ENTRE JULGAMENTO E ESCOLHA: AS CATEGORIAS DE ANÁLISE CONJOINT EM PESQUISAS DE MARKETING

BETWEEN JUDGMENT AND CHOICE: THE CATEGORIES OF CONJOINT ANALYSIS IN MARKETING RESEARCH

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Comunicação:
O XIV SINGEP foi realizado em conjunto com a 14th Conferência Internacional do CIK (CYRUS Institute of Knowledge) e com a SPARK (Society for Promoting Academic Research and Knowledge), em formato híbrido, com sede presencial na UNINOVE - Universidade Nove de Julho, no Brasil.

Agradecimento à orgão de fomento:
Bolsa de estudos oferecida pela UNINOVE

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Objetivo do estudo
O estudo investiga por que a pesquisa de marketing concentra a escolha de análise conjoint em apenas duas das oito famílias existentes, e propõe um protocolo metodológico que reconecte a escolha da família à estrutura cognitiva do problema de pesquisa investigado.

Relevância/originalidade
A escolha do método é tratada como hábito, não como decisão deliberada: apenas 10 dos 247 artigos analisados justificam explicitamente a família adotada. O estudo evidencia essa lacuna e argumenta que ela oculta famílias mais adequadas ao problema investigado.

Metodologia/abordagem
Revisão de literatura, seguindo o protocolo SPAR-4-SLR, aplicada a um corpus de 247 artigos publicados entre 2016 e 2025 em periódicos Q1/Q2 do SJR (categoria Business), com codificação da família de análise conjoint empregada e da presença de justificativa metodológica.

Principais resultados
As famílias CBC/DCE e CVA respondem por 89,9% do corpus, a Menu-Based Choice está ausente e apenas 4% dos artigos justificam a escolha metodológica A análise cruzada entre família e objetivo revela decisões recorrentemente desalinhadas com a literatura seminal de cada método

Contribuições teóricas/metodológicas
O estudo propõe um protocolo de decisão em cinco passos, ancorado em objetivo, número de atributos, tarefa cognitiva, recurso computacional e formato de aplicação, reconectando a escolha metodológica ao problema de pesquisa e tornando essa decisão auditável e transferível entre pesquisadores.

Contribuições sociais/para a gestão
Ao tornar explícita a escolha metodológica, o protocolo apoia gestores e pesquisadores aplicados na seleção da técnica de análise conjoint mais adequada para decisões de precificação, portfólio e estratégia de oferta, reduzindo o risco de resultados enviesados por método inadequado.

Palavras-chave: análise conjoint, escolha discreta, métodos de pesquisa em marketing, preferência do consumidor, protocolo de decisão

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Study purpose
The study investigates why marketing research concentrates its choice of conjoint analysis in only two of the eight existing families, and proposes a methodological protocol that reconnects family choice to the cognitive structure of the research problem investigated.

Relevance / originality
Method choice is treated as a habit, not a deliberate decision: only 10 of the 247 articles analyzed explicitly justify the family adopted. The study evidences this gap and argues it conceals families better suited to the problem.

Methodology / approach
Literature review, following the SPAR-4-SLR protocol, applied to a corpus of 247 articles published between 2016 and 2025 in Q1/Q2 SJR journals (Business category), coding the conjoint analysis family employed and the presence of methodological justification.

Main results
The CBC/DCE and CVA families account for 89.9% of the corpus, the Menu-Based Choice family is absent, and only 4% of the articles justify the methodological choice. The cross-tabulation between family and objective reveals decisions recurrently misaligned with each method's seminal literature.

Theoretical / methodological contributions
The study proposes a five-step decision protocol, anchored in objective, number of attributes, cognitive task, computational resource, and application format, reconnecting the methodological choice to the research problem and making that decision auditable and transferable among researchers.

Social / management contributions
By making the methodological choice explicit, the protocol supports managers and applied researchers in selecting the conjoint analysis technique best suited to pricing, portfolio, and offer-strategy decisions, reducing the risk of results biased by an inadequate method.

Keywords: conjoint analysis, discrete choice, marketing research methods, consumer preference, decision protocol

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Introduction

Conjoint analysis is one of the most well established families of methods in marketing research and, at the same time, one of the most underused in its diversity. Under the same term coexist eight families, from traditional conjoint to choice experiments, from adaptive to compositional variants, each designed for a distinct type of decision problem, with its own assumptions about how the respondent judges, chooses, and reveals preference. Given this repertoire, one would expect the choice of family to be, in itself, a deliberate methodological act. That is not what is observed. As this essay documents, the field has concentrated almost all of its output in two of the eight families and, in the vast majority of cases, does not record why that family was preferred over the others.

This contrast arises the argument that organizes this essay: the choice of conjoint analysis family in marketing research has become a habit guided by familiarity and software availability, rather than by the cognitive structure of the problem under investigation. This decoupling between method and object carries a cost that goes beyond reporting; it keeps hidden, even from the researcher, the families that would best solve their problem. The question that operationalizes the argument is: what methodological foundations should guide the marketing researcher in choosing the conjoint analysis family most suited to their object of study?

From the Conjoint Measurement of Green and Rao (1971) emerged variations such as the Adaptive Conjoint Analysis of Johnson (1987), Random Utility Theory/Discrete Choice Experiment of McFadden (1974) and Louviere and Woodworth (1983), Adaptive Choice-Based Conjoint of Johnson et al. (2003), Menu-Based Choice of Liechty et al. (2001), Best-Worst Scaling/Maximum Difference Scaling of Finn and Louviere (1992), Self-Explicated of Srinivasan (1988), and hybrid models combining compositional and decompositional elements of Green (1984). This diversity of families contributes a broad methodological repertoire available for marketing research, but on the other hand, it also creates a challenge. The result observed is that the choice of which conjoint family to use, and why, is usually not justified by researchers.

The evidence for this research was gathered through the analysis of 247 articles published in journals classified in the Q1 or Q2 quartiles of the SJR indicator, Business category, between 2016 and 2025, identified through the SPAR-4-SLR protocol (Paul et al., 2021).

