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MARKETING RESEARCH IN THE DIGITAL ERA: A COMPARISON BETWEEN ADAPTIVE CONJOINT ANALYSIS METHODS

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We live on an island surrounded by a sea of ignorance.
As our island of knowledge grows, so does the shore of our ignorance.

John Archibald Wheeler (1992, Scientific American , Vol. 267)

Abstract

Marketing research methods are evolving fast and literature concerning this area is still dispersed. This work tries to address this gap by systematizing the state of the art regarding digital research tools - not only by describing the existent methods but also by referring to its advantages and limitations -, which could be useful both for academics and professionals in this area. The present research introduces several digital research methods, such as marketing online communities (MROCs), online focus groups, online chat, research games and web-based surveys. This last method is widely used today, but, in an Era when the quantity of information that individuals receive through several devices is starting to be viewed as a burden - the difficulty to keep respondents engaged in studies is already indicated as a problem. Time is considered precious and the need to design and implement effective surveys is increasing. In this context, we funneled this work to a specific survey-based multivariate statistical technique that has already proven to be an important tool for marketeers: Conjoint Analysis. The main objective of this method is to estimate the relative importance that consumers give to product attributes and the utility they associate to the different levels of each attribute. More specifically, this work explores the adaptive methods within Conjoint Analysis, which demand the aid of a computer to be administered. By comparing Adaptive Conjoint Analysis (ACA) and Adaptive Choice-Based Conjoint Analysis (ACBC) through the design of two surveys that consider the same product attributes and were tested in the same sample, we hope to give marketing managers a better understanding of this tool, so that it could be considered more often as a potential research method in future market studies. Our conclusions show that (1) both methods produce the same estimated utilities when considering a small number of attributes, (2) the share of attribute preferences is similar in both cases, with the particularity of ACBC appearing to be more sensitive, detecting even small shares of preference for some attributes, (3) response time is practically the same in both techniques.

Keywords: new technologies; market research; digital research methods; web surveys; conjoint analysis; adaptive conjoint analysis; choice-based conjoint analysis

Resumo

Os métodos de pesquisa em estudos de mercado estão a evoluir rapidamente e a literatura referente a esta área ainda é dispersa. Este trabalho tenta responder a esta lacuna, sistematizando o estado da arte em relação às ferramentas de pesquisa digital - não apenas descrevendo os métodos existentes, mas também referindo-se às suas vantagens e limitações -, o que poderá ser útil tanto para académicos como para profissionais nesta área. A presente investigação introduz vários métodos de pesquisa digital, como comunidades de marketing online (MROCs), focus group online, chats online, jogos de pesquisa ou inquéritos via web. Este último método é amplamente utilizado hoje, mas, numa Era em que a quantidade de informação que os indivíduos recebem através de vários dispositivos está a começar a ser encarada como um fardo, a dificuldade em manter os respondentes envolvidos em estudos é apontada como um problema. O tempo é considerado precioso e a necessidade de desenhar e implementar pesquisas eficazes está a aumentar. Neste contexto, afunilámos este trabalho para a análise de uma técnica estatística multivariável que já provou ser uma ferramenta importante para os profissionais de marketing: análise conjunta. O principal objetivo deste método é estimar a importância relativa que os consumidores atribuem aos atributos de um determinado produto e à utilidade que associam aos vários níveis de cada um desses atributos. Mais especificamente, este trabalho explora os métodos adaptativos dentro da análise conjunta. Ao comparar Adaptive Conjoint Analysis (ACA) com a Adaptive Choice-Based Conjoint (ACBC) através da construção dois inquéritos que consideram os mesmos atributos de produto e foram testados na mesma amostra, esperamos dar aos gestores de marketing uma melhor compreensão dessa ferramenta, para que esta possa ser considerada mais frequentemente como um potencial método de pesquisa em futuros estudos de mercado. As conclusões mostram que (1) os dois métodos produzem os mesmos resultados no que diz respeito à utilidade considerando um número pequeno de atributos, (2) as percentagens de preferência de atributos são aproximadas em ambos os casos, com a particularidade de ACBC aparentar ser mais sensível, detetando pequenas percentagens de preferência para alguns atributos, (3) o tempo de resposta é praticamente o mesmo nos dois métodos.

