# Belief - Based Marketing vs. Conjoint : An Illustration Using the Indian Mobile Phone Market


** Philip Truscott*

*** Michael Chiam*

**** Nilanjan Raghunath*



## Abstract

Many market research surveys conducted in the past have been engineering surveys and not genuine surveys of consumer beliefs. Brand managers should not only be able to simulate the market share of a newly designed product, but show the market share changes that result from changing consumer beliefs about existing products. The current research contrasted traditional conjoint with a variant that also collected data on consumer beliefs about what features a product has: the Boolean user belief (BUB) approach. This study compared BUB to the existing fixed data (FD) approach. Random assignment allocated 608 respondents one of the three methods: ACA, ACBC, and a self-explicated scale. Though the predictive accuracy of the research method improved using the BUB approach, the current research was more important, as an illustration, of how product feature surveys can impact market shares earlier in a product's life cycle than is possible now with most forms of conjoint. Where brand managers can single out one or two popular features that the public is not aware of, marketing messages can increase sales without a product re-design. In the case of traditional conjoint surveys, brand managers are limited to predicting changes in market share that would result from a new combination of features, rather than changing beliefs about existing products. If a manager finds that his/her product has a popular feature that consumers are unaware of, that feature becomes the advertising focus.



***Keywords:*** **conjoint analysis, self-explication, choice models, perceptions**

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Market researchers have long debated how surveys can help brand managers to predict consumer interest in new products. The research should predict the combination of a given product's features that will help it to capture the highest market share. Conjoint techniques that require respondents to choose between entire products have been increasingly popular since the early 1970s as first described by Green and Rao (1971).

The current paper will argue that current conjoint models give undue attention to the engineering domain. While conjoint surveys sometimes give information about non-physical attributes (such as price and warranty length), the bulk of the data generated suggests only physical changes to a given product.


* *Associate Professor,* Southwest Baptist University, 1600 University Avenue, Bolivar, Missouri 65613, USA.
E-mail: ptruscott@sbuniv.edu

** *Senior Lecturer,* Ngee Ann Polytechnic, 535, Clementi Road, Singapore 599489. E-mail: Michael_Chiam@Np.Edu.Sg

*** *Assistant Professor,* Singapore University of Technology and Design, 8 Somapah Road, Singapore 487372.
E-mail: Nilanjan@Sutd.Edu.Sg



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We will contrast current conjoint models with an approach that measures both: (a) the value respondents place on individual product features, (b) the Boolean beliefs that respondents have about whether a product has a given feature.

The inclusion of user belief data both enhances predictive accuracy and gives brand managers insights about how to advertise the features of existing products.

## Literature Review

**(1) Contrasting User Belief and Fixed Data Approaches :** This paper will make the case that Boolean User Beliefs (described below) have never had a meaningful evaluation in academic market research (or even mentioned Boolean consumer belief variables as distinct from continuous or ordinal belief variables). The most significant proponent of the approach is Eric Marder, who described it in The Laws of Choice: Predicting Customer Behavior (1997). To illustrate the distinctive nature of this concept, one must consider the conventional use of conjoint utilities. Typically, a product manager gathers fixed data on the features of his/her own brand and its competitors. To compute each product's total score, one adds the utility value that relates to each feature. For example, if a cell phone screen size of 4 inches has a utility of +11 and an iPhone has a screen of this size, the iPhone receives +11 for this attribute. The iPhone is given the 4 inch utility value, whether or not a given respondent believes the product has a four inch screen. In fact, traditional conjoint surveys do not collect data on what type of screen the respondents believe each product to have, so the scoring process must use fixed data, which assumes the same product configuration for the iPhone for all respondents.

The Boolean belief approach rejects the use of fixed feature data for all the respondents in a given survey. Its proponents argue that it is not facts that drive the buying decision, it is beliefs. Suppose a consumer believes the iPhone 4 has a battery life of 800 hours, when it is only 300 hours. It will be the higher value that influences purchase for this particular consumer. The belief - based approach "defines the value of a brand for a particular respondent as the sum of the values of those characteristics which that respondent, correctly or incorrectly, believes the brand to possess" (Marder, 1998, p. 8).

