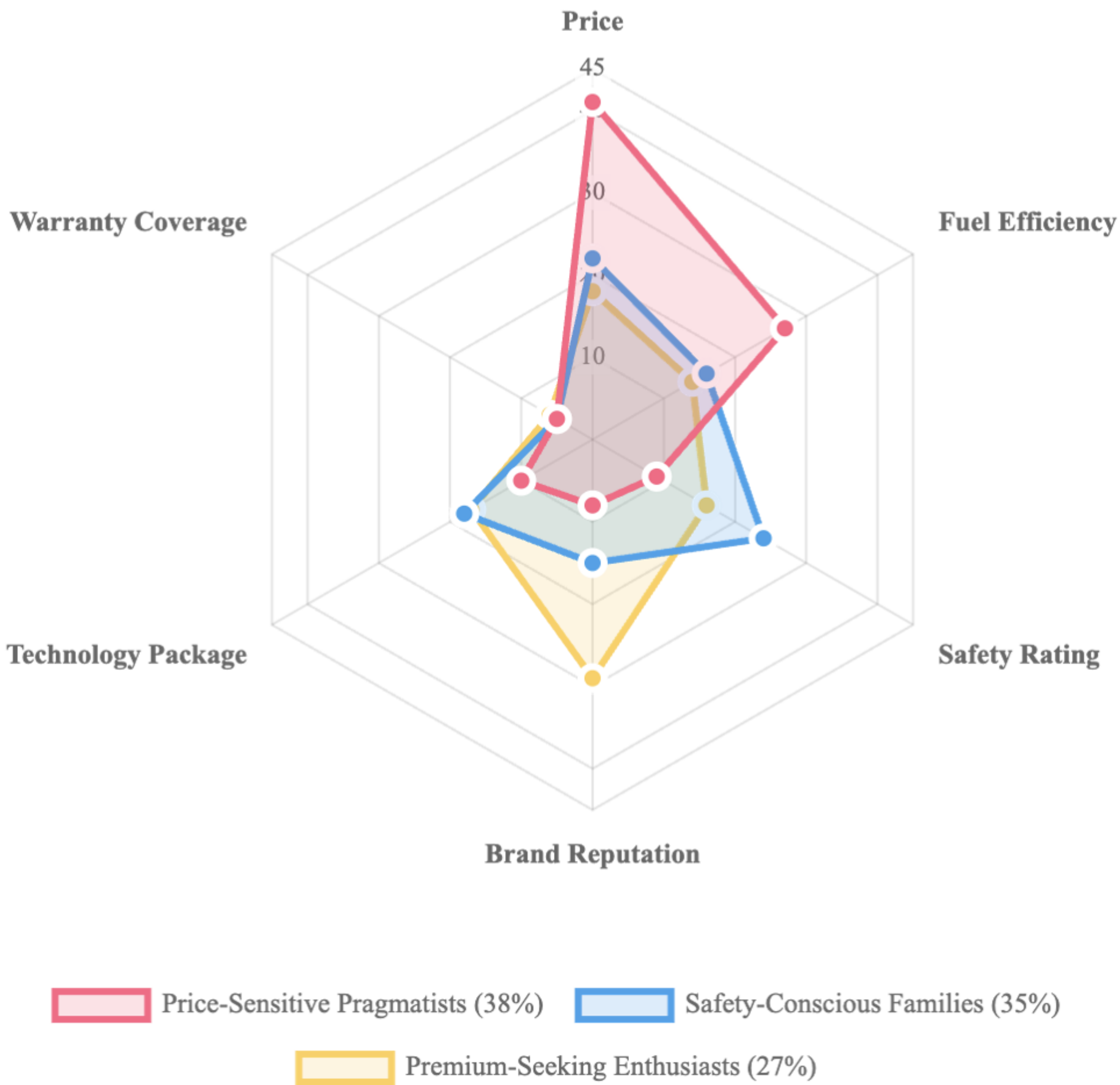


Figure 3 Attribute importance comparison across market segments

Strategic Implications

Pricing Strategy Optimization

The conjoint analysis results are used to see the below useful information for creating pricing strategies using several analytical methods.
Willingness-to-pay (WTP) analysis measures how much the customer is willing to pay for a feature of the product. Comparison between the utility difference with the utility coefficient for price, researchers can find the implicit price of a feature (Orme, 2010). For example, The utility difference between a car with 25 MPG and another car with 40 MPG fuel efficiency is 1.54 units

and the price coefficient is 0.065 utility units per $1,000 means that the consumer is willing to pay about $2,369 more for the 40 MPG efficiency, where we assume everything else remains the same. The formula for Willingness to pay is,

$$WTP = \frac{\text{Utility Difference}}{|\text{Price Coefficient}|}$$

WTP estimates help companies make different types of pricing decisions. They will be able to know the maximum additional cost the company might incur when adding new features to be competitive and to increase willingness to pay for customers. WTP can be used by companies to know which features to keep at which trim level, where customers will have choices to make and those interested and willing can go for the interested trim. One example is a hybrid powertrain offering 40 MPG and the WTP is $2,369. The manufacturer can charge this extra amount for the car with a hybrid powertrain offering 40 MPG, but they also must consider other factors like competitor pricing and production costs.

Table 4 Willingness to pay

Attribute Enhancement	Utility Gain	Willingness to Pay	Strategic Implication
25 MPG to 40 MPG	1.54	$2,369	Supports premium pricing; strong market for efficient cars
Economic brand to Premium brand	1.23	$1,892	Brand value commands substantial premium, brands who wants this should focus on quality and brand building
Safety 4-star rating to 5-star advanced rating	1.19	$1,831	Consumers highly value advanced safety, brands can implement latest ADAS technology
Basic Technology to Premium Technology	0.85	$1,308	Technologies packages can be sold for a premium
3-year warranty to 10-year warranty	0.57	$877	Extended warranties can be seen as a feeling of safety by consumers paying the modest premiums

Market simulation can be done using conjoint analysis to see which price works for the business. Researchers can estimate market share for different product or trim combinations in different market scenarios by adding up all the individual utilities to make a full product offering. This type of market share prediction can help in revenue optimization analysis. Companies can figure out the best way they are making the most money. Estimation of total revenue can be seen in this simulation by multiplying the predicted market share by the target market size and the profit per unit. The businesses can further test how changes made in the prices can affect both the market share and profit to find the best price according to what the company wants. For example, lowering the price from $34,000 to $30,000 might lower the market share from 18% to 24%. It can further check if selling fewer cars with high price or selling more cars with lower prices is more beneficial to them in terms of higher total profit.

Limitations and Further Research:

Firstly, there are a few limitations to conjoint analysis where it assumes that respondents will correctly express their preferences through choices, which might not be the perfect emulation of real-world purchasing scenario. In consumer research, the discrepancy between the stated preferences and the revealed preferences is a recurring problem (Winer, 1999).

Second limitation was not being able to use a real data and using a hypothetical data for the test. Where real world data should be used in the future to get real problems during research and to also see the proper use of this analysis in different product categories. In this research, many factors were not taken into consideration due to the time constraints which are interior space, ride quality, acceleration performance, and styling appeal were not included in the study due to it making the research too complex for now. A deeper study with all of this included for the auto market should be done in the future research.

Third, this study is done in regards where there is no reference to new emerging technology and future enhancements where the same thing that we are regarding as an expensive upgrade in today's market can be a very cheap upgrade in a very recent future. In future the study should look at this matter as well by using concepts like Longitudinal conjoint studies tracking preference evolution over time.

Finally, this research examined preferences for mid-sized sedan cars where it is not taking in consideration of any fully electric vehicle and autonomous driving cars. Future research should put these into consideration as well because of the increase in fully electric vehicles, this is a very important step for future research. Many cars today like Tesla vehicles come with supervised autonomous driving features which is very advanced and stuff like this should also be included in future study.

Conclusion:

This research has demonstrated the value of conjoint analysis on pricing and product strategy. Quantifying the consumer preferences and analyzing it to derive actionable insights for decision making was the main goal of this project. The approach reveals the trade-offs consumers make when assessing multi-attribute products by breaking down overall preferences into attribute-level utilities.

The automotive industry was selected in this study to better showcase the practical implementation of conjoint analysis. Here conjoint analysis revealed that consumers are making decisions holistically where they are balancing different attributes like price, fuel efficiency, safety, and brand name. These insights from the research will help businesses in tailor making their products to fit the market and to achieve greater sales and profit.

Using the concepts of willingness-to-pay estimation and market simulation, conjoint analysis has been used to translate the data derived from consumer preferences into an actionable strategic guidance for the businesses to enhance their pricing and product strategies. In the future integrating it with machine learning and behavioral modeling with further expand the overall scope for conjoint analysis and the concepts used in this research.

Finally, conjoint analysis works as a bridge between the customer preference insights and strategic execution for businesses.

References:

Brownstone, D., & Train, K. (1999). Forecasting new product penetration with flexible substitution patterns. *Journal of Econometrics, 89*(1–2), 109–129. https://doi.org/10.1016/S0304-4076(98)00057-8

Eggers, F., & Eggers, F. (2011). Where have all the flowers gone? Forecasting green trends in the automobile industry with a choice-based conjoint adoption model. *Technological Forecasting and Social Change, 78*(1), 51–62. https://doi.org/10.1016/j.techfore.2010.06.014

Green, P. E., & Rao, V. R. (1971). Conjoint measurement for quantifying judgmental data. *Journal of Marketing Research, 8*(3), 355–363. https://doi.org/10.2307/3149575

Green, P. E., & Srinivasan, V. (1978). Conjoint analysis in consumer research: Issues and outlook. *Journal of Consumer Research, 5*(2), 103–123. https://doi.org/10.1086/208721

Green, P. E., & Srinivasan, V. (1990). Conjoint analysis in marketing: New developments with implications for research and practice. *Journal of Marketing, 54*(4), 3–19. https://doi.org/10.2307/1251756

Huber, J., & Zwerina, K. (1996). The importance of utility balance in efficient choice designs. *Journal of Marketing Research, 33*(3), 307–317. https://doi.org/10.2307/3152127

Kuhfeld, W. F., Tobias, R. D., & Garratt, M. (1994). Efficient experimental design with marketing research applications. *Journal of Marketing Research, 31*(4), 545–557. https://doi.org/10.2307/3151882

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy, 74*(2), 132–157. https://doi.org/10.1086/259131

Lenk, P. J., DeSarbo, W. S., Green, P. E., & Young, M. R. (1996). Hierarchical Bayes conjoint analysis: Recovery of partworth heterogeneity from reduced experimental designs. *Marketing Science, 15*(2), 173–191. https://doi.org/10.1287/mksc.15.2.173

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: Analysis and applications.* Cambridge University Press.

Louviere, J. J., & Woodworth, G. (1983). Design and analysis of simulated consumer choice or allocation experiments: An approach based on aggregate data. *Journal of Marketing Research, 20*(4), 350–367. https://doi.org/10.2307/3151440

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in econometrics* (pp. 105–142). Academic Press.

Orme, B. K. (2010). *Getting started with conjoint analysis: Strategies for product design and pricing research* (2nd ed.). Research Publishers LLC.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker.* Cambridge University Press.

Wedel, M., & Kamakura, W. A. (2000). *Market segmentation: Conceptual and smethodological foundations* (2nd ed.). Kluwer Academic Publishers.

Winer, R. S. (1999). Experimentation in the 21st century: The importance of external validity. *Journal of the Academy of Marketing Science, 27*(3), 349–358. https://doi.org/10.1177/0092070399273005