Palavras-chave: novas tecnologias; estudos de mercado; métodos de pesquisa digitais; inquéritos online; análise conjunta; análise conjunta adaptativa; análise conjunta baseada em escolhas

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Introduction

Currently, 48% of the world's population uses Internet. Broadband services account for 4.3 billion subscriptions, growing at a rate of 20% per year since 2012. The number of mobile network subscriptions is 7.74 billion, a figure that surpasses the world population. (International Telecommunication Union, 2017). The democratization of Internet access created opportunities in many areas and marketing research is no exception. In recent years, researchers have seen the emergence of new research techniques with potential to lead to efficiency gains and innovation. Suddenly, it became possible to bring together individuals of different nationalities into a virtual focus group in a short period of time or to collect quantitative data at a very low cost. "The attractiveness of cyberspace lies in its versatility as a medium that offers possibilities in an arena that is not restricted by geography and where researchers can interact with participants in ways that might not be possible in the real world." (O'Connor and Madge, 2003, p. 133)

Considering the impact of the Internet revolution on marketing research, we propose to present and analyze various digital data collection tools, which are gaining increasing importance for conducting marketing research. We will try to take stock of the opportunities and risks that each of these tools entail. It should be noted that some of these tools, being very recent, are not yet subject of in-depth research.

After a thorough review of the digital research methods currently available, it felt like a pressing matter to further investigate web-based surveys, one of the most used research techniques today. What other options within web-surveys should we be exploring? Are traditional web-surveys the best method to use when we need to apply a survey? With the objective of giving a useful managerial contribution and hoping to create a discussion about alternatives which may not be very well-known in the Portuguese research market sector, we decided to explore Conjoint Analysis – which is both considered a research and analysis tool at the same time- and compare and test two adaptive methods of Conjoint Analysis. This comparison was put in practice using one of the most popular Conjoint Analysis software's in the market, Lighthouse Studio, provided by Sawtooth Software (Lighthouse Studio 9.5.3, 2017). In the context of this work, Sawtooth Software accepted a grant request and conceded a license which allowed the use without costs of the software during a specific period for academic purposes.

The structure of this work was designed – in the first place - with the intention of giving a broader perspective and context of the theme itself and, after that, funnel it to more specific subjects. Chapter 2 is an example of that, presenting literature review about several market digital research techniques and exploring its advantages and limitations and finishing with a thorough revision of the state of the art regarding Conjoint Analysis. Chapter 3 introduces the research questions of this study and presents the methodology in which it is based on. Results are presented in Chapter 4 according to the research questions previously defined and further discussed in Chapter 5, which includes the main conclusions of this work and the managerial contributions it contains.

2. Literature Review

2.1 Marketing Research

According to the definition of the American Marketing Association, approved in October 2004 (American Marketing Association, 2004), "marketing research is the function that links the consumer, customer, and public to the marketeer through information - information used to identify and define marketing opportunities and problems; generate, refine, and evaluate marketing actions; monitor marketing performance; and improve understanding of marketing as a process. Marketing research specifies the information required to address these issues, designs the method for collecting information, manages and implements the data collection process, analyzes the results, and communicates the findings and their implications". Or, as put by Kotler (2012), marketing research "is a systematic problem analysis, model building and fact finding for the purpose of improved decision-making and control in the marketing of goods and services".

Quantitative vs. Qualitative Research

Taking into consideration the scope of this work it is important to define qualitative research and quantitative research. According to Malhotra (2012, p. 109), qualitative investigation is "an unstructured and exploratory research methodology based on small samples that provide insights and understanding about the context of the problem". On the other hand, Malhotra states defines quantitative research as a "research methodology that seeks to quantify the data and which typically applies some form of statistical analysis". We can conclude that qualitative investigation is based on data of subjective nature, using methods based on the interpretation of the respondents' point of view. Alternatively, quantitative investigation is highly structured and uses objective data. Qualitative investigation is often used to explain conclusions reached through quantitative studies.