Academic reviewers have so far not written about this aspect of Marder's technique, which adds up product feature desirability scores based on each respondent's beliefs about brand characteristics. All varieties of conjoint sum the scores based on a fixed matrix of product features that is the same for all respondents in a given survey. There has certainly never been a simulation that combines different versions of conjoint with Marder's technique for summing desirability scores based on respondent beliefs. To illustrate the Boolean user belief approach, consider the way that market simulators combine attribute values to predict product choice. Typically, multinomial LOGIT computes coefficients to represent the utility value for each attribute - level. In formula (1) mentioned below, $U_{ai}$ is the utility value of the $i$th respondent for the $a$th attribute level. $F_{ap}$ represents a matrix describing the features of a specific product. It contains Boolean (0, 1) values that indicate which level of a given attribute a product has. To take the example of a mobile phone, if the largest screen size takes the value '1' and the iPhone 6 has this screen size, then it will take the value '1' for this level and all other levels of the screen size attribute will be zero. $F_{ap}$ is the presence of feature $F$ for the attribute - level $a$ for product $p$. The total product value $PV_{pi}$ is the sum of a product's utilities for the $i$th respondent for product $p$ (given the feature configuration $F_p$).

$$PV_{pi} = \sum_{a=1}^{amax} U_{ai} * F_{ap} \qquad .....(1)$$

The consumer belief approach avoids this use of fixed data product configurations. In formula (2), let $B_{aip}$ represent the product feature belief of the $i$th respondent about the $a$th attribute level of product $p$. Notice that the feature configuration now varies from respondent to respondent based on each person's beliefs about a given product. $B$ takes value 1 if the product possesses a given attribute level and is otherwise zero. Marder's technique uses self-explicated desirability ratings for each attribute-level (rather than multinomial LOGIT coefficients). Therefore, formula (2) below expresses the first term as $D_{ai}$ : the desirability rating of the $i$th respondent for the $a$th attribute level.

$$PV_{pi} = \sum_{a=1}^{amax} D_{ai} * B_{aip} \qquad .....(2)$$

Here, we will call this approach 'Boolean User Belief' (BUB) as opposed to 'Fixed Data' (FD). Marder (1997) only used this approach in combination with his form of self-explicated ratings. However, multinomial LOGIT coefficients could also employ BUB. The current study combines the BUB approach with two conjoint methods (ACA and ACBC). The formula (3) describes the scoring process for a BUB conjoint market simulation, where the user-belief approach is applied to the two conjoint methods. $U_{ai}$ is the coefficient for attribute-level $a$ and respondent $i$. As in formula (2), the coefficient value used to compute the total product score is based on matrix $B$. This matrix determines which coefficient value is used to compute the total product score. As in formula (2), $B$ contains data on product configuration beliefs that vary from respondent to respondent. The BUB concept is thus *modular* in the sense that it may be combined with any of the major conjoint or self - explicated methodologies.

$$PV_{pi} = \sum_{a=1}^{amax} U_{ai} * B_{aip} \qquad .....(3)$$

**(2) Boolean User Beliefs Contrasted with Subjective Belief Scales :** To understand how BUB differs from older product research methodologies, the qualifying adjective 'Boolean' cannot be stressed strongly enough. There have been many published methodologies that incorporate beliefs, but none of these were designed to capture consumer knowledge about whether a product possessed a specific objective feature. In other words, one must differentiate Boolean belief variables from other belief scales.

A traditional belief scale asks questions like "Employees in excellent _____ companies will give prompt service to customers". Respondents are required to respond to this question on a 7 -point scale from *"strongly disagree"* to *"strongly agree"*. The crucial point here is that this type of belief question invites respondents to give a subjective opinion about a product based on a sliding scale, rather than Boolean user beliefs which require a simple true/false judgment on whether a product has a given feature (e.g. does this phone "Have GPS" or "Has No GPS"). Other subjective belief questions have been described by Lemke, Clark, and Wilson (2010). All these authors used scales to elicit shades of consumer beliefs with five or six categories of opinions. None of these papers involved true/false data about the presence/absence of product features that could be determined objectively.

## Research Methodology

The current study uses three different methodologies to elicit product feature utilities. One of the methods, adaptive choice based conjoint (ACBC), is clearly in the conjoint category in the sense that it does not ask any self-explicated questions at all. The unbounded write-in scale (UWS) is a method of pure self - explication in that it never asks questions about combinations of product features. The third technique, adaptive conjoint analysis (ACA), is a hybrid ; respondents give self-explicated ratings at the start and later respond to combinations of product features. Both ACA and ACBC are adaptive in the sense that respondents see different questions during later stages of an online questionnaire depending on their earlier responses.

**(1) The Unbounded Write - in Scale (UWS) :** The essential feature of this rating system is that respondent effort must be proportional to the recorded desirability. According to Marder (1997) :

> If we want to measure how much the respondents like or dislike something, we need to give them something to push against, a device that will require them to make some expenditure of effort, however slight, to convey higher desirability. (p. 156)

Pen - and - paper surveys require the respondents to write the letter "L" as many times as they want to indicate how much they like a feature. They can write the letter "D" as many times as they want for dislike. "N" represents the neutral concept. Internet surveys achieve the same effect by multiple clicking of buttons showing the plus sign, the minus, and the zero. The instructions avoided any mention of an upper or lower limit to the ratings that can be given. This gives rise to the technique's name: the unbounded write-in scale (UWS). Marder (1997) reported the results of an experiment in which Americans rated political leaders with UWS, while another group of respondents used a traditional bounded rating scale. The unbounded ratings had normal distributions. The mode was located near the middle of the range with a gradual tapering on either side. Bounded questions produced 'cliff distributions' ; in each case, the most commonly selected value was often the maximum or the minimum value permitted.

