JMP Academic Case Study 044

Pricing Spectacles

Conjoint Analysis/Discrete choice Modeling

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JMP STATISTICAL DISCOVERY

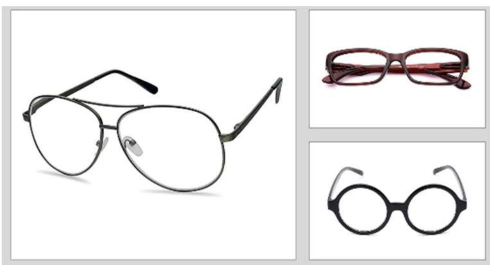
Pricing Spectacles

Conjoint Analysis, Discrete Choice Model, Willingness to Pay

Key Ideas

This case study requires the use the Choice platform in JMP to design and analyze choice experiments. It is designed to determine or estimate customer preference for one product versus another. Choice experiments, specifically discrete choice experiments, are used to help discover which product or service attributes are preferred by potential customers. Discrete choice design involves creating an experimental design to combine the levels of the attributes to derive choice alternatives that are then presented to subjects or potential customers to understand their preferences. One can also use this information to design products or services that have the attributes that customers most desire.

Background



Lenzmart is a famous eyewear retail chain that has both an online and offline presence. Of the many products it designs and sells, reading glasses are very popular. There are multiple attributes for a pair of reading glasses, including the frame's material, shape, color, weight, type and price. The levels of each of these attributes are displayed in Exhibit 1.

Exhibit 1 Product Attributes and Levels

Attribute	Number of Levels	Description
Material	3	Thermoplastic
		Acetate
		Steel
Shape	3	Rectangle
		Round
		Aviator
Color	3	Black
		Brown
		Golden
Weight	3	Feather Light
		Light
		Heavy
Type	2	Full
		Half
Price	2	425
		725

The Task

To customize and better position each product, the marketing team of Lenzmart performs the following tasks so that they can understand customer preferences:

- Create an effective and efficient design or set of profiles comprising varying product attributes for their experiment.

- After conducting the experiment, the team hopes to understand:
  - Which attribute is perceived of high value by their customers?
  - What is the relative importance of each attribute?
  - What is the optimized configuration?
  - How much are customers willing to pay if there is a change in attribute levels?

Design Creation

Before we create the design, let us refresh some terminologies associated with discrete choice models. An attribute is a feature of the product, while a profile is a specification of product attributes (levels). A choice set is a collection of profiles; the survey represents a collection of choice sets.

In a discrete choice experiment, respondents are presented with a survey containing several choice sets. Choice sets usually contain only a small number of profiles to facilitate the decision process. Within each choice set, each respondent specifies which of the profiles he or she prefers.

To present the choice sets to the participants, the team must design a choice experiment involving the multiple attributes and their levels. After designing the experiment, they must then conduct it. The experiment can be viewed as collection of the choice preferences from the respondents when they were presented the choice sets, followed by analysis of the data collected.

