
Influence of automobile seat form and comfort rating on willingness-to-pay

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Abstract: Customers nowadays consider the driver's seat, specifically its comfort and aesthetic form, during the automobile purchase decision. As a result, much research has been recently conducted into seat comfort and the influence of the visual appearance of the seat on the perception of comfort.

However, the cost of the seat remains an important contributor to overall vehicle cost, and the visual appearance of a seat may influence a customer's willingness to pay. We conducted an experiment measuring this tradeoff using hierarchical Bayesian conjoint analysis, a marketing method that elicits customer preferences and willingness-to-pay at the individual customer level. Utility models are statistically inferred for three brand segmentations using a dataset obtained through an online interactive web application. Results indicate that in a heterogeneous market, willingness-to-pay is affected by seat form and comfort rating, with particularly significant tradeoffs for the luxury automotive brand segment.

Keywords: aesthetic seat form; seat comfort; willingness-to-pay; conjoint analysis; choice models; hierarchical Bayesian.

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1 Introduction

The *seat comfort* of automobiles has a significant and well-documented effect on customer preferences when assessing new automobile purchases, thus is an important

design goal in the automotive industry (J.D. Power, 2015; Johnson Controls, 2015). Similarly, the *aesthetic seat form* of automobile seats has been shown to affect customer preferences (Branton, 1969; Helander, 2003; Kolich et al., 2004; Kolich, 2008; Kyung et al., 2008). These previous studies have treated aesthetic form as either an implicit factor within overall seat comfort (Kolich et al., 2004), or seat conditions were controlled to minimise aesthetic effects (Kyung et al., 2008). An unexplored yet complementary direction to these previous research approaches assumes that overall customer preference is independently affected by both aesthetic seat form and ergonomic seat comfort. This work takes this direction, and aims at understanding the relative importance of both aesthetic seat form and ergonomic seat comfort as separate independent variables, particularly when assessed by the targeted customer segment against changes in price, and thus offers an opportunity for automotive seat designers when making design tradeoffs (Kolich, 2008).

General practice for automobile seat design has primarily aimed to satisfy ergonomics criteria such as physiological and anthropometric, for example, by investigating both discomfort and comfort simultaneously (De Looze et al., 2003; Kyung et al., 2008). Similarly, static comfort and dynamic comfort evaluations have been conducted according to exposure to vibration (Ebe and Griffin, 2001; Mansfield et al., 2015). At the same time, Kolich (2003) showed that satisfying ergonomic criteria do not guarantee positive automobile seat comfort, as seat comfort ratings are based on subjective perception. To deduce the relationship between subjective perceptions and objective standards, various objective measures have been studied such as posture and body movement, electromyography, pressure distribution, spinal load, and foot swelling (De Looze et al., 2003; Fazlollahatabar, 2010). These research approaches have been aided by increases in computational power, as improved computational modelling techniques such as multi-body and finite element analysis have reduced time and cost of the development process that typically relied on testing prototypes (Verver et al., 2005). Moreover, such research has been linked to other design goals as vehicle level performance (Franz et al., 2011), and perhaps at a greater level, applicable to the industry (Gyi and Porter, 1999; Kamp, 2012).

Our research goal is not to model seat comfort as previous studies have focused on; instead, we assume that seat comfort can be quantified as a single ordinal comfort rating (e.g., J.D. Power stars). Moreover, we assume seat form is quantifiable through customer response to visual representations. Our research goal in this study is to make a quantitative inroad into the tradeoffs among aesthetic seat form, comfort rating, and price from the customers' viewpoint. In other words, we are interested in pulling apart the relative contribution of design attributes the customer *sees* (i.e., aesthetic form) and design attributes the customer *feels* (i.e., seat comfort). This research goal is nuanced by the notion that while comfort rating and price sensitivity are often 'rational' (i.e., less price and more comfortable is rationally preferred), aesthetic seat form is not as straightforward to assess.