Unlike ACA, UWS surveys do not have a separate 'weighting' or 'importance' stage. Netzer and Srinivasan (2011) also showed the results of un-weighted self-explicated questions. None of these studies included unbounded or effort-proportional ratings questions (such as UWS). Marder (1997) himself conducted lengthy experiments with attribute weights but eventually also concluded that they did not add to the predictive accuracy of UWS.

**(2) Adaptive Choice Based Conjoint (ACBC) and Adaptive Conjoint Analysis (ACA) :** In order to simulate most closely market - place applications, two of the three methodologies, ACA (SSI, 2007) and ACBC (SSI, 2014) were implemented using Sawtooth Software.

**(3) The Experiment :** The product category was smartphones. The respondent pool (608 respondents participated in the study) was selected through the website : oDesk.com. This is a service that matches workers to employers and takes a percentage commission on the wages paid. Its website separates workers into geographical areas and occupational sub-specialisms. At the time of conducting this study, the site listed the profiles of 28,000 developers of "mobile apps" from South Asia (mainly India). The site expressly forbids employers from offering work compensated through a prize draw. All employers must pay according to a fixed-fee-for-service or an hourly rate.

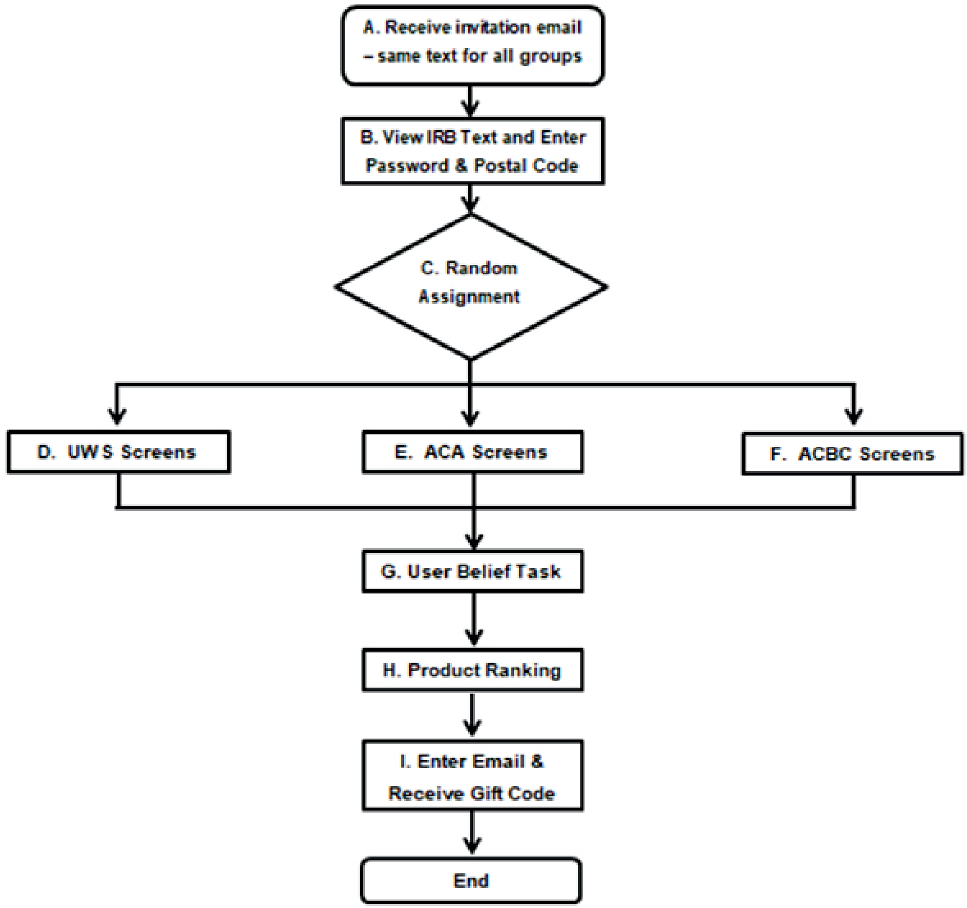
The survey software released a payment (Stage I in Figure 1) to all persons completing the survey in the form of a gift code worth INR 500 for purchases on the website Flipkart.com (an e-commerce website that is India's closest equivalent to Amazon.com).

The Figure 1 illustrates the process flow. Respondents received an email to enter the survey with a unique password embedded in a link to the survey web page. After viewing information on their rights as survey subjects, the software automatically rotated the respondents into one of the survey versions (Process C in Figure 1). The time that the respondents happened to log in governed the allocation to one of the three survey groups; there was no pre-allocation by the survey organizers.

