Integrating Consumer Goals in Conjoint Using Archetypes

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Summary

In situations where the market is heavily dominated by brand, price, and design it can be challenging to find product feature changes that are impactful enough to change the market share landscape. In markets where product features change very fast, conjoint results can be short-lived as whichever feature is most important and may be distinct today will be a commodity and not important tomorrow. We illustrate that by integrating goals and benefits into a conjoint analysis we can mitigate both situations. We show that by using Archetypal analysis we can identify switchable consumers. These are more prone to respond to changes in product features. We also illustrate that by integrating goals and benefits into our conjoint model, we get more strategic insights that have a longer shelf life.

Introduction

It is well known with conjoint analysis that the resulting insights into attribute level utilities in combination with a market simulator can be used to optimize which attribute combinations maximize expected market share. However, there are situations where such information is not fully sufficient to extract actionable insights. Two factors specifically can have a big impact on how useful the conjoint is and over what time. One, there are situations where the product choices are more heavily dominated by brand and price (and in our study, form factor, as opposed to other (micro) attributes). Two, in technology-driven markets, the set of available features can change quickly. A newly tested feature in the conjoint can be seen as a commodity or even obsolete because new features enter the market fast. In this paper we outline an approach that helps us get actionable strategic insights when these two factors are at play. We propose to integrate consumers' goals and perceived product benefits with the conjoint results using Archetypal analysis.

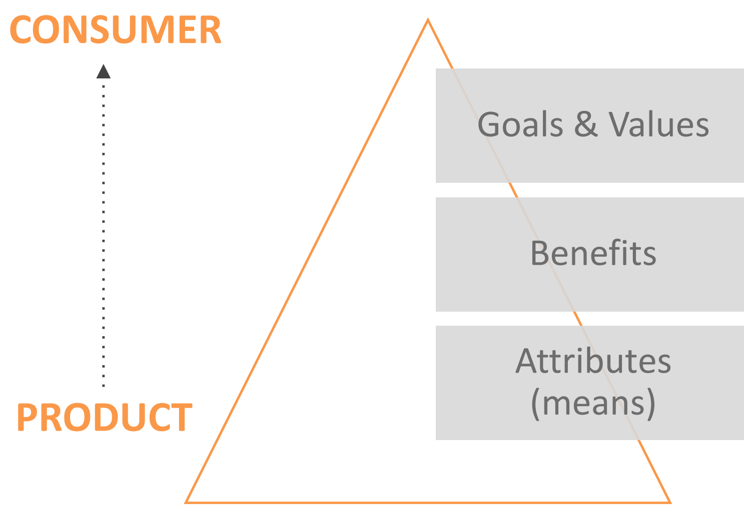
In the next section, we discuss the value of consumer goals and benefits. In section three, we outline the survey design and analysis steps. In section four we present some selected key results. Lastly in section five, we offer some key takeaways.

The Value of Goals and Benefits

Goals and values are foundational drivers of consumer behavior (Gutman, 1982; Van Osselaer and Janiszewski, 2011). Integrating goals with conjoint has two practical benefits. One, it helps with integrating product and marketing decisions. Two, by linking goals to attribute utilities we can extend the life span of the conjoint as goals are typically more stable than preferences for specific features.

A well-known framework that links the importance of product attributes to benefits and goals is the means-end chain framework. See Figure 1.

Figure 1. The Means-End Chain Framework



The framework shown in Figure 1 has been used in consumer research for decades. Attributes have value because they lead to benefits and/or goals, and they provide in essence the first reason why. Benefits have value because they are associated with achieving certain benefits or goals. It is a nice way to link the consumer to a product as attributes are completely features of products and goals are completely features of consumers. Goals are assumed to be enduring motivators of consumer choices. For example, thinking of fitness bands and wearables, step counting (a product attribute) can lead to losing weight (a benefit), and losing weight can be seen as an important aspect of improving overall health (goal). You can see how understanding the importance of the goal can extend the longevity of conjoint results, because even as step counting by now has become a commodity feature, the consumer goal, improving health probably hasn't changed. If I know that losing weight is more important than less stress, then as new features become available that elicit these benefits, the feature associated with losing weight is probably more important.

