Combining Attribute Classification with Utilities in Conjoint Studies

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Abstract
Non compensatory choice rules are gaining more and more attention among marketing practitioners. The traditional conjoint model implies a full compensatory choice rule with unsatisfactory optimistic choice forecast. This work exemplifies a possible extended conjoint model where traditional utility theory is combined with attribute classification ending up with an approximation of a conjunctive choice rule.

Key Words: conjoint, choice rule, non compensatory, attribute classification, Bayes

1. The problem

Non compensatory choice rules are gaining attention among market researchers. In some cases, conjoint models start becoming questionable, because they assume all attributes to behave as perfectly compensable. The de-compositional nature of the conjoint model entails full compensation *per se*, because of the obvious equivalence between *de-compositional* model and *full compensatory* choice rule. In a conjoint model, the choice forecast for a *compound of parts* or *product*, is based on the *straight sum* of the utilities of all parts entering the compound. It is thus possible to keep the same sum whenever utility loss in some attributes is counterbalanced by a utility gain in some other ones. Overcoming a full compensatory choice rule is a *tremendous instance* in making simulation models better fit with market evidence. To quote just a reference from a large body of literature, in the paper "*Compensatory versus non-compensatory models for predicting consumer preferences*" [1] we read that "*Standard preference models in consumer research assume that people weigh and add all attributes of the available options to derive a decision, while there is growing evidence for the use of simplifying heuristics*".
The growing evidence is based on the *comparison with real market data*, the ultimate judge of model forecasts. The assessment of *internal validity* and, at some extent, also of *external validity* is model dependent. You never can justify the model this way, because validity assessments are grounded on the basic assumption that *the model is right*. Only when factors in the choice experiment *have fully exchangeable values* are such validity assessments useful, because in this case the model is plausible. Anytime a non compensation originates between factors, the conjoint model is *not right*. Such a model would be of dubious value for marketing managers, who use to compare *simulation outcomes* with *market data*.
This comparison may seem impossible. But you can *approximately* assess the *lack of fit* by the comparison between *independent consumers data* and *suitably grouped simulation outcomes* in a reference scenario representing *at best* the actual market. For instance, you can compare market brand shares with simulated brand shares, product feature market

shares with simulated feature shares, etc. in a wide scenario that includes major brands with known market offerings.
Comparisons between market data and conjoint simulation outcomes will often prove unsatisfactory. So you are led to:

1. *Include* in the choice experiment only compensatory factors. This is difficult because you *don't know in advance what is vital* in R's view
2. *Allow* for some non compensatory choice rules.

Consumers can compensate something, but not everything. A factor can be compensated by another one only if the loss is not dramatic. A gain in some factors can thus be enough to compensate for the loss in some other ones. But if the loss is dramatic, talking about compensation is *even meaningless*. In essence, the validity of conjoint simulation outcomes has to be assessed by a thorough and meditated comparison with market data.
A partial answer to this issue lies, in author's opinion, in the delimitation of *consideration sets* at R's level. This can be accomplished by a two phase choice experiment where a suitable combination of an *information and scoring phase* with a *choice phase* leads R's to be focused only on stimuli that are relevant in their view. "Two-stage, *consider*-then-*choose* decision rules are particularly relevant in the automobile market" is a remarkable statement in the important paper [2]. Conjoint stimuli are often picked up from a *common, often very large, design* with possibly some hundreds cards with each R just watching at a 5% fraction of the design.
To allow some deviations from a pure compensatory choice rule, a basic strategy is in the *full exploitation of an extended information bulk* provided by R's. A preliminary *information* and *scoring phase* allows to restrict R's choices only on what is relevant in their view, thus keeping R's focused on what they deem worth consideration and also making them more comfortable in the choice completion. This also allows to show R's just a small fraction of a possibly very large design.
A more effective way to address the *non compensation* issue is by the *attribute classification* as discussed later on. *Non compensatory choice rules* are nowadays still under heated debate among specialists. They are often *considered as alternatives* to the common conjoint simulation. In our opinion, there is a viable strategy for keeping the traditional compensatory simulation by an enrichment in the estimation process that allows some non compensations between factors.

