TRUTH BEYOND COMMON BELIEFS

BOOSTING THE VALIDITY OF CONJOINT-BASED MODELLING

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PREFACE

The deduction of partial utilities within conjoint analyses is based on the assumption that people maximise their utility ("homo oeconomicus"). This assumption is contradicted by a broad swathe of empirical findings which have demonstrated that people systematically fail to make rational decisions. They nonetheless make predictable errors, so their decisions essentially remain 'calculable'. Consciously or unconsciously, they simply follow a decision rule that complements utility-maximising choice behaviour.

In a first step, we were able to statistically model this sub-optimal choice behaviour, and in a second step we combined both algorithms – the classic utility-maximising choice model and its sub-optimal counterpart – within one "Multi-Rule Conjoint Analysis" (MRC) that adaptively models a respondent's behaviour on the basis of either of these choice models.

Overcoming the narrow perspective of rational assumptions, MRC is able to improve predictions by more than 45% compared to standard CBC merely by more extensively exploiting the existing set of data.

STARTING POINT: CLINGING ONTO ASSUMPTIONS THAT HAVE OFTEN BEEN REFUTED BLOCKS BETTER PREDICTIONS

Ranging from product development, brand management, and communication design via customer segmentation through to price optimisation, conjoint analyses can be applied to an extremely wide area of topics. In recent decades, this method has developed into one of the market research tools that is most used throughout the world (Wittink, Vriens and Burhenne, 1994; Hartmann and Sattler, 2002).

During the course of a conjoint analysis, respondents repeatedly select the most attractive one out of a group of two to four options. These options may be products, service offerings or tariff plans. An option consists of a set of attributes that can take on different attribute levels. Throughout the successive rounds the attribute levels of the different options are systematically varied based on an experimental design.

If, for example, the intention is to optimise the attractiveness of a price model, several rounds are used to present the respondent with some price models from which they are meant to select the one they consider most attractive (see figure 1). The price models differ with respect to their attribute levels, which are explained in detail to the respondent prior to the actual conjoint analysis.

Using the link between the individual attribute levels of a specific option and the frequency with which respondents selected this option, the partial utilities for each individual attribute level can be deduced. In every version of conjoint analysis, the underlying analytical algorithm is based on two axioms that are also the basis of rational decision making which is assumed to be taking place when respondents are choosing between options in a conjoint task:

1. *Intrinsic partial utility:* a concrete partial utility value can be ascribed to each attribute level. From the respondent's perspective, the partial utility value is more or less inherent in the attribute level itself.
2. *Selection through the comparison of aggregated utilities:* in order to select the most attractive option, the total utilities of every option are compared with one another; the total utility of an option arises from the sum of all the partial utility values of its constituent attribute levels (see figure 2).

FIGURE 1
CONJOINT ANALYSIS USING THE EXAMPLE OF A CUSTODY FEE MODEL FOR FINANCIAL SERVICES PROVIDERS

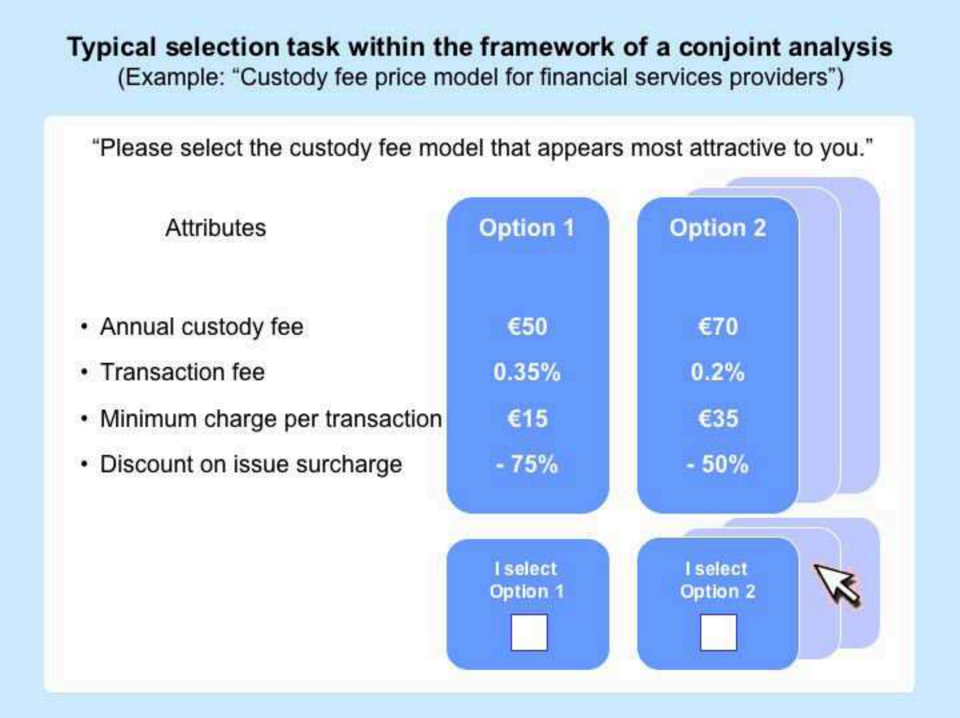
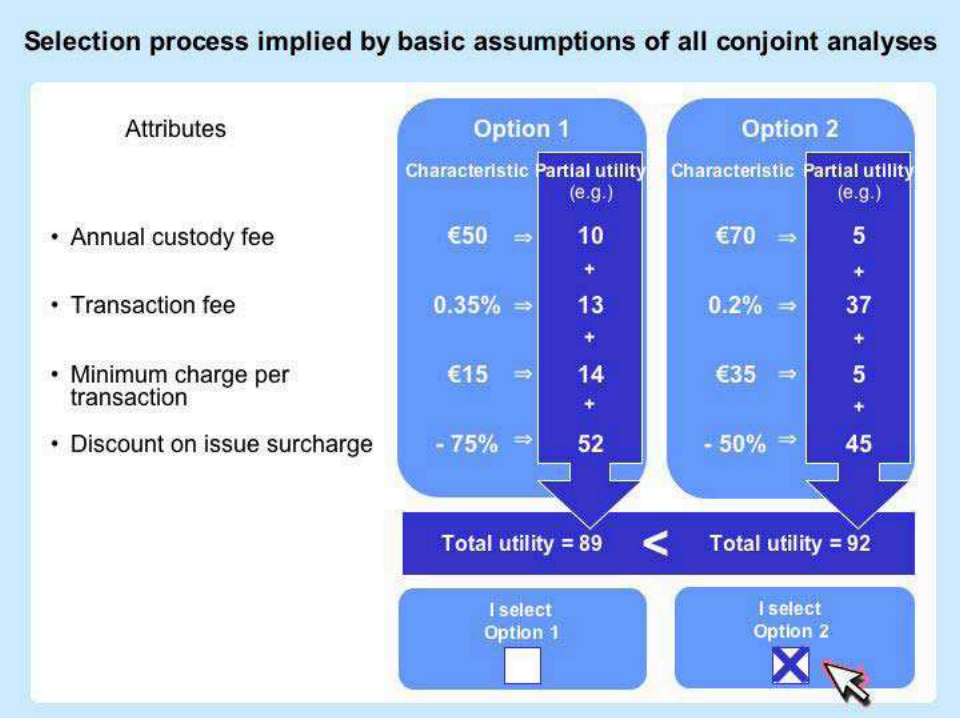


