Using conjoint across the marketing value chain

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1. Introduction

Conjoint has been called the most applied marketing research method (e.g. Green et al., 2001) and has been a popular research topic for academics and applied researchers (e.g. Agarwal et al. 2015; Green, Krieger & Wind, 2001). This is both a blessing and a curse. A blessing because advances have resulted in conjoint being able to address more 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 flavor of conjoint to use in which context. Choice-based conjoint (CBC; Louviere & Woodworth, 1984) is considered the de facto standard for most applications. However, even with CBC there are numerous varieties and many methodological choices: 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 minimize hypothetical bias in the data collection, do we need to include benefits or other meta-attributes in the estimation, should the model always be compensatory, how should willingness-to-pay (WTP) be determined, etc. In many cases there is not a determinable best answer. We review advances through the lens of how it has 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.

2. 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 on-going success with effective packaging, promotion, advertising, and branding. Figure 1 below outlines the marketing value chain concept.

Figure 1. The marketing value chain

MARKETING VALUE CHAIN	
STAGES	**(NEW) PRODUCT DEVELOPMENT**
1	Idea & concept development.
2	Concept & feature evaluation: Assessing interest and importance of features. Prioritizing of an initial large set of features.
3	Pricing & feature willingness-to-pay (WTP): Determinming the $ value of what consumers are willing to pay for a new feature.
4	Product & product line optimization. Finding the feature combination and product line that optimizes 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 (compensatory versus non-compensatory) & the use of potential shortcuts.
	GO TO MARKET
8	Packaging.
9	Advertising & positioning: Identifying how an improved or new product should be advertised or positioned.
10	Distribution
11	Promotions & sponsorship: 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 & media usage variables.
	BRANDING & BRAND TRACKING
14	Assessing brand equity: Measuring the $ value of a brand.
15	Assessing importance and $ value of brand attribute perceptions. Measuring how changes in brand perceptions impact brand equity.
16	Importance of and $ value of brand associations.
17	Brand tracking: Tracking brand value over time.

CBC analysis can be applied in each of these steps, but we may encounter challenges that can be addressed better with a specific CBC conjoint variant that differs from standard CBC or another conjoint approach. Some challenges are generic, and some are more likely in some applications than others. See Figure 2 for common challenges across the various applications.

Figure 2. Methodology challenges

METHODOLOY CHALLENGES	STEPS WHERE CHALLENGE ENCOUNTERED
Dealing with many attributes and many attribute levels.	Across all stages.
Challenging to define all relevant packaging attributes. Creating profiles is visual, cannot be done with verbal descriptior	Packaging.
Consumers may use short cuts/non-compensatory decision rules or even choose irrationally	Across all stages
Hypothetical bias/risk of over-estimating WTP.	Mostly in product development & pricing.
Accounting for consumer budgets.	Pricing.
Accounting for competive 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 & branding.
Soft brand perceptions cannot be directly be included in the conjoint.	Branding.
In integrating binary brand associations we may be limited because of data sparsity.	Branding.

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 we include many attributes in a conjoint study, we may run into the problem that the task simply becomes too large for respondents resulting in unacceptable low data quality and respondents dropping out of the survey altogether. Also, respondents are less likely to engage in the tradeoff exercise we want them to do, and mental fatigue will set in sooner. Respondents can react to that by using extreme simplification strategies by 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 just make random choices just to get the task over with.

Conjoint analysis assumes that attributes are in a compensatory relationship with each other, i.e., an unattractive level in one attribute (e.g., an unknown brand) can be compensated with an attractive feature of another attribute (e.g., a low price). However, sometimes features are non-compensatory. For example, a vegetarian would not choose any meal that contains meat. Identifying whether respondents engage in a 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 since they overestimate their WTP in non-consequential scenarios, i.e., they typically are more likely to buy hypothetically than in real life (Wlömert & Eggers, 2016).

Research has shown that preferences are often constructed during the exercise and are not fixed (e.g. Amir & Levav, 2008). The construction can be influenced by the type of task and context (e.g. Agarwal et al., 2015). 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 behavior.

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, integrating consumer goals and benefits into the conjoint as they are often targeted in advertising campaigns (Reynolds & Gutman, 1988), 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. Yet, 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 $ 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.

3. Dealing with methodological challenges

Dealing with many attributes or many attribute levels
In the initial stages in the new product development cycle, such as concept development feature evaluation, choice experiments can be used to screen for the most appealing features. In this stage especially, we are likely to have many potential features. There are specific varieties of conjoint that work best. There are several available alternatives:

- MaxDiff
- Individualized two-level CBC (HIT-CBC)
- Holistic conjoint
- Bridging designs,
- Other methods (e.g. partial full profile analysis, adaptive conjoint methodologies).

MaxDiff (also referred to as best-worst scaling or BWS; Louviere, Flynn, & Marley, 2015) 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 (e.g., ad campaign) and study a multitude of mutually exclusive levels (e.g., slogans). Another variant called Hybrid Individualized Two-level Choice-based Conjoint (HIT-CBC; Eggers and Sattler 2009) customizes the conjoint experiment to the individually perceived best and worst levels of an attribute to determine the attribute relevance, which allows scoring the remaining levels outside the conjoint. Holistic conjoint incorporates a heuristic that consumers perceive more features as better and optimized the experimental design accordingly (Vriens & Eggers, 2025). Though the holistic conjoint approach does not per se simplify the conjoint task, it does model the likely simplification strategy used by consumers. Bridging designs require more than one conjoint study that can be connected via joint attributes (e.g. Lenk, et al., 1996). Other methods exist to deal with many attributes or levels, such as partial profiles designs, in which only a randomized subset of attributes are shown in a conjoint task, or adaptive methodologies that aim to customize the conjoint tasks.