Our research methodology uses an online web-based interactive survey experiment to tradeoff the comfort rating, aesthetic seat form, and seat price, thus using 'stated' preference data. The seat comfort model itself was built on results of an offline in-person seat comfort experiment using 'revealed' preference data. To conduct data analysis of the data obtained through the online interactive survey, we employ conjoint analysis (Green and Krieger, 1996), a statistical utility modelling technique to capture customer choice

behaviour with its roots in the product marketing domain. In particular, we use Hierarchical Bayesian (HB) conjoint analysis, which makes it possible to elicit individual-level utility by capturing heterogeneity, or the notion that individual customers in a population have different preferences due to the wide variability in rationale for customer purchase decisions (Rossi et al., 2005; Orme, 2009).

While HB conjoint analysis has traditionally focused on ‘functional attributes,’ or attributes which are *objective* (e.g., miles per gallon/litres per kilometre, or price in Euros); recent work has extended conjoint analysis to handle perceptual and aesthetic attributes, or attributes that are *subjective* (e.g., preferred headlight shape). The current paper takes a similar approach to applying conjoint analysis to evaluate the trade-offs among attributes from different domains (i.e., marketing, ergonomics, mechanical design, and industrial design) with a shared objective of being a profitable design (Kang et al., 2013, 2015, 2016, 2017); specifically, this paper focuses on price, aesthetic seat form, and comfort ratings, and assumes that these three attributes are independent variables. An additional methodological extension to HB conjoint is in the incorporation of the customer’s ‘willingness-to-pay’ (WTP), or a first-order correction that adjusts how likely an individual customer would actually pay for a design attribute (Train, 2003). We accordingly assess WTP according to customer preferences of comfort rating and aesthetic seat form, with an end goal of helping designers decide appropriate option prices for different vehicle trim levels.

We conducted an experiment with 240 customers to statistically estimate heterogeneous customer preferences on automobile seats over comfort rating, aesthetic seat form, and market-driven prices using HB conjoint analysis. We compared three brand segments, thus building three separate brand-segment population-level utility models. Likewise, we calculated corresponding WTPs for each individual customer, and assessed the relative importance of seat comfort, aesthetic seat form, and price attributes.

Our contribution in this work is our finding that statistically significant differences exist when assessing relative importance comfort rating and aesthetic form. This finding is most pronounced for the ‘luxury’ brand segment, suggesting that seat designers must account for aesthetic form as well as seat comfort. Note that our research goal is only to assess whether differences in customer preferences exist when controlling for both aesthetic seat form and seat comfort ratings; we do not make inroad to understanding ‘why’ customers may have preferences, nor do we make inroad to understand which aspects of the seat design influences the customer preferences (e.g., the lower lumbar). Our experimental findings indicate that further research in these directions may be promising.

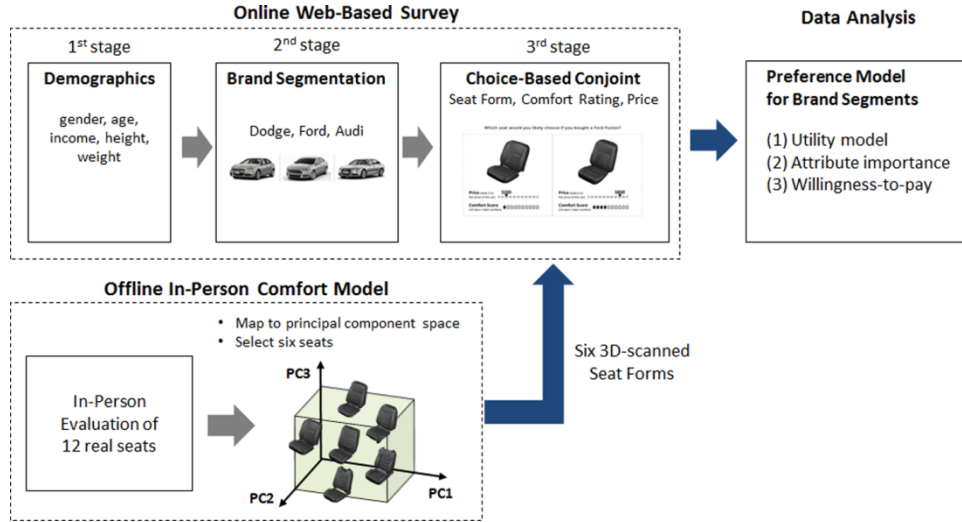
The remainder of the paper is organised as follows. Section 2 introduces the methodologies for modelling customers’ seat preference and estimating WTP. Section 3 presents a process of experiment design. Section 4 shows and discusses results. Section 5 concludes the paper.