Several methods have been proposed to integrate product attributes, benefits, and consumer goals. This overview below is probably not completely comprehensive, but it shows some existing methods to connect attributes to goals. One of the oldest methods is probably the laddering method (e.g., Vriens and ter Hofstede, 2001), where we literally ask people what attributes they see connected with which benefits and goals and values, and which benefits they see connected with which goals and values. The downside of this method is that we don't get attribute level utility values, although laddering can be combined with conjoint. Another method is benefit conjoint (see Kim et al., 2017). This model is similar to the model proposed by Wedel et al. (1998). The problem with this approach is that we don't really know what benefit it is that consumers are seeing. All we know is that a certain combination of attributes shares a latent variable. If these attributes have a certain theme in common, then we may interpret that as a benefit, but it is not guaranteed that this will happen. A third method explicitly links attributes and benefits in different conjoint designs and is referred to as Hierarchical conjoint (e.g., Oppewal, Louviere and Timmermans, 1993; and Oppewal and Vriens, 1998). This method is a little convoluted, and not super practical we think. Lastly, we can try to ask about benefits and goals using Archetypal analysis (e.g., Liu, Korz and Allenby, 2023). Our approach is similar. It has the advantage that it is transparent and easy to implement.

Survey Design and Analysis Steps

In this section, we briefly outline the survey design that we used to capture the attribute tradeoffs, benefits and consumer goals and we outline the analysis steps.

Survey Design

There are 3 components in the survey that involve our methodology: Benefits, goals, and a conjoint exercise. Specifically, we included: 12 benefits, 15 goals and we used 2 conjoint exercises: a Macro and a Micro conjoint. These are the elements we are trying to tie together in our analysis.

The benefits section in our study was presented in a series of semantic differential tradeoffs. For example:

For me brand is very important............................I believe most brands are more or less the same.

Respondents then subsequently indicate on a 4-point scale whether the left statements describe them more or whether the right statement describes them more. As an additional benefit, such semantic differential benefit exercises have been tested in conjoint studies and can improve the conjoint responses (e.g., Kurz and Binner, 2021).

The goals were simply listed, and respondents had to indicate whether the stated goal applied to them; simple Yes/No questions. They ranged from general health, general fitness, to more specific health or fitness goals. For example, goals such as “Reduce stress,” “Live pain free,” “Reduce my A1C,” and “Get Stronger.”

We have two conjoint exercises, a macro, and a micro design. The market in our case has a wide price range, from as low as $ 50 to as high as $ 700. Also, the brands in this market were distinct and choosing a particular brand could affect other products the consumer was using. Last, the full list of attributes was large. Hence, the conjoint was structured as follows:

1. A Macro Conjoint

The Macro conjoint only included brand, form factor, and price as the attributes along with product images so respondents could better identify products. Actual product combinations were used in half the tasks to ensure current market tradeoff choices. The specific prices shown for each product were rotated but only within +/- 1 level of the actual product price. This was done because the main purpose of the Macro conjoint was to channel respondents into the appropriate price range of their perceived preference while still being able to inform some price elasticity. Respondents saw eight choice sets, each set containing six alternatives (including a none option).

Based on their selections in the Macro conjoint, each respondent was allocated to a Low/Mid/High price band. As shown below in Table 1, we allowed there to be an overlap in the prices shown between each price band. Knowing that the attributes tested in the Macro conjoint can heavily influence the product choice, the brand shown was not constrained to any specific price band.

2. Micro Conjoint

The Micro conjoint was utilized to gain insight into the value of various health, fitness, and safety features. Respondents in different price bands would get exposed to different price levels. The Micro conjoint was set up so that there was some overlap between the low and mid-range price bands and some overlap between the mid and high price range. See Table 1 below.

Table 1: Price Levels Across the Three Price Bands

	Price Band		
Price Shown in Micro	Low	Mid	High
Price 1	X		
Price 2	X		
Price 3	X	X	
Price 4	X	X	
Price 5	X	X	X
Price 6		X	X
Price 7		X	X
Price 8			X
Price 9			X

The Micro conjoint was designed with 16 attributes. Respondents saw 11 sets, each set containing four alternatives including the none-option.

In addition to the brand, form factor, and price attributes, some examples of the Micro conjoint attributes we tested were:

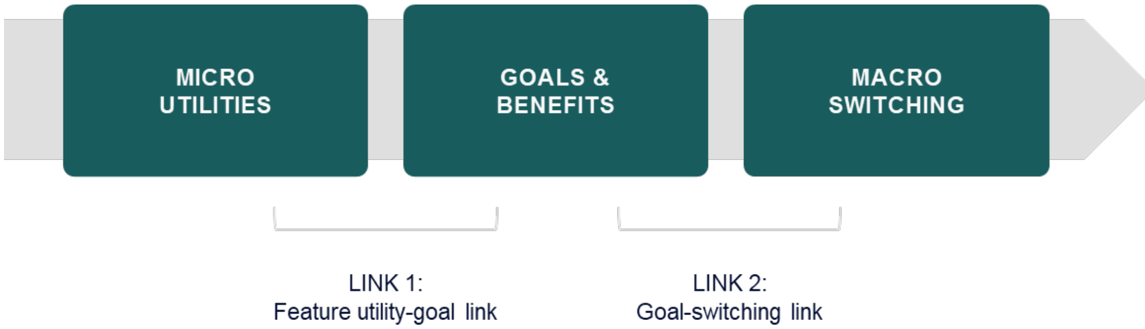
- Safety
- Stress
- Training
- Tracking
- General Health
- Sleep

