Conjoint Measurement

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Introduction

The conjoint measurement approach (also referred to as conjoint analysis or trade-off analysis) is an empirical research method for studying individual preferences or (purchase) decisions, determining trade-offs, segmenting groups with similar values, and simulating reactions to novel products or scenarios.

The theoretical groundwork of conjoint analysis reaches back to the 1920s, but the foundation for the applied conjoint measurement approach was laid in the 1960s by the mathematical psychologist Luce and the statistician Tukey (Luce & Tukey, 1964). The method was—and still is—predominantly used in marketing research for designing and positioning new products, estimating product demand or pricing decisions (Green & Srinivasan, 1978; Kohli & Sukumar, 1990). Today, conjoint studies are established in various other scientific disciplines such as health care (Ryan & Farrar, 2000), transportation (Bunch, Bradley, Golob, Kitamura, & Occhiuzzo, 1993), or environmental studies (Álvarez-Farizo & Hanley, 2002). In contrast, in communication science the conjoint measurement approach is rarely used so far, although it could provide valuable contributions to communication science research issues. Hence, the aim of this entry is an introduction to conjoint analysis and an overview of its application in the field of communication science.

Basic assumptions

Conjoint analysis allows the researcher to decompose a product, service, or scenario into its constituent parts in order to determine which characteristics influence individual preferences or purchase decisions and which trade-offs are made between different decision-relevant criteria. Conjoint measurement is based on the assumption that the preference for a hypothetical product, service, or scenario, that is, the "utility," is a function of a set of explanatory variables (referred to as "attributes" and "levels"), which additively contribute to respondents' preferences or purchase decisions. The following example illustrates these basic concepts: A mobile phone has the *attributes* "display size," "operating system," "price," "weight," and "camera features." Each attribute comprises different levels, for example, for the attribute "display size," the *levels* are "4 inches," "5 inches," and "6 inches." In a conjoint study, different combinations of attribute levels, referred to as *stimulus profiles*, are evaluated by respondents in order

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to find out which level configuration is the most attractive, which attribute influences preferences the most, and which trade-offs are made between attributes. Hence, the conjoint approach is especially well suited for complex decision scenarios in which more than one attribute affects preferences.

Procedure and design of conjoint studies

Although a multitude of conjoint analysis methods exist (for a taxonomy, see Rao, 2014), which predetermine conjoint study design, some generic design considerations regarding the procedure and design of conjoint studies can be derived.

Selection of attributes and levels

One of the most important steps in applying conjoint analyses is the identification and selection of relevant attributes and levels. This requires both scientific expertise, to understand the decision-making process among respondents, and sensitivity in choosing and operationalizing relevant attributes and levels. The designer of a conjoint study must ensure that all relevant attributes, which determine respondents' preference on the one hand, and are relevant for managers or policy-makers on the other hand, are considered. A broad variety of qualitative and quantitative empirical methods are available to identify salient or decision-relevant attributes, for example, (expert) interviews, focus groups, think-aloud protocols, and so on. At this stage of attribute and level selection, it is important to include all stakeholders, that is, experts, managers or policy-makers, as well as potential users or customers to capture all relevant attributes.

Following that, the designer of the conjoint study has to reduce the collection of attributes to a few important core attributes. These core attributes have to meet specific requirements: they have to be (i) *independent* (or "orthogonal") from each other, (ii) *relevant* for preference judgments or choices, (iii) *feasible* or *actionable* from a managerial or policy-maker point of view, (iv) not in a *compensatory* relationship with other attributes, which means no usage of "No-Go criteria" that lead to a total rejection of a product or scenario independent from other attribute levels, and (v) *measurable*.