2 Methodology

We introduce the research methodology, as shown in Figure 1, and formalise the statistical utility model – Hierarchical Bayesian choice-based conjoint analysis – used to capture customer preference decisions between various design alternatives.

Furthermore, due to the discrepancy with a customer's stated design preferences and their actual purchase decisions, we use a model extension termed 'willingness-to-pay' as a simple discrepancy mitigation factor.

Figure 1 Overall research methodology depicting online web-based survey that segments customers across three brand segments, followed by a choice-based survey trading off seat form, comfort rating, and price. Note that the comfort rating model was derived from an offline in-person experiment (see online version for colours)



2.1 Hierarchical Bayesian choice-based conjoint analysis

Quantitatively modelling a customer's decision-making process when presented with various competing design concepts is a common task in the field of marketing. The general workflow is to:

- create a survey that presents design concepts to the customer
- collect 'choice' preference data from customers of the targeted market segment
- infer a statistical model using the collected survey data to predict preferences between design concepts for a given 'future' customer.

In this work, we selected Hierarchical Bayesian (HB) choice-based conjoint (Rossi et al., 2005; Orme, 2009) as the technique for capturing customer's heterogeneous seat preferences. Choice-based conjoint is a statistical modelling technique that maps a design concept to a numerical value capturing the customer's preference, while the extension of HB is to model heterogeneity of the set of customers.

The individual-level utility for this study is a function of attributes (seat form, comfort rating, and price) and associated partworths is defined as:

$$u_{ij} = \sum_{i=1}^L (\beta_{f,il} f_{il}) + \beta_{c,i} c_j + \beta_{p,i} p_j. \quad (1)$$

Here u_{ij} is the utility of seat j to individual i . f_{jl} is a binary dummy variable (0 or 1) indicating that seat j possesses seat form at level l . $\beta_{f,il}$ is the partworth that represents the value to the individual i of the seat form at level l . For example, if the seat j has a seat form at level k , $\sum_{l=1}^L (\beta_{f,il} f_{jl}) = \beta_{f,ik}$ where $f_{jk} = 1$ and $f_{jl} = 0$ ($l \neq k$). c_j is a continuous variable indicating comfort rating of seat j . $\beta_{c,i}$ is the partworth coefficient that represents the value to the individual i per unit of comfort rating. p_j is a continuous variable indicating price of seat j . $\beta_{p,i}$ is the partworth coefficient that represents the value to the individual i per unit of price. Note that we summarise the notation introduced here in Table 1.

Table 1 Description of notation used in this work

Notation	Category	Definition
i	Index	Individual
j	Index	Seat alternative
l	Index	Seat attribute level
u_{ij}	Utility	Utility
$\beta_{f,il}$	Partworth	Discrete partworth of seat form level
$\beta_{c,i}$	Partworth	Continuous partworth coefficient of comfort rating
$\beta_{p,i}$	Partworth	Continuous partworth coefficient of price
f_{jl}	Attribute	Binary dummy variable of discrete seat form level
c_j	Attribute	Continuous variable of comfort rating
p_j	Attribute	Continuous variable of price
l_i	Importance	Relative attribute importance
$w_{f,i}$	WTP	WTP for seat form
$w_{c,i}$	WTP	WTP for comfort rating

The HB choice model is hierarchical via its two statistical levels: the ‘upper level’ of the hierarchy models the distribution of individual-level partworths, while the ‘lower level’ of the hierarchy captures the choice probability. Formally, the upper level partworths, β_i , have a multivariate normal distribution, $\beta_i \sim N(\theta, \Lambda)$, where θ is a vector of means of the distribution of individuals and Λ is the covariance matrix of that distribution. At the lower level, choice probabilities for a logit model are used:

$$P_{ij} = \frac{e^{u_{ij}}}{\sum_{j' \in J} e^{u_{ij'}}}, \quad (2)$$

where P_{ij} indicates the probability that individual i chooses seat j from a set of alternatives J . To statistically infer the values of the various parameters – namely, the set $\{\}$ —we used Markov Chain Monte Carlo (MCMC) sampling methods rather than optimisation methods. Each customer had a single utility model with partworths following a distribution modelled using 5000 sampling draws.