Analysis Steps

While we now have many tasks with many attributes to model, the first step was to determine the best modeling approach to combine the Macro and Micro conjoint. Ultimately, we chose HB utility estimation using tasks from each conjoint to optimize the mean absolute error (MAE) and hit rate.

As we expected, brand, price and form factor were dominating attributes in the model. This limited our ability to analyze which specific health/product attributes led to brand switching. Or to put another way, which features (or combination of features) enticed the largest number of respondents to switch brands. So, we decided to pull in the benefits and goals. The analysis framework is shown in Figure 2.

Figure 2: Analysis Framework



To home in on respondents most likely to switch brands we proceeded as follows:

Step 1. Determining Who is Open to Brand Switching

In step one we aim to identify those respondents most open to switching between brands. For this we used Archetypal analysis (e.g., Cutler and Breiman, 1994) on the macro conjoint data. Preferences were strongly brand driven and hence we expected to find archetypes around preference for the tested brands A, B and C.

Archetypal analyses allow us to look at each respondent's probability of belonging to an Archetype. This benefit allows us to identify those respondents who have similar probabilities across multiple segments without having a dominant archetype. In our case, we decided a respondent has a dominant brand archetype if their probability of association (coefficient) is more than 0.5. As we detail in the results section, this allows us to differentiate between respondents who are not likely to be open to switching between brands (i.e., Brand Loyalists) and those who are open (i.e., Brand Switchers). This "Switchable Consumer" designation becomes our dependent variable later.

Archetypal analysis is only one of many partitioning methods available to help identify Brand Loyalists. Unlike most consensus or distance-based methods (e.g., k-means clustering, ensemble clustering, etc.; see Vidden, Vriens and Chen, 2016), the archetypal coefficients clearly articulate switching opportunities, rather than simply identifying areas of uncertainty between classification. This structure had the additional benefit of representing market share across competitors better than other partitioning solutions. In this study, the impact of a dominant brand exists beyond just those who are loyalists. Archetypal analysis does a better job than other approaches at revealing the subtle impact of a dominant brand, even among those individuals who have mixed brand preferences.

Step 2. Incorporating Goals and Benefits

The next step in our analysis is an archetypal analysis of the goals and benefits. We expected respondents to differ regarding the number of goals, and we expected that respondents would be different in the types of goals (e.g., some more health focused, others fitness focused).

In the next steps, we use both the goals and benefits data directly and we use the archetypal goal segments and archetypal benefit segments.

Step 3. Predicting Brand Switching Based on Goals and Benefits

In the third step, we ran Decision Trees (Breiman, et al., 1984) with the Switchable Consumer designation (yes/no) as the dependent variable. The independent variables are 1) the goal archetypes membership probabilities, 2) the goals variables directly, 3) the benefit archetypes probabilities, and 4) the benefits directly.

Step 4. Linking Micro Conjoint Utilities to Goals

Once we derived the connection between the Switchable Consumer and the goals/benefits, we tied the specific features tested in the Micro conjoint to the goals and benefits using regression analysis.

Results

First, we looked at the macro conjoint choices knowing that brand, price, and form factor can heavily dominate in the product choice process. We used Archetypal analysis on the stated macro choices. Then, we use the probabilities of association to identify those with high or low brand preferences. Look at Table 2 below.

Table 2: Example of Coefficients from Brand Preference Archetypal Analysis

	Probability of Association (Alpha Coefficient)			
Respondent	Brand A	Brand B	Brand C	
1	0.1	0.7	0.2	
2	0.3	0.2	0.5	
3	0	0	**1**	--> Strong Brand Affinity
4	0.2	0.2	0.6	
5	0.2	0	0.8	
6	**0.3**	**0.35**	**0.35**	-->Uniform Brand Affinity
7	0.6	0.2	0.2	
8	0	**0.9**	0.1	--> Strong Brand Affinity

As Table 2 shows, there are some respondents with a dominant probability for one archetype (for example, respondents 3 and 8). However, there are also some respondents whose probabilities are very similar across two or three brands (like respondent 6 in Table 2). In essence, we are identifying those who do not have a strong brand affinity and are more likely to switch brands. We have dubbed these as “switchable consumers,” then used this switchable consumer designation as the basis for understanding brand preference.