Sawtooth Software's SSI Web (version 8.2.4) generated the data collection screens for the ACA and ACBC versions of the study. All versions included 17 attributes with 64 levels. However, an 18$^{th}$ attribute, brand preference, with eight levels caused problems. The design screen of SSI Web warned against including an 8-level attribute in an ACBC survey, so the ACBC version omitted the brand preference question.

After completing the utility screens, the software routed all respondents back to a uniform set of user belief screens. The eight column headers displayed the product names. The row labels showed text that described the levels of each attribute. Respondents filled in a grid chart for each attribute to indicate which products possessed which level. Since the product name included the brand name, the belief stage omitted this attribute.

Figure 1. Survey Flow Chart




The validation task was designed to be particularly robust and more representative of real world buying decisions (when compared to typical conjoint validation tasks). Many advertising professionals would have difficulty in recognizing conjoint validation tasks as real world purchasing decisions. A consumer walking into a brick-and-mortar shop may have accurate knowledge about a few brands, model names, and their more well-known features. However, conjoint validation tasks typically involve displaying a matrix of product features so that respondents have equal knowledge of all the products during this part of the survey. This could mean that so much information is displayed to respondents that the ability to predict the correct product is reduced to a tautology. Such 'full profile' validation tasks only simulate the real world in the case of Internet buyers using a comparison-shopping tool that displays all the product features in a grid chart. This type of holdout task ensures that respondents have perfect feature knowledge during validation. However, even in the USA, about 90% of the purchases (Economist, 2012) still happen in physical stores where shoppers do not have a feature comparison chart in front of them when they buy. Thus, the full profile holdout tasks can only represent realistic buying procedures for a minority of shoppers (mainly those buying on the Internet).

For the current study, a simple validation task required respondents to rank order a list of eight mobile phones designated only by a brand and model name. Respondents were shown two list spaces. On the left was a product list randomized for each respondent. On the right was an empty list that the respondents had to fill by clicking products on the left. The instructions requested a rank ordering from most likely to least likely to purchase. This dual column screen did not allow respondents to proceed until they ranked all eight products. It should be stressed that this validation task was, therefore, much more robust than those used in studies where respondents were shown a matrix of product features (ensuring they have equal knowledge about more famous and less famous brands).

## Analysis and Results

As mentioned above, the instructions for Sawtooth software warned against including an 8-level attribute in an ACBC survey, so the ACBC version omitted the brand preference question.

In order to include the ACBC version in the comparisons, the Table 1 shows a three-way comparison (ACBC, ACA, and UWS) based on only the first 17 attributes.

When the brand preference attribute was included (see Table 2), both ACA and UWS increased their predictive accuracy (the ACBC version did not include the brand question for the reasons stated above). Moreover, the MAD decreased with the BUB under both methodologies. The MAD of ACA fell from 16.6% to 3.1%. For UWS, it fell from 7.8% to 2.1%. The Bowker - McNemar test indicated that in both cases, the predicted values were significantly different under the user belief approach ($p < 0.001$). Moreover, when the user belief predictions were compared to the product distribution produced by the product ranking task, neither the ACA nor the UWS values were significantly different (at $p < 0.05$). In this sense, the product distributions using BUB data and product ranking were statistically the same.

The Table 3 shows the choice shares for each product user UWS with user beliefs compared to the choice shares that emerged from the product ranking validation task.

**Table 1. Results Based on 17 Attributes (Excluding Brand Attribute)**

| | (1) *N* Cases | (2) Hit Rate : Fixed Data | (3) Hit Rate : User Beliefs | (4) Choice Shares - Mean Absolute Deviation : Fixed Data | (5) Choice Shares - Mean Absolute Deviation : User Beliefs | (6) Choice Shares Different : Bowker-McNemar Test |
|---|---|---|---|---|---|---|
| UWS | 201 | 19.9% | 28.4% | 9.3% | 5.0% | 68.747 ** |
| ACA | 203 | 18.3% | 21.2% | 16.6% | 5.5% | na |
| ACBC | 204 | 19.1% | 20.1% | 8.6% | 4.4% | 38.556* |
| Means | | 19.1% | 23.2% | 11.5% | 5.0% | |

Bowker-McNemar Test *N* of Cases: UWS (*n* = 201), ACBC (*n* = 193)

