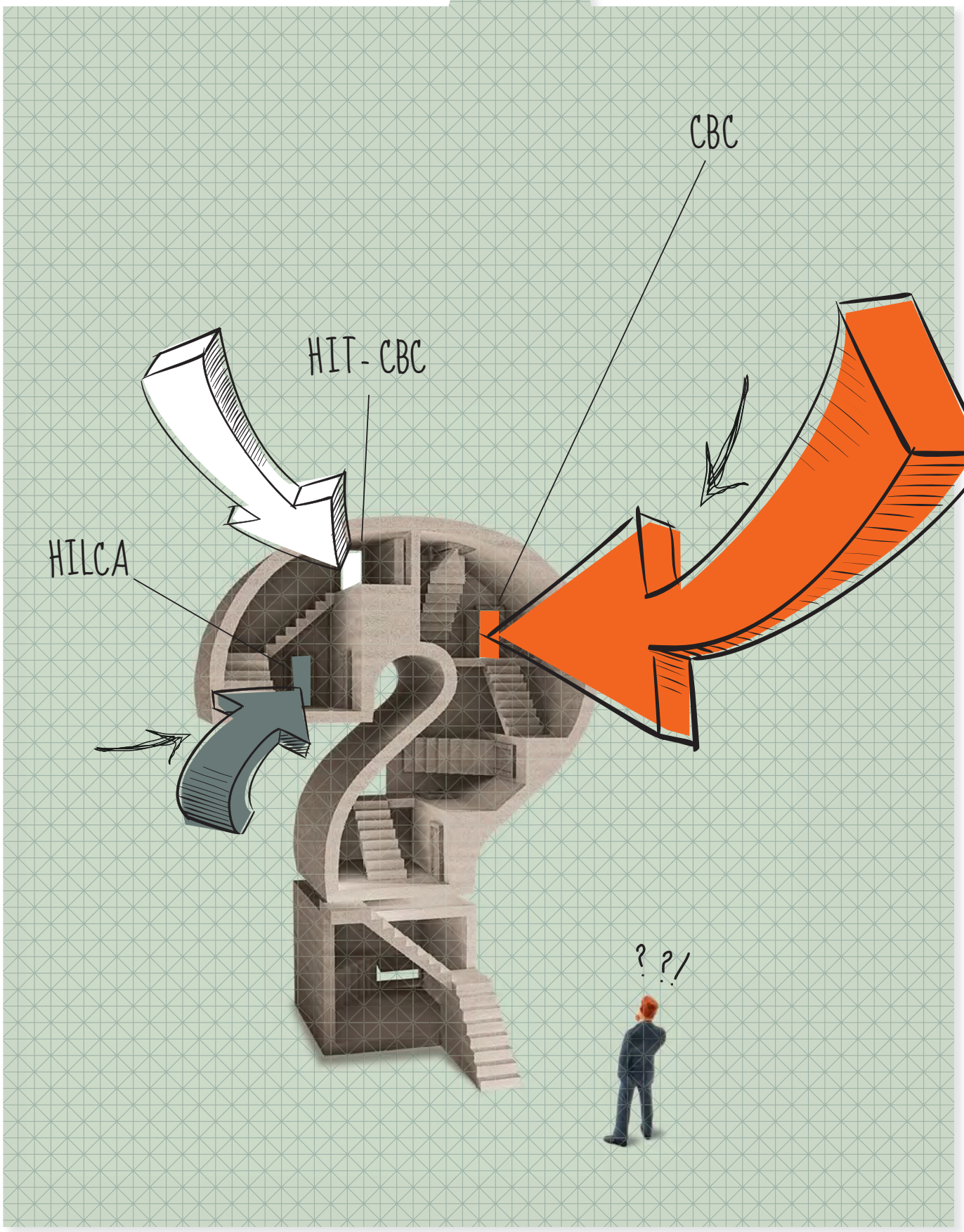
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Preference Measurement with Conjoint Analysis
OVERVIEW OF STATE-OF-THE-ART APPROACHES AND RECENT DEVELOPMENTS

Felix Eggers and Henrik Sattler

Determining consumer preferences is still one of the most important topics in marketing research. Not surprisingly, numerous approaches have been developed for this task. Conjoint measurement techniques are among the most prominent and different forms have emerged over the years. Depending on the specific research setting, all of them have their advantages and drawbacks. The authors discuss the nature and applicability of recent conjoint approaches and provide examples. Guidelines for selecting the optimal technique help to identify which approach works best in a given situation.

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This article summarizes various publications by the authors.