2.2. Digital research methods

Digital technologies have created many opportunities for marketing research along with the emergence of new methods for gathering and analyzing data. Currently, there is a growing need for researchers to be well-informed about the innovations and new methods available so that the best decisions regarding methodology ca be made. Next, we present several digital research methods being used today, most of them identified in GRIT - Greenbook Research Industry Trends Report 2017 as emerging research methods (Greenbook, 2017).

2.2.1 Marketing Research Online Communities (MROCs)

Marketing Research Online Communities (MROC) run in private platforms, where a group of people, chosen according to pre-defined criteria, are invited to participate. Usually, the sample used in MROCs is relatively small (from 50 to 500 people) and require a regular participation to gather detailed inputs. This communities answer several needs, such as to identify new tendencies, generate ideas, test strategies and marketing campaigns, studying behaviour or, for example, test the most adequate language to be used with a certain target.
Given that the participants are pre-selected, this technique is useful in situations that demand a quick gathering of data. This means that it is possible to initiate a discussion about a certain topic in a short period of time, by inviting, for example, 150 participants that correspond to the sample criteria and start a discussion with the first 30 that show availability. Unlike an online focus group, where participants are recruited for a single interview, MROC participants are called to participate continuously via the platform (Pattino et al., 2012). One of the main advantages identified to this tool is the possibility to hear the participants opinion while interacting with them. MROCs generate instant feedback from the participants inputs, allowing efficiency gains regarding time and costs (Baldus, 2015). Nevertheless, it is necessary to keep some limitations in mind: the initial investment that is necessary to recruit enough respondents for the study might be high. It is also necessary a great capacity of coordination to keep the participants interested and lead them to participate in a productive way.

My-Take (my-take.com), an American marketing research that uses MROCs, owns an online community platform that gathers data through several tools as discussion forum, surveys, journal, polls, live chat, activity stream. Another company providing this service is, for example, Civicom (civicommrs.com), that allows respondents to post comments, images and video and integrates gamification features in the platform as, for example, rewards systems.

In a time when traditional methods suffer with low response rates, MROCs appear as a potential good alternative (Pattino et al., 2012) and the research market indicates that it sees it as a valuable tool too, considering that, regarding emerging methods, 60% of research suppliers and clients say they use MROCs and a combined 82% say they use it or consider using it in the future (Greenbook, 2017).

2.2.2 Online Chat

In the 1990s, chats were one of the first qualitative research techniques used to replace face-to-face or telephone interviews. Although video conferencing is a closer approach to face-to-face focus groups, chats continue to be a service offered by many marketing research firms. O'Connor and Madge (2002) consider that the data collected through this method can be as rich and advantageous as traditional face-to-face interviews. However, they stress that the potential of this type of research should not be inflated. The authors leave some recommendations regarding the use of chat rooms, noting, for example, that there is a need to adapt the interviews to the online platforms to overcome the difficulties created by the lack of eye contact. The researchers also point out that, despite its limitations, the online search method has advantages such as low costs, opening new possibilities for international marketing research and ease of transcription of interviews.

Scholl et al. (2002) point to this same advantage, noting that annotations of online group appearances have no flaws (because they are recorded automatically), but indicate that there is more difficulty in analyzing data than in face-to-face focus groups. Because there is no visual contact in discussions in chats it becomes difficult to make an association about who said what. "Physical appearance, clothing, grooming, and dialect all convey information about the personality, attitude and lifestyle of the respondents, basic information we take into account when interpreting what people say." (Scholl et al., 2002, p.218). On the other hand, they indicate the anonymity conferred by chats lead interviewees to feel more comfortable and make statements that they probably would not do in a focus group by video conference or in person:

"(...) the relative anonymity of the situation and the fact that respondents can participate in the groups from their homes, makes them feel comfortable right from the start" (Scholl et al., 2002, p.214).. The authors recommend participants to be recruited via telephone whenever possible, since in their study they found that many people contacted online would eventually not show up at the time of the interview.

2.2.3 Online Focus Group

The online focus group follows the same rules as a traditional focus group, bringing more convenience and the possibility to gather respondents from several locations. There are many companies offering this service, as for example itracks (itracks.com). Contrary to what happens with live chats, with this technique the researcher can also gather visual and sound information and perceive whether the participant is paying attention to the course of the discussion. Naturally, this method has some limitations, such as finding participants who meet the criteria of the sample and, at the same time, the need to have an Internet connection and a functional webcam. There are already several companies that provide specific software to carry out this type of focus group, with features such as immediate transcription of what is said, possibility to mark the most important comments of the participants while the discussion is taking place, add a quantitative strand with the realization of polls. One of the questions that Casey Sweet raises in his study "Designing and Conducting virtual focus groups (Casey, 2001)" is whether online groups will replace traditional focus groups. Sweet believes that this cannot occur in many cases, since non-verbal elements are very important for a correct assessment of data and because online groups do not always allow responses to have the desired depth. Online focus group do not seem to be popular in the research market as only 3% of suppliers and clients of qualitative research use it, compared to 26% saying that they use in- person focus groups (Greenbook, 2017).

2.2.4 Research Games

Online research can often be limited by the ease with which respondents disregard the survey or interview they are responding to. To address this problem, companies are trying to make research more engaging and even fun for the participants. An example of one of this companies is Research Through Gaming (researchthorughgaming.com) that creates games that can be used in both online and offline studies and present surveys in an animated format. Recent studies (Cechanowicz, J. et al., 2013) have showed that gamifying market research surveys increases participation and that game mechanics increases motivation regardless of demographic factors.

2.2.5 "In the moment" research (via mobile devices)

As more people choose to give up their fixed telephones (International Telecommunication Union, 2017), mobile devices play a key role in everyday life in modern society and are already the primary device used by new users to access Internet (eMarketer, 2018). Thus, marketing research also had to adapt to this change. Consequently, several companies are interested in surveys through mobile devices, namely mobile phones.

One of the most recent techniques applied to mobile devices is the "in the moment" research, through which one can access data on the opinions and emotions of consumers as they are exposed to marketing campaigns or other situations under study. This type of research is carried out through mobile phones with Internet access and, according to one of the companies that provides this service, On Device (ondeviceresearch.com), this method allows "respondents to record their reactions and responses to the very moment they encounter them".

A very recent study (Bakolis et al., 2018) contains an example of the use of "in the moment" data collection method. The researchers developed a mobile application, Urban Mind, which allowed the assessment of the respondent's real-time disposition to understand if the contact with elements of Nature in an urban context would impact the well-being of the individual. One of the advantages identified by the researchers regarding the use of mobile devices is that "people tend to carry and use them multiple times as part of their daily lives; in contrast, the deployment of paper diaries or stand-alone electronic devices places greater demands on the individual, resulting in high rates of missing responses". There is substantial investment when it is necessary to develop an app from scratch, but after that, it can be downloaded and installed anywhere in the world allowing large numbers of participants to provide research data with minimal operational costs. (Bakolis et al., 2018). One downside to self-tracking methods relates to the risk of contributing to "a substantial rise in the—already high—informational burdens of modern life" (Beute et al., 2016, p.15).

2.2.6 Text mining

Social networks text mining

Currently, it is estimated that one third of the world population is enrolled in a social network, with Facebook still at the top with more than 2,23 billion monthly active users (Statista, 2018). This means that, daily, billions of people around the world publicly share information about their preferences, feelings, wishes and fears. In the marketing field, several methods have arisen to gather and analyze this kind of data. Among them, there are three important digital ethnography tools identified by Kotler (2017): Social Listening, Netnography and Empathic Research. Social listening is related to monitoring what is being said in social networks and usually requires software to filter big amounts of unstructured data and transform it in condensed data that can be analysed. One of the advantages identified by Kotler regarding this method is that in a social network environment the consumers are more comfortable to tell their peers what they are feeling and thinking than when they are answering surveys. Netnography is a method that aims to understand behaviour in electronic tribes by immersion on them in a discreet way. Empathic Research, on the other hand, demands contact between the researchers and the consumers and requires a multidisciplinary team that works together to collect and analyse consumer insights in online communities.

In the 2008 presidential campaign, Barack Obama's team used the collection and analