Using conjoint analysis across the marketing value chain

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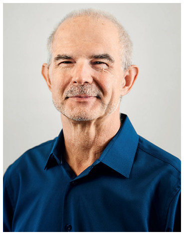

Marco Vriens
CEO, Kwantum, USA

Marco Vriens is CEO of Kwantum, an analytics and AI-driven brand intelligence firm. He has a Master's degree in psychology and a PhD in marketing analytics and is an expert in brand research, analytics and marketing research. He is a recognised authority in brand density and holistic conjoint analysis. He is the author of 'The Business of Marketing Research' (2020), 'From Data to Decision: Handbook for the Modern Business Analyst' (2023) and 'Handbook of Marketing Research' (2006).

Kwantum, Sausalito, 48 Marion Ave., CA 94965, USA
Tel: +1 4154505241; E-mail: marco.vriens@teamkwantum.com

Felix Eggers
Chief Consumer Science Officer, Kwantum and Professor, Copenhagen Business School, Denmark

Felix Eggers is Chief Consumer Science Officer at Kwantum and a full professor at the Copenhagen Business School. His research has a methodological and a managerial focus. Managerially, he is primarily researching topics about digitisation, such as digital business models. Methodologically, he focuses on quantitative research methods about consumer decision making, such as conjoint analysis and discrete choice experiments. He is also a collaborator in the Measuring the Digital Economy Initiative and the development of GDP-B.

Copenhagen Business School, Solbjerg Pl. 3, 2000 Frederiksberg, Denmark
Tel: +4538152107; E-mail: fe.marktg@cbs.dk; felix.eggers@teamkwantum.com

Abstract Conjoint analysis, best known in its choice-based form, has become one of the most commonly applied techniques in marketing research since it was introduced in the early 1970s. Its popularity stems from its ability to provide a systematic, experimental framework for collecting and analysing data on how product attributes and their levels influence consumer preferences and decision making. By simulating real-world trade-offs, conjoint analysis generates managerial insights such as the relative importance of product features, consumers' willingness to pay and predicted market shares, making it an essential tool for product design, pricing strategies and competitive positioning. Methodological advances have enabled researchers to apply conjoint across the entire marketing value chain, as well as to deal with the associated challenges, such as how to deal with (too) many attributes, which type of experimental design to use, how to minimise hypothetical bias, whether to include benefits or other meta-attributes, how to account for non-compensatory decision making, how to account for consumer budgets, etc. This paper discusses the challenges encountered when applying conjoint across the marketing value chain, and the methods best suited to manage these challenges. In this way, the paper provides a concise user's guide to making good methodological choices without getting drowned in the vast literature on this topic.

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INTRODUCTION

Conjoint analysis has been called the most applied marketing research method[1] and has been a popular research topic for academics and applied researchers.[2,3] This is both a blessing and a curse: a blessing because advances have resulted in conjoint being able to address an increasing number of marketing problems; a curse because there are now so many methodological varieties that it is hard for the average market research practitioner to determine which flavour to use in which context.

For most applications, choice-based conjoint[4] (CBC) is considered the *de facto* standard. However, even with CBC there are numerous varieties and many methodological choices, such as how do to deal with many attributes or attribute levels, which experimental design approach to use, how to adapt the design to specific consumers, how to minimise hypothetical bias in the data collection, whether to include benefits or other meta-attributes in the estimation, whether the model should always be compensatory, how willingness-to-pay (WTP) should be determined, etc. In many cases, there is not a determinable best answer.

This paper reviews advances through the lens of how they have enabled a widening use of conjoint across the marketing value chain and what methods are available to manage the challenges that are encountered in practice. Although we assume that the reader is familiar with the basic concepts of conjoint, a short summary of the methodology is provided.

THE MARKETING VALUE CHAIN

The marketing value chain can be defined as the specific successive steps in which marketing can add value to the business, from the identification of customer needs, developing products that consumers want, launching the product successfully in the market to supporting its ongoing success with effective packaging, promotion, advertising and branding. Table 1 outlines the marketing value chain concept.