The motivation for new methodological approaches is based on *Eggers, F. and Sattler, H. (2009)*: "Hybrid Individualized Two-level Choice-based Conjoint (HIT-CBC): A New Method for Measuring Preference Structures with Many Attribute Levels", International Journal of Research in Marketing, 26 (2), pp. 108 – 118.

Why Preference Measurement is Important

Preference measurement, one of the most important topics in marketing research, helps marketing and management decision makers by revealing what consumers like and prefer. In addition to describing what consumers do, preference-based analyses reveal the underlying motives for their actions. In turn, the analyses generate sustainable consumer insights and a solid basis for predicting consumer behavior, including their purchase decisions.

In preference measurement products (including services) represent attribute bundles, i.e., combinations of attribute levels. Accordingly, a television is a bundle of its attributes, such as its brand (with the attribute levels Sony, Samsung, Grundig, and Panasonic, for example), screen technology, screen size, interfaces, price, and so on. Preference measurement tries to analyze how consumers value each component and come up with a quantifiable result. Formally, this valuation produces a utility function that translates the specific characteristics of a product into consumers' perceived preferences. This function can then predict purchase decisions in varying conditions, such as for product modifications, competitive reactions, or various pricing scenarios. With these predictions, managers can recognize which attributes and characteristics have the greatest impact on consumers' choice processes or can measure price elasticity. Beyond pricing and product management, preference measurement supports brand management; for example, it can assess the potential for a brand extension into other product categories or determine a brand's monetary value. Other applications include predictions about the diffusion of innovations or preference-based market segmentation.

» Although choices are omnipresent and CBC has conceptual advantages, this method is often not the final answer. «



In the past 40 years, various methods have tried to elicit consumer preferences using experimental questionnaires. Generally, these methods can be categorized into three groups:

> ***Compositional approaches***. Respondents evaluate the product attributes and levels separately, and then the total utility of a product can be computed by a simple linear aggregation rule. The perceived utility of an entire product therefore is ***composed*** of the ratings of its specific attributes and levels. The most prominent compositional approach is the self-explicated method.

> ***Decompositional approaches***. Respondents evaluate entire products by ***considering*** the product attributes and levels ***jointly*** (i.e., conjoint analysis). These preferences then can be ***decomposed*** using statistical methods.

> ***Hybrid approaches***. Combinations of the compositional and decompositional approaches.

Although there is no golden rule for selecting one of these approaches, conjoint analysis has become the most popular method for measuring customers' preference structures.

Conjoint methods differ in how the respondent evaluates the examined product. Traditional conjoint methods use a ranking or rating procedure as a proxy for people's preferences. In choice-based conjoint (CBC), as initiated by Louviere and colleagues, consumers repeatedly choose their most preferred product from a set of alternatives. The CBC approach is effective, because choices are an integral part of people's everyday life. Buying a specific product or deciding to read this journal, rather than another, represent choices that are ''natural'' manifestations of a person's preference, and they are easy to accomplish. In contrast, rating products, e.g., on a scale from 1 to 7, is not a behavior that a person usually adopts in typical purchase decisions. Moreover, the meaning of the values on the rating scale is more or less open for interpretation. Ratings are especially problematic in cross-cultural studies (e.g., international brand valuation), because different cultures react differently to rating scales (e.g., some cultures always avoid scale endpoints or specific numbers).

Although choices are omnipresent and CBC has conceptual advantages, this method is often not the final answer. A weakness is that analyzing choices generates limited information: which alternative was chosen and which were not. The differences in the attractiveness of the alternatives remain unclear. In this respect, ranking- or rating-based conjoint methods provide more information, because the respondents evaluate each alternative explicitly. As a relatively new methodological approach, CBC continues to require extensive research, including efforts to test variations of its procedure, choice design, or estimation—or completely new choice-based methods. Next, we will discuss the required steps when conducting CBC surveys and highlight under which conditions the method is likely to perform well. We then describe some of the newer adaptive conjoint approaches, each of which attempts to overcome some of the limitations of a standard CBC approach.

{ *Box 1* }

STEPS WHEN CONDUCTING CBC STUDIES

1. Study design
2. Choice design
3. Choice elicitation (survey)
4. Estimation
5. Analysis and interpretation

{ *Box 2* }

CHALLENGES WHEN SELECTING THE NUMBER OF LEVELS

1. Estimation error
2. Number-of-levels effect
3. Range effect

State of the Art: Choice-Based Conjoint (CBC)

Conducting CBC studies requires decisions about five steps (Box 1). We describe these steps in more detail and highlight some current issues. As an example, we describe measuring preferences in the airline industry, which can be used to improve the product portfolio based on consumer demand.