Next, we derived two archetypal solutions. One for the binary health goals and another for the semantic differential product benefits statements. Archetypal analysis of benefits yielded four archetypes (not shown in this paper). Below, we are only showing the profiling for the health goal archetypes. We have incorporated both solutions in the rest of the analysis. See Table 3 below.

Table 3: Goals Archetypes

Health Goal Archetypes	A1	A2	A3	A4	A5
Descriptive Labels	Unmotivated	Maintain Health	Fitness Improvers	Become Healthy	Better in everything
Specific Goals	Few	Some	Several	Many	Exhaustive
Top Goals	Goal1	Goal1; Goal2	Goal1; Goal3; Goal4	Goal1; Goal2; Goal4; Goal5	Goal1; Goal2; Goal3; Goal4; Goal5; Goal6; Goal7

After generating the two archetype solutions on health goals on product benefits, as well as identifying the switchable consumers designation, we wanted to find out if we could predict whether a respondent was a switchable consumer using the goals and benefit data. Several statistical methods can be used for this, but we settled on using a decision trees (DT) analysis (Breiman et al., 1984). One of the benefits of DT is that it automatically identifies interaction effects.

The results of the first DT analysis are shown below in Figure 3.

Figure 3: Decision Tree with Goals and Benefit and Macro Archetypes as Independent Variables

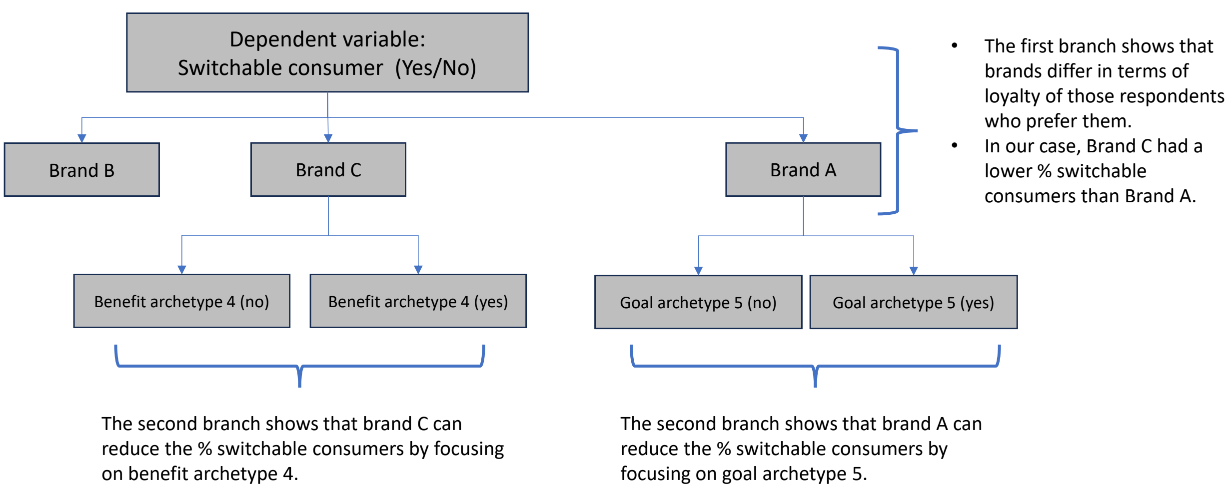
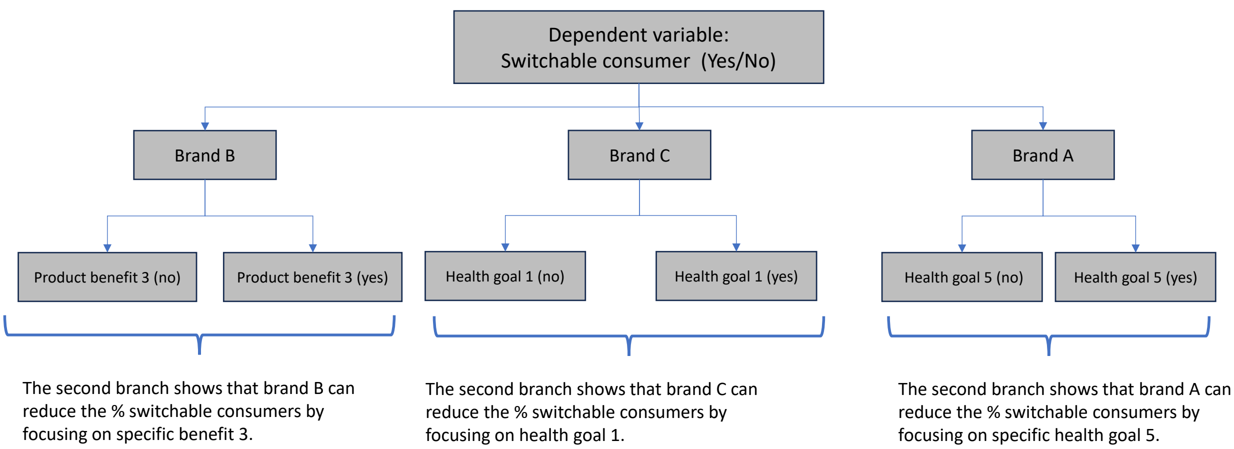