Further, to ensure model uniqueness, we added a constraint for the discrete attribute ‘seat form’. This study uses six seat forms (see Figure 2), and accordingly, we set the partworth of seat form 6 to have a value of 0 as a reference. Note that if we do not set a

reference, there will be different models with different scales of partworth; moreover, note that Seat Form 6 was arbitrarily chosen, as this does not influence the result. Lastly, the partworths for other seat forms could have been either positive or negative, but in fact, Seat Form 6 had the lowest partworth and other seat forms had all positive partworths (see Section 4).

For the continuous attributes, price and comfort rating, the following constraints are used: the partworth coefficient of price is always negative and the partworth coefficient of comfort rating is always positive. The partworth coefficient of continuous attribute captures the relative contribution of the customer's utility for a particular design attribute. For example, a large negative partworth coefficient for seat price would indicate that a customer would not want to pay for more than is necessary; likewise, a coefficient close to 0 indicates that the customer is not sensitive to price.

Attribute importance is defined as the relative magnitude of an attribute in its contribution to the utility. After modelling the utility function, an attribute importance can be calculated using the range of values (i.e., partworth \times attribute) for each attribute. For example, seat form importance $I_{f,i}$ of individual i in the utility function of equation (1), is calculated by:

$$I_{f,i} = \frac{\max(\beta_{f,il}f_{jl}) - \min(\beta_{f,il}f_{jl})}{\{\max(\beta_{f,il}f_{jl}) - \min(\beta_{f,il}f_{jl})\} + \{\max(\beta_{c,i}c_j) - \min(\beta_{c,i}c_j)\} + \{\max(\beta_{p,i}p_j) - \min(\beta_{p,i}p_j)\}} \times 100, \quad (3)$$

where max indicates maximum values that each component can have; min indicates minimum values that each component can have. Here, the numerator is the range of contribution between the best seat forms and the worst seat forms among alternatives. The denominator is the sum of the ranges of values of all attributes including seat form. The numerator can be switched with other attributes, comfort rating or price. In sum, the range between maximum and minimum values of an attribute indicates the how much the utility is sensitive to change in attribute.

2.2 Willingness-to-pay

While HB conjoint analysis is an improvement on conventional choice-based conjoint analysis via its modelling of individual-level design preferences, another significant factor that must be considered and modelled accordingly is the discrepancy between a customer's stated preferences and their subsequent revealed preferences, i.e., purchases. A simple yet effective method to account for this discrepancy is the customer's 'willingness-to-pay' (Train, 2003). Willingness-to-pay (WTP) adds an additional factor to the individual customer's utility function for a given design. Based on the utility function of equation (1), WTPs for seat form and comfort rating are computed as:

$$w_{f,i} = -\frac{\beta_{f,il2} - \beta_{f,il1}}{\beta_{p,i}} \quad (4)$$

$$w_{c,i} = -\frac{\beta_{c,i}}{\beta_{p,i}}. \quad (5)$$

Here, $w_{f,i}$ is WTP of individual i for changing seat form from level l_1 to level l_2 ; $\beta_{f,il2}$ is the partworth for the seat form she wants to switch to; $\beta_{f,il1}$ is the partworth for the seat form she wants to switch from; and $\beta_{p,i}$ is the partworth coefficient of price. $W_{c,i}$ is WTP of individual i for upgrading one score of comfort rating and $\beta_{c,i}$ is the partworth coefficient of comfort rating. The reason to put a negative in equations (4) and (5) is to make WTP a positive value because the partworth coefficient of price is always negative. Individual i is willing to pay money (\$) in exchange for one unit of a non-price continuous attribute such as comfort rating as well as in exchange of a non-price discrete attribute such as seat form. When a non-price attribute improves, price (WTP) increases so that the utility does not change.