Study Design

The initial step in designing a research study is perhaps the most important part in measuring preferences. It has to answer how products might be decomposed into their attributes and levels. Eventually, we need to be able to construct our own product offering, as well as competitors', from the determined list of attributes and levels. For airlines that offer, for example, flights to a European city, the following attributes (levels) might be relevant: destination (Rome, Paris, London), airline (Lufthansa, Air Berlin, easyJet), stops (direct flight, one stop), meals (included, not included), free baggage (10 kg, 15 kg, 20 kg), and ticket price (49 €, 75 €, 99 €, 125 €, 149 €).

Number of attributes: Because of the low information efficiency of choices and due to the increasing complexity in information processing for the respondent when the number of attributes becomes larger, it is generally advisable to include only a few (i.e., about six) attributes in the study design. If additional attributes seem relevant (e.g., business or economy class seats, legroom) but are not the primary focus of the research question, they could be included to increase realism but remain fixed in the survey. For example, the study design could inform respondents that all the flight offers feature economy class seats with standard legroom. If the number of experimentally varied attributes exceeds six by a lot, a compositional, hybrid, or adaptive approach should be used instead — which we discuss subsequently.

Number of levels: For each attribute, we need to determine specific levels to vary in the experiment. To be applicable, the levels must provide a realistic representation of the marketplace, and they have to be broadly acceptable to most respondents. Unacceptable levels (e.g., poor safety records) would provoke noncompensatory decision rules and prevent any realistic trade-off decisions by the respondents. It does not matter how appealing a price is, if the airline cannot get the respondent to the destination safely.

Moreover, the number of levels for each attribute should be reasonable in number. Three challenges evolve regarding the number of levels: (Box 2)

Estimation error. The more levels are integrated the more preference values have to be estimated, which means that each estimate becomes less reliable. For quantitative attributes like price, which could potentially exhibit a continuous range of levels, it is advisable to have more reliable information about fewer levels rather than less precisely measured information about more price points. As a general rule of thumb, the number of levels should not exceed seven. However, for large sample sizes or when measuring only a few attributes, more levels might be feasible.

Number-of-levels effect. This effect arises when the number of levels is not distributed equally across the attributes (e.g., five levels for price but two for meals). The effect leads to a higher relative importance for an attribute with more levels, which artificially biases the results. This bias is especially likely in pricing studies, in which managers want to investigate multiple price levels, such as when they attempt to discover price thresholds. In any pricing study that combines multiple price levels with a yes-or-no attribute (e.g., meal or no meal), the price attribute gets overrated and leads to an artificially higher price sensitivity. We have shown empirically that willingness-to-pay measures derived from such a study can differ from the unbiased result by 20 %. Having prices that are 20 % less than the optimal price clearly demonstrates the negative impact this effect can have on managerial implications. Thus, the number of levels should be kept balanced across all attributes. However, if they cannot be balanced, the adaptive HIT-CBC method is available (as we describe subsequently); alternatively, compositional approaches are immune to the number-of-levels effect.

Range effects. The importance of an attribute should depend on the range of its levels. For example, when a consumer considers an airline trip to several destinations for prices ranging from 100 € to 500 €, price as an attribute should be more important than it would be in a situation with the same set of airline trips but prices ranging from 250 € to 350 €. People adjust attribute weights for different ranges less than would be theoretically required, which results in a biased attribute weight. This bias occurs particularly for compositional approaches and to a lesser extent for CBC. In any case, it is advisable to use levels that lead to a typical range for the studied purchase decision.

{*Box 3*}

CRITERIA TO SELECT CHOICE DESIGNS

1. Balance:
All attribute levels appear an equal number of times.

2. Orthogonality:
Each attribute level pair appears an equal number of times.

3. Minimal overlap:
The alternatives within a choice set are maximally different from one another, i.e., avoid equal levels within one attribute.

4.Utility balance:
The alternatives within a choice set are equally attractive to the respondent, such that choice sets avoid dominating or dominated alternatives.

Choice Design

The choice design, unfortunately, is often neglected when developing a research project. It refers to which alternatives, i.e., which attribute level combinations, should be included in the survey and how to allocate them across choice sets (see Figure 1). Thus, choice design is particularly important in CBC studies, because it has a direct effect on the reliability of the results. Because of the low information efficiency of analyzing choices it has to be made sure that the right alternatives are presented in a choice set so that none of the information they gather gets wasted.

Determining an optimal choice design remains one of the most complex research issues, so it receives a lot of attention in scientific research. In the airline context, we can offer an example of this complexity: The six attributes and levels we mentioned would create (3 × 3 × 2 × 2 × 3 × 5) 540 possible flight trip combinations. It is clearly unreasonable to ask a respondent to evaluate 540 product stimuli, and the complexity increases even more when we allocate the stimuli to different choice sets. If there are three alternatives per choice set, we come up with more than 26 million possible sets!