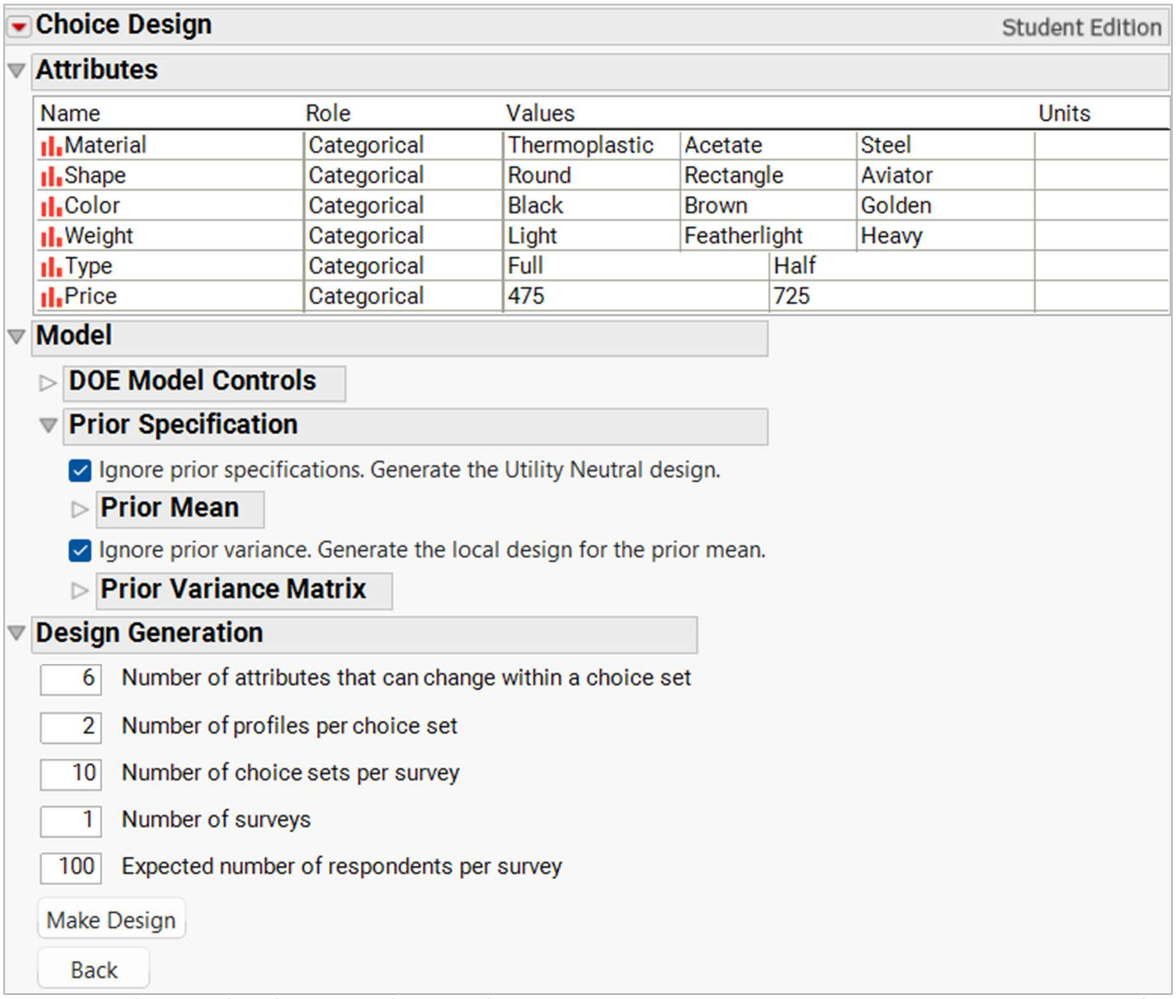
The attributes of reading glasses or spectacles include material, shape, color, weight, type, and price of the frame. (The quality of glass is kept out of the scope of this case study.) Different combinations of these attributes make product profiles. A choice set mostly consists of two profiles. From each choice set, a respondent chooses the profile that he or she prefers. Since discrete choice models are nonlinear in their parameters, the efficiency of a choice design depends on the unknown parameters. The choice design platform uses a Bayesian approach, optimizing the design over a prior distribution of likely parameter values that are specified.

First, let us design an experiment with the following structure:

- Two profiles per choice set.
- 10 choice sets.
- 100 respondents.
- One survey per respondent containing all 10 choice sets.

The experiment will result in 10 responses per respondent. Choice Design, found in the Design of Experiments (DOE) platform, creates experiments or runs using attributes of the product. One can enter factors either manually or automatically using a preexisting table. Since we are designing a new experiment, let us enter the factors manually as shown in Exhibit 2.

Exhibit 2 Choice Design Platform



Choice Design Student Edition

Attributes

Name	Role	Values			Units
Material	Categorical	Thermoplastic	Acetate	Steel	
Shape	Categorical	Round	Rectangle	Aviator	
Color	Categorical	Black	Brown	Golden	
Weight	Categorical	Light	Featherlight	Heavy	
Type	Categorical	Full	Half		
Price	Categorical	475	725		

Model

DOE Model Controls

Prior Specification

Ignore prior specifications. Generate the Utility Neutral design.

Prior Mean

Ignore prior variance. Generate the local design for the prior mean.