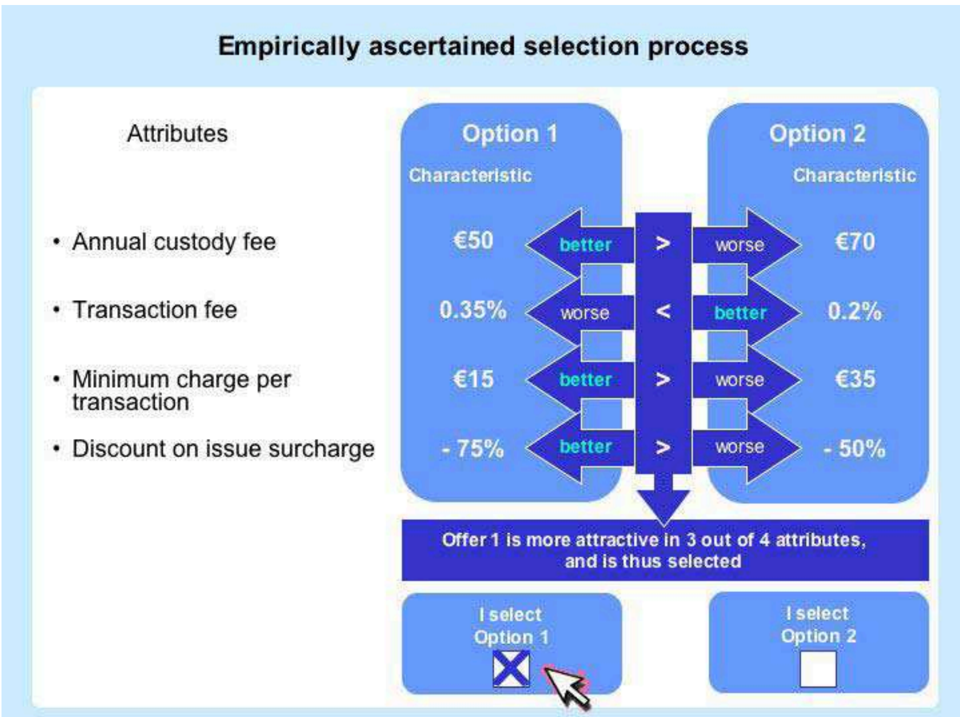
FIGURE 2
SELECTION PROCESS IMPLIED BY BASIC ASSUMPTIONS OF ALL CONJOINT ANALYSES



However, an overwhelming number of empirical findings fly in the face of these two theoretical assumptions: in relation to the *first assumption* regarding '*intrinsic* utility', we nowadays know that people do not assess the absolute attribute level, but the relative gap between them and psychologically relevant reference values instead. When assessing a price, this *external* reference value can for example be the price of a competitor product, the manufacturer's recommended retail price, or the earlier price at which an item was on sale (cf. Lichtenstein and Bearden, 1988 or Biswas and Blair, 1991, Tversky and Kahneman, 1981). In a conjoint analysis, the options that are simultaneously presented naturally constitute such external reference values. If respondents now assess these levels relatively (in accordance with the empirical findings) rather than absolutely, then in the case of Option 1 a specific partial utility is not inherent in the absolute amount of the annual custody fee (€ 50.-), but instead it only arises from the percentage price difference (+40%) compared to Option 2.

With regard to the *second assumption* that is dealing with the actual selection process, we have for a good while been asking some in-depth questions after running through a conjoint analysis. One of these questions is geared towards the actual procedure respondents used to select the most attractive option. For example, in the above-mentioned project relating to the topic of 'custody fee models', only 26% of n=486 respondents indicated that they systematically followed a rule, as implied by the second assumption of conjoint analysis. By contrast, 59% stated they consistently followed a selection process as shown schematically in figure 3. Obviously, many respondents are not comparing the overall utility of different options but are comparing them step by step, at the level of their individual attributes – just like this hypothetical inner dialogue describes it: *"Option 1 has the less expensive custody fee and lower minimum charges plus a higher discount on issue surcharges. The only thing that's more attractive about Option 2 is the transaction fee. Option 1 is thus superior in three out of four attributes, and for this reason I select Option 1."*

FIGURE 3
EMPIRICALLY ASCERTAINED SELECTION PROCESS



Thus in the process of deciding between the two alternatives, many people evidently do not choose by adding up partial utilities, but directly compare the options at the level of their constituent attributes (see also Bauer, 2000 and 2004, Felser, 2001 and Jansen, 2006). Analogous to the two axioms of classic conjoint analysis as described above, we derived two complementary assumptions that are not so much geared towards how a 'homo oeconomicus' should decide, but instead towards how people actually choose:

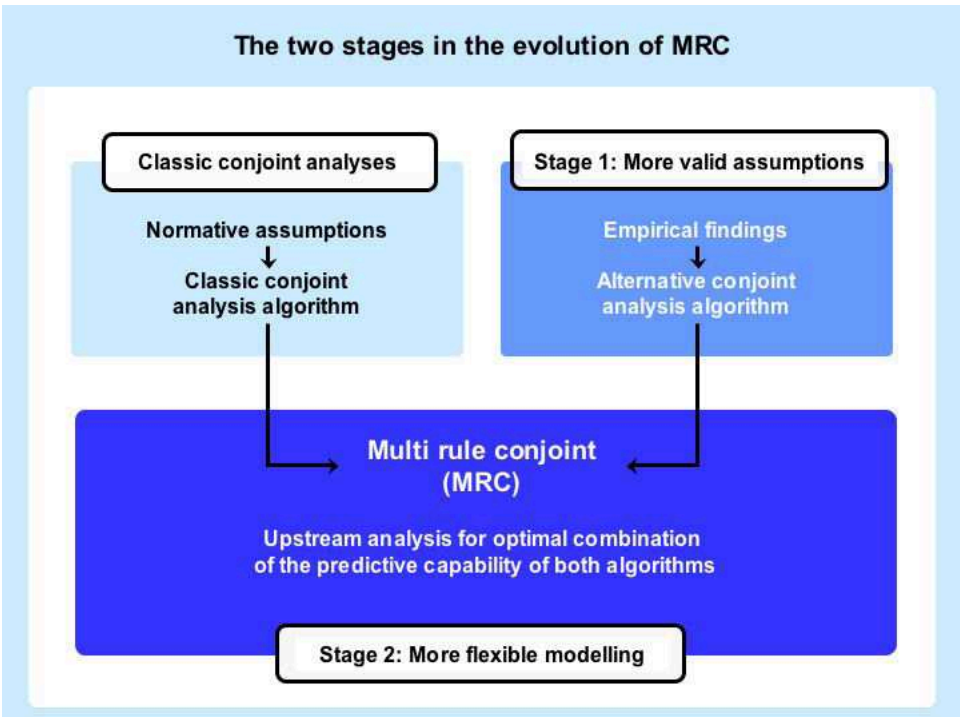
1. *Extrinsic partial utility:* the partial utility of an attribute depends on the comparative anchors the respondents are relying on. In this sense it is 'extrinsic' because in psychological terms it is not inherent in the attribute level itself but it is influenced by external reference values, such as the attribute levels of other available options.

2. *Selection through the aggregation of utility comparisons:* in order to select the more attractive of two options, the levels of each attribute are compared separately with one another and the results of these relative comparisons are aggregated as described in figure 3.

TOOL: MORE VALID ASSUMPTIONS AND MORE FLEXIBLE MODELLINGS LEAD TO FAR BETTER PREDICTIONS

All existing versions of conjoint analyses are 'rational single rule' approaches in a sense that they are assuming all respondents to make choices by implicitly following the same rational choice rule. Having found that a large percentage of respondents is systematically following another choice rule which can be described by complementary assumptions, we wanted to develop a "Multi-Rule Conjoint Analysis" that can flexibly capture both rules. Hence, the basic idea when developing MRC analysis was to combine the two complementary decision rules in one tool. With this goal, MRC was developed in two stages (see figure 4).

FIGURE 4
THE TWO STAGES IN THE EVOLUTION OF MRC



1. *More valid assumptions - the development of an empirically founded analytical algorithm:* the perhaps not always rational yet human tendency to rely on readily available reference values when assessing individual attributes was translated into a formal equation system ('algorithm') that simulates this decision behaviour ('rule'). In addition to this, we developed a statistical procedure by which it is possible to estimate and optimise the parameters in this equation system. The precise derivation of the equation system is described in the appendix.

We used this analytical procedure instead of the classic conjoint algorithm to predict actual decisions made by respondents in conjoint analyses. It was thus possible to compare the accuracy of the predictions of the alternative algorithm with that of the classic algorithm. *This comparison demonstrated that the alternative algorithm was mostly far superior, and never inferior to classic conjoint modelling.*

In a typical example (optimising a product concept in the telecommunications sector with n=369 respondents), conjoint analysis using a classic algorithm (CBC) was able to correctly predict 61% of actual decisions, whereas conjoint analysis using the alternative algorithm was correct in 67% of cases. If one deducts from each of these percentages the proportion of accidentally correct predictions that could be expected (i.e. 33% with three options), we were able to improve the net predictive capability of CBC by 22% just by only employing the alternative algorithm (see figure 5).

2. *More flexible modelling - a combination of the strengths of both approaches:* we have seen above that most respondents pursued a choice rule different to the one implied by the classic conjoint analyses. Nevertheless, 26% pursued a process that matches it. Given this diversity in respect to two complementary choice rules, it doesn't seem very sensible to force everybody into the framework of a single rule – be it the classical or the "new" one.