Which of these 26 million sets should appear in a survey? To answer this question, four criteria have been formulated by Huber and colleagues that identify an efficient choice design: (Box 3)

The first three criteria can be addressed and tested, e.g., using computerized searches for an efficient choice design. However, utility balance requires prior assumptions about consumers' anticipated utilities, which is often not feasible or advisable. E.g., assuming that Lufthansa is more preferred than Air Berlin cannot be generalized across all consumers. Therefore, recent developments suggest some dynamic approaches, such as fast polyhedral adaptive conjoint estimation, proposed by Toubia and colleagues. These methods try to adapt choice designs individually during the questionnaire, in response to a person's specific answers. This approach is generally promising, but the currently available algorithms are not efficient enough and require simplifying assumptions about the utility structure. Therefore, they do not consistently lead to better (i.e., more efficient) choice designs. Adaptive conjoint methods take a more general approach to utility balance (e.g., avoid dominating alternatives), which makes them appealing, as we discuss subsequently.

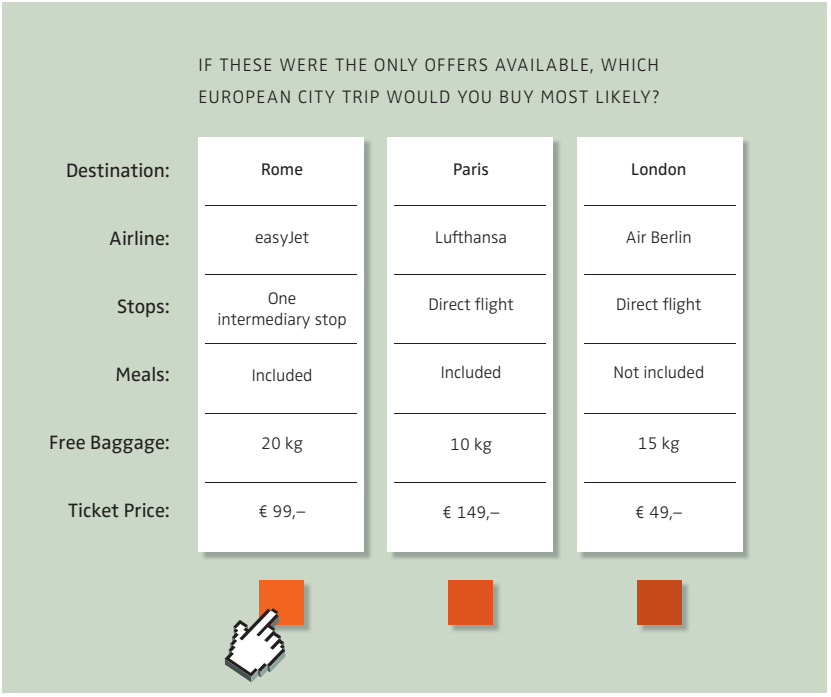


FIGURE 1:
Example of a Choice Set

Choice Elicitation: Survey

The choice elicitation task involves how to present the choice sets to respondents in the survey. Generally, it is not advisable to start with the choice sets but rather to let the respondent become familiar with the attributes and levels first.

One of the major benefits of CBC is that it can include a no-choice option (e.g., "I would not buy any of these alternatives"), which increases realism. However, if a respondent chooses none of the alternatives in a set, information about his or her relative preference for the other alternatives is lost. The worst-case scenario would be that a respondent chooses "none" in all the choice sets, which prevents the estimation of preferences. Therefore, it can be preferable to include the no-choice option as a separate question, after each choice task (e.g., "Would you actually buy your preferred choice if it was available?").

Because answering choice sets repeatedly can be monotonous, respondents tend to get tired or bored after a while. Research shows that respondent fatigue and decreasing attention changes the choice behavior over the course of the survey. For example, respondents tend to use brand or price as their main criteria later in the survey, instead of processing all the attribute information in the choice sets. To avoid this behavior, the survey design should include only about 12 – 15 choice sets (though the total also depends on the study design) or should motivate the respondents throughout the survey.