This essay, following Bergh et al. (2022), produces a contribution by analyzing, comparing, and guiding the use of research methods based on systematically built argumentative and empirical foundations. For MacInnis (2011), this type of careful and propositional contribution in the domain of research procedures distinguishes what appears similar, articulates the criteria that differentiate applications, and proposes guidance for method choice, as Ladik and Stewart (2008) also argued.

The purpose of this essay is to understand what each conjoint category contributes, in methodological foundations, assumptions, and support, to the study of consumer judgment and choice, and to suggest a decision framework that guides future researchers in selecting the conjoint analysis most suited to their research context.

Theoretical Background

Under the generic term conjoint analysis, eight categories of methods are gathered, distinguished by the design of the stimuli presented to the respondent, the response task requested, and the procedure used to measure utility values. This section presents each of these categories, assigns the abbreviation that will be used throughout this essay, and identifies the seminal authors who ground each family.

Grouping these families under a common term is not consensual. There is a position in the literature holding that discrete choice experiments derive from random utility theory and experimental economics, not from conjoint measurement of psychometric origin, so that treating them as a variant of conjoint conflates two traditions with distinct assumptions about the nature of the data and the interpretation of parameters (Louviere, Flynn & Carson, 2010). This essay adopts the broad scope, which groups the families by the practical problem they solve, the estimation of partial attribute values from judgments or choices, because this is the understanding current in marketing research practice and the one that corresponds to the use of the term in the corpus articles. The choice is operational and does not imply theoretical equivalence between the families, a distinction revisited in the comparison of foundations in Tables 4 through 7.

Traditional conjoint, also referred to in the literature as Conjoint Value Analysis and which we will call in this study by the abbreviation CVA, was introduced by Green and Rao (1971) as a conjoint measurement method capable of decomposing global preference judgments about hypothetical product profiles into partial values (part-worths) attributed to each attribute level. Green and Srinivasan (1978, 1990) consolidated the method in marketing research, establishing the fractional factorial design, full-profile presentation, and regression estimation procedures that characterize CVA.

To reduce respondent cognitive load in the face of a large number of attributes, Johnson (1987) proposed Adaptive Conjoint Analysis, which we will call in this study by the abbreviation ACA. In this family, the task is divided into an initial self-explication stage of the respondent's priorities and a stage of evaluating pairs of partial profiles. The questionnaire adapts computationally to each respondent's answers, reducing the number of judgments required without compromising precision.

Grounded in McFadden's (1974) Random Utility Theory, found in the literature as Choice Based Conjoint or Discrete Choice Experiments and introduced into marketing research by Louviere and Woodworth (1983), we will call this family in this study by the abbreviation CBC/DCE. Louviere et al. (2000) consolidated its theoretical foundations and procedures in an experimental design with choice tasks for applying the method to consumer behavior.

Combining the adaptive logic of ACA with the choice task of CBC, Johnson et al. (2003) proposed Adaptive Choice-Based Conjoint, which we will call in this study by the abbreviation ACBC. The method structures data collection into three phases: configuration of an ideal profile (build-your-own), formation of a set of alternatives, and finally choice tasks between profiles close to that ideal construct, yielding individualized utility estimates with fewer tasks.

When the object of choice is not a single profile but a combination of products, services, or components selected from a menu of options, the category has been called Menu-Based Choice, which we will call in this study by the abbreviation MBC. Liechty et al. (2001) formalized this method to model customization decisions, in which respondents simultaneously select multiple items, extending the scope of conjoint to decisions involving not just a single product or service but a portfolio.

Introduced by Finn and Louviere (1992), this approach is known as Best-Worst Scaling or Maximum Difference Scaling, which we will call in this study by the abbreviation BWS/MaxDiff. Because it requires only ordinal best versus worst judgments, rather than rating

scales or full-profile choices, the method produces priority measures with greater discriminating power between items and lower likelihood of bias.

In contrast to the decompositional families, the Self-Explicated approach directly asks the respondent to rate the importance of each attribute and its desirability, combining these ratings compositionally to estimate total utility. Srinivasan (1988) formalized this procedure in a two-stage conjunctive-compensatory model, which we will call in this study by the abbreviation SE.

Finally, the family of hybrid models combines compositional elements, such as the SE category, with decompositional elements, such as the CVA category. Judgments about profiles or choices between alternatives, in a single collection design, were systematized by Green (1984) in this method, which we will call in this study by the abbreviation Hybrid.

Methodology

To build the corpus of this essay, the SPAR-4-SLR protocol (Scientific Procedures and Rationales for Systematic Literature Reviews) proposed by Paul et al. (2021) was used, structured in three sequential stages: Assembling, Arranging, and Assessing, each stage divided into sub-stages that guide search, refinement, and analysis decisions for the corpus. In the Assembling stage, under the sub-stage called Identification, the central focus of the study was defined, along with the research question and the strategy for identifying how conjoint analysis categories have been used in marketing research. Next, as a rigor and quality-certification criterion for the sources used, only articles from scientific journals classified in the Q1 or Q2 quartiles of the SJR (Scimago Journal Rank) indicator were considered.

In the Acquisition sub-stage, the search was carried out on June 25, 2026, in the Web of Science and Scopus databases, using the Boolean string (conjoint OR "discrete choice experiment" OR "choice-based conjoint" OR "choice based conjoint" OR "adaptive choice-based conjoint" OR "best-worst scaling" OR maxdiff OR "max-diff" OR "adaptive conjoint" OR "self-explicated" OR "menu-based choice" OR "menu-based conjoint" OR "hybrid conjoint"), using the databases' own filtering tools, selecting articles with the keywords in the Title, Abstract, and Keywords fields. The search was restricted to the 2016 to 2025 period (10 years), article-type documents only, in the Business, Management and Accounting category, open-access publications, in the English language.

The open-access filter reduced the base from 1,806 to 744 records, a criterion unrelated to the content of the studies. It should be noted that this filter operates jointly with the source-quality criterion applied afterward and tends to under-represent the field's most selective journals, mostly published under subscription. Since these are also the outlets in which the methodologically more elaborate variants tend to be reported, the family distribution presented in Table 2 should be read as characteristic of open-access production, not of the field as a whole, a point revisited in the limitations.