2. Noriaki Kano attribute classification

The *type* classification of *satisfaction items* is a standard analysis in all *customer satisfaction* studies. A very interesting classification, extensively used for prioritizing corrective actions, is due to Noriaki Kano. For a *given consumer* in Kano's language an attribute can be:

1. *Attractive,* when the increase in attribute functionality implies an increase in consumer's satisfaction, while the decrease in functionality does not imply a similar decrease in consumer's satisfaction. Attractive attributes are *not considered mandatory*, but something contributing to the increase of user's satisfaction with the product.
2. *Must be*, when the decrease in the attribute's functionality implies a decrease in consumer's satisfaction, while an increase above a *threshold* does not imply a corresponding increase in consumer's satisfaction. The attribute is *mandatory*. Consumers would never accept a product whit that attribute under a *threshold*

functionality, while a functionality above that threshold would be considered immaterial.

3. *One dimensional*, when the effect on consumer's satisfaction is the same either in the increase or in the decrease of the attribute's functionality.

Kano attribute classification has been popular for years in the domain of customer satisfaction, where both *product features* and *conditions of use* contribute to the perceived fitness between user's expectation and user's experience. In a conjoint study a *revised attribute classification* still makes sense. We suggest a slightly different one from the very Kano classification, we deem better suited for product design.

First of all, our focus will be on *scores* as an assessment of the *expected level of fitness* rather than the ex post *satisfaction* from usage experience for the factor level in question. In a graph of *preference* (*0 to 100*) towards *functionality*, three shapes can be observed. (In the following the term preference is used as a *generic equivalent* for *fitness* with customer needs).

1. The *enhancing* shape typically has a minimum around the *indifference point* of *50* and grows with functionality until around *100*.
2. The *mandatory* shape typically starts around *0* for a *0* functionality and grows until the *indifference point* of *50* for the maximum possible functionality.
3. The *dominant* shape spans fitness from *0* to *100* while functionality spans the full range.

This classification differs at a good extent from the Kano classification. For the *attractive* case, Kano suggests a preference *acceleration* towards the maximum possible functionality, with a *reversed curve concavity*. We think that the *preference saturation principle* should always be kept. Thus we combine the *magnitude scaling approach* with the *Kano classification* of attributes. In our approach, curve always *saturate to the right*. The difference stems from the different meaning of Kano classification and the new one. Kano is for *satisfaction from experience*, the new classification is for *product design*.

In *customer satisfaction*, attractive attributes someway interpret the case of a satisfaction *above expectations*. Customer satisfaction is due both to product characteristics and to product conditions of use. A consumer could be impacted by an enhancement of satisfaction because of the conditions of use, and this has to be interpreted in customer satisfaction models.

The new classification is mostly oriented to product design, where a saturation in preference is the standard case. Product designers very seldom include conditions of use in the design. Taguchi *off line quality control* does consider conditions of use, but from a technical standpoint. Marketing view of product design can't consider conditions of use in full detail. So, within design limits, the axiom of *diminishing* marginal growth of preference should always be kept. That's why, to avoid any confusion, the author suggests a *different terminology*. An attribute will be called

1. *Mandatory*, when a loss in functionality implies a steep preference decline while a functionality growth above an *upper* subject specific *threshold* doesn't significantly impact the corresponding preference. Preference saturation is attained at the threshold value, well before the maximum possible functionality. An accelerated decline takes place around the minimum possible functionality.
2. *Enhancing*, when a functionality increase makes the preference to grow up to the maximum possible preference, while a functionality decrease under a *lower* subject specific *threshold* virtually implies no effect. Preference saturation is attained at the maximum possible functionality and no acceleration is observed when the functionality attains the lower threshold value.