One way to keep respondents engaged and avoid hypothetical bias is by using incentive-alignment procedures. These methods grant respondents a budget in the beginning of the survey, which they can spend in each of the subsequent choice sets. After they have made all their choices, the researcher randomly selects one set and fulfills the respondent's choice in that set—that is, the respondent receives the alternative he or she chose for the price shown, as well as the remainder of his or her budget (if there is any). If he or she chooses none of the alternatives, the respondent receives the cash. Recent research even shows that not every respondent has to receive the money at the end; it is enough to use a raffle that gives the money to a few respondents. In an empirical study about consumer electronics (n=177) we were able to increase the amount of correctly predicted choices by 20 %

{*Box 4*}

ASSUMPTIONS TO BE CHECKED WHEN INTERPRETING PREFERENCE DATA

- There are no external effects, and all attributes that affect a buyer's decision in the real world have been accounted for. For example, if choosing a flight is also based on earning miles for it and this attribute has been left out of the study, predictions will be less accurate.
- Marketing efforts are equally effective, and buyers are aware of all products.
- All alternatives are equally available, and there are no out-of-stock conditions.
- There are no switching costs.

with this incentive-aligned procedure compared to the standard CBC approach. Although this approach certainly is promising and works well, its application is limited to specific product categories. For example, it cannot work for new product innovations, because the alternatives in the sets would not be available for purchase.

Estimation

The estimation approach determines the level of detail of the results. Initially, CBC studies relied on an aggregate level, pooling the answers of all the respondents, to overcome the low information efficiency associated with choices. However, such an aggregation assumes that all the respondents are clones, with no differences in their preferences—clearly an unrealistic expectation, e.g., brand preferences and price perceptions are complex psychological constructs that are distributed heterogeneously across consumers.

To account for this consumer heterogeneity and still overcome the information inefficiency, we need to make additional assumptions in an estimation. For example, hierarchical Bayes (HB) analyses assume that respondents' preferences are linked by a common multivariate normal distribution. Because this assumption does not constrain the data very much but offers a high level of detail, HB is currently the most widespread technique applied to CBC data.

An alternative approach, which may be more managerially relevant, identifies segments on the basis of the choice data, such that the responses get pooled at the segment level. Finding segments that differ in their preferences, e.g., discovering a price sensitive segment or a segment for which free baggage is important, is often a better basis for product differentiation and targeting than is segmentation based on age, gender, profession, or the like. Estimation procedures that cluster respondents into segments based on their choice data and simultaneously calculating their preferences are latent class analyses (LC), also known as finite mixture procedures.

In addition to the estimation algorithm, the researcher must test whether interaction effects between the attributes are significant and might lead to better predictions. Interaction effects occur if, for example, respondents express a different price sensitivity when they evaluate different destinations.

Predictions also can be enhanced by using prior knowledge about the order of preferences for attribute levels as a type of constraint on the estimates. For example, we could constrain the choice model to show that a direct flight is always better than a flight with a stop or that a free meal is better than having to pay for it. However, such constraints should be kept to a minimum, and it is generally not advisable to constrain the price attribute at all, because many results show nonlinear, non–monotonically decreasing price functions. For example, in an airline setting, we have found that about 25 % of the respondents preferred the second lowest price to the lowest price, presumably because they worried about low quality and safety issues when the price was too low (i.e., informational effect of price). If we had constrained the preference order in this case, essential information would have been lost.

Analysis and Interpretation

Finally, the preference values should not be analyzed in isolation but rather—as they were measured—con-

jointly. The most popular way to assess conjoint preference data is through the use of market simulations. For a given market scenario with different alternatives (specified according to the attributes and levels of the survey), shares can be simulated according to the preference data. These preference shares cannot be interpreted directly as market shares though, because simulations rely on several assumptions (Box 4) that likely differ from real market conditions.

The better these assumptions can be accounted for in the study, e.g., by integrating switching costs, the better the results will match actual market shares.

A good starting point for simulations is a specific benchmark scenario that reflects current market conditions, e.g. several airlines serving different destinations for specific prices. Based on this benchmark scenario, the marketer can change product specifications and analyze whether they result in simulated preference share improvements. For example, how might the shares change if we discontinued free meals or routed flights to Paris instead of Rome? Moreover, with this approach, we can measure price sensitivity as price elasticity (i.e., the price changes of our own product) or as cross-price elasticities (e.g., competitor's price changes), which then can reveal optimal prices.

This price optimization process also can turn to willingness-to-pay (WTP) measures. One such measure divides the preference value of a specific attribute level by the preference value of price, which generates an incremental WTP measure:

PRICE/LEVEL (WTP MEASURE) =
Preference level : Preference price

However, this approach very often yields unrealistic high WTP measures when price sensitivity is low or even misleading results, e.g., when the price function is (partly) positive.

A more robust way to determine WTP is to detect the price at which an alternative changes from being the most preferred to being equally preferred to a second best option (or the no-choice option). This price then is the maximum WTP for that alternative, because at higher prices, another option would be chosen instead. Yet calculating WTP from preference values remains a topic of continuous debate, marked by various alternative approaches.