Significance: ** *p*. < 0.001, **p*. < 0.05

**Table 2. Results Based on 18 Attributes (i.e. Including Brand Attribute)**

| | (1) *N* Cases | (2) Hit Rate : Fixed Data | (3) Hit Rate : User Beliefs | (4) Choice Shares - Mean Absolute Deviation : Fixed Data | (5) Choice Shares - Mean Absolute Deviation : User Beliefs | (6) Choice Shares Different : Bowker-McNemar Test |
|---|---|---|---|---|---|---|
| UWS | 201 | 22.9% | 31.8% | 7.8% | 2.1% | 64.566* |
| ACA | 183 | 22.7% | 25.1% | 16.6% | 3.4% | 113.333* |
| Means | | 22.8% | 28.4% | 12.2% | 2.7% | |

Bowker - McNemar Test - *N* of Cases: UWS (*n* = 201), ACA (*n* = 183)

Significance: * *p*. < 0.001

**Table 3. Product Results Based on 18 Attributes and Unbounded Write - In Scale**

| | iPhone 5 with 32 GB | Samsung Galaxy Note 2 | Black-berry Curve 9220 | XOLO Q1000 | Spice Mi-495 | Micromax Canvas 4 A210 | Nokia Lumia 520 | Lava Iris 504Q |
|---|---|---|---|---|---|---|---|---|
| Estimated by UWS | 41.0% | 20.0% | 9.5% | 5.0% | 5.0% | 7.5% | 7.5% | 4.5% |
| Ranking Task | 41.5% | 21.0% | 6.0% | 4.0% | 2.5% | 6.5% | 13.0% | 5.5% |
| Difference | 0.5% | 1.0% | -3.5% | -1.0% | -2.5% | -1.0% | 5.5% | 1.0% |

**(1) Boolean User Beliefs and Predictive Accuracy :** It is a common feature of comparative choice modelling studies to claim an advantage for one particular method of eliciting feature utilities. This study makes no such claim. Considering both sets of predictions (user belief and fixed data), all methodologies seem reasonable. Moreover, with Boolean user beliefs, all three methods appear more consistent with each other. Considering only the first 17 attributes and fixed data, the range in MAD went from a low of 8.6% (ACBC) to a high of 16.6% (ACA). With BUB, the range of values declined considerably. The low value was 4.4% (ACBC) and the high value was 5.5% (ACA).

**(2) Improving Conjoint's Predictions of the Choice Share of New Product Offerings :** Formula (3) suggests a methodology for summing the coefficients from a conjoint study to incorporate the data from Boolean user beliefs. This is the formula used to produce the ACA and ACBC data shown in Tables 1 and 2 (in the user belief columns). How can this process be adapted to predict the market share of a new product offering ? To take a specific example, let us consider the task of the iPhone brand manager at the launch of the iPhone 6. Let us imagine that only two attributes change: the screen size and the price level both increase. We will assume all other features stay the same.

The brand manager's product designer software (illustrated in Figure 2) produces a copy of the existing iPhone. Within the software, he/she will label it as the “iPhone6”. The product list shown in Table 3 would increase to nine products. He/she now edits the new product. The belief data about the new product's price and screen size attributes are changed. They become 'controlled perceptions'. The market simulator now assumes that the respondents 'know' that the iPhone6 has the new price and screen attributes. The brand manager calculates the total utility scores for the nine products for all respondents. If the new product is worth launching, then the total score for the iPhone6 will be the 'winning' (highest scoring) product for some respondents. The proportion of respondents who 'give' the new product the highest total utility indicates its projected market share.

The current discussion avoids the use of traditional terms like “what-if analysis” to avoid giving the impression that the BUB is an exact equivalent of traditional conjoint. To illustrate the difference, consider the following case where there is no new product and the brand manager merely advertises an existing set of products.

## Discussion

Consider the following brand manager's dilemma. He/she is responsible for the Micromax smartphone (see the Appendix for its list of features). His/her BUB survey data implies that he/she can raise his/her market share by 10% if he/she can increase the number of consumers who know that his/her product has two SIM card slots from 50% to 80%. He/she is realistic enough to assume that no advertising campaign is perfect. It will not be possible to make 100% of the consumers change their beliefs, so he/she settles on a more modest target of reaching 80%. How could one simulate this using traditional market simulators ? Traditional market simulators such as that produced by Sawtooth Software do not allow for this type of analysis. The software only allows him/her to assume that 100% of the consumers in the new market believe the Micromax to have two SIM card slots. In fact, the brand manager's position would be far worse than this. Since traditional choice modelling does not collect consumer belief data, he/she would have no way of knowing what proportion of consumers have incorrect beliefs about his/her product's SIM card feature. For these reasons, the current discussion preserves Marder's (1997) original term: 'controlled perceptions'. 'Controlled perceptions' can :

- *either* describe a situation where advertising changes beliefs about existing products,
- *or* simulate a new product offering.

In the second case, the process looks like traditional What-If analysis :

$$PV_{pi} = \left[\sum_{b=1}^{bmax} U_{ai} * B_{aip}\right] + \left[\sum_{co=1}^{comax} U_{ai} * C_{ap}\right] \quad .....(4)$$

Formula (4), which is a variant of formula (3), formalizes this process. It describes the use of controlled perceptions. The constant *bmax* is the number of attributes where the respondent's original beliefs (from the survey data) determine the utility values. These belief - based calculations are the same as in formula (3).

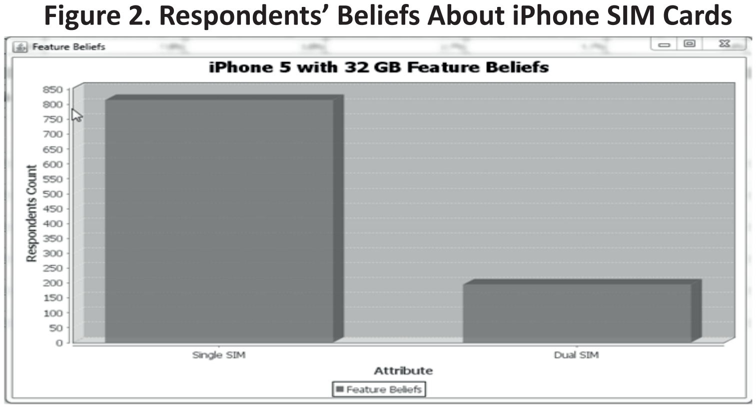
The constant *comax* is the number of attributes where the brand manager is simulating changed beliefs (usually as a result of a proposed advertising campaign). For these attributes, the utility value selected is determined by the controlled perception matrix *Cap* where *a* is the *a*th attribute-level and *p* is the *p*th product. For any given attribute, the level of the product's controlled level will have the value 1 and all other levels of the same attribute will be zero. The level selected represents the new feature. In the case of the iPhone 6, the screen attribute would be the level that represents the enlarged screen size.

This description assumes that the new product represents a line extension. Therefore, two iPhone products take part in the simulation. If the new product is a replacement for the existing one, the brand manager would delete the current offering from the frame before calculating the choice shares.

There is a bias of perspective built into survey methodologies that measure feature utilities but not Boolean user beliefs. They draw managers towards solutions that involve physical changes to the product. Since the informational base of the technique stresses physical characteristics of the product, it is natural that corrective policies should involve re-design.

Surveys that include feature beliefs add another dimension to brand management. Sometimes, changing consumer beliefs can raise the market share of an existing product. Boolean user beliefs allow a brand manager to understand what consumers believe about his/her brand and its competitors. Suppose a brand manager represents an Indian brand, the Micromax, as shown in the Table 3. Let us imagine that Micromax's main competitor is the iPhone. The brand manager can analyze the iPhone brand and the SIM card attribute to generate the data (see Figure 2). About one quarter of the respondents believe that the iPhone had two SIM cards. Dual SIM card slots are an extremely popular feature in India. This type of information should immediately suggest an advertising strategy : publicize the popular feature that your competitor *lacks* and that your own product *has*.

**Figure 2. Respondents' Beliefs About iPhone SIM Cards**



To take a concrete example of traditional product feature analysis, Goyal and Shiva (2016) described an excellent conjoint survey to identify the most desirable features of mid-segment cars. The survey was able to identify specific preferred car attributes such as an engine capacity of 1400 -1500 cc. For the CEO of a car-maker, such data is invaluable in planning the development of future models, but what is its utility for the marketing manager of an existing car ? If the marketer knows both that this engine capacity is popular and that the public is unaware of it, then the marketing path is clear : advertise the engine capacity of one's brand. If the user belief section of the BUB survey shows that the public already knows about this feature, then the marketer should identify the most popular feature that the public seems to be unaware of.

A survey of breakfast products by Tomar (2017) sought to identify the utility of attributes, including health, nutrition, satiation, taste, and convenience. While there is no doubt that knowing these utility scores is valuable to a marketer, it does not inform the marketer about what the consumer believes about the product the marketer is responsible for. If the public already believes the breakfast cereal to be the most nutritious, it may be pointless to advertise that feature.

Conjoint was used in combination with other statistical techniques in a survey of mixer grinders by Azhagaiah and Ezhilarasi (2012). This study was unusual in that it did describe consumer brand beliefs. However, this study was conducted in the tradition of earlier user belief research that assessed product qualities that can be described as continuous variables rather than Boolean questions (e.g. does the product have this feature? “yes/no”). The BUB approach described by Marder (1997) is also different in that it describes a generic modelling approach that can simulate market - share maximization for any database of attribute - utilities and brand - beliefs (the approach described below).