After the attributes have been selected, the number of levels, that is, the range of the single attributes, needs to be specified. The attribute levels should be (i) *realistic* in order to obtain valid judgments, (ii) *feasible and actionable* to managers and policy-makers, and (iii) *comprehensible* to respondents. The level range of an attribute should be pretested to ensure that the minimum and maximum levels as well as the gradations in between are realistic and relevant for respondents and actionable for the implementation of results. To avoid biases, the number of levels for the different attributes should be comparable, because attributes with a higher number of levels reach higher importance results (Wittink, Krishnamurthi, & Reibstein, 1990). In practice, the number of levels used in conjoint studies varies between two and six. Although the number of attributes and levels depends on the research question under study, their number should be limited. If a full factorial design is chosen, that is, all combinations of attributes and levels are presented, the number of judgments quickly leads to fatigue effects among respondents. To reduce the number of choices or conjoint tasks, factorial or part-profile designs can be chosen.

Selection of a preference model

In order to explain the preference judgments made in the conjoint study, a preliminary decision on the nature of the underlying preference function, that is, the relationship between attributes and their utility values, is necessary. The type of function depends on the attributes, that is, if they are categorical (nominal scale) or numerical (interval or ratio scale). There are three basic types of preference functions: (i) the vector model, (ii) the ideal-point model, and (iii) the part-worth model (Green & Srinivasan, 1978).

The *vector-model* assumes that the utility increases (or decreases) linearly with the numerical value of the attribute. This model is adequate for benefits or quality aspects such as security, well-being, or profitableness ("the more the better").

The *ideal-point model* is based on a curvi-linear function and assumes that the utility rises up to a maximum and then decreases again. This model is suited for attributes with an optimum, such as physical characteristics of products, for example, temperature, sweetness, or frequencies ("some amount is best"). This model can also be presented as anti-ideal-point model with a local minimum ("some amount is worst").

In the *part-worth model*, a discrete function is assumed in which every attribute level is related to its own utility. This model is highly flexible ("everything is possible") but not efficient enough for quantitative attributes.

The conjoint approach assumes an additive model where individual part-worths sum up to the overall utility.

Construction of the data collection method and stimulus set

After having defined the attributes and levels, the researcher has to decide about the data collection method, that is, (a) how the stimuli will be presented, meaning the construction of stimulus profiles by using a statistical experimental design, (b) how many stimuli will be evaluated, (c) which preference measurement scale will be chosen, and (d) in which form the survey will be conducted.

The general aim in the *construction of stimulus profiles* is to present the stimuli in a realistic and efficient way. Two methods are mainly used, the full profile approach and the trade-off approach (also called "two-factor method").

In the *full profile approach* (Green & Rao, 1971) all combinations of attribute levels are presented to each respondent, mainly on a stimulus card. In a rating task, the respondents indicate their preference or the likelihood of a purchase. In a conjoint study with three attributes with three levels, respectively, the full profile yields $3 \times 3 \times 3 = 27$ profiles to be evaluated. This approach closely mimics real choice or purchase situations, because respondents evaluate the stimulus profiles holistically. On the other hand, it requires relatively complex decisions by respondents and too large numbers of profile evaluations (due to a large number of attributes and/or levels) might exceed respondents' motivation. In this case, fractional factorial designs with a reduced number of profiles are recommended.

In the *trade-off approach*, only two attributes are presented at a time. Based on a trade-off matrix, respondents have to evaluate all logically possible combinations of two attributes and their respective levels. If more than two attributes are used, the number of matrices increases. Even though the single evaluation is less complex for the respondent, it is also less realistic (the other attributes have to be kept constant at an unspecified level). It also requires a large number of evaluations, which might lead to a stereotypic response behavior.

Although these traditional conjoint approaches used to be the "gold standard" in marketing research, they have two main disadvantages: first, the number of attributes and levels to be used is limited, and second, rating- and ranking-evaluations do not allow inferences on the actual selection of a product or scenario. Along with the development of conjoint software products, two approaches for conjoint stimulus profile construction emerged that overcome these problems: (a) Adaptive conjoint analysis (ACA), and (b) Choice-based conjoint analysis (CBC). In *adaptive conjoint analysis*, a two-step procedure is pursued. First, respondents evaluate the levels of each attribute and the relative importance of the attributes used, which yields an individual preference structure. Second, based on the selection of relevant attributes in the first part, respondents receive a reduced subset of the complete attribute list, which significantly reduces the number of possible decisions. The ACA requires computer-based testing and allows including up to 30 attributes. However, in most ACA studies, 8–15 attributes with approximately five levels are used. Since it is difficult for the respondent to give consistent responses in a complex decision situation with a large number of attributes, the ACA bears the risk that unimportant attributes are overestimated while important attributes are underestimated (Green, Krieger, & Agarwal, 1991).