The search conducted resulted in hundreds of articles. In the Arranging data-organization stage, the retrieved records were coded and exported into an Excel file in XLSX format. The spreadsheet was structured with fields for bibliographic identification, source database, citation count, open access status, thematic category, among others. The merging of Web of Science and Scopus results and the removal of duplicate articles (by DOI and by title) was carried out using Excel's duplicate-removal tools, reducing the 721 records to 557 articles. It was necessary, in the Purification sub-stage, for the 557 records to undergo title-and-abstract screening, which excluded 206 articles outside the marketing scope and 12 false positives of the term "conjoint," resulting in 339 marketing articles eligible for the next stage.

Continuing, the source-quality criterion (Q1/Q2 SJR, Business category) was applied, restricting the corpus to 284 articles. Finally, the last step was carried out, in which 37 articles

that used the term conjoint generically, as an English-language adjective rather than as a method, were identified and excluded. Collection, identification, filtering, and selection resulted in a final total of 247 articles composing the corpus of this essay. Below is the sequence of procedures and the resulting numbers of each stage of the article-filtering process, up to the final corpus, as shown in Table 1.

Table 1
Corpus selection funnel, by stage and filter applied in each database

Stage	Web of Science	Scopus	Integrated corpus
Initial result without filters	22,905	21,781	44,686
Filter: period from 2016 to 2025 (10 years)	13,033	12,528	25,561
Only article-type documents	11,261	10,938	22,199
Only Business, Management and Accounting category	541	1,265	1,806
Only open access (Open Access)	214	530	744
Only in the English language	210	521	731
Final base adjustment[1]	207	514	-10
Total before merging (WoS + Scopus)			721
Duplicates removed (same DOI in both databases)			−164
Unique corpus after merging			557
Marketing relevance screening[2]			339
Source quality filter (SJR Q1/Q2, Business category)			284
Final total corpus articles[3]			247

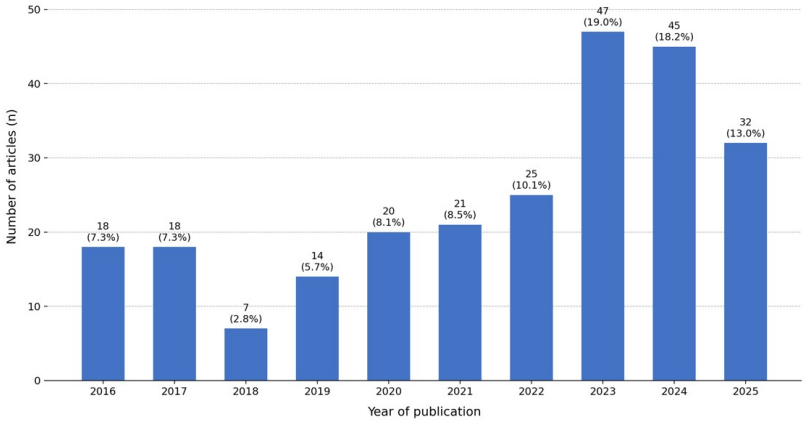
Notes. [1]Cut of 10 early access articles classified as 2026 (Web of Science) and restriction to records with Publication Stage Final (Scopus). [2]Removal of 206 articles outside the scope of marketing research and 12 false positives of the term "conjoint". [3]Exclusion of 37 articles for using the term conjoint as an English adjective and not as a method.

Still within the Assessing stage (Evaluation sub-stage), the 247 articles were classified according to the conjoint analysis family employed. The initial screening searched for terms in the title, abstract, and keywords. Since the variant is usually stated in the method section, this screening was not taken as the final classification; articles with no identifiable family in those fields, as well as all articles from the less frequent families, had their full text consulted. The coding followed documented decision rules, assigning the family based on the design of the stimuli and the response task described, not merely the label used by the authors. Each article was also coded for the presence of an explicit justification for the choice of family (fit to the objective, number of attributes, nature of the cognitive task, comparison with other families, or operational constraint), in mutually exclusive categories that record the study's primary objective; when there was more than one objective, the one linked to the variable of interest of the conjoint analysis prevailed. In the Reporting sub-stage, the results are synthesized in Table 2.

Results Analysis and Discussion

The 247 articles composing the final corpus were analyzed along four dimensions: temporal distribution of publications, conjoint analysis category, industry or market segment studied, and research objective. Figure 1 presents the evolution of conjoint analysis research output in marketing over the last 10 years.

Figure 1
Evolution of conjoint analysis research output



Note. N = 247 articles. Evolution of the production of articles on conjoint analysis applied in marketing between 2016 and 2025.

Table 2 indicates a significant concentration in two families, CBC/DCE and CVA, which together account for 89.9% of the corpus (66.0% and 23.9%, respectively), while the remaining five categories, BWS/MaxDiff, Hybrid, ACBC, ACA, and SE, together account for only 10.1% of the publications. This distribution indicates that, in a field with eight methodologically distinct categories, nine out of every ten studies use only two of them.

No study employing the MBC family was identified in the corpus. This result should be read with caution in two respects. The first concerns coverage: Menu-Based Choice studies that do not use the term conjoint in the title, abstract, or keywords are only retrieved through the method's own descriptor. The second concerns outlet: MBC application is concentrated in offer-configuration and package-pricing contexts, with relevant output in applied and technical literature that is not part of the open-access Q1/Q2 journal scope adopted here. The absence in the corpus therefore indicates low penetration of the family in the academic marketing literature retrievable within this scope, not the nonexistence of applications.