3 Vehicle seat experiment design

We gathered choice data from an online based survey to model individual-level preference and compute WTPs using the methodology described in Section 2.

3.1 Seat designs

Three attributes – seat form, price, and seat comfort rating – were used for the choice-based conjoint survey. For the survey design, we discretised both the price and seat comfort rating to 10 levels. Price was assigned in the range from \$0 to \$900 (i.e., \$0, \$100, \$200, \$300, \$400, \$500, \$600, \$700, \$800, and \$900). Comfort was assigned a ‘star rating’ from one star to 10 stars. Note that price and seat comfort are treated as a continuous variable in the utility model.

Seat form was presented at six levels (i.e., six different seats) shown in Figure 2. The seat shapes were captured using 3D-scanning techniques. Head restraints were removed to simplify the comparison. These six seats were chosen from among the 12 seats used in a pilot study. The selected seats were those that best spanned the range of comfort ratings according to a previously conducted eigenvector decomposition. Each seat form used in the survey was presented using the same view orientation and colour shown in Figure 2.

Figure 2 3D scanned automobile seat images



3.2 Customers

Men and women in the US who had a valid US driver’s licence were recruited through Clear Voice Research (Clearvoice, 2015). Clear Voice has pre-verified panels, and emails were sent to those who met the survey conditions. These customers received two dollars for participating in the survey from Clear Voice.

A total of 261 customers responded the survey, with 240 customers used for data analysis after post-hoc filtering. In particular, all customers with mean survey completion time of less than 100 s (i.e., 5 s per question) were deleted.

The online survey consisted of three stages. In the first stage, questions for demographic data were asked (e.g., gender, age, income, weight, height) and the data are shown in Table 2.

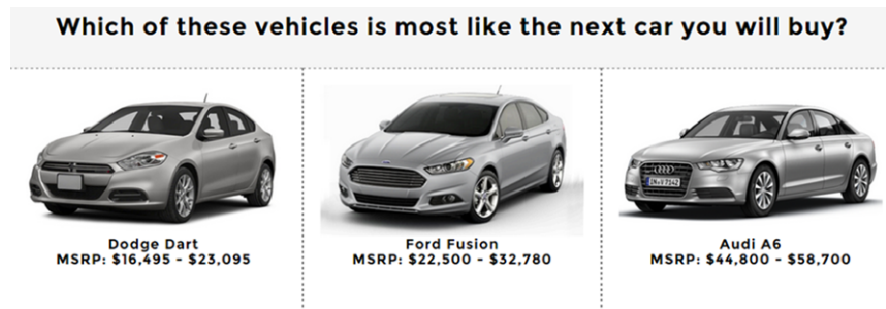
Table 2 Demographic data

<i>Items</i>	<i>Demographic variable</i>	<i>Percentage (%)</i>
Gender	Male	47.1
	Female	52.9
Age	15–24 years	1.3
	25–34 years	10.5
	35–44 years	14.6
	45–54 years	23.4
	55–64 years	27.6
	Over 64 years	22.6
Income	Under \$15,000	5.8
	\$15,000–\$30,000	15.4
	\$30,001–\$55,000	22.9
	\$55,001–\$70,000	14.2
	\$70,001–\$85,000	12.1
	\$85,001–\$100,000	10.8
	\$100,001–\$130,000	7.5
	\$130,001–\$160,000	5.4
	\$160,001–\$200,000	2.1
	Over \$200,000	2.1
	Prefer not to answer	1.7
Height	Under 150 cm (under 4' 11'')	0.4
	150–160 cm (4' 11''–5' 3'')	22.3
	161–170 cm (5' 4''–5' 6'')	28.2
	171–180 cm (5' 7''–5' 11'')	31.9
	181–190 cm (5' 12''–6' 3'')	14.7
	Over 190 cm (over 6' 3'')	2.5
Weight	Under 50 kg (under 110 lbs)	1.7
	50–70 kg (110–154 lbs)	35.3
	71–90 kg (155–198 lbs)	26.9
	91–110 kg (199–243 lbs)	23.5
	111–130 kg (244–287 lbs)	6.7
	131–150 kg (288–331 lbs)	4.2
	Over 150 kg (over 331 lbs)	1.7

3.3 Brand segment identification

In the second stage, three model year 2015 vehicles – Dodge Dart, Ford Fusion, and Audi A6 – were shown and customers were asked ‘which of these vehicles is most like the next car you will buy?’ This question was used for separating customers according to brand segments as shown in Figure 3.