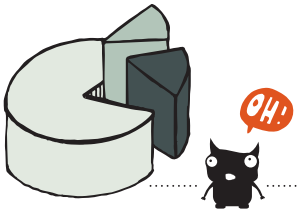
	B keeps price constant	**B decreases price**
A keeps price constant	A: 5.0 B: 5.0	A: 4.0 B: 6.0
A decreases price	A: 6.0 B: 4.0	A: 4.5 B: 4.5

TABLE 1:
Investigation of Potential Competitor Reactions Using Market Simulations

To increase the validity and to generalize conjoint simulations, it is promising to combine preference data with a data mining approach. In that way, predictive hypothetical data are merged with actual historical sales data. This procedure can reduce the hypothetical bias created by conjoint analysis and decrease prediction errors by considering different sources of information. Moreover, it offers a way to translate relative preference shares into absolute sales. This translation is most effective for repetitive conjoint analyses, which offers ongoing calibration in a self-learning system.

As a further step, after conducting market simulations and deriving managerial implications, managers should keep in mind that these simulations allow for dynamic variations. For example, an interesting simulation investigates how competitors (who also use conjoint analyses) might react to product modifications (Table 1). This investigation likely needs a game theoretical approach. Imagine that a specific destination is served by two airlines A and B and each airline is earning €5 million in sales from these flights (upper left box in Table 1). If A decreas-

» To increase the validity and to generalize conjoint simulations, it is promising to combine preference data with a data mining approach. «



es its price, market simulations predict it will increase its shares and revenues to €6 million, leaving B with a revenue of €4 million (lower left box). The best option for B would be to decrease its prices as well to increase its shares again (lower right box). But now both competitors charge lower prices, so their revenues fall from €5 to €4.5 million. Thus, knowing and anticipating potential competitor reactions can generate valuable information that might prevent the market from falling into such a prisoner's dilemma, which destroys both market and brand value.

Future of the Art: Adaptive Conjoint Approaches

With computer-aided surveys, adaptive conjoint approaches are becoming increasingly popular. Unlike static questionnaires, adaptive surveys can react directly to the answers given by each respondent. Therefore, these approaches can exclude unimportant or unacceptable features, prior to eliciting a person's preferences.

Despite their recent growth in popularity, adaptive conjoint questionnaires are nothing new. ***Adaptive conjoint analysis*** (ACA), introduced in 1987, uses a hybrid approach that combines a compositional phase and a decompositional rating-based conjoint phase. Only the most important attributes identified in the compositional phase appear in the subsequent conjoint phase. Both the compositional and the conjoint phase produce preference data; then, a purchase likelihood calibration procedure combines these data sets into one optimized set. Because of its adaptive approach and different phases, ACA can include more attributes than traditional or choice-based conjoint applications. However, ACA has become less popular in practice, likely because it often results in approximately equal attribute importance weights across all attributes and an understated weight of price (see figure 2).

A similar adaptive method proposed by Voeth, also based on rating-based conjoint but more sensitive to detecting attribute importance for a large number of attributes, is the ***hierarchical individualized limit conjoint analysis*** (HILCA). To mitigate the high cognitive burden placed on a respondent who must assess many attributes, HILCA uses the principle of information hierarchy to select the five most important attributes, based on a compositional rating phase that also can indicate unacceptable levels. Only the five attributes move on to the ratings-based conjoint phase, which means the procedure generates the most comprehensive information for those attributes with the greatest impact on the purchase decision. Finally, HILCA presents all alternatives again in the order of their preference ratings and asks the respondent to indicate which alternative is the least attractive that is still considered for buying. This is accomplished by placing a "limit" card, which separates the attractive alternatives from those that the respondent would not choose. This threshold provides a proxy for the no-choice option, which otherwise cannot be integrated directly into traditional conjoint approaches. In an empirical application with 17 attributes we have shown that this individualized hierarchical procedure yields importance weights that are more realistic than those discovered by ACA. Figure 2 shows that the attribute importance weights derived by ACA are flat and have low discrimination while those estimated by a HILCA-like procedure clearly highlight important features.