Table 2
Distribution of articles by conjoint analysis family (n = 247)

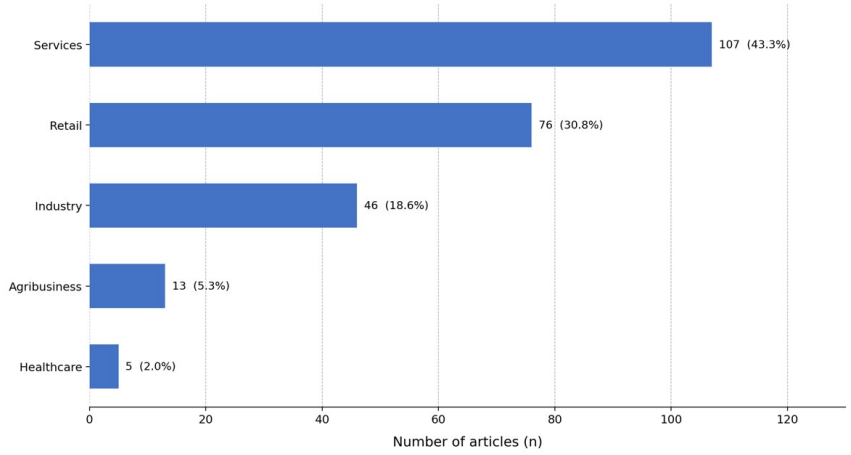
Family	Abbreviation	n	%
Choice Based Conjoint / Discrete Choice Experiment	CBC/DCE	163	66.0
Traditional Conjoint (Full-Profile)	CVA	59	23.9
Best-Worst Scaling / MaxDiff	BWS/MaxDiff	15	6.1
Hybrid Models	Hybrid	5	2.0
Adaptive Choice-Based Conjoint	ACBC	2	0.8
Adaptive Conjoint Analysis	ACA	2	0.8
Self-Explicated	SE	1	0.4
Menu-Based Choice	MBC	0	0.0
Total		**247**	**100.0**

Notes. Corpus built using the SPAR-4-SLR protocol (Paul et al., 2021), with the search conducted on 06/25/2026 in the Web of Science and Scopus databases. Percentages refer to the total of 247 articles after relevance screening and source quality filtering (SJR Q1/Q2, Business category, 2016–2025). The MBC family is reported with n = 0 so the table covers the eight categories described in Section 2.

Figure 2 shows concentration in two segments: Services (43.3%) and Retail (30.8%), which together account for 74.1% of the corpus, reflecting the predominance of conjoint analysis in business-to-consumer (B2C) contexts, in which measuring consumer preference is central to portfolio, pricing, and brand-positioning decisions. The industrial segment represents 18.6% of the publications, indicating relevance in product-design contexts, though with lower intensity. The Agribusiness segment (5.3%) appears especially in the evaluation of preferences for agricultural product attributes, and the Health industry (2.0%) appears only marginally in the corpus.

Figure 2

Distribution of articles by market segment

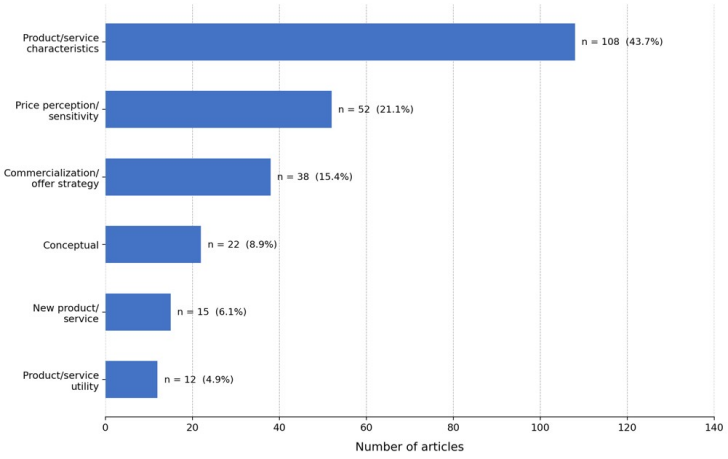


Note. N = 247 articles. Classification based on the reading of the title, abstract, and keywords of each article. Agribusiness includes studies in agricultural, rural, and farm-input contexts. Percentages calculated over the total of 247 articles published between 2016 and 2025.

More than 80% of the corpus is concentrated in three main objectives, as shown in Figure 3: product and service attribute characteristics (43.7%), price perception and sensitivity evaluation (21.1%), and definition of commercialization and offer strategy (15.4%).

Figure 3

Distribution of articles by research objective



Note. Classification based on the reading of the title, abstract, and keywords of each article. The Conceptual category covers studies that used conjoint analysis as an object of review or methodological discussion, without direct empirical application. The categories are mutually exclusive and represent the primary objective identified in each article. The area of each rectangle is proportional to the number of articles in the category.

The Conceptual category (8.9%), in turn, groups review and methodological-discussion studies, signaling that a portion of the literature recognizes conjoint analysis as an object of reflection, not merely as a research resource or tool.

However, one notable finding is the low share of objectives aimed at the design of a new product/service (6.1%) and at product/service utility (4.9%), contexts in which categories such as ACBC, ACA, and Hybrid present recognized methodological advantages over conventional CVA and CBC/DCE, since they were developed to handle larger numbers of attributes and adaptive tasks. Next, Table 3 presents a global view through the data obtained from the corpus, with the cross-tabulated distribution between each family used and the research objective, indicating some effective patterns of use.

Table 3

Cross-tabulated distribution between conjoint analysis families and research objective

	Characteristics Product/ service		Price Sensitivity		Commercialization Strategy offer		Conceptual		New Product/ service		Utility Product/ service		Total	
Family	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
CBC/DCE	65	39.9	42	25.8	27	16.6	13	8.0	10	6.1	6	3.7	**163**	**66.0**
CVA	33	55.9	8	13.6	7	11.9	4	6.8	3	5.1	4	6.8	**59**	**23.9**
BWS/MaxDiff	8	53.3	1	6.7	3	20.0	1	6.7	1	6.7	1	6.7	**15**	**6.1**
Hybrid	1	20.0	-	-	-	-	3	60.0	-	-	1	20.0	**5**	**2.0**
ACBC	1	50.0	1	50.0	-	-	-	-	-	-	-	-	**2**	**0.8**
ACA	-	-	-	-	1	50.0	1	50.0	-	-	-	-	**2**	**0.8**
SE	-	-	-	-	-	-	-	-	1	100.0	-	-	**1**	**0.4**
Total	**108**	**43.7**	**52**	**21.1**	**38**	**15.4**	**22**	**8.9**	**15**	**6.1**	**12**	**4.9**	**247**	**100**

Note. n = absolute number of articles. In the rows, % = percentage calculated over the total for the conjoint category. In the Total column, % represents each family's share of the corpus (n = 247). Percentages for the SE, ACA, ACBC, and Hybrid rows are calculated on bases of 1 to 5 articles and should not be interpreted as stable proportions. They are reported only to show the internal composition of each row.