Short cuts and non-compensatory decision making

Though in practical situations the compensatory model is assumed, i.e., 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 short cuts, non-compensatory decision rules or may choose in a way that seems to be irrational (Ding et al. 2011). To capture such decision styles, several modeling approaches have been used:

- Models that include a consideration set step
- Models that allow for disjunctive or elimination of aspects, and
- Adaptive or learning conjoint
- Holistic conjoint,
- Models that allow for context effects.

For example, 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. Second, the conjoint experiment will include only those stimuli that are considered and consists of compensatory elements.

The consideration step allows 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 need to be acceptable (Ding et al. 2011). Another strategy is that consumers can eliminate certain alternatives because of unacceptable features (e.g., Hauser et al., 2010). 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 do not simplify the decision difficulty for conjoint studies.

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 optimize 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 optimize 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 by Toubia, Hauser & Simester (2004).

As another simplification strategy, one that to our knowledge has not been fully investigated yet, 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 (e.g. Jenke et al., 201). We might call this the "gestalt" heuristic. Vriens & Eggers (2024) model this decision strategy and show that it substantially improves predictive accuracy. They found in two studies that such a holistic dimension, measured as the number of features, was the most important attribute after brand and price.

Sometimes consumers act seemingly irrational, as they choose alternatives that will not maximize 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). That way 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 to 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 (Rooderkerk, van Heerde, Bijmolt 2011).

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 respondents are truly willing-to-pay. Several conjoint varieties have been proposed to mitigate this issue:

- Dual conjoint (Brazell et al., 2006)

- Truth-telling or incentive-aligned mechanisms (Ding 2007; Ding, Grewal, and Liechty 2005; Dong, Ding, and Huber 2010) for conjoint.
- Real-world calibration,
- Budget constrained conjoint (Pachali, Kurz & Otter, 2023), and
- Accounting for competitive reactions (Hauser, Eggers, and Selove 2019)
- Creating realistic profiles

Dual 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 (Wlömert and Eggers 2016).

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.

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 (Hauser, Eggers, and Selove 2019).

Budget-constrained conjoint

Pachali, Kurz & Otter (2023), asked respondents 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. They found that a standard linear pricing approach overestimates the price for a premium brand by 20%. A model that accounts for budget constraints increases the accuracy of price predictions (their approach was used for high ticket price laptops.

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 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 (Allenby et al. 2014; Hauser, Eggers, and Selove 2019). 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-spiraling prices.

Craft: Creating realistic profiles
Most conjoint applications are performed using text descriptions of stimuli. Yet, few commercial offerings are available on the market solely described by text. Often product depictions or videos are also available. Neglecting these more realistic representations of options in the conjoint study can lead to systematic biases as they don't show how the stimuli are presented in real life. 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, creating realistic looking stimuli or product videos at scale is now possible that can be incorporated as stimuli (Eggers, Hauser, Selove 2016). Creating and displaying prototype stimuli in Virtual or Mixed Reality is the next step.

Integrating goals and benefits
Consumers are goal focused, and their decision may reflect that (Fisher et al., 1999). 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 to conjoint model (Vriens, Elder & Mills, 2023), or by deriving them directly from the conjoint task. Two approaches are available to do this. In the Vriens, Elder & Mills (2023) study, the conjoint task was preceded by asking respondents what goals (e.g. weight loss) they have and what benefits they are seeking (e.g. 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 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 (e.g. Vriens & Frazier, 2001). So, brand perception responses are collected outside of the conjoint and integrated in the modeling stage (e.g., Eggers & Eggers 2022). For example, if we use a Hierarchical Bayes approach, the brand utility parameter can be a function of the brand perception ratings.

Sometimes, brands are being assessed via open-ended questions (e.g. What comes to mind when thinking of brand X; see Vriens, Chen and Schomaker, 2019), 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. This 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 modeled as a function of which respondents have which associations with the brand. This can then be converted into a $ value for each brand's association.

Valuation of free goods

Many services are provided for free to consumers, for example by being ad-funded or following a platform strategy. Not having a price attribute, these studies prevent calculating willingness-to-pay and other monetary measures. If monetary measures are desired, it is possible to apply consumer surplus measures in these contexts. The Consumer Surplus Value approach (Eggers et al. 2024) asks consumers to imagine living without a certain product for one month in exchange for monetary compensation. Varying the monetary amount and observing consumers decision to give up the product allows to identify the surplus that consumer achieve from these products.

Outlook

Conjoint analysis has been around for more than 50 years. With the transition to choice-based models they are now allowed to study general effects of consumer decision making and will continue to be relevant also for the years to come. With the advent of Generative AI and Large Language Models conjoint experiments can also be conducted on artificial personas that can be asked which options they would prefer. AI could also be used to identify decision rules and non-compensatory aspects (Dong 2024). 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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