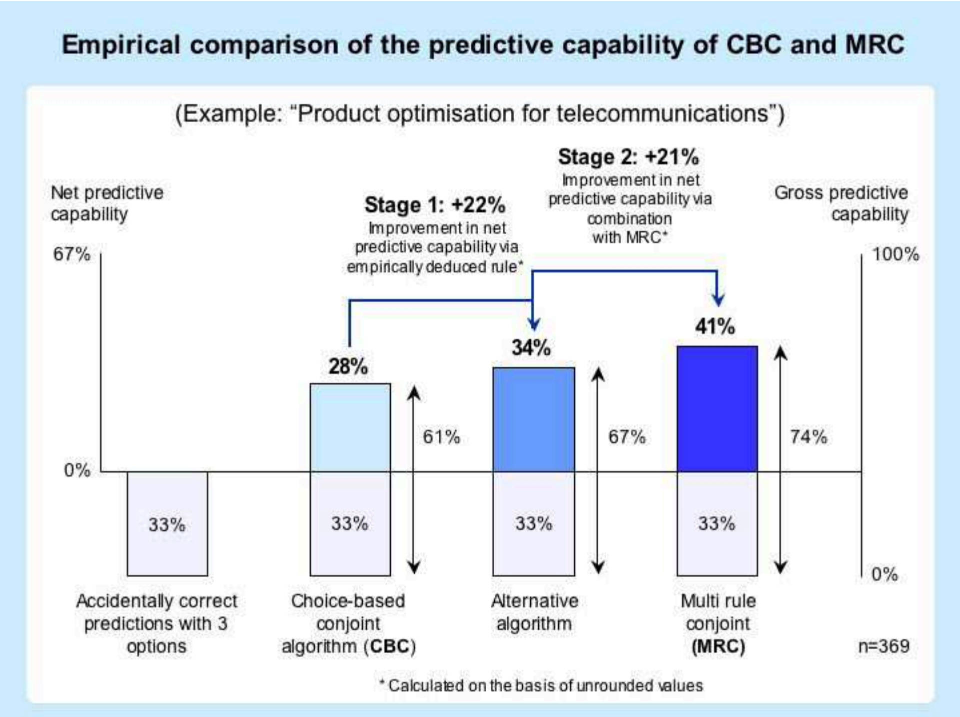
In the second stage we therefore supplemented the classic conjoint analysis with an additional upstream analysis within whose framework we analyse what proportion of respondents consciously or unconsciously are likelier to follow the assumed selection rule (figure 2) and what proportion of respondents are likelier to follow the empirically deduced selection rule (figure 3). This analysis is a purely statistical optimisation, i.e. in order for it to happen, respondents don't have to make any statements about their behaviour. Once each respondent has been assigned to a rule in accordance with their individual decision behaviour, the corresponding model parameters with the accompanying algorithm are statistically optimised for each of the two groups. Thanks to the combined predictive power of the two decision rules, the thus expanded and more flexible Multi-Rule Conjoint analysis achieved far better predictions.

The reason for this can again be illustrated by the mentioned sample project: we analysed the behaviour of individual respondents throughout the various rounds (in this case fifteen), and we found that if a person can be better predicted with the classical algorithm the "new" algorithm would have correctly predicted only very few of the decisions that weren't explained with its counterpart, and vice versa. The behaviour of individual respondents seems to follow either one rule or the other, and indeed for the most part does so consistently.

If one now duly applies the two algorithms in a selective manner, one achieves a combined gross accuracy of prediction of 74% (see figure 5). Since all the respondents weren't 'lumped together', but the more individually appropriate prediction model was employed in each individual case, it was possible to further increase the net predictive capability of MRC compared to conjoint analysis based on the "new" algorithm by another 21%.

If one takes Stages 1 and 2 together, it was possible to increase the predictive capability compared to classic CBC analysis by as much as 47%. Moreover, the practical relevance of this result was demonstrated in totally different recommendations relating to optimal product design that emerged from MRC versus CBC analysis. Other studies have even been able to show an increase

FIGURE 5
EMPIRICAL COMPARISON OF THE PREDICTIVE CAPABILITY OF CBC AND MRC



in the gross predictive capability to over 80%, and in the net predictive capability by far in excess of 60%. Even if these values are the exception, the combination of the two algorithms' predictive capability virtually always leads to a clear improvement.