Table 1: The marketing value chain

Stage
(New) product development
1. Idea and concept development; creative challenge. For really new products, consumers may not be able to give valid feedback.
2. Concept and feature evaluation — assessing interest and the importance of features; prioritising an initial large set of features.
3. Pricing and feature willingness-to-pay (WTP) — determining the monetary value of what consumers are willing to pay for a new feature.
4. Product and product line optimisation — finding the feature combination and product line that optimises market share and/or revenue.
5. Estimating primary demand for new features or new concepts.
6. Understanding consumer heterogeneity and market segments.
7. Identifying consumer decision rules and the use of potential shortcuts.

(*continued*)

Table 1: The marketing value chain (*continued*)

Stage
Go to market
8. Packaging — creating realistic profiles requires visuals, and cannot be done with verbal descriptions alone.
9. Identifying how an improved or new product should be advertised or positioned.
10. Distribution.
11. Assessing effectiveness of a specific promotions or sponsorship.
12. Pricing and setting sales quotas.
13. Understanding market segments and targeting — linking attribute-level utilities to demographic and media usage variables.
Branding and brand tracking
14. Assessing brand equity — measuring the monetary value of a brand.
15. Assessing importance and monetary value of brand attribute perceptions; measuring how changes in brand perceptions impact brand equity.
16. Importance of and monetary value of brand associations.
17. Brand tracking — tracking brand value over time.

A BRIEF SUMMARY OF CONJOINT

Conjoint, and the current standard choice-based conjoint, can be applied across the marketing value chain. A full introduction of conjoint is not the intention of this paper as several exist already.[5–7] Conjoint analysis starts with breaking down the product (or problem) in attributes and attribute levels. As a simple example, we could define smart watches on two attributes: brand and price. Each attribute will be defined on several discrete levels. For example, brands could be Apple, Google, Garmin and Fitbit; price levels could be: US$50, US$100, US$150, US$250 and US$400. By combining brands with prices, we can create 20 possible smart watches (some may exist, some may not). With CBC, we create a set of possible watches and allocate these into various choice sets. In this example, 20 possible watches would be randomly assigned to five choice sets, where each choice set contains four possible watches. Survey respondents will then see these choice sets, and for each choice set they will be asked to indicate which smart watch they would buy, if any. These choices are multinomial choices that can be analysed with logit (MNL) models. In this case, the independent variables are whether a level of an attribute is present or not. This analysis yields utility estimates for all the levels included in the study. From this, we can make predictions as to what combination of levels is most attractive to our target audience. Of course, as we use more attributes and levels to define our products, the number of possible watches grows very quickly and the task for the respondents becomes increasingly undoable. We use experimental design techniques to select a manageable number of possible watches. Even though respondents will only evaluate a small set of watches, the use of our experimental design allows us to infer overall appeal even for watches that were not shown.

Different experimental design strategies and options to analyse/model the data have been proposed. In general, we choose an experimental design that enables us to create a manageable task for the respondent that still yields reliable parameter estimates and enables us to estimate the main effects of all levels and, often, also potential interactions between attribute levels. For the analysis, hierarchical Bayes (HB) MNL models[8] are used, so we can obtain insight into individual differences in respondents' preferences.

CHALLENGES

If the task becomes bigger, even with experimental designs to reduce the set, it may become too hard for respondents, thus compromising data quality. In fact, we may encounter several challenges that may lead to results that do not represent how consumers make decisions in the real world. Some challenges are generic, and some are more likely in some applications than others. Table 2 describes common challenges across the various applications.

Except for identifying unmet needs and creating initial product ideas, product development is probably the sweet spot for conjoint. In (new) product development, the methodological challenges are dealing with many attributes, many attribute levels, creating realistic profiles, understanding what decision styles consumers use (compensatory versus non-compensatory), and dealing with hypothetical bias to infer WTP.

When a conjoint study includes many attributes, the task may simply become too large for respondents, resulting in unacceptably low data quality and respondents dropping out of the survey altogether. In addition, respondents are less likely to engage in the trade-off exercise in the desired manner, and mental fatigue will set in sooner. Respondents can react to this by using extreme simplification strategies, such as focusing just on brand and price. If these simplification strategies differ from what consumers are doing in real purchase situations, the conjoint insights will not be valid. In the worst case, respondents could make random choices just to get the task over with.