Prior Variance Matrix

Design Generation

6 Number of attributes that can change within a choice set

2 Number of profiles per choice set

10 Number of choice sets per survey

1 Number of surveys

100 Expected number of respondents per survey

Make Design

Back

(To create: Select DOE>Consumer Studies>Choice Design>add attributes and their corresponding levels. Click continue. Notice that there are only main effects and for our example, we are interested in a model that contains the main effects of six factors. Include any means and variance from previous studies. Otherwise, tell JMP to ignore the prior means and variance by checking the relevant boxes.

In the Design Generation panel, the number of attributes that can change within a choice set should be 6. The number of profiles per choice set is 2; the number of choice sets per survey is 10. In this example, the respondents evaluate 10 choice sets. The expected number of respondents per survey is 100. Click Make Design.

Under the Choice Design red triangle, select Set Random Seed and enter 123456 to ensure that the exact results are shown in this case study.)

Exhibit 3 Choice Sets and Descriptions

Design

Choice Set	Material	Shape	Color	Weight	Type	Price
1	Acetate	Rectangle	Black	Light	Half	475
1	Steel	Round	Brown	Featherlight	Full	725
2	Thermoplastic	Round	Brown	Light	Half	475
2	Acetate	Rectangle	Golden	Featherlight	Full	725
3	Thermoplastic	Rectangle	Black	Heavy	Full	475
3	Acetate	Aviator	Brown	Light	Half	725
4	Thermoplastic	Aviator	Golden	Featherlight	Half	475
4	Acetate	Round	Black	Heavy	Full	725
5	Steel	Rectangle	Golden	Heavy	Half	725
5	Acetate	Aviator	Black	Featherlight	Full	475
6	Thermoplastic	Round	Golden	Light	Full	725
6	Steel	Aviator	Brown	Heavy	Half	475
7	Steel	Round	Black	Featherlight	Half	475
7	Thermoplastic	Aviator	Brown	Heavy	Full	725
8	Steel	Aviator	Golden	Light	Full	475
8	Thermoplastic	Rectangle	Brown	Featherlight	Half	725
9	Acetate	Rectangle	Brown	Light	Full	475
9	Thermoplastic	Aviator	Black	Heavy	Half	725
10	Acetate	Round	Golden	Heavy	Half	475
10	Steel	Rectangle	Black	Light	Full	725