The coding of the methodological justification reveals the most direct finding of this analysis: of the 247 articles in the corpus, 10 (4.0%) present an explicit justification for the choice of conjoint family employed. In the remaining 237 articles, the method is described and its seminal source is cited, but there is no passage explaining why that family was preferred over the others. The pattern is consistent between the two majority families and is not concentrated in any specific period of the interval analyzed.

This result requires a qualification. The absence of explicit justification in the published text does not imply the absence of methodological deliberation: editorial norms of conciseness and the familiarity of the field's reviewers with the methods may make the justification dispensable in the eyes of authors and editors. What the data establishes is that the decision is not recorded and is therefore neither auditable nor transferable to other researchers, which is already sufficient to support the need for an explicit protocol.

The data show that the CBC/DCE category is the most used family across all six research objectives identified in the corpus, including the "new product/service" objective (n = 10; 6.1% of the articles using CBC/DCE), a context for which the seminal literature attributes an advantage to the ACBC family, whose ideal-profile configuration phase maps the space of acceptable configurations before the choice tasks (Johnson et al., 2003). This does not mean that the ten studies identified were poorly served by CBC/DCE, since fit depends on the number of attributes and the collection constraints of each design, information not available in the coded

fields. What the cross-tabulation indicates is that the alternative recognized in the literature for this objective remains practically absent from the corpus, with only two articles in total.

Likewise, the CVA category, the second most used family across all objectives, appears in four research articles on "product/service utility," an objective the literature associates with the ACA, ACBC, or Hybrid-with-SE categories, in which product and service attributes are explained to respondents (Srinivasan, 1988). Hybrid models concentrate three articles in the Conceptual category, indicating that this family has been discussed theoretically but applied empirically to a limited extent within the scope analyzed.

To explain why certain families are methodologically more suited to certain objectives than others, it is necessary to examine the structural dimensions that distinguish them. Tables 4, 5, 6, and 7 form a detailed comparison based on five dimensions: theoretical foundation, type of response task requested from the participant, fixed or adaptive nature of the questionnaire, scope of attributes supported without compromising collection validity, and the research objectives for which each family presents a methodological advantage recognized in the field's seminal literature

Table 4

Comparison of the CVA methodology and its evolution, ACA

Family	Theoretical Foundation	Response Task	Questionnaire	Attribute Scope	Best-Suited Objective	Example in Corpus
CVA	Conjoint Measurement (Green & Rao, 1971)	Rating or ranking of complete profiles. The respondent receives physical or digital cards or forms with product profiles in which all attributes appear simultaneously (full profile). The respondent evaluates each profile with a score (rating from 1 to 10) or ranks them from most to least preferred (ranking). The task is transparent and easy to explain to the respondent, but more demanding, since as the number of attributes increases, all levels appear at once on each card.	Fixed. All respondents receive exactly the same set of profiles, defined by a factorial design before collection. This facilitates control of the experiment and allows comparison across groups, but does not adapt to individual preferences.	Up to 6 to 8 attributes. This is CVA's operational limit. With full profiles, each card shows all attributes simultaneously. Above 6 or 8 attributes, cognitive load makes evaluations unstable and the respondent begins to ignore peripheral attributes. For a larger number of attributes, the ACA or ACBC models are more appropriate.	Product/service attribute characteristics or utility. CVA is suggested when the objective is to identify which attributes and levels of a product or service determine preference, or to estimate the utility of each characteristic for the respondent.	Penttinen et al. (2018); Keyser et al. (2022); McColl et al. (2019)
ACA	Adaptive Conjoint Analysis (Johnson, 1987)	Self-explication and comparison of partial pairs. The questionnaire operates in two phases. In the first, the respondent rates each level of each attribute for desirability (e.g., a 0 to 4 scale) and then assigns an importance score to each attribute, generating initial utility estimates. In the adaptive phase, the algorithm uses these estimates to select pairs of partial profiles, typically with 2 or 3 attributes each. The respondent indicates which of the two profiles they prefer, and the algorithm updates the estimates with each response.	Adaptive. This is ACA's key structural difference from CVA. Each respondent receives a different set of comparison pairs, determined in real time by their previous answers. The questionnaire cannot be applied on paper, since it requires computer or tablet administration. The adaptation reduces the total number of tasks and concentrates cognitive effort on the attributes that actually drive preferences.	Up to 30 attributes. This is ACA's other advantage over CVA. The self-explicated phase collects information on all attributes individually, one at a time, and the adaptive phase presents only 2 to 3 attributes per pair, regardless of the study's total number of attributes.	Utility with a large number of attributes. ACA is indicated when the objective is to estimate individual attribute utility across diverse contexts. It is not indicated for price-sensitivity analysis, since the self-explicated phase can inflate the perceived importance of price. It is suitable for complex categories such as industrial equipment, software, and financial services, in which it is common to have up to 30 relevant attributes.	Luhmann and Theuvsen (2018)

Table 5

Comparison of the CBC/DCE methodology and its evolution, ACBC

Family	Theoretical Foundation	Response Task	Questionnaire	Attribute Scope	Best-Suited Objective	Example in Corpus
CBC/DCE	Random Utility Theory / Discrete Choice Experiment (McFadden, 1974)	Choice among competing alternatives. The respondent receives choice sets with 2 to 5 alternatives and indicates which they would choose, with a possible “none of the above” option. The task is repeated 8 to 15 times with different combinations of attributes and levels. This task is cognitively closer to real purchase behavior, since the consumer chooses one option rather than rating all of them, which gives greater face validity to inferences about purchase behavior.	Fixed. Uses an experimental design defined before collection, ensuring that attribute levels vary independently across choice sets. All respondents receive the same sets, which facilitates experiment control and group comparison. There is no adaptation to respondent answers.	Up to 6 to 8 attributes. Like CVA, CBC/DCE presents full profiles in each choice set, which limits the number of attributes. Studies with more than 8 attributes tend to generate less reliable responses, as respondents begin to ignore peripheral attributes.	Characteristics, price, and offer strategy for products and services. Produces stable estimates for managerial decisions. For pricing and willingness to pay, price is included as one of the attributes and estimated by the ratio between the attribute's coefficient and the price coefficient. For offer strategy, the model allows simulating market share under different configurations, which makes CBC/DCE the market standard for	Kostyra et al. (2016); Delmas and Lessem (2017); Huang et al. (2024)

Family	Theoretical Foundation	Response Task	Questionnaire	Attribute Scope	Best-Suited Objective	Example in Corpus
					competitive analyses.	
ACBC	Adaptive Choice-Based Conjoint (Johnson et al., 2003)	Ideal-profile configuration, screening, and choice. ACBC operates in three phases. In the BYO (build your own) phase, the respondent configures their ideal product by selecting the preferred level of each attribute, generating the individual reference profile. In the screening phase, the algorithm generates alternatives close to the BYO profile and the respondent evaluates each with a binary response, which identifies unacceptable and must-have levels. In the choice phase, the respondent performs choice tasks among alternatives that passed the screening, i.e., close to their preference space.	Adaptive. The three phases are generated in real time based on the respondent's answers. The BYO determines the reference point, screening determines the acceptable space, and choice sets are built within that space. ACBC cannot be applied on paper forms, since it requires specialized software.	Up to 30 attributes. Like ACA relative to CVA, ACBC solves CBC/DCE's scope problem. The BYO phase collects information on all attributes sequentially without overloading the respondent with full profiles. Screening and choice operate on relevant subsets for that respondent, keeping cognitive load controlled.	New products and a large number of attributes. For new product research, the BYO phase maps the space of ideal configurations, screening identifies acceptability limits, and the choice phase discriminates among viable alternatives. This produces information beyond the relative importance of attributes: which configurations are acceptable, which attributes are decisive, and which levels are deal-breakers. For large attribute spaces, it distributes cognitive load across the phases.	Mazurek and Prey (2025); Muller and Wittmer (2023)

Table 6

Comparison of the MBC and BWS/MaxDiff methodologies

Family	Theoretical Foundation	Response Task	Questionnaire	Attribute Scope	Best-Suited Objective	Example in Corpus
MBC	Menu-Based Choice (Liechty et al., 2001)	Selection of menu components. Instead of choosing one product among competing alternatives, as in CBC/DCE, the respondent receives a menu with individual items and prices and freely selects which to include in their purchase, being able to choose any combination. The task is repeated across multiple scenarios with variations in price or menu composition, which replicates real purchase situations.	Fixed. The menu presented is defined before collection. Components, prices, and scenarios are the same for all respondents, and what varies is the selection made in each scenario. Multiple scenarios with different price structures are presented to allow estimation of each component's price elasticities and the interdependencies among them.	Combinations. MBC does not operate on the conventional logic of attributes and levels. It works with discrete components that can be selected or not, generating a combinatorial choice space with up to 10 available components. The design's relevance lies not in the number of attributes, but in the combinatorial structure of possible selections, which grows exponentially with the number of items on the menu.	Commercialization strategy and product/service bundles. Indicated when the objective is to understand how to structure the offer: define which components to include in basic and premium bundles, identify which combinations are jointly most demanded, estimate the impact of price changes for one component on the selection of others, and simulate revenue under different bundling strategies. Not suitable for estimating preference for a single product.	No occurrence in the corpus
BWS/ MaxDiff	Best-Worst Scaling / Maximum Difference Scaling (Finn & Louviere, 1992)	Identification of the best and worst. In each round, the respondent receives a subset of 3 to 5 items and indicates which is most important and which is least important among those presented. The task is repeated 8 to 15 times, each round with a different subset. Identifying extremes is more natural and less prone to response bias than Likert scales, which suffer from concentration of responses at the higher values. The method forces differentiation.	Fixed. The experimental design, i.e., which items appear in which subset and in which rounds, is defined before collection using balanced or similar incomplete block designs, ensuring each item appears the same number of times and each pair of items is presented with the same frequency. All respondents receive the same design, which facilitates comparison across groups and segments.	10 to 40 items. Works with lists of items that can be product characteristics, perceived benefits, communication messages, brand values, prices, or any set of elements the researcher wants to prioritize. The 10-to-40 item range reflects the method's practical limits.	Prioritization of attributes and price sensitivity. Indicated when the objective is to rank the relative importance of a list of items without presenting complete product profiles: prioritization of attributes or benefits for positioning, message testing, brand-value ranking, and identification of relevant satisfaction or loyalty attributes. For price, it is used to rank price points, which is useful when the objective is not to estimate a demand curve but to identify acceptable ranges.	Kim et al. (2019); Carl et al. (2024); Parvin et al. (2016)