3. *Dominant*, when variations in functionality have a *big impact* on the consumer preference both in *increase* as well as in *decrease*. Attribute *importance*, a standard conjoint output, would classify dominant attributes among the *most important* ones.

You may correctly assume that designers know well in advance if an attribute is, say, *mandatory*. But this assumption, while possibly correct at aggregate level, may be wrong at subject level because of R's personal tastes. As a basic requirement in conjoint models, you should always keep the *subject level approach*.

If you actually want a *positive R's choice*, all *mandatory* attributes should be set at *least to their threshold values*. Attributes falling in the other kinds, *enhancing* or *dominant*, freely tradeoff between each other.

For a more comprehensive choice model, where compensatory and non compensatory choice rules coexist, the only distinction that applies is between

1. *compensatory* attributes:
    a. *enhancing* factors freely tradeoff with other *enhancing* or *dominant* factors.
    b. *dominant* factors freely trade off with other *dominant* or *enhancing* factors.
2. *non compensatory* attributes. Compensation can't take place in the case of *mandatory* factors. Unsatisfactory functionality under the subject *upper threshold* for an attribute level would end up with the consumer refusing any offering including that level for the attribute in question.

3. How the extended conjoint model works

The first step is the transformation of *intentions to buy* from the *preliminary scoring phase* into *choice probabilities*. Scoring is a task where R's are asked to provide an answer for *each factor level* in *all factors* according to the following table where only four possibilities are admitted

1. *I would certainly buy if the decision was pending just on this level*
2. *I would probably buy if the decision was pending just on this level*
3. *I wouldn't probably buy if the decision was pending just on this level*
4. *The level shown would drive me to refuse any combination with that level, even if all the other factors were set at a level of my satisfaction*

In a Bayesian mood, we pick up a suitable Beta distribution through a couple of parameters (α, β). Starting values are not so important, because the process goes through iterations. While α is kept between 1 and 2 and is almost immaterial, β is made to increase from 1 to 20 as the intention to buy deteriorates.

The statistics chosen for the assessment of convergence is the *Kruskal gamma* for the fit of shown cards.

Just three iterations are shown from a real case here in Italy:

iteration 1.

Probability of choosing (10 intervals)

Obs	1	2	3	4	5	6	7	8	9	10
NO	282	257	228	226	241	278	280	319	351	385
YES	0	0	1	3	11	14	31	65	234	1838

1613 “NO” estimated above 0.50 choosing probability, with “optimism” ratio = 31.97%

iteration 2.

	Probability of choosing (10 intervals)									
Obs	1	2	3	4	5	6	7	8	9	10
NO	561	367	310	283	302	214	225	232	207	146
YES	2	4	9	8	18	19	48	104	267	1718

1024 “NO” estimated above 0.50, “optimism” ratio = 20.30%

iteration 3.

	Probability of choosing (10 intervals)									
Obs	1	2	3	4	5	6	7	8	9	10
NO	983	420	307	276	218	152	147	135	111	98
YES	19	15	19	19	32	47	66	125	257	1598

653 “NO” estimated above 0.50, “optimism” ratio = 12.74%

You can see that mandatory factors, when dealt with if they were compensatory, make a good fraction of shown cards to be optimistically forecasted. This is the *wrong effect* of not considering that some factors are not compensable for a sizable part of the sample.

In the real case shown above, the customer expecation for the number of choosers of the new product was 310.000. Before iterations, the overestimation was around 48%. This falls to 31.97%, 20.30% and 12.74% after the third iteration. Both the customer and the researcher decided to stop here because the optimism ratio was considered acceptable.

References

[1] Anja Dieckmann, Dippold Katrin and Dietrich Holger, *April 2009, Journal of Decisions Making,* “Compensatory versus non-compensatory models for predicting consumer preferences”

[2] John R. Hauser, Olivier Toubia, Theodoros Evgeniou, Rene Berfurt, Daria Dzyabura*, June 2010, Journal of Marketing Research*, “Disjunctions of Conjunctions, Cognitive Simplicity, and Consideration Sets”