Conjoint analysis assumes that attributes are in a compensatory relationship with each other, that is an unattractive level in one attribute (eg an unknown brand) can be compensated with an attractive feature of

Table 2: Methodology challenges across the marketing value chain

Challenge	Steps where challenge encountered
Dealing with many attributes and many attribute levels	Across all stages
Consumers may use shortcuts/non-compensatory decision rules or even choose irrationally	Across all stages
Hypothetical bias/risk of over-estimating WTP	Mostly in product development and pricing
Task dependency and learning — How type of task affects results	Across all stages
Accounting for consumer budgets	Pricing
Accounting for competitive reactions	WTP, pricing
Understanding consumer heterogeneity and market segments	Across all stages
Creating realistic profiles	Packaging, new product development
Understanding the role of consumer goals and benefits	Promotions, advertising and branding
Soft brand perceptions cannot directly be included in the conjoint	Branding
In integrating binary brand associations, we may be limited because of data sparsity	Branding

another attribute (eg a low price). However, sometimes features are non-compensatory. For example, a vegetarian would not choose any meal that contains meat, even if it were priced very attractively. Identifying whether respondents engage in non-compensatory decision making or which attributes it relates to is a challenge because non-compensatory models are typically more complex analytically.

Hypothetical bias refers to the fact that we are eliciting responses from choice sets that do not exist in the real world and are presented in a survey that has typically no buying obligation. Especially responses to pricing scenarios may not reflect what customers do in a real-world scenario as they overestimate their WTP in non-consequential scenarios, ie they typically are more likely to buy hypothetically than in real life.[9]

Research has shown that preferences are often constructed during the exercise and are not fixed.[10] The construction can be influenced by the type of task and context.[11,12] For example, as respondents go through the conjoint task, they may become more familiar with the attributes or may become fatigued. Both can alter their choice behaviour.

The methodological challenges we encounter in go-to-market include creating realistic profiles (when determining packaging), creating realistic choice scenarios to avoid hypothetical bias, accounting for potential competitive reactions,[13] integrating consumer goals and benefits into the conjoint as they are often targeted in advertising campaigns[14] and linking attribute-level utilities to demographic and media usage variables or available budgets, for instance.

Many conjoint studies aim to determine the strength of the brand, relative to other product attributes. The brand strength can serve as an important input to determine brand price premia or monetary brand value. Still, the conjoint study cannot readily determine the sources of the brand's equity: what brand associations contribute to the brand's strength?

The goal in branding and brand tracking is to determine the monetary value of a brand and to determine the value of perceptual brand positioning statements and unaided brand associations. The challenge here is if the respondent's task is small and short enough to include in a tracking study.

DEALING WITH METHODOLOGICAL CHALLENGES

Dealing with a large number of attributes

In this stage especially, we are likely to have many potential features. There are specific varieties of conjoint that work best to avoid a task that is too hard or too fatiguing:

- MaxDiff;
- individualised two-level CBC (HIT-CBC);
- holistic conjoint;
- menu-based conjoint;
- bridging designs and other methods (eg partial full profile analysis, adaptive conjoint methodologies).

Maxdiff and HIT-CBC

MaxDiff (also referred to as best–worst scaling)[15] ignores specific levels of an attribute and has the objective to scale a multitude of attributes according to their perceived relevance. Ignoring the levels of an attribute allows one to focus on a multitude of attributes. Alternatively, it would also be possible to focus just on a single attribute (eg advertising campaign) and study a multitude of mutually exclusive levels (eg slogans). Another variant, hybrid individualised two-level choice-based conjoint (HIT-CBC),[16] customises the conjoint experiment to the individually perceived best and worst levels of an attribute to determine the attribute relevance, making it possible to score the remaining levels outside the conjoint.

Holistic conjoint

Holistic conjoint incorporates a heuristic that consumers perceive more features as better.[17] Although the holistic conjoint approach does not *per se* simplify the conjoint task, it does model the likely simplification strategy used by consumers.

Menu-based conjoint

Menu-based conjoint (MBC)[18] is an extension of traditional conjoint analysis that allows respondents to build their own product or service by selecting from a set of features and options, often with associated prices. MBC better reflects real-world purchasing scenarios where consumers can customise offerings (eg when building a PC) or are offered bundles (eg a phone with a cellular contract).