The *choice-based conjoint analysis* is the most popular conjoint approach today, because it closely mimics realistic purchase and decision situations. Respondents do not rate or rank profiles but have to choose between two and eight complete product concepts. CBC also allows for "none options," that is, when the respondent refuses to choose a product concept. Instead of evaluations of hypothetical product profiles, CBC assesses stated choices and develops a model about the probability of choice. Hence, it is not based on the linear-additive part-worth model but on choice models (multinomial logit or probit model). Compared to other conjoint methods, the design of CBC studies is more complex due to the generation of choice sets (Rao, 2014). Moreover, the instructional effort is higher, because all attributes and levels need to be comprehensively introduced to enable respondents to evaluate complete product or scenario concepts. Finally, some respondents perceive difficulties in making a choice when large attribute numbers lead to complex choice sets.

A further decision has to be made about the *number of stimuli* to be evaluated. In a *complete factorial design*, all logically possible combinations of attribute levels are evaluated. A saturated model like this is necessary whenever the researcher wants to determine all main effects and interaction terms between attributes. Empirical research practice recommends 30 evaluations in a conjoint study as upper limit (Green & Srinivasan, 1978). Instead, *reduced designs* are often used, either by random sampling, where single profiles are taken randomly from the complete profile set or by systematical reducing, where the orthogonality (independence) of factors is preserved (Rao, 2014).

The researcher also has to decide about the preference measurement scale, that is, if the participants evaluate the products or scenarios by ranking, paired comparison, or rating. In *ranking tasks*, which are used in the two-factor approach, the respondents have to rank the presented alternatives from best to worst. Ranking tasks require the formation of a preference order, that is, the characteristics of a product or scenario have to be weighted relative to one another, which represents the basic idea of conjoint analyses. In complex decision scenarios, with a large number of attributes, ranking tasks run the risk of overloading the respondents. *Paired comparison* is a way to reduce this overload. Respondents receive a pair of products or scenarios and have to choose their preferred alternative. Again, the number of paired comparisons rapidly increases with rising numbers of attributes. One advantage of paired comparison is that it closely mimics realistic purchase situations in which the customer has to choose between two products (instead of ranking them). Using *ratings* is the most important metric method in assessing preferences. Respondents are asked to evaluate each alternative on a measurement scale (most commonly on a scale between 0 and 10). Although the assessment and statistical analysis of rating data is comparably simple, the researcher has to consider validity constraints: if participants do not discriminate between alternatives and rate them equally, if they interpret the numerical rating scale differently, or if they do not relatively weigh the alternatives against each other. Apart from rating-based conjoint analysis models, *choice*-based models are also widely used. Respondents have to choose the most preferred product configuration from a set of alternatives, which closely mimics purchase situations in a competitive context. However, compared to rating data, choice data contains less information about the relative preferences for the rejected products or if the chosen product was strongly or just slightly preferred (Moore, 2004).

Before running the conjoint study, the researcher also has to decide about the *form of the survey*. This refers to the selection of stimulus modality (verbal description, visual (pictures), or both), to the channel of data selection (face-to-face, via telephone, per paper-and-pencil survey, or with an online survey), and to the assessment of additional survey information.

Most conjoint studies use verbal descriptions as *stimuli modality*, which is the easiest way to compose product profiles. The presentation of pictorial stimuli requires more design work and bears the risk that respondents interpret pictures differently. The combination of verbal and visual information in stimulus presentation can facilitate information perception and processing (Paivio, 1971), but the researcher has to carefully weigh between the advantage of increased comprehensibility and the risk of information overload. However, to ensure comprehensibility, the conjoint study should contain a detailed introduction and instruction as well as a glossary of terms.