Table 7

Comparison of the SE and Hybrid methodologies

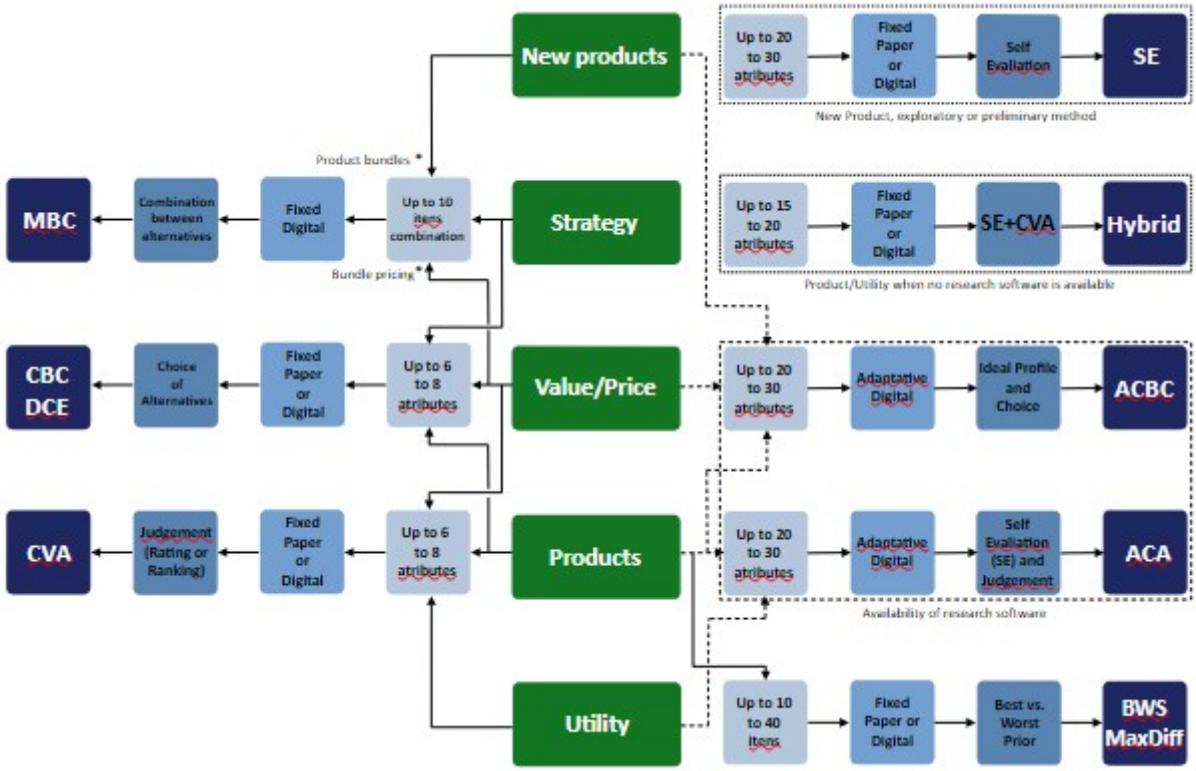
Family	Theoretical Foundation	Response Task	Questionnaire	Attribute Scope	Best-Suited Objective	Example in Corpus
SE	Self-Explicated (Srinivasan, 1988)	Direct evaluation of importance and desirability. The questionnaire operates in two sequential stages. In the first, the respondent rates the desirability of each level of each attribute on a numerical scale, typically 0 to 10. In the second, the respondent rates the importance of each attribute as a whole, by scale or point allocation. No product profile is presented and no choice between alternatives is requested. This simplicity makes SE the fastest method to administer.	Fixed. All respondents evaluate the same attributes and levels, in the same structure. The order of attributes may be randomized to control for position effects, but the content is identical for everyone. It can be applied on paper, in an online survey, or in person, with no need for specialized software.	Flexible, with limitations. Since SE does not present full profiles, there is no cognitive limit tied to stimulus complexity, allowing 20, 30, or more attributes to be included. In studies with a large number of attributes, however, the respondent starts to assign similar scores to all items to finish the questionnaire faster, which compromises response quality.	Utility and exploratory studies. Indicated when the objective is to identify which attribute levels are most desirable and which attributes carry the most importance, a function similar to CVA's but at lower collection cost. In an early research phase, it functions as preliminary screening of relevant attributes before a CBC/DCE or ACBC study. The main limitation is social-desirability bias, which makes the method less suitable for purchase-behavior studies.	Conceptual (Srinivasan, 1988)
Hybrid	Hybrid Conjoint Model (Green, 1984)	Two distinct, sequential stages. In the compositional module, the respondent directly rates the desirability of each level of each attribute and the importance of each attribute, as in SE, covering all of the study's attributes quickly. In the decompositional module, a smaller set of product profiles is evaluated, as in CVA, built around the attributes identified as most relevant in the previous module. Final utility combines the results of both modules, using the profile data to calibrate and correct biases.	Fixed or adaptive. In the fixed version, the decompositional module's profiles are predefined and the same for all respondents. In the adaptive version, profiles are selected based on each respondent's answers in the previous module. This second version is structurally closer to ACA.	Up to 30 attributes. Hybrid was designed to overcome CVA's 6-to-8 attribute limit. Since the compositional module rates all attributes directly and sequentially, and the decompositional module works only with a relevant subset, the model can handle 20 to 30 or more attributes. It was the first solution to conjoint's attribute-limitation problem, a function later taken over by ACA and, more efficiently, by ACBC.	Exploratory studies with a high number of attributes. Indicated when the number of relevant attributes exceeds CVA's and CBC/DCE's capacity, but the researcher wants more valid utility estimates than SE alone would provide. Applies to exploratory research that needs to map a broad field of attributes before a confirmatory study, and to segmentation studies with many product or service characteristics.	Masiero and Hrankai (2022)

General note for Tables 4 through 7. The attribute-scope ranges indicated in the comparison tables correspond to operational conventions consolidated in each family's seminal literature and in the technical documentation of the software that implements them. They do not constitute limits derived from systematic empirical testing and should be treated as a practical design reference, subject to the number of levels per attribute, sample size, and respondent familiarity with the product category.

The protocol presented in Figure 4 derives from the gaps identified in the cross-tabulated distribution in Table 3, not from an a priori classification of the families. Three patterns in the corpus determine its steps. The first is that the family employed varies little across research objectives, indicating that the objective has not operated as a selection criterion, which places it as the first step of the protocol. The second is that the objectives for which the adaptive families would have a recognized advantage, new product design and utility estimation, are precisely those with the lowest share in the corpus, suggesting that the number of attributes and the type of cognitive task remain criteria not considered, positioning them as the second and third steps. The third is that the families absent or nearly absent from the corpus are precisely those that require administration through specialized software, which makes the availability of computational resources a practical constraint to be made explicit, rather than assumed, in the last two steps.

Figure 4

Decision framework for choosing the conjoint analysis family



Note. Paths marked with an asterisk indicate applications aimed at product bundles.

Figure 4 synthesizes the decision protocol proposed in this essay in an operational visual format. The framework organizes the eight conjoint analysis families based on the objective, placed in the central column, and guides the researcher along two paths. On the left side are the categories that use fixed, direct-application questionnaires, MBC, CBC/DCE, and CVA, identified by the limit of attributes supported and by the research strategy that varies according to the cognitive task.

On the right side are the families that allow a larger number of attributes, ACBC, ACA, and BWS/MaxDiff, differentiated by adaptive questionnaire models and by the technological resources available in specific research software. In the upper right corner is the SE family, an exploratory and preliminary entry-level method that, together with the CVA category, forms the Hybrid method, indicated for researchers who do not have access to research software.

The framework starts from the research objective and guides the researcher through the methodological criteria, number of attributes, type of cognitive task, and application format, until identifying the family best suited to the study's context.