Bridging design and other methods

Bridging designs require more than one conjoint study that can be connected via joint attributes.[19] We typically create two tasks: (1) one with only foundational or macro attributes and (2) other with specific or micro attributes. By having some attributes in both tasks, we can link them. Other methods exist to deal with many attributes or levels, such as partial profiles designs, in which only a randomised subset of attributes is shown in a conjoint task, or adaptive methodologies that aim to customise the conjoint tasks.

Shortcuts and non-compensatory decision making

Although in practical situations the compensatory model is assumed, that is an unpreferred level of one attribute can be compensated by an attractive feature of another attribute, we know that this is not always a fully realistic representation of consumers' decision making: they can use various shortcuts, non-compensatory decision rules or may choose in a way that seems to be irrational.[20] To capture such decision styles, several modelling approaches have been used:

- models that include a consideration set step; models that allow for disjunctive or elimination of aspects;
- adaptive or learning conjoint;
- holistic conjoint; and
- models that allow for context effects.

Consideration set models

We can use models that include a consideration set element, such as a consider-then-choose model. The idea is that alternatives that are not considered consist of some elements that are not compensatory. The model then entails two steps. First, consumers would indicate all options that they would (not) consider for purchase. Secondly, the conjoint experiment will include only those stimuli that are considered and consists of compensatory elements.

The consideration step makes it possible to identify which decision rules a consumer may employ. For example, disjunctive or conjunctive decision rules have been proposed. Disjunctive screening assumes that consumers consider a product if it has at least one acceptable feature. In conjunctive screening, all features must be acceptable.[21] Another strategy is that consumers can eliminate certain alternatives because of unacceptable features.[22] This will limit the number of options but could still leave many open. Identifying decision heuristics such as disjunctive or conjunctive rules allow us to understand consumers' choice better. However, they add a layer of analysis to a conjoint study, and they do not substantially simplify the decision difficulty for conjoint studies. Generative AI may help identify decision rules outside of the conjoint part.[23]

Learning conjoint

Another interesting development could be referred to as learning conjoint. As respondents go through the conjoint exercise, we learn what they like and could use this information to optimise subsequent choice sets shown. Adaptive procedures aim to adjust the conjoint experiment based on what the model has learned so far about the decision maker. Some methods, such as adaptive CBC, aim to identify unacceptable levels that are then subsequently excluded from the exercise. Others aim to optimise the experimental design to show more relevant options in the choice sets or options that help to identify the underlying parameters better, such as the fast polyhedral adaptive conjoint estimation.[24]

Holistic conjoint

As another simplification strategy (which to our knowledge is yet to be fully investigated), consumers may look at some features very specifically while at the same time evaluating another group of attributes more holistically in terms of certain perceived benefits or goals, or even just to get a feeling for overall value for money.[25] We might call this the 'gestalt' heuristic. A model for this decision strategy is the holistic conjoint approach, which has been shown to substantially improve predictive accuracy.[26] Indeed, in two studies conducted by Vriens and Eggers, such a holistic dimension, measured as the number of features, was the most important attribute after brand and price.

Irrational conjoint

Sometimes consumers act seemingly irrational, as they choose alternatives that will not maximise their utility. Some of these choices can be explained by context effects. Two important context effects are the attraction effect and the compromise effect. The attraction effect occurs if, for example, one alternative is dominating another alternative (a decoy). Here, the dominating alternative appears to be much more attractive even though another alternative might be the best rational choice. The compromise effect describes the phenomenon that consumers increasingly choose options that have average features, compared with a high-priced premium option and a low-cost basic option. Marketers often use such context effects to promote their offerings. If creating such a choice architecture is relevant, then these context effects can be estimated from the conjoint data.[27]

Hypothetical bias

Hypothetical bias is a challenge in conjoint, especially in pricing and willingness-to-pay applications. The conjoint task, by definition, is hypothetical because the profiles shown often do not exist (yet) and because we ask respondents to make product choices in a survey which obviously is not the same as buying something. Not surprisingly, the estimated WTP for new features often overestimates the price that respondents are truly willing to pay. Several conjoint varieties have been proposed to mitigate this issue:

- dual response conjoint[28;]
- truth-telling or incentive-aligned mechanisms for conjoint[29–31;]
- real-world calibration;
- budget-constrained conjoint[32;]
- accounting for competitive reactions[33;] and
- creating realistic profiles.