Regarding the *channel or type of survey* most conjoint information in the past was assessed via face-to-face or telephone interviews. The advantage of personal interviews is that the researcher can directly react to respondents' questions if they encounter difficulties during the study. The synchronous interview situation also contributes to the completion of the survey and to valid statements. Recent developments in conjoint and survey software (Sawtooth, www.sawtooth.com; Survey Analytics, www.surveyanalytics.com; Qualtrics, www.qualtrics.com) have led to a shift to online conjoint surveys. The software packages cover survey construction and programming, and the assessment phase as well as data analysis. The main advantage of online surveys is that they allow for asynchronous data collection and that larger sample sizes can be assessed.

Finally, the researcher has to decide about additional information to be assessed in the survey, such as biographic data, socioeconomic information, or attitudes, which might be relevant in the context of the research question. This additional information is useful for describing the sample under study and to consider user diversity (e.g., age or gender effects); it also allows for segmenting the data.

In any case, pretests of both the supplementary survey part and the actual conjoint study are indispensable. They ensure that respondents understand the described products and scenarios and that they are able to give valid evaluations.

Regarding the appropriate sample size, the general rule of thumb is usually a minimum of 200–300 completed surveys, which allow for robust quantitative analyses without subgroup comparisons. For comparisons of respondent groups (e.g., age or gender differences) or segmentation studies (e.g., consumer profiles) the recommended sample size is about 200 per subgroup. For exploratory research questions and hypotheses development, a minimum of between 40–60 respondents is sufficient (Orme, 2010).

Data analysis

The major aim of conjoint analyses is to estimate *utility functions*, that is, to decompose preference evaluations into part-worth utilities, based on the assumptions of the additive model, and, in a next step, to determine the relative importance of each attribute and level. The utility function reveals the perceived importance of each attribute and indicates preference changes due to changes in attribute levels. The selection of which specific statistical analysis method to use depends on the chosen conjoint method, that is, its data structure and underlying statistical model. A common classification of estimation methods according to their measurement scale is (a) ordinal, (b) interval, or (c) choice-based (Green & Srinivasan, 1978). If the conjoint data is ordinal (using ranking scales for measurement), nonmetric methods are applied such as MONANOVA, LINMAP, or PREFMAP. For interval-scaled conjoint data (using rating scales for measurement), OLS regression, multiple linear regression, or analyses of variance (ANOVA) can be used. For choice-based data (categorical data), probabilistic models such as logit or probit are utilized.

Another way of analyzing conjoint data is the market *segmentation*, where the sample is post hoc divided into groups or segments based on similar preferences (Green & Krieger, 1991). Latent class analysis (LCA) estimates the utilities for each segment and, simultaneously, the probability for each respondent to belong to this segment. By linking these segments to demographic data, specific groups or profiles can be defined, which allows developing target-group-specific strategies or interventions.

In a further step, preference *simulations* can be applied by using market simulators that allow "what-if" analyses. A market simulation shows relative preferences for a scenario in relation to other scenarios when one level of an attribute is changed while the others are kept constant. This simulation allows the researcher to model and test different products, scenarios, or service options to evaluate potential preference and their changes depending on changes in the product or scenario configuration (Gustafsson, Herrmann, & Huber, 2013).

Conjoint analyses in communication science

Conjoint analysis as a quantitative research approach has been rarely used in communication science so far, although it is particularly suitable due to its flexibility as a research tool and its application-oriented results. A potential field of application for conjoint analyses is the development of communication concepts and strategies. Conjoint analyses can shed light on preferred communication channels (email, text messages, social networks, TV ads, etc.), the type, content, and frequency of information, as well as wording issues, and so forth. By including different respondent groups in conjoint analyses, either post hoc by segmentation or a priori by recruiting specific samples (e.g., laypeople vs. experts), communication concepts can be individually tailored to specific demands of different target groups. Thereby, the optimal design of communication events for different target groups can be designed and empirically evaluated (e.g., information design in risk communication). One example of using conjoint analyses for communication concept planning is the adaptive conjoint study by Jensen (2008) in which the optimal mix of business-to-business (B2B) marketing activities (online vs. offline) for a Danish company was investigated. Another application of conjoint analysis in communication science can be found in Berger, Matt, Steininger, and Hess (2015), where several media content formats (e.g., print edition, e-paper, smartphone app) were judged according to consumer preferences and willingness to pay.