However obvious the idea of combining complementary algorithms might now appear, this idea was 'inconceivable' so long as it was assumed that 'irrational' decisions cannot be predicted. Only after we have been able to prove that suboptimal choice behaviour is not purely random but can also be modelled mathematically, did it become meaningful to combine two rules in one tool. In this respect, both stages in the evolution of MRC build directly upon one another, and jointly explain this impressive increase in predictive power. At the end of the day, this is achieved because MRC allows far better for the nature and diversity of human decision behaviour.

CONCLUSIONS: THE STRENGTHS OF TWO RESEARCH TRADITIONS COMBINED IN ONE INNOVATIVE TOOL THAT HAS CONSIDERABLE PRACTICAL BENEFITS

If we want to validly predict real-life consumer behaviour we should base their modelling on the heuristics real-life consumers do employ when making decisions. We should not too readily succumb to the temptation of simply assuming what would be rational choice behaviour as those assumptions have eventually proven to be too naïve and idealistic. We should rather try to go the "extra mile" of understanding the psycho-logic of human choices first. Especially since those choices are not purely random but follow a certain rule that – although not rational – can still be modelled mathematically.

This is exactly what MRC does in the first stage. Furthermore, in the second stage MRC allows for the fact that not all people follow this suboptimal choice rule; some still are behaving quite "rational". Thus, MRC accounts for both, for the fact that most people are not behaving like a "homo oeconomicus", and for the fact that some still do.

In short, the particular advantages of "Multi-Rule Conjoint Analysis" can be summarised under the following aspects:

• *Scientific anchoring:* The core of MRC is the logical application of empirical research findings to the conjoint analysis modelling of decision behaviour.
• *Twofold innovation:* Firstly, the alternative modelling algorithm and secondly, its combination with the strengths of the classical conjoint algorithm make MRC a twofold innovation
• *Increase in effectiveness and efficiency:* MRC demonstrably delivers much better predictions without any greater expenditure of time or effort as the data collection procedure is still the same

Overcoming the narrow frontiers of rational assumptions within classical market research tools paves the way for much better predictions. By that, even such a classical and widely accepted tool like conjoint analysis can still be significantly improved.

References

Bauer, F. (2000). Psychologie der Preisstruktur: Entwicklung der "Entscheidungspsychologischen Preisstrukturgestaltung" zur Erklärung und Vorhersage nicht-normativer Einflüsse der Preisstruktur auf die Kaufentscheidung. München: CS Press.

Bauer, F. (2004). Der "gefühlte" Preis: Vom Einfluss der Preisstrukturen auf Kaufentscheidungen. Wirtschaftspsychologie aktuell, 2, 31-35.

Biswas, A. & Blair, E. A. (1991). Contextual Effects of Reference Prices in Retail Advertisements. Journal of Marketing, 55, 1-12.

Felser, G. (2001). Werbe- und Konsumentenpsychologie. 2nd edition. Stuttgart: Schäffer-Poeschel.

Hartmann, A. & Sattler, H. (2002). Commercial Use of Conjoint Analysis in Germany, Austria and Switzerland. Research Papers on Marketing and Retailing. University of Hamburg.

Jansen, J. (2006). Validierung von Choice-based Measurement Analysen: Eine empirische Arbeit zur Optimierung der klassischen Choice-based Conjoint durch Hinzunahme aternativer Nutzenmodelle und bewusst verbalisierter Entscheidungsregeln. Diplomarbeit Universität Lüneburg.

Kahneman, D., Slovic, P. & Tversky, A. (1982). Judgment Under Uncertainty: Heuristics and Biases. Cambridge, New York, Melbourne: Cambridge University Press.

Lichtenstein, D. R. & Bearden, O. W (1988). An Investigation of Consumer Evaluations of Reference Price Discount Claims. Journal of Business Research, 17, 189-200.

Tversky, A. & Kahneman, D. (1981). The Framing of Decisions and the Psychology of Choice. Science, 22, pp. 453-458.

Wittink, D. R.; Vriens, M. & Burhenne, W. (1994). Commercial Use of Conjoint Analysis in Europe: Results and Critical Reflections. International Journal of Research in Marketing, 11, pp. 41-52.

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