To quantify the effectiveness of this campaign, the brand manager could run a new choice share calculation that assumed the SIM card attribute would be a 'controlled perception'. Let us imagine an effective advertising campaign highlighting the fact that the Indian product has two SIM cards and the iPhone only has one. We can simulate the effect of this campaign by treating the SIM card attribute as a controlled perception for these two products. As the respondent data is processed again, the total utility scores of the Micromax will go up (for those respondents who did not know it had two SIM cards), and the scores for the iPhone will go down (for those who falsely believed that it had two SIMs). To the extent that consumers appear to 'switch' products, a given feature difference is worth advertising. If a given set of changed beliefs does not increase a brand manager's product sales, then those features are not worth his/her marketing dollars/ruppes.

## Conclusion and Implications

This is the first study to compare fixed data and Boolean user beliefs employing both conjoint and self - explicated methodologies. Boolean user beliefs are compatible with a variety of methods for eliciting feature utilities. Though designed for use with Marder's self-explicated method, conjoint methods are feasible companions to it. Interesting results have been published for the fast polyhedral method (FPM) (Toubia, Hauser, & Garcia, 2007) and the adaptive self-explicated approach (ASE) proposed by Netzer and Srinivasan (2011). Any of these methods could be combined with BUB.

The current study is the first attempt to evaluate Boolean user beliefs used in conjunction with a variety of preference elicitation methods. The results indicate that they can produce significant improvements in predictive accuracy, without restricting researchers to any particular conjoint or self-explicated method.

The study also highlights the philosophical differences between engineering research and advertising research. Engineering research will be satisfied to produce abstract products that may not have any brand or model name associated with them. Traditional conjoint studies usually take this form and avoid large sample sizes that can predict market shares in a specific national market.

In practice, brand managers need tools that go beyond the simulation of abstract products. They need to simulate the market share of actual products within a real population of consumers. Furthermore, they need to simulate the effect of engineering re-design that might take years and advertising campaigns that might have an effect in weeks or months. The Boolean user belief approach enhances predictive accuracy and allows both these objectives to be achieved.

## Limitations of the Study and the Way Forward

The BUB approach shares a drawback with traditional conjoint in that it requires respondents to complete lengthy survey questionnaires. In the case of Marder's original BUB surveys, this problem was mitigated by the fact that the product attributes were identified by a set of direct product utility questions (the UWS method) rather than lengthy comparisons of different product feature combinations.

As mentioned above, it would be feasible to combine BUB with a form of conjoint by asking a set of BUB questions after the product comparisons. However, this may not be practical if the number of brands or the number of product features is large. In general, a product category with a small number of brands will be easier and cheaper to survey using BUB. Further research on the BUB approach should concentrate on assessing its predictive power using other product categories.

## References


Azhagaiah, R., & Ezhilarasi, E. (2012). Consumer behavior regarding durable goods. *Indian Journal of Marketing, 42* (2), 27 - 39.

Economist. (2012, February 25). Clicks and bricks. *The Economist*. Retrieved from http://www.economist.com/node/21548241

Goyal, A., & Shiva, A. (2016). Investigating the consumer’s perception on selection of mid segment cars by students : A conjoint approach. *Indian Journal of Marketing, 46*(9), 53 - 63. DOI : https://doi.org/10.17010/ijom/2016/v46/i9/101041

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

Lemke, F., Clark, M., & Wilson, H. (2010). Customer experience quality: An exploration in business and consumer contexts using repertory grid technique. *Journal of the Academy of Marketing Science, 39* (6), 846 - 869.

Marder, E. (1997). *The laws of choice : Predicting customer behavior.* New York : Free Press.

Marder, E. (1999). The assumptions of choice modelling: Conjoint analysis and SUMM. (Single unit marketing model). *Canadian Journal of Market Research, 18* (1), 1 - 12.

Netzer, O., & Srinivasan, V. (2011). Adaptive self-explication of multi attribute preferences. *Journal of Marketing Research, 48*(1), 140 - 156. DOI : https://doi.org/10.1509/jmkr.48.1.140

SSI. (2007). *ACA technical paper.* Sawtooth Software Inc. Retrieved from http://www.sawtoothsoftware.com/support/technical-papers/aca-related-papers/aca-technical-paper - 2007

SSI. (2014). *The adaptive choice based conjoint (ACBC) technical paper.* Sawtoth Software Incorporated. Retrieved from http://www.sawtoothsoftware.com/support/technical-papers/adaptive-cbc-papers/acbc-technical-paper-2009

Tomar, V. S. (2017). Analysis of breakfast attributes and utility among Indian urban youth. *Indian Journal of Marketing, 47*(12), 7 - 18. doi : https://doi.org/10.17010/ijom/2017/v47/i12/119897

Toubia, O., Hauser, J., & Garcia, R. (2007). Probabilistic polyhedral methods for adaptive choice - based conjoint analysis: Theory and application. *Marketing Science, 26* (5), 589 - 730. DOI : https://doi.org/10.1287/mksc.1060.0257