Dual response conjoint

Dual-response conjoint separates the no-choice option, which is often integrated into the choice sets if none of the options are attractive ('I would not buy any of these options'), to a separate question. When shown a choice task, respondents first choose their preferred option, and then in a second question, respondents answer a binary question: would they actually buy their preferred alternative or not. The purchase question then becomes more salient, which has been shown to produce more realistic adoption predictions and WTP estimates.[34]

Truth-telling or incentive-aligned conjoint

Incentive-aligned conjoint connects a reward that is given to a selection of participants to the decisions that were made in the study. For example, telling consumers that they will obtain one of the chosen options in the conjoint experiment (or being able to buy it from a provided budget) has been shown to induce truth telling, resulting in higher predictive accuracy. Another option to calibrate the results to reflect realistic choices is to validate and scale the estimates by predicting real marketplace transactions or a realistic holdout task.[35]

Using real-world calibration

Using real-world calibration can be done by using actual market data (sometimes referred to as revealed preferences) to tune the conjoint results. This is more applicable to branding conjoint studies in which actual market shares may be available to serve as a validation benchmark; it is less applicable for product innovation studies in which real products may not exist yet.

Budget-constrained conjoint

In this approach, respondents are asked about their disposable income, and to state their available budget after they learn about the attributes and levels. These two indicators are used to derive a latent budget. In their study using this approach for high-price laptops, Pachali *et al*. found that a standard linear pricing approach overestimates the price for a premium brand by 20 per cent.[36] A model that accounts for budget constraints increases the accuracy of price predictions.

Accounting for competitive reactions

One of the objectives of CBC is to predict choice shares, given specific scenarios. For example, given a certain product configuration and competitors' alternatives, what are the expected market shares? Given these predictions marketers can aim to identify the best product configuration and price that increases market or revenue shares. However, competitors will most likely not remain static given these actions but will react with their own product modifications or price changes. It is possible to model the best competitive reactions into the simulators with the aim to identify an equilibrium.[37,38] These simulations will be able to tell if a specific marketing activity will lead to a long-term gain or result in higher competition and downward-spiralling prices.

Understanding consumer heterogeneity

An important strength of CBC analysis is its ability to uncover consumer heterogeneity in preferences and translate these insights into marketable actions. Different estimation techniques provide distinct approaches to understanding this heterogeneity, each with its own strategic and technical implications.

From a marketing strategy perspective, latent class analysis (LCA) is particularly useful for segmentation, targeting, differentiation and positioning. By grouping consumers into discrete segments based on their choice behaviour, LCA allows firms to identify segments with distinct preference structures. These segments can then guide product design, pricing and messaging strategies. However, LCA faces methodological challenges when applied to large sample sizes, as the number of segments may increase beyond a manageable level and may identify segments that differ only on minor aspects or the variability that they show in their choices.

In contrast, HB analysis[39] estimates individual-level preferences by incorporating prior assumptions about the distribution of those preferences. While understanding individual choices may be less directly useful from a managerial standpoint, HB offers strong predictive capabilities and can often improve market share predictions, making it a valuable tool for demand forecasting and scenario planning. We can also take the individual-level utilities from the HB estimation and use these as input into a clustering algorithm (eg K-means, latent class).

Ultimately, the choice between LCA and HB depends on the analytical objective: LCA provides clear, actionable segments for targeting and strategic positioning, whereas HB offers a more granular understanding of preferences, leading to robust choice and market share predictions. Marketers must weigh these trade-offs to effectively harness consumer heterogeneity in decision making.

The identification of conjoint based segments is not per se a huge challenge. Nevertheless, because conjoint segments are in a sense needs-based segments they typically cannot be predicted very well using background and media usage variables like we do in typing tools. This is a vital part in a segmentation project as firms will want to apply the segments to their customer database and will need to know how to reach these segments. For this, several advanced classification tools have been shown to improve the predictive quality of typing tools such as Support Vector Machines.