Adaptive choice-based conjoint analysis (ACBC) also aims to reduce irrelevant information to make the conjoint task more engaging for the respondent. However, unlike HILCA, it does not focus on selecting relevant attributes (though they can be integrated as well) but rather on selecting relevant alternatives by identifying a consideration set prior to the conjoint phase. This effort requires two steps: a "build-your-own" step, in which the respondent chooses the best level of each attribute and identifies an optimal product for him or her, and a variation step that alters the optimal version in some attri-

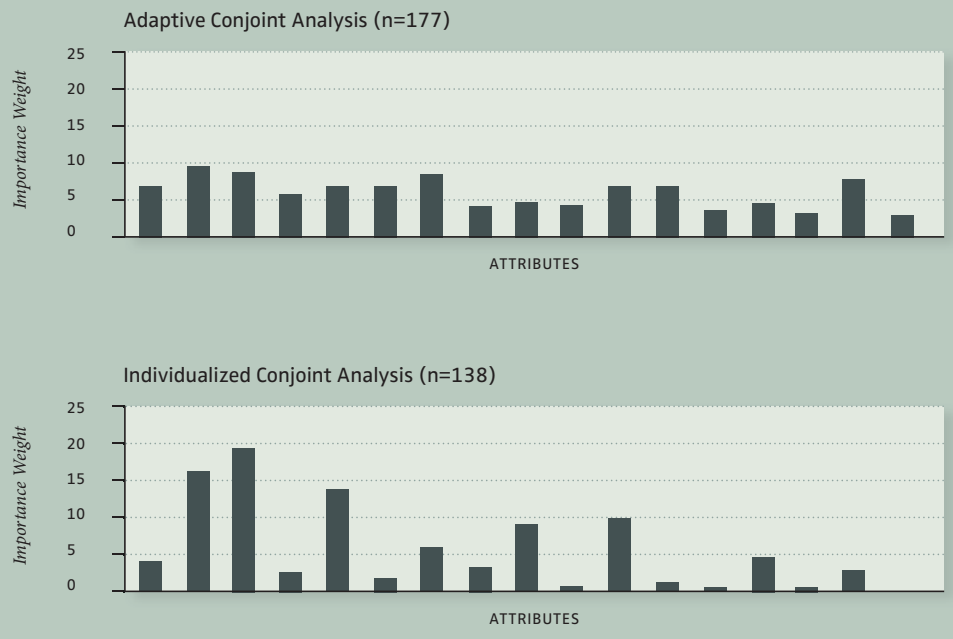


FIGURE 2:
Importance Weight Comparison Between ACA and a HILCA-Like Individualized Conjoint Analysis

	Compositional (Self-Explicated)	Traditional Conjoint (Rating/ Ranking)	CBC	HILCA	ACBC	HIT-CBC
Choice-based	No	No	Yes	No	Yes	Yes
Adaptive	No	No	No	Yes	Yes	Yes
Number of attributes	High	Small	Small	High	Medium	Small
Number of levels	High	Medium	Medium	Medium	Medium	High
Vulnerable to number-of-levels effect	No	Yes	Yes	Yes	Yes	No
No-choice option	No	No (indirectly via limit card)	Yes	Indirectly through limiit card	Indirectly through screening and calibration tasks	Yes
Estimation model	None	Linear	Logit (HB, LC)	Linear	Logit (HB, LC)	Logit (HB, LC)
Minimum sample size (for estimation)	Small	Small	Large	Small	Medium	Medium

TABLE 2:
Characteristics of Conjoint Approaches



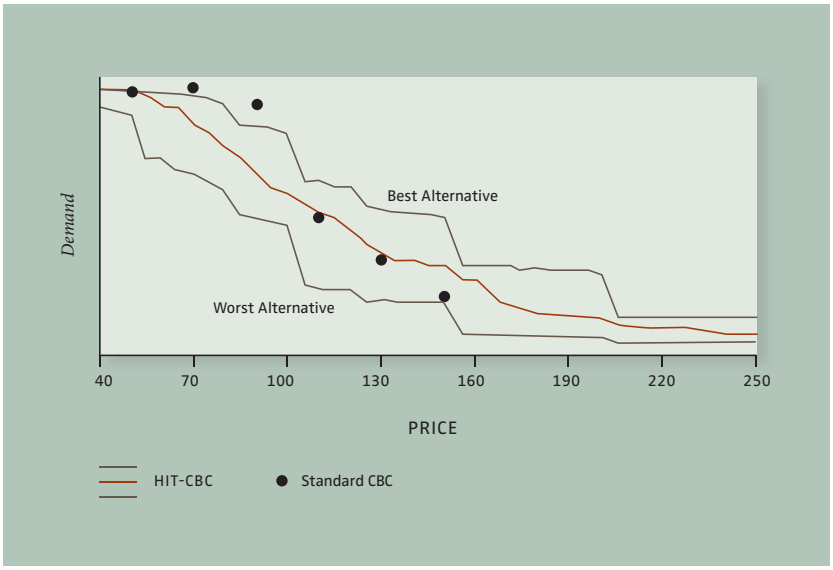


FIGURE 3:
Demand Function Generated by HIT-CBC Compared to a Standard CBC Approach

bute levels, such that the respondent indicates whether this alternative is generally acceptable. This repeated screening leads to the consideration set. Apart from building the consideration set another key aim of the screening section is to detect attribute levels that are either must-haves or unacceptable and as such would not be compatible with the conjoint model. This is integrated implicitly into the screening phase because it is often found that too many levels are excluded as unacceptable when elicited directly at the beginning of the survey. Afterwards, only alternatives that are considered for buying are shown in the choice-based conjoint section. Because all alternatives are acceptable a none-option in the choice sets is not necessary. An alternative 'none weight' can be estimated by an optional ACA styled likelihood-to-buy calibration phase or by analyzing the unacceptable alternatives of the screening section.