Figure 3 is a simplified representation of the actual decision tree. We don't show the actual differences in percentage switchable consumers in each brand. In branch 1, brand C had a lower number of switchable consumers than brand A. In branch 2, under brand C, the biggest difference in percentage of switchable consumers was found between archetype 1 and 4, where respondents who score high on archetype 4 had the lowest percentage switchable consumers. In branch 2 under brand A, the lowest percentage switchable consumers were found for those scoring high on goals archetype 5.

It shows two key insights. First, the first branch shows that the three brands in our study differ with respect to the percentage of switchable consumers. This was not entirely surprising, but it was still useful to see the magnitude of this "brand loyalty." Second, we can see that brand C needs to compete on benefits whereas brand A needs to leverage how consumers view it as instrumental in achieving certain goals. This is an important strategic insight for the product roadmap process. Next, is there a way to identify or predict who is more likely to switch (to switch from your brand, or to switch from a competitor's brand)?

What we are missing in this decision tree is what predicts brand loyalty for brand B. To investigate this further, we ran the DT using the individual benefits and goals that make up each archetypal solution to see if those did a better job of teasing out these differences (see Figure 4 below).

Figure 4: Decision Tree with Specific Goals and Benefit and Macro Archetypes as Independent Variables



Note: The decision tree shown above is a simplified version. The actual tree had multiple branches. For the sake of simplicity, we are only showing two branches. There are two key insights here. One, in this tree, we do find what differentiates respondents who are loyal vs. less loyal for brand B. Further branches of the tree showed that loyalty for brand B hinges mostly on whether the respondents require very specific product benefits. Two, this decision tree gives us more tactical insights as it identifies very specific benefits and goals.

The next step was to tie the health and benefit archetypes to the specific attributes tested in the micro conjoint. If we know the goals can help predict and add context to brand switching, what specific health attributes best predict the health goals: i.e., link 1 in Figure 2. To answer this, we modeled the number of health goals as a function of the attribute utilities. See Table 4 below.

Table 4: Regression Results *(disguised)*

Independent variables	Coefficient	p-value
Constant	1.73	0
Safety	0.01	0.31
Stress	0.04	0.49
Training	0.47	0
Tracking	0.22	0
General health	0.01	0.77
Sleep	0.22	0

Note: adjusted $R^2 = 0.36$

These regression results exposed the features that best forecast the health goals and product benefits separately across all brand archetypes.

If we want to complete the linkage from attribute features to goals to switching, we need to subset the sample by each of the brand archetypes to have a concrete roadmap for each brand. So, referring to the Decision Tree where brand A switching revolved around health goals (Figure 3), we can tie the filtered (brand A archetype) regression's significant contributors (denoted with ***) to the health goals and ultimately to the brand switching. Now we can connect the dots in tackling how to turn health goals into integrated product features. In other words, the attributes identified in the regression can be positioned to capture health goals that lead to switching.

Then brand A can use this high-level roadmap to influence product development and marketing outreach from a defensive position to retain likely switchers. Conversely, brand C could use those findings to attract likely brand A customers.

For this paper due to time constraints, we only included these findings tying the health goals with the health attribute utilities, but we repeated the analysis focusing on the benefit archetypes as a function of the utilities with similar findings.

Conclusions and Takeaways

Incorporating goals and benefits have humanized the conjoint analysis and extended the longevity of the findings as they are foundational consumer elements that remain stable longer than preferences specific product features.

Second, in situations where consumers' choices are heavily dominated by brand, it is hard to extract specific attribute-level insights that can inform product decisions and the product roadmap. By identifying the switchable consumer, via an Archetypal analysis of the macro conjoint in our study, we were able to extract insights that are not visible at the overall sample level. This showed both a strategic insight into how differently the different brands should compete, and for our client yielded insight into an effective high level strategic product roadmap.

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