Figure 3 Brand segmentation question using the choice-based survey



In the brand segmentation question, 61 (25.4%) customers chose the Dodge Dart, 139 (57.9%) customers chose the Ford Fusion, and 40 (16.7%) customers chose the Audi A6. Since we selected subjects randomly, we did not have information about their brand preferences and the subsequent brand segmentation memberships were distributed unevenly.

3.4 Conjoint survey

In the third stage, the choice-based conjoint survey was presented to customers. These choice questions used binary choices showing two seat profiles (i.e., combinations of seat form, price, and comfort rating), without the ‘None’ option, as shown in Figure 4. For example, if a customer chose the Ford Fusion in the brand segmentation question from stage 2, the choice question presented to the customer was stated as, ‘Which seat would you likely choose if you bought a *Ford Fusion*?’

A total of 20 questions – 16 questions for training utility models and four questions for validation of the utility models – were asked of each customer. The 16 survey questions for constructing each customer’s individual utility model were created using the Latin hypercube sampling technique (McKay et al., 1979) in MATLAB (Mathworks, 2015), while the four survey questions for validation were generated randomly. We used the Django web application package for building the online web-based survey.

During the Latin hypercube sampling, constraints were applied such that profiles never ‘dominated’ each other with respect to the price and comfort rating. In other words, a customer would never see a choice pair question with one seat having both lower price and higher comfort rating, as is typical in the design of a conjoint survey (Sawtooth, 2014). This was based on the notion that customer preferences often obey seemingly rational constraints, thus forcing the model to always learn this constraint, while still allowing the possibility of lower comfort and higher price assuming the seat form is sufficiently important.

Figure 4 Example of choice-based conjoint survey question presented to customers. Note that each survey question consists of a binary preference choice between two seat profiles represented by three attributes – seat form, price, and comfort rating



Further, note that the validation set was generated without constraints, (i.e., generated randomly within the space of all possible design combinations. Based on this rule, we generated 100 questionnaire sets, from which customers were assigned for their last four validation survey questions.

4 Experiment results and discussion

The goal of this experiment was to measure the tradeoffs customers from three separate brand segments made between three design attributes – seat form, price, and comfort rating. We used ‘hit rate’ as our performance measure to assess the predictive performance of the utility models constructing using HB conjoint analysis. Hit rate is defined as the percentage of time that the trained model (using 16 survey questions) predicts correctly the four validation questions. Table 3 shows the average hit rates across customers. Note that a hit rate of 50% corresponds to a ‘baseline’ model given that our survey questions were binary choice (i.e., random chance is 50%).

Table 3 Hit rates of the utility model

	<i>Dodge</i>	<i>Ford</i>	<i>Audi</i>
Hit-rate	89.3%	89.0%	86.3%

4.1 Analysing model according to segmentations

We calculated all customers’ individual-level partworths. This estimation was conducted by MCMC sampling each individual with 5000 draws, using the shared random variables describing population-level mean and covariance as described in Section 2.1. This resulted in mean estimates of partworths in Table 4 for three brand segments. In addition, we compute the ‘importance’ of attributes using equation (3).