When communication science research is connected to other domains, such as life sciences, environmental sciences, biotechnology, or food production, the number of potential applications of conjoint analyses increases. Voordouw et al. (2011) studied preferences of food-allergic consumers with regard to different information provision scenarios (e.g., food label, in-store booklet, ICT-solution) (Voordouw et al., 2011). Dohle, Keller, and Siegrist (2010) determined public preferences for base-station siting, varying the location, appearance, type of building and the preceding public participation and decision process of base-station siting. Further examples of conjoint analysis applications can be found in Alriksson & Oberg (2008), Rao (2014), and Ryan & Farrar (2000).

These applications demonstrate that conjoint analyses are a useful instrument to enhance the dialogue between different stakeholders, for example, policy-makers, companies, and customers, and to derive concrete guidelines for communication concepts and strategies, given that the results are comprehensively reported and communicated.

Limitations and future developments

Although conjoint analysis is a promising approach, which delivers valuable insights into individuals' preferences, it has some—especially methodological—limitations.

However, it is necessary to differentiate between (a) an incorrect application and interpretation of the conjoint analysis method by the researcher, and (b) method-immanent weaknesses, which require a further methodological development.

The outcome of conjoint studies directly depends on the quality of the study design: a poor research design due to too many, irrelevant or confounded attributes as well as inappropriate levels, incomprehensive instructions or a too small or unrepresentative sample of respondents cannot provide meaningful results.

Although hybrid and adaptive conjoint approaches for investigating larger numbers of attributes already have been presented, conjoint analysis still allows for the analysis of a limited number of relevant object attributes. Here, the researcher has to find a trade-off between an economic research design, using a small number of attributes, and the external validity of the chosen scenario, where a higher number of relevant factors might affect the judgment or decision. Since an economic research design is often preferred in research practice, conjoint analyses have a “narrow” or specific research focus, which might not be sufficient for studying complex decision situations. For broader and more exploratory research questions, other empirical research methods such as surveys are more appropriate.

Further criticism refers to the missing integration of the preceding stage of object perception as well as behavioral and context effects (Rao, 2014). Regarding object perception and context effects, conjoint analysis approaches assume that respondents completely and correctly perceive the objects to be judged, even though cognitive, affective, and context effects might affect the type and stability of preference structures. Accordingly, future advances in conjoint analyses will be focused on underlying psychological processes and contextual factors that influence decision-making but also on issues of research design (e.g., larger numbers of attributes, choice-based models), data collection (e.g., best–worst scaling, conjoint poker), and data analysis (e.g., combining multiple sources of data) (Agarwal, DeSarbo, Malhotra, & Rao, 2014). Referring to behavioral effects, it is important to consider that conjoint analyses do not assess human behavior in realistically complex environments, but rather perceptions, attitudes, or behavioral intentions based on evaluations of specific scenarios or products. Hence, the outcomes of conjoint analyses should be triangulated and validated with other behavioral data sources (e.g., purchase behavior).

Taking these limitations in account, conjoint analyses are a valuable approach in communication science research and practice to give empirically based recommendations about the design of and the communication strategy for innovative or “critical” products by including recipients (the public, potential consumers, etc.) in the design process.

SEE ALSO: Analysis of Variance; Cognitive Assessment: Think-Aloud and Thought-Listing Technique; Communication Focus Groups; Data, Types of; Empirical and Nonempirical Methods; Evaluation Research; Experimental Design; Interview Methods, Quantitative; Latent Class Analysis; Measurement of Attitudes; Measurement of Behavior; Online Research Methods, Quantitative; Operationalization; Quantitative Methodology; Scale Types; Survey Methods, Online; Validity; Variables, Types of

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