Output separate tables for profiles and responses

Combine profiles and responses in one table

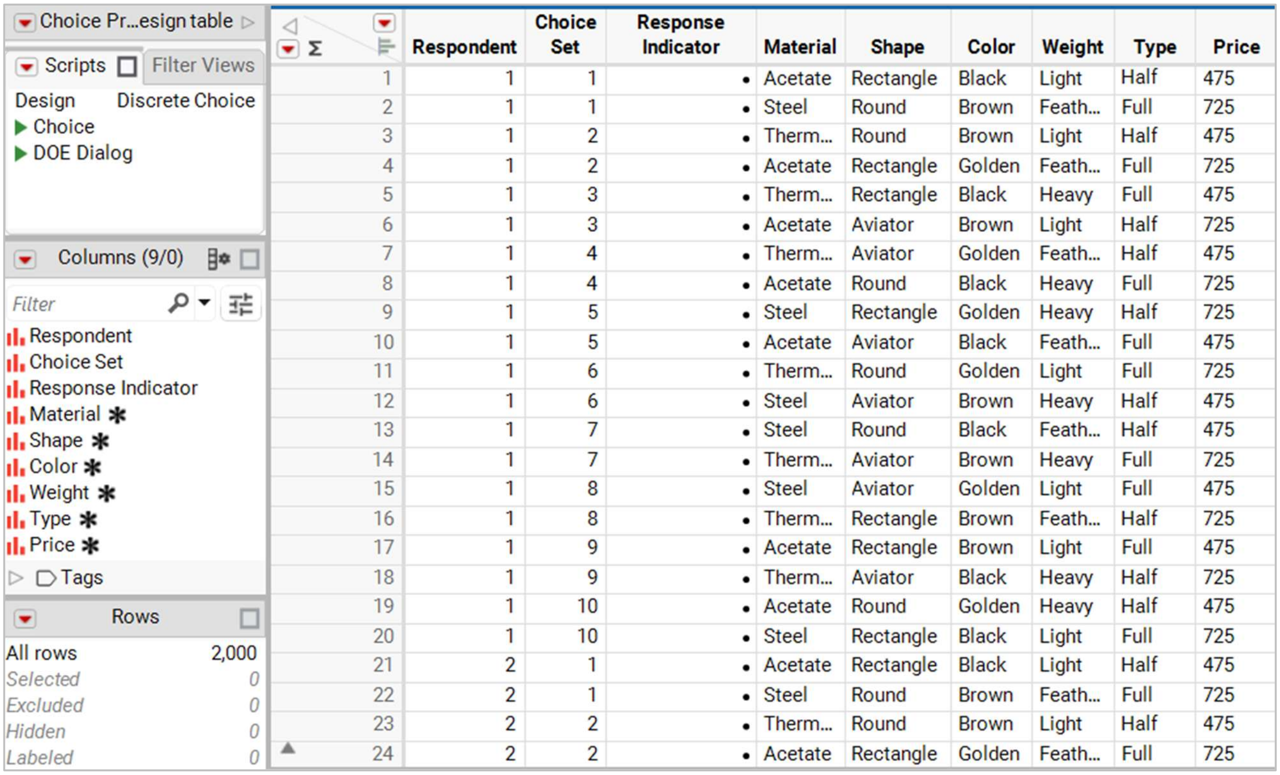
Make Table

Back

Once you create the design, the choice design displays the choice set and provides two options as shown in Exhibit 3. You can either choose two separate output tables for profiles and responses or an output that combines them into one table.

Choose the second option and select Make Table to produce a separate JMP data table, as shown in Exhibit 4. This table will have the predefined script that can be leveraged for analysis after the response indicator for each experiment is populated.

Exhibit 4 JMP Data Table for Capturing Response Indicators from Field Study



	Respondent	Choice Set	Response Indicator	Material	Shape	Color	Weight	Type	Price
1	1	1	•	Acetate	Rectangle	Black	Light	Half	475
2	1	1	•	Steel	Round	Brown	Feath...	Full	725
3	1	2	•	Therm...	Round	Brown	Light	Half	475
4	1	2	•	Acetate	Rectangle	Golden	Feath...	Full	725
5	1	3	•	Therm...	Rectangle	Black	Heavy	Full	475
6	1	3	•	Acetate	Aviator	Brown	Light	Half	725
7	1	4	•	Therm...	Aviator	Golden	Feath...	Half	475
8	1	4	•	Acetate	Round	Black	Heavy	Full	725
9	1	5	•	Steel	Rectangle	Golden	Heavy	Half	725
10	1	5	•	Acetate	Aviator	Black	Feath...	Full	475
11	1	6	•	Therm...	Round	Golden	Light	Full	725
12	1	6	•	Steel	Aviator	Brown	Heavy	Half	475
13	1	7	•	Steel	Round	Black	Feath...	Half	475
14	1	7	•	Therm...	Aviator	Brown	Heavy	Full	725
15	1	8	•	Steel	Aviator	Golden	Light	Full	475
16	1	8	•	Therm...	Rectangle	Brown	Feath...	Half	725
17	1	9	•	Acetate	Rectangle	Brown	Light	Full	475
18	1	9	•	Therm...	Aviator	Black	Heavy	Half	725
19	1	10	•	Acetate	Round	Golden	Heavy	Half	475
20	1	10	•	Steel	Rectangle	Black	Light	Full	725
21	2	1	•	Acetate	Rectangle	Black	Light	Half	475
22	2	1	•	Steel	Round	Brown	Feath...	Full	725
23	2	2	•	Therm...	Round	Brown	Light	Half	475
24	2	2	•	Acetate	Rectangle	Golden	Feath...	Full	725

Once the experimental design was created, the marketing team collected the responses from 100 participants. After being shown the choice set on a card, each respondent was asked to choose the alternative he or she prefers. The response indicator was marked 1 if that alternative was selected and the one not chosen was marked 0.

The Data **Spectacles_Choicedata.jmp**

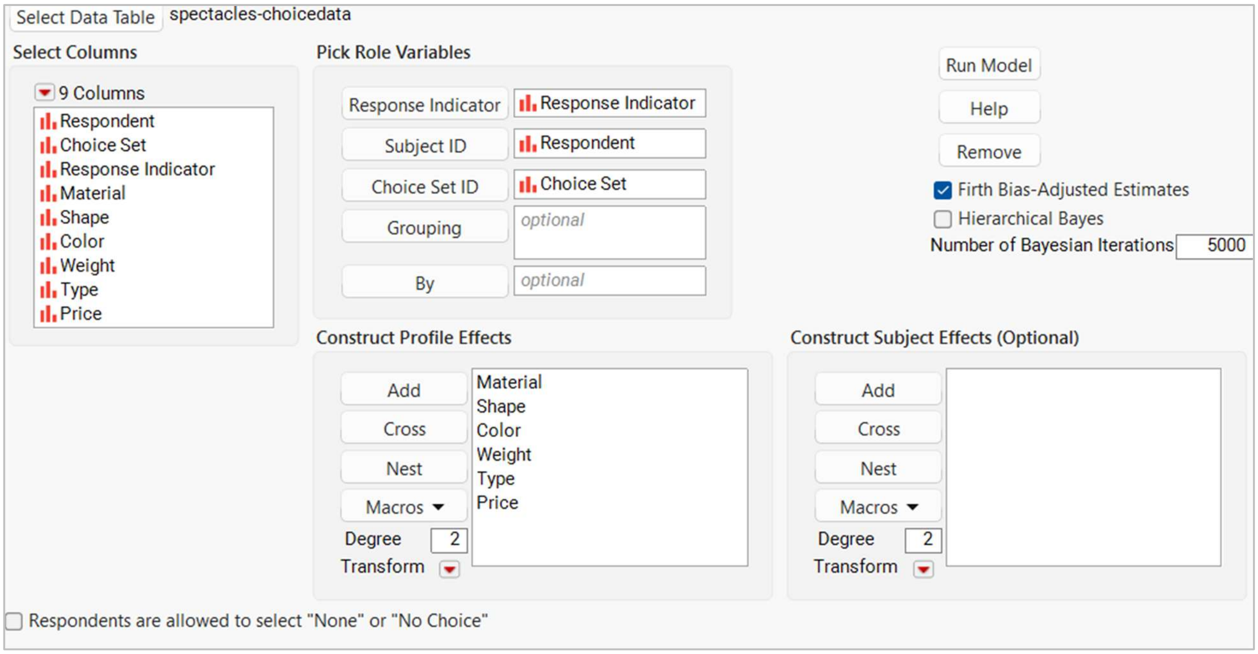
After a successful field study, the response data from all of the 100 respondents, along with the choice set information, is populated in a single jmp file. This is called one table and stalked format. (One can also have multiple tables with cross references.) Note that all the variables are nominal.

Respondent	ID of the respondent. There are 100 respondents.
Choice Set	ID of the choice set. There are 10 choice sets.
Response Indicator	Preference of the respondent over the choice set (1 or 0).
Material	Frame material (three levels).
Shape	Shape of the frame (three levels).
Color	Color of the frame (three levels).
Weight	Weight of the frame (three levels).
Type	Type of the frame (two levels).
Price	Price of the product (two levels).

Analysis

Discrete choice models are nonlinear in their parameters and the Choice Design platform uses a Bayesian approach, optimizing the design over a prior distribution of likely parameter values that you specify. In this section, we will analyze the data from the final experimental design and field study using Choice Model platform as shown in Exhibit 5.

Exhibit 5 Choice Model Launch Window



(To create, Analyze>Consumer Research>Choice>Select One Table, Stacked from Data Format drop down. Response Indicator = Response Indicator; Subject ID = Respondent; Choice Set ID = Choice Set. Add Material, Shape, Color, Weight, Type and Price as Profile Effects. Click Run Model.)

Exhibit 6 Initial Analysis of the Spectacles Choice Design

Choice Model: Response Indicator

Effect Summary

Source	Logworth	PValue
Type	23.846	0.00000
Price	20.861	0.00000
Material	17.502	0.00000
Color	14.560	0.00000
Shape	3.797	0.00016
Weight	2.378	0.00419

Remove Add Profile Effect Add Subject Effect FDR

Parameter Estimates

Term	Estimate	Std Error
Material[Thermoplastic]	0.4782852741	0.0914197575
Material[Acetate]	0.1704212358	0.1014415167
Shape[Round]	0.0902583301	0.0654342449
Shape[Rectangle]	0.5117520968	0.1125649626
Color[Black]	0.5511085547	0.1075469766
Color[Brown]	0.0545321967	0.0889638646
Weight[Light]	0.1482606808	0.0931145452
Weight[Featherlight]	0.2037687830	0.0909160280
Type[Full]	0.5760379534	0.0736967030
Price[475]	0.5518886460	0.0783929045

AICc	874.45299
BIC	923.3081
-2*LogLikelihood	854.23054
-2*Firth LogLikelihood	800.7703

Converged in Gradient
Firth Bias-Adjusted Estimates

Likelihood Ratio Tests

Source	L-R ChiSquare	DF	Prob>ChiSq
Material	80.602	2	<.0001*
Shape	17.485	2	0.0002*
Color	67.053	2	<.0001*
Weight	10.950	2	0.0042*
Type	104.694	1	<.0001*
Price	91.084	1	<.0001*

Exhibit 6 shows the initial analysis. Both the Effect Summary and Likelihood Ratio Tests show that all the attributes are significant at the 0.05 level. Since the p-value for each effect is very small, a transformation called the LogWorth helps us rank the attributes. The most significant effects are mentioned at the top and the least significant at the bottom.

Note that type of frame has the most significant effect and weight has the least, which means that the type of the frame (full frame or half frame) is a key factor in choice.
The Parameter Estimates report shows that the parameters of all the attributes are significant.

Effect marginals

Effect marginals shows the marginal probabilities and marginal utilities for each main effect in the model. The marginal probability is the probability that an individual selects Attribute A over B with all other attributes set to their mean or default levels.

Exhibit 7 shows that the marginal probability of any subject choosing a full frame over half frame is 0.75 (keeping other attributes constant).

Similarly, one can learn that steel is least preferred, while rectangle and black colors have high marginal probabilities.

Exhibit 7 Effect Marginals

Effect Marginals

Marginal Probability	Marginal Utility	Material
0.4857	0.47829	Thermoplastic
0.3570	0.17042	Acetate
0.1574	-0.64871	Steel

Marginal Probability	Marginal Utility	Shape
0.3306	0.09026	Round
0.5039	0.51175	Rectangle
0.1655	-0.60201	Aviator

Marginal Probability	Marginal Utility	Color
0.5200	0.55111	Black
0.3165	0.05453	Brown
0.1635	-0.60564	Golden

Marginal Probability	Marginal Utility	Weight
0.3755	0.14826	Light
0.3969	0.20377	Featherlight
0.2277	-0.35203	Heavy

Marginal Probability	Marginal Utility	Type
0.7599	0.57604	Full
0.2401	-0.57604	Half

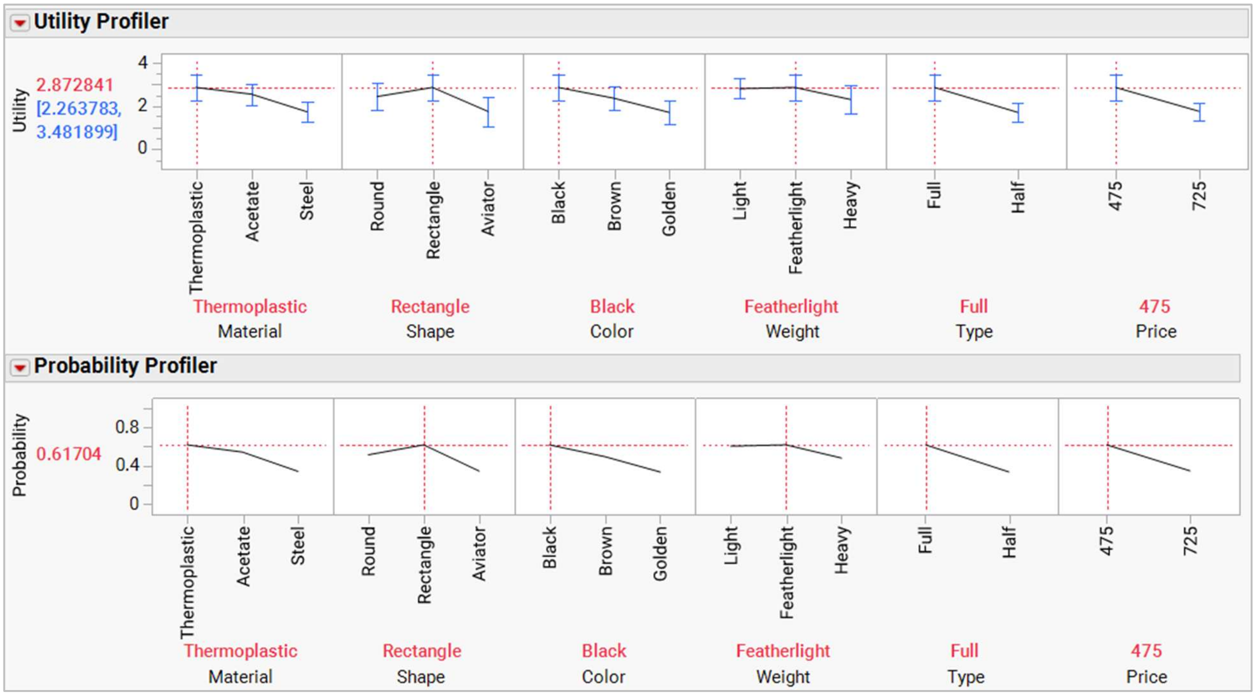
Marginal Probability	Marginal Utility	Price
0.7510	0.55189	475
0.2490	-0.55189	725

(To create, select Effect Marginals under the red triangle next to Choice Model.)

Utility and Probability profiler

The Utility Profiler provides the information related to utility of different attribute levels. When each attribute value is set to its lowest utility value, it is shown as -3.36. Setting each attribute to its highest value will result in a value of 2.87.

Exhibit 8 Utility and Probability Profiler



The highest utility is of thermoplastic material, rectangular in shape, black color, featherlight, full frame, priced at $475.

Let us determine the unit utility cost. Set each attribute to its lowest utility value, -3.36. Now move the slider for price to $475. When price changes from $725 to $475, the utility changes from -3.36 to -2.23. In other words, lowering the price of the spectacles by $250 increases the utility (or desirability) by approximately 1.13 units. Therefore, you can estimate the unit utility cost to be approximately $221 (225/1.13). With this unit utility cost estimate, you can now vary the other attributes and note the change in utility to find an approximate monetary value associated with attribute changes.

The Probability Profiler enables us to compare choice probabilities among alternatives using a baseline product and a comparison product. Probabilities are easier to interpret than raw utilities, and the Probability Profiler is a useful alternative if you have a baseline product that you want to compare against potential products.

Willingness to pay

The term willingness to pay refers to the price that a customer is willing to pay for new features and is calculated to match a customer’s utility for baseline features. It helps in ascertaining how much people are willing to pay for a marginal change in a feature of an attribute.

To calculate it, one must have a price variable, which should be set as numeric continuous.

Exhibit 9 Willingness to Pay

Willingness to Pay, Contingent Pricing

Specify Situation to Price, Willingness to Pay

Factor	Baseline	Role
Material	Thermoplastic	Feature Factor
Shape	Round	Feature Factor
Color	Black	Feature Factor
Weight	Light	Feature Factor
Type	Full	Feature Factor
Price	475	Price Factor

Enter baseline factor values and role.
Exactly one role must be a continuous pricing factor.