Creating realistic profiles

Most conjoint applications rely on text descriptions of stimuli. By contrast, most commercial offerings supplement their text-based descriptions with product images and/or videos. Conjoint studies that neglect to provide a realistic representation of the stimuli can suffer from systematic biases. Importantly, these biases often go undetected as consumers can learn to choose consistently based on text stimuli so that validity scores remain high. Given the advances in generative AI, it is now possible to create realistic-looking stimuli or product videos at scale for inclusion as stimuli.[40] Creating and displaying prototype stimuli in virtual or augmented reality is the next step.

Integrating goals and benefits

Consumers are goal focused, and their decisions may reflect that.[41] A few methods have been proposed to get insight into consumer goals and benefits either by asking about these outside the conjoint task and then integrating them back into the conjoint model, or by deriving them directly from the conjoint task. Two approaches are available to do this. We ask about goals and benefits outside the conjoint or we derive goals and benefits from the conjoint itself such as in holistic conjoint. In the study by Vriens *et al.*,[42] the conjoint task was preceded by asking respondents what goals (eg weight loss) they have and what benefits they are seeking (eg many features vs. simplicity). The goals and benefits were then used to predict who was most likely to switch from one brand to another.

The last challenge is easy to accommodate, as demographic and media usage variables can be added to the market simulator and simulations can be done for specific target groups.

Including soft brand perceptions and brand associations

Including brand positioning statements is a challenge in conjoint because such associations are typically soft attributes that cannot easily be defined on discrete levels and hence cannot directly be included in the conjoint design.[43] Brand perception responses are therefore collected outside of the conjoint and integrated in the modelling stage.[44] For example, if we use a HB approach, the brand utility parameter can be a function of the brand perception ratings.

Sometimes, brands are being assessed via open-ended questions (eg 'What comes to mind when thinking of brand X?'[45]) and discrete brand associations are extracted from such data. These can be integrated into conjoint models as well. Given that brand associations differ across brands, and can be numerous, we end up with a very sparse matrix with only a few associations that have been sufficiently mentioned by respondents. Such data can be collected outside the conjoint experiment and integrated into the analysis so that it is possible to determine the associations that contribute most. The brand utility is modelled as a function of which respondents have which associations with the brand. This can then be converted into a monetary value for each brand's association.

Valuation of free goods

Many services are provided for free to consumers, for example by being advertisement-funded or following a platform strategy. The lack of price attribute makes it considerably harder to calculate willingness-to-pay and other monetary measures. If monetary measures are desired, however, it is possible to apply customer surplus value (CSV) measures in these contexts. The CSV approach[46] asks consumers to imagine living without a certain product for one month in exchange for monetary compensation. Varying the monetary amount and observing the consumer's decision to give up the product make it possible to identify the surplus that the consumer achieves from these products.

CONCLUSION

Conjoint analysis has been around for more than 50 years. With the transition to choice-based models, conjoint can be used to study the general effects of consumer decision making and will continue to be relevant for years to come. This paper has summarised the main challenges one encounters when applying conjoint across the marketing value chain.

This concise overview will be useful for practitioners who may find it challenging to keep track of the enormous volume of literature on conjoint. We hope this will help practitioners make smarter choices when they use conjoint. For academics, it may be useful to see which challenges are still in need of better solutions. At the societal level, when increasingly dealing with privacy issues, and the value of giving up one's personal data in exchange for 'free' goods, conjoint and conjoint-like methods such as customer surplus value can be used to quantify what consumers are being 'paid' for their personal data.

The advent of generative AI and large language models will lead to several new developments. We are seeing several distinct possibilities. First, we can use generative AI to create synthetic respondents. This would eliminate the use of surveys; as a result, dealing with many attributes would become less of a problem. Secondly, we can use generative AI to create more realistic stimuli. Thirdly, generative AI can be used as a pre-study and the results be used to create more efficient experimental designs. Fourthly, AI could also be used to identify decision rules and non-compensatory aspects.[47] Lastly, the advent of advanced text analysis allows us to combine open-ended survey questions with conjoint data. These developments pave the way for promising hybrid methods that combine AI-based and human data to allow for more efficient data collection or applications to very complex contexts.

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