Choice Modeling Analytics–Benefits Of New Methods
By John V. Colias

Over the past two decades, the marketing research industry has witnessed rapid growth in the use of choice models. These types of models are valuable in their ability to do the following:

- Optimize marketing strategy.
- Determine optimal pricing strategy.
- Create effective promotional offers.
- Maximize the appeal of product features.
- Optimize product lines.
- Define bundles of features and benefits that maximize profitability.
- Predict market share and source of volume for new brands or products.

This brief article aims to help marketing researchers understand the benefits of several technical advances in choice analysis, such as:

- Improved experimental design algorithms.
- Latent Class and Hierarchical Bayes models.
- Model calibration.

Advances in these areas have provided significant benefits, summarized in the diagram at the bottom of this page.

Next we will explain how the benefits of new methods are realized.

These new choice modeling techniques can provide marketing researchers with:

- An understanding of customer purchase decision processes.
- A prediction of revenue and profit.
- Recommendations for market strategy options.
- Marketing simulators called Decision-Simulators™.
- Recommendations for increasing ROI for marketing programs.

Improved Experimental Design

- Increased realism of survey tasks
- More reliable responses
- Easier respondent tasks

Latent Class and Hierarchical Bayes

- Segment- or customer-level models
- Improved return on marketing investment (ROMI)
- More complete models of purchase decisions

Model Calibration

- Greater accuracy of market share and revenue estimates

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Improved Experimental Design Algorithms

Experimental designs select combinations of attributes and levels for each alternative in a market scenario. The combinations are selected to ensure that the relative value to customers of each part of a brand or product (e.g., price, size, and packaging) can be measured with maximized reliability.

Improved experimental design software has enabled researchers to produce more realistic scenarios to test in survey choice tasks. For example, suppose one wireless communications provider offers multiple service plans. It would be unrealistic for the same brand to offer two wireless plans that are identical in all aspects, except that one includes more minutes and a lower monthly fee than the other. Today, experimental design software can avoid such combinations of attributes, while still producing experimental designs with high reliability.

Another benefit of improved experimental design software is that survey choice tasks can be made easier for the respondent, while still handling complicated products that have many features.

Choice Task Example With 9 Attributes

	Wireless Carrier 1	Wireless Carrier 2	Wireless Carrier 3
Monthly Fee For Single Line	$39	$49	$55
Anytime Minutes	100	500	300
Overage Rate Per Minute	40 cents	65 cents	55 cents
Roaming Charges Per Minute	50 cents	60 cents	70 cents
Night & Weekend Minutes	4000 minutes	1000 minutes	3000 minutes
Long Distance Charges Per Minute	50 cents	70 cents	65 cents
Mobile To Mobile Minutes	Unlimited	Not available	Unlimited
Contract Term	2 years	No contract term	1 year
Family Plan	No family plan	$10 per additional line	$25 per additional line
Which of these wireless phone plans do you prefer?	O	O	O

Newer software can produce partial profile choice designs that select a subset, say 5 out of the total set of 9 or more attributes to present in each choice scenario. If only 5 attributes vary across brands, then only these 5 attributes need to be shown to respondents.

Choice Task Example With 5 Attributes

	Wireless Carrier 1	Wireless Carrier 2	Wireless Carrier 3
Monthly Fee For Single Line	$39	$49	$55
Anytime Minutes	100	500	300
Long Distance Charges Per Minute	50 cents	70 cents	65 cents
Contract Term	2 years	No contract term	1 year
Family Plan	No family plan	$10 per additional line	$25 per additional line
Which of these wireless phone plans do you prefer?	O	O	O

Showing only 5 attributes per choice task reduces the amount of time required to read through each scenario and the overall length of interview and increases the quality of respondent choices. Reduced respondent burden offers a huge advantage in today's lifestyle, where survey respondents have many demands on their time and want shorter interviews.

For example, respondent survey choice tasks that elicit a choice from among multiple wireless phone service brands, where each brand is described by nine or more attributes, can be quite tiring. Imagine a respondent evaluating 10 or more scenarios such as the choice task example on the previous page.

Latent Class and Hierarchical Bayes Models

Latent Class models have unique parameters (e.g., price response, brand preference) for each subsegment of the total population of customers. During model development, segments of customers (who share similar market responses to changes in product prices and features) are discovered, and separate model parameters are produced for each segment.

Hierarchical Bayes models have unique parameters for each individual customer or survey respondent. Since every individual truly has unique tastes and preferences, customer-level choice models are more realistic. For example, one customer might be very price sensitive and brand loyal, while another might be moderately sensitive to price but not loyal to any brand.

Customer-level modeling uses survey responses to (a) determine the most likely distributions (across customers) for price and brand preference parameters and (b) estimate each individual respondent's price sensitivity and brand preferences.
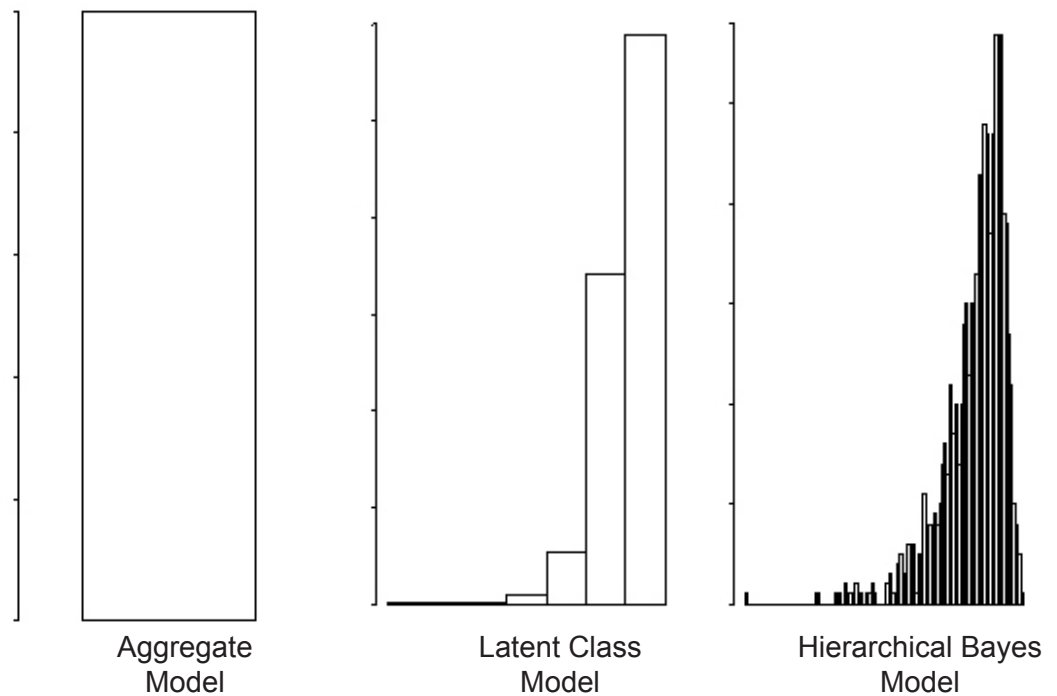
In the diagram on the following page, price elasticity is a parameter derived from choice

Hierarchical Bayes delivers results for each customer.

Distribution of Price Elasticities

Aggregate Model	Latent Class Model	Hierarchical Bayes Model

model coefficients, and it represents the percent increase in demand due to a one-percent increase in price; i.e., price sensitivity.

The three histograms represent the movement from one total population, price elasticity parameter at the left with an aggregate model (traditional approach before Latent Class and Hierarchical Bayes) to segment-level price elasticities in the middle histogram (Latent Class model) to customer-level price elasticities at the right (Hierarchical Bayes model).

As the distribution of price elasticities is more fully modeled with Latent Class and Hierarchical Bayes, marketers can more effectively target price promotions to customers who are most sensitive to price.

Latent Class and Hierarchical Bayes models use very different statistical algorithms to produce the final model parameters, and in many cases the final results are similar. This author has estimated both Latent Class and Hierarchical Bayes choice models using the same source data and has found similar patterns of responses; however, experts still debate the relative benefits between the two techniques.

In general, Hierarchical Bayes methods enable researchers to investigate more complex decision-making processes. For example, a recent application (Allenby and

Gilbride, 2004) applies a Hierarchical Bayes model with two decision-making stages. First, consumers use a screening process to decide which products to consider. Second, consumers make a purchase decision among the products that are considered. This Hierarchical Bayes model not only delivers relative preferences for the various product features, but also estimates customer-level threshold values for price and feature functionality that must be exceeded in order for a product to be considered. As you can see from this example, Hierarchical Bayes gives sophisticated researchers extreme flexibility to try out new models of consumer behavior.

Segment- and customer-level models have enabled companies to:

- Develop new products and services for targeted subgroups of the total population (based on customer-level model parameters).
- Improve retention and acquisition campaigns by targeting segments or individuals that exhibit high preferences for particular product features (based on customer-level model parameters).
- Test more complete and complex models of purchase decision making.

Calibration of Choice Models

With really new products—that is, new concepts yet to be introduced to category buyers —choice models based on survey data will usually produce biased results.

For example, placing a new product into an existing competitive set can produce a predicted market share that is too low. On the other hand, exposing a new product concept to respondents before showing choice scenarios will almost always produce a predicted market share that is too high.

For existing products, price and feature elasticities can be biased if the survey questionnaire's choice scenarios (a) provide too much or too little information relative to real market scenarios or (b) omit the impact on market choices of busy lifestyles and attitudes towards change.

Choice models can be calibrated to reduce bias in model predictions. The mathematics behind calibration of choice models can be explained in terms of the random utility model–the most-used utility specification used by practitioners of marketing research. The random utility model assumes that the total utility (attractiveness of a product

Latent Class and Hierarchical Bayes models help companies to:

- Develop new products and services.