Finally, another adaptive approach, the ***hybrid individualized two-level choice-based conjoint analysis*** (HIT-CBC), reduces information processing in the conjoint phase by asking for the best and worst level of each attribute first. Only these levels then appear in the choice-based conjoint phase; the remaining levels get evaluated on a rating scale, such that conjoint estimates can be interpolated according to that rating. Although HIT-CBC reduces information processing for the respondent, its primary purpose is to avoid the number-of-levels effect. Because HIT-CBC reduces every attribute to two levels, the number-of-levels effect cannot occur. Another benefit of this method is that it reduces the complexity of the choice design significantly. In our airline example, only 64 possible flights exist for HIT-CBC, rather than 540 in standard CBC. Moreover, information about the best and worst levels can indicate the choice sets that best support the efficiency criterion of utility balanced alternatives by avoiding dominated sets. This approach also improves the conjoint estimation, because fewer parameters need to be retrieved, and the transformation to the best and worst levels better accounts for consumer heterogeneity. Stated otherwise, with HIT-CBC it is possible to ask 25 % fewer choice sets and obtain at least the same estimation accuracy of a standard CBC approach. Finally, because the number-of-levels effect is especially likely in pricing studies, HIT-CBC features the possibility of using dynamic price levels, aligned with the respondent's WTP. Adjusting price levels to the price sensitivity of each respondent results in greater flexibility for modeling demand functions (e.g., identifying price thresholds) than does using a fixed number of price levels (see Figure 3).

Summary and Implications

> ***Conjoint analysis remains a very popular method for marketing research.***
Choice-based conjoint methods have been examined intensively in the last years and shown to produce valid results. However, current research shows no conclusive proof that CBC dominates other methods in terms of its validity. Choice-based conjoint, traditional conjoint, and adaptive conjoint methods all work generally well for modeling preferences. But as we have highlighted, many aspects of CBC are still under examination so that future research might identify further improvements of the method, e.g., regarding the choice design or choice elicitation task. Until then, the selection of a method that is most suitable depends on the research context.

> ***How to select the appropriate method***
Table 2 (page 45) can be used to select an appropriate method and summarizes the characteristics of each approach. Generally, CBC is a good contender when the research problem can be described with just a few (i.e., up to six) attributes and when the number of attribute levels is low (i.e., up to seven). The number-of-levels effect can be avoided when the levels are kept balanced across the attributes. Caution should be exercised if at least one attribute has more than twice as

many levels as another attribute. In that case the number-of-levels effect is very likely and the HIT-CBC method should be used instead. HIT-CBC is also a better choice for applications that require more than seven levels per attribute.

If a large number of attributes (i.e., more than six) is relevant to describe a research problem HILCA or ACBC are suitable. However, these also suffer from the number-of-levels effect. An alternative method for studies with many attributes that is immune to the number-of-levels effect can be a compositional (self-explicated) approach, which however cannot consider a no-choice option.

The no-choice option should be integrated into the research design whenever price sensitivity or willingness-to-pay is measured. With the no-choice option respondents have the possibility to refuse a selection when the prices of the alternatives shown are too high. Otherwise, a choice would be forced and willingness-to-pay would be overstated. If the no-choice option is not of primary interest it is a good idea to integrate it as a separate question after each choice task (e.g., "Would you actually buy your preferred choice if it was available?"). In that case the no-choice option can either be included or left out of the estimation model.

> ***State-of-the art estimation procedures***

Regarding the estimation model, individual-level regressions for linear models or hierarchical Bayes procedures for logit models exhibit the greatest level of detail because they compute preference values for each respondent. Knowing preferences for each individual helps understanding consumer preferences and allows further analyses, e.g., by building clusters based on, e.g., gender or age groups etc. However, for new product development or product differentiation the latent class approach can also be appropriate because it segments the respondents based on their preferences and choice behavior. Analyzing these segments can reveal a demand potential that is not met by current market offerings. •

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Preference Measurement, Conjoint Analysis, CBC, ACA, HILCA, ACBC, HIT-CBC