## Appendix. Questionnaire Text

Programmatic checking ensured text describing the levels had the same spelling and capitalization. The text was identical for the UWS and ACBC versions. However, on some of the ACA screens, the level text lost its meaning when separated from the attribute text. Therefore, on some of the ACA screens, the two were joined. For example, in ACA, the biggest screen size was labelled "Screen 5 Inches and over" while the other three versions omitted the word "Screen." For ACBC, the brand preference question was asked in the form of a self-explicated (values 1 - 9) rating question. To illustrate the content of the questionnaire, the ACA version of the questionnaire is reproduced below.

| | **ACA Variant of Survey:** |
|---|---|
| 1 | Android |
| 2 | Symbian |
| 3 | Windows |
| 4 | Blackberry |
| 5 | iOS (iPhone OS) |
| 6 | Screen less than 3 inches |
| 7 | Screen 3.0 - 3.4 inches |
| 8 | Screen 3.5 - 3.9 inches |
| 9 | Screen 4.0 - 4.4 inches |
| 10 | Screen 4.5 - 4.9 inches |
| 11 | Screen 5 inches and over |
| 12 | Camera Memory below 2 megapixels |
| 13 | Camera Memory 2 - 4.9 megapixels |
| 14 | Camera Memory 5-7.9 megapixels |
| 15 | Camera Memory 8 megapixels and above |
| 16 | Storage Memory below 8 GB |
| 17 | Storage Memory 8 - 15.9 GB |
| 18 | Storage Memory 16 - 31.9 GB |
| 19 | Storage Memory 32 - 63.9 GB |
| 20 | Storage Memory 64 GB or more |
| 21 | Talk Time Less than 6 hours |
| 22 | Talk Time 6 - 11 hours |
| 23 | Talk Time 12 - 23 hours |
| 24 | Talk Time 24 - 35 hours |
| 25 | Talk Time 36 hours or more |
| 26 | Standby Time Under 50 hours |
| 27 | Standby Time 50-99 hours |
| 28 | Standby Time 100-199 hours |
| 29 | Standby Time 200-299 hours |
| 30 | Standby Time 300 hours or more |
| 31 | Price ₹ 5000 or less |
| 32 | Price ₹ 5001 - ₹ 10,000 |
| 33 | Price ₹ 10,001 - ₹ 18,000 |
| 34 | Price ₹ 18, 001 - ₹ 35,000 |
| 35 | Price ₹ 35, 001 and above |
| 36 | Phone thickness less than 6 mm |
| 37 | Phone thickness 6 -7 mm |
| 38 | Phone thickness 8 - 9 mm |
| 39 | Phone thickness 10 - 11 mm |
| 40 | Phone thickness 12 mm or more |
| 41 | CPU Speed 1 GHz or less |
| 42 | CPU Speed 1.0 to 1.3 GHz |
| 43 | CPU Speed 1.4 to 1.5 GHz |
| 44 | CPU Speed 1.6 to 1.9 GHz |
| 45 | CPU Speed 2.0 GHz or more |
| 46 | Free Repairs for 6 months |
| 47 | Free Repairs for 1 year |
| 48 | Free Repairs for 1.5 years |
| 49 | Free Repairs for 2 years |
| 50 | Free Repairs for 2.5 years |
| 51 | Has GPS |
| 52 | No GPS |
| 53 | Has Wi-Fi |
| 54 | No Wi-Fi |
| 55 | Has a touchscreen |
| 56 | No touchscreen |
| 57 | Has a USB Connection |
| 58 | No USB connection |
| 59 | Single SIM |
| 60 | Dual SIM |
| 61 | Has 3G Connectivity |
| 62 | No 3G Connectivity |
| 63 | Has a QWERTY Keyboard |
| 64 | No QWERTY Keyboard |
| 65 | Apple |
| 66 | Samsung |
| 67 | Blackberry |
| 68 | XOLO |
| 69 | Spice |
| 70 | Micromax |
| 71 | Nokia |
| 72 | Lava |

## About the Authors

**Philip Truscott is an Associate Professor in the Department of Behavioral Sciences, Southwest Baptist University, Missouri, USA. He has a Ph.D. (Sociology) from the University of Surrey and an M.A. (Politics and Social Administration) from the University of Edinburgh in the UK. His areas of interest are choice modelling and symbolic regression.**

**Michael Chiam is a Senior Lecturer at Ngee Ann Polytechnic in Singapore. He has a Ph.D. (Marketing Management) from the University of Western Australia and an M.Sc. (Management Sciences and Quantitative Methods) from Louisiana State University. His areas of interest include consumer preferences of tourists and conjoint analysis.**

**Nilanjan Raghunath has a Ph.D. (Sociology) from the National University of Singapore and an M.A. (Sociology) from the University of Surrey, Roehampton Institute. Her research interests include collaborative teams, disruptive innovation, and skilled migration in the digital age.**