The protocol in action: application to a case from the corpus

To show the difference the protocol produces, it is applied to a real case: one of the corpus articles that employed CBC/DCE with the combined objective of price/value and product characteristics. The study by Tapia et al. (2024) investigated the preferences of Chilean consumers for e-commerce delivery service attributes, working with four attributes (time to product availability, delivery time window, late-delivery compensation policy, and price) collected through fixed choice sets, with 10 tasks per respondent and three alternatives per task, among 424 respondents from a market research panel. The article does not cite the specific seminal sources this essay adopts for CBC/DCE (McFadden, 1974; Louviere & Woodworth, 1983), nor does it present a passage justifying the adoption of CBC/DCE over another family, falling, therefore, among the 237 studies without explicit justification. Following the protocol:

Step 1. Objective: The study's identified objective is twofold, price/value and product/service, the same pair for which the protocol positions CBC/DCE: to estimate consumers' willingness to pay for delivery-service attributes and to determine the relative importance of each service attribute in the purchase decision.

Step 2. Number of attributes: With only four attributes, the study nominally sits at the lower bound of the six-to-eight attribute range associated with CBC/DCE, but the article's own literature review indicates the actual attribute space is wider: the studies of Nguyen et al. (2019) and Garver et al. (2012), cited by the authors themselves, identify five to six relevant delivery attributes (fee, speed, time slot, delivery date, daytime/evening period, and tracking). The authors acknowledge this gap directly, stating that some potentially valuable features for consumers were omitted from our survey instrument. Because the study pursues two objectives at once, willingness to pay and relative importance, over a set of attributes narrower than the problem itself, the protocol flags this step as a point of departure from the CBC/DCE range: capturing the fuller configuration space these related studies describe falls within the wider attribute range for which the protocol indicates ACBC.

Step 3. Cognitive task: The task consisted of a choice among fixed, predefined sets: each respondent received a questionnaire with ten cards, each presenting three delivery-service alternatives with the price value. This fixed-choice design is well suited to comparing a small, closed set of predefined configurations, but it does not let the respondent build a reference configuration across a wider attribute space. Given the additional attributes identified in the article's own literature review, the build-your-own phase of ACBC would have let respondents indicate which combinations of the fuller attribute set they would actually consider before the choice task narrowed the comparison, closing the gap the authors themselves note.

Step 4. Computational resource: The choice-set design was generated using idefix, a free, open-source R package, for a fixed CBC/DCE design; the article does not report evaluating or attempting an adaptive design. ACBC requires administration through specialized software (e.g., Sawtooth Lighthouse Studio); the availability of that resource is a practical constraint that needs to be declared, not assumed. Since the article does not mention such a resource, it is not possible to determine from the published text whether the authors adopted CBC/DCE because it best fit the problem or because it was the accessible option under resource constraints.

Step 5. Application format: Collection was digital, administered to 424 respondents drawn from a panel of 346,261 Chileans by a market research firm. The survey's application mode fits the Fixed Digital model, which the protocol also associates with CBC/DCE.

Applying the protocol this essay proposes to the study by Tapia et al. (2024) is not meant to declare that the authors' choice was mistaken in an absolute sense, since fit also depends on collection factors the published text does not report, such as budget and access to adaptive software. The difference is that, applied ex ante, the protocol would have turned a silent choice into an argued decision: given the two combined objectives (price/value and product characteristics) and the wider attribute space that the article's own literature review documents, the protocol points toward ACBC as the more adherent family, and the study would either have migrated to it or registered, in a paragraph, why it remained with CBC/DCE despite the narrower attribute set. In either outcome, the choice becomes auditable and transferable, precisely what the 96% of articles without justification fail to offer. It is this shift, from habit to declared decision, that this essay and its protocol seek to provoke.

Conclusions / Final Considerations

This essay started from a contrast between a repertoire of eight conjoint analysis families and a practice that uses only two. By reviewing 247 articles, it showed that this concentration coexists with a silence, 96% of the studies do not say why they chose the family they employed, and argued that this silence is not a reporting detail but the symptom of a choice decoupled from the research problem. The cross-tabulation between family and objective made the decoupling visible: for example, the adaptive families, designed for problems with greater attribute complexity, are precisely those absent from the corpus, while CBC/DCE occupies even the objectives for which the seminal literature points to another family as more suitable.

In response, this essay proposed a five-step protocol: study objective, number of attributes, type of cognitive task, need for computational resources, and application format, and illustrated it on a case from the corpus itself, showing where the actual choice diverged from the most suitable family. The protocol is not a new technique; it is, in the terms of Bergh et al. (2022), guidance on the use of methods, whose function is to reconnect the methodological decision to the problem investigated and to make it, above all, explicit.

The argument also opens new fronts. The protocol proposed here is normative and calls for empirical validation in marketing experimental designs, and the coding of justification can be extended to other fields that employ choice experiments, to test whether methodological silence is a trait specific to marketing or a broader pattern; the review itself, redone without the open-access restriction, would allow verification of which of the patterns described here hold.

What is asked of the marketing researcher, in the end, is simple and verifiable: state the conjoint analysis family adopted, state why it was adopted, and anchor that justification in the structure of the problem, in the number of attributes, in the cognitive task the respondent actually performs, and in the intended level of analysis, not in the tool the researcher already knows. One paragraph of justification, absent today in 96% of studies, is what separates an auditable choice from an inherited habit.

Four limitations bound the scope of the results. The first, and most consequential, is the restriction to open-access publications, which reduced the base to less than half by a criterion unrelated to content, and which interacts with the source-quality filter applied afterward. Marketing's most selective journals operate mostly under subscription and are also the outlets in which the methodologically more elaborate variants tend to be reported, so the concentration observed in two families may be, in part, an effect of the scope. The second stems from the retrieval strategy: families whose current name does not include the term conjoint depend entirely on their own descriptor, and the coverage of MBC and SE is, for this reason, the weakest in the corpus. The third is that coding the family employed and the presence of justification involves interpretive judgment about the text of the articles, especially in studies

that combine procedures from more than one family. The fourth is that the proposed protocol is normative in nature and has not yet undergone empirical validation.

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AI Use Declaration: This study used the Claude AI platform, LLM Sonnet 4.6, on 07/16/2026 to assist with grammar review activities, organization of the 247 articles, structuring of ideas, creation of images and visual elements, organization of references in APA 7, and text and layout formatting. The prompts used requested AI suggestions for organizing the text, without generating additional content, keeping the original text created by the author.