Table 4 Means of partworths and importance by segment

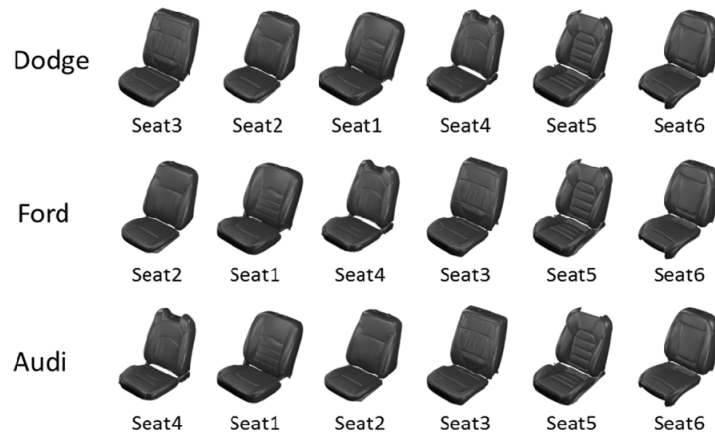
Brand segment	Seat form partworth						Price Part-worth	Comfort Part-worth	Importance		
	Seat1	Seat2	Seat3	Seat4	Seat5	Seat6			Form	Price	Comfort rating
Dodge	0.33	0.53	0.54	0.17	0.01	0.00	-1.39	1.53	14.2%	38.7%	47.1%
Ford	1.37	1.39	0.86	1.26	0.49	0.00	-1.10	1.43	18.9%	32.3%	48.8%
Audi	1.78	1.43	0.65	2.60	0.17	0.00	-0.75	3.01	26.4%	14.6%	59.0%
Significance (<i>p</i> -value)	0.000**	0.000**	0.332	0.000**	0.013*	—	0.007**	0.000**	0.011*	0.000**	0.047*

*5% significance level ($p \leq 0.05$), **1% significance level ($p \leq 0.01$).

We also conducted one-way ANOVA to check the statistical significance of the differences among three segments. The last row in Table 4 shows the *p*-values of each test. Differences among three segments are significant in all attributes partworths and importances, with the exception of the seat form partworth of Seat 3.

Observation 1: Seat preferences differ by brand segment.

Note that Seat 6 has all zero values to ensure model uniqueness as discussed in Section 2.1. For all cases, interestingly, Seat 6 has the lowest utility and Seat 5 has the second lowest utility. Other seats vary according to segmentation. Seat 3 is the most preferred seat form for Dodge, Seat 2 is the most preferred seat form in Ford, and Seat 4 is the most preferred seat form in Audi. This shows that preferences on seat form are different according to the brand segmentation, possibly due to customers considering whether a particular seat form fits their given vehicle type. The ranks of seat form based on partworths are shown in Figure 5.

Figure 5 Rank of seat form preference according to brand segmentation (highest rank left)

Observation 2: Luxury customers care more about seat form and comfort.

The price and comfort partworth coefficients can be compared, with each unit of price equally discretised in units of \$100, and similarly by one star on the comfort scale (out of 10). For the Dodge brand segment, the partworth coefficients for price and comfort are similar, suggesting each additional comfort star is worth about \$100. However, for the

Audi segment, an increase of one comfort star is about four times more valuable than an increase in the price of \$100.

When comparing the low-price brand segment (i.e., Dodge) with the high-price brand segment (i.e., Audi), seat form importance increases, price importance decreases, and comfort rating importance increases. This is consistent with the expectation that luxury sedan customers are more sensitive to styling and less to price. The seat form importance increase from the Ford to Audi segments (39%) is almost twice the comfort rating importance increase (21%).

4.2 Willingness-to-pay (WTP) under brand segmentation

We computed median WTP, which are post-calculated using partworth draws for individuals as explained in Section 2.2. These values are then averaged across each population segment. The results of WTPs and one-way ANOVA are shown in Table 5, with WTP results given in units of \$100. Of these results, we use the median values, as such values are more reasonable to use than means when looking at WTP (Orme, 2009). This is because customers who are not sensitive to price (i.e., almost zero price coefficient) have unrealistically large WTPs and these values can affect the average of the population; consequently, we omitted zero price coefficient draws because they produce infinite WTPs.

Table 5 Heterogeneous mean (across individuals) median WTP (\$100's) according to segmentation

Brand segment	Comfort	Seat form					
		Seat 1	Seat 2	Seat 3	Seat 4	Seat 5	Seat 6
Dodge	3.02	0.52	1.06	1.07	0.24	0.19	–
Ford	2.21	2.94	2.84	1.98	1.57	0.64	–
Audi	6.48	10.3	8.17	6.36	11.3	3.65	–
Significance (p-value)	0.000**	0.002**	0.003**	0.039*	0.000**	0.038*	–

*5% significance level ($p \leq 0.05$), **1% significance level ($p \leq 0.01$).