- Improve customer retention and acquisition.

- Test complex models of purchase decision making.

Calibrate choice models to improve predictions.

in terms of its attributes) is the sum of a
measurable component (systematic utility)
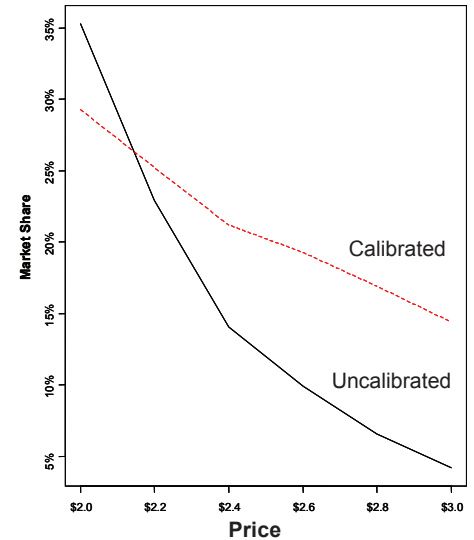and a random component (random utility).

Total Utility of Brand A = Systematic Utility + Random Utility

In its simplest form, choice models specify
systematic utility to be a sum of part-worth
utilities (worth of each part of the product)
minus the worth of the money required to
purchase. For example, the total utility for a
$2.00 bottle of Heinz ketchup would be the
sum of part-worth utilities for *brand name,
type of bottle, and size of bottle minus the
part-worth of $2.00*.

Systematic Utility = Part-Worth of Heinz Brand + Part-Worth of Glass + Part-Worth of 14-Oz Bottle - Part-Worth of $2.00

When using survey responses to estimate
part-worth utilities, utilities may be biased. In
order to reduce or eliminate bias that causes
inaccurate predictions, researchers can

Demand Curves

calibrate choice models by adjusting utilities
to better predict actual market choices.

While all serious practitioners acknowledge
that choice models can produce market
shares and price and feature responses
that differ substantially from those of actual
markets, different calibration solutions have
been implemented.

Traditional calibration solutions include:

- *Not Calibrating*–But using the choice
  model results as valuable inputs for
  strategic and tactical decision making.

- *Calibrating Brand Part-Worth*–Adjusting
  part-worth utilities for brands to force a
  choice model to produce market shares
  from an external source; for example,
  scanner data or a forecast.

- *Rescaling Price or Featuring Part-
  Worth Utilities*–Proportionately rescaling
  price and featuring part-worth utilities
  based on the relative variability of random

utilities from survey responses vs. actual market choices.

- ***Calibrating Brand Part-Worth and Rescaling Price or Featuring Part-Worth Utilities***–Not only adjusting brand utilities, but also rescaling price and feature utilities.

The figure above illustrates how calibrating brand part-worth and rescaling price utilities alters the shape of a demand curve. In this example, the Uncalibrated Demand Curve exhibits an exaggerated price sensitivity and, at the lowest price, an upward-biased estimate of market share. Calibration corrects these biases to produce a more realistic demand curve, enabling the researcher to predict market share more accurately.

Several solutions are being investigated in academic and business circles to improve choice model calibration. First, research on rescaling of price and feature utilities includes very detailed comparison of survey choice models with household scanner data (Renkin, Rogers, and Huber, 2004). This research has focused on how much to rescale price utilities so as to minimize differences between survey choice model and household scanner data model predictions.

Based on personal experience, market share predictions for really new products can be greatly improved by incorporating additional survey responses. For example, survey responses that measure positive attitudes about a new brand or product concept statement can be combined with choice

model simulations to deliver more reliable first-year market predictions.

Finally, laboratory experiments have been proposed (Allenby et. al., 2005) to understand the amount of adjustment of brand, price, and feature utilities for different types of customers, bringing calibration to the individual customer level.

All of these calibration approaches have a goal of increasing the accuracy and reliability of market share and revenue predictions from choice models.

Implications for Marketing Researchers

Recent advances in choice modeling enable marketing researchers to do the following:

- Reduce survey length for choice modeling research.
- Deliver segmentation algorithms that increase ROI for target marketing programs.

Decision-Simulators™ enable researchers to:

- Predict bottom-line revenue and profit impacts.
- Simulate hundreds of "what if" pricing and competitive scenarios.

For example, one can answer "what if" questions such as: What happens to my brand's market share if I increase price, if I add a product to my brand's product line, or if a competitor drops its price?

References

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- Deepen understanding of customer purchase-decision processes.
- Handle extremely complicated products with many features.
- Predict bottom-line revenue and profit impacts.
- Recommend market strategy options.
- Deliver market simulators, (DecisionSimulators™)

DecisionSimulators™ enable researchers to investigate hundreds of "what if" pricing and competitive scenarios.

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