☐ Include baseline settings in report table
☐ Output data table also

OK Cancel Help

Willingness to Pay

Factor	Baseline Value
Material	Thermoplastic
Shape	Round
Color	Black
Weight	Light
Type	Full
Price	475

Baseline Utility
-0.2532

Factor	Feature Setting	Price Change	Std Error	Lower 95%	Upper 95%	New Price
Material	Acetate	($69.73)	2.91489	($75.44)	($64.02)	$405.27
Material	Steel	($255.26)	3.15816	($261.45)	($249.07)	$219.74
Shape	Rectangle	$95.47	2.57344	$90.42	$100.51	$570.47
Shape	Aviator	($156.80)	2.81744	($162.32)	($151.27)	$318.20
Color	Brown	($112.47)	3.4743	($119.28)	($105.66)	$362.53
Color	Golden	($262.00)	4.03989	($269.92)	($254.08)	$213.00
Weight	Featherlight	$12.57	2.75139	$7.18	$17.96	$487.57
Weight	Heavy	($113.31)	3.87017	($120.90)	($105.73)	$361.69
Type	Half	($260.94)	1.9725	($264.81)	($257.07)	$214.06

Standard deviations for Price Change calculated by Delta method.

(To create, right-click on the price variable on the data sheet, select Continuous from the Format drop-down and then click Apply. Doing so converts the Price variable to continuous. Rerun the analysis of regression. Under the Choice Model Response Indicator red triangle, select Willingness to Pay. Select include base line settings in the report table > Click OK)

For example, suppose that a customer is willing to pay $475 for spectacles with a round shape, the willingness to pay for round shape spectacles is calculated by setting the shape to round and then solving for the price that delivers the same utility as the $475 round shape spectacle.

Exhibit 8 shows the baseline value for each factor, as well as baseline utility values. For each factor, the report shows the feature setting, estimated price change and new price.

Note that customers are willing to pay almost $95 more for rectangle shape than the round shape, which has a base price of $475, meaning that the new price for the rectangle shape should be $570.

Summary

Statistical insights

Discrete choice modeling is a powerful analytic method used to estimate the probability of individuals making a particular choice from presented alternatives. A choice experiment studies customer preference for a set of product or process (in the case of services) attributes. In discrete choice modeling, a respondent might choose between two alternatives that are described by a combination of attributes.

The Choice Modeling platform uses a form of conditional logistic regression to estimate the probability that a configuration is preferred. Unlike simple logistic regression, choice modeling uses a linear model to model choices based on response attributes and not solely upon subject characteristics.

Implications

Although customer satisfaction surveys can disclose what is wrong with a product or service, they fail to identify consumer preferences about specific product attributes. When product team designs a product, they routinely make hundreds or thousands of small design decisions. If customer testing is feasible and respondents are available, one can use choice experiments to make better design decisions.

Reduction in survey deployment, modeling, and prototyping costs facilitate the customer evaluation of many attributes and alternatives when a product or service is designed. Choice experiments obtain data on customer preferences, and choice modeling analysis reveals such preferences.

The above analysis shows that customers perceive high level of utility from type attribute and weight has the least utility. The optimal product as perceived by the customer is of thermoplastic material, rectangular in shape, black color, featherlight, full frame priced at $475.

JMP Features and Hints

This case used the Design of Experiments (DOE) platform to design the choice experiments. For analyzing the experimental data, the nominal logistic regression technique is applied through the consumer research platform of choice design.

Effect marginals provides marginal probabilities and marginal utilities for each main effect in the model. Probability Profiler enabled us to compare choice probabilities and Utility Profiler helped us visualize the predicted utility for different factor settings.

Willingness to pay helped us calculate the maximum price increase or decrease that customer is willing to pay for a new feature over the baseline feature cost.

Exercise

The marketing team wants to optimally price contact lenses. Exhibit 10 displays the various attributes and their levels.

Exhibit 10 Contact Lens Attributes and Levels

Attribute	Number of Levels	Description
Brands	3	A
		B
		C
Disposability	3	Daily
		Biweekly
		Monthly
Color	4	Blue
		Brown
		Green
		Turquoise
Lenses Per Box	2	10
		20
Price in USD	2	30
		60

The team decided to conduct choice experiments and collect the preferences from prospective customers.

- Create an effective and efficient design or set of profiles that comprise the above-mentioned product attributes for the experiment.

- Use **ContactLens_choicedata.jmp** and analyze the data to answer the following questions:

    - Which attribute is perceived of high value by customers?
    - What is the relative importance of each attribute?
    - What is the optimized configuration?
    - How much are customers willing to pay if there is a change in the level of attributes?