In Table 5, we can see for example that Audi customers are willing to pay \$648 for a one-star increase of comfort rating. When reading this value, we must note that WTP is read as a change from Seat 6, which was set as a reference value of 0. In other words, the difference between the reference value of Seat 6 and the design in question is divided by price coefficient as given in equation (3). Accordingly, for the Audi segment, WTP for Seat 4 is \$1,134. On the other hand, the Dodge segment has WTP for comfort rating of \$302 whereas the WTP for Seat 3 is \$107. The Audi segment has larger WTP for both seat form and comfort.

Observation 3: Customer-stated importance and willingness-to-pay can be different.

One interesting point is that WTP and attribute importance can lead to different interpretations. In Table 4, Ford users value comfort rating more than Dodge segment customers, although they are similar (i.e., Ford segment: 48.77%, Dodge segment: 47.10%). However, in Table 5 we observe that Dodge segment customers have larger

WTP for comfort rating than Ford (i.e., Ford: \$221, Dodge: \$302). This shows that attribute importance and WTP may not lead to the same interpretation.

This discrepancy can arise for three reasons. First, WTP depends on only the price coefficient while attribute importance depends on all other attributes' importance. For example, even if the importance of comfort is small, WTP becomes large if the importance of price (i.e., price coefficient) is small. On the other hand, even if the importance of comfort is large, WTP becomes small if the importance of price is large. Second, because the market is heterogeneous, WTP across the population can be affected by customers who are not sensitive to price. If a market is homogeneous (i.e., same partworths across the population), unusual customers' preference will not affect WTP. Third, attribute importance is relative and cannot exceed 100%, while WTP is unbounded, allowing outliers to have a strong effect on the mean variance of WTP. However, using median values for comparison reduces the influence of these outliers.

4.3 Limitations

This study has important limitations, beginning with the nature of the online survey. Customers self-identified brand segment and we did not have the means to verify this information. Future work could target individuals with expressed preferences, for example, those who have already purchased particular vehicles. The survey sample was relatively small (240 customers). A larger sample may have provided more stable estimates, particularly for the analyses within the brand segment. Seat form was presented using a single static image for each seat, and images of production seats were used. Possible improvements include presenting the seat form within the vehicle and providing multiple images or an interactive 3D view. The seat form could also be parameterised in the manner that overall vehicle shape has been parameterised in recent work (Kang, 2014) so that the effects of specific attributes, such as bolster height, on the perception of form could be explored.

The comfort rating representation also represents an important limitation, because the comfort was not actually experienced by the customers but by an in-person seat comfort experience. We believe the current approach has value as it suggests how people might trade off form, price, and comfort as presented in online or print consumer information sources. Future work in which customers actually experienced the seats would be valuable to determine if the importance and WTP would be similar.

5 Conclusion

This work quantitatively investigates tradeoffs among the seat design attributes of aesthetic seat form, price, and comfort rating by treating each as independence variables affecting customer preference. Data from an online survey were analysed for three brand segments using hierarchical Bayesian conjoint analysis.

From the results, we obtained the following three insights: First, seat preferences are heterogeneous according to brand segmentations, consistent with typical expectations in the seat design community. That is, individual customers differ in their personal preferences and tradeoffs for comfort rating, price, and seat form, and the distributions of these preferences differ by brand segment. Second, aesthetic seat form is as important as the ergonomic comfort rating, and luxury customers care more about seat form and

comfort rating. Third, in a heterogeneous market, attribute importance (based on a utility model) and WTP results can give us different interpretations, suggesting that designers should carefully consider customers who are less sensitive to price.

This work represents an initial foray into assessing how aesthetics, price, and comfort independently tradeoff for automotive seat design, building on similar research without independence assumptions, and using recently popularised marketing methods that elicit customer preferences and willingness-to-pay at the individual customer level. This general approach and its independence assumptions offer product designers the opportunity for quantitative justification when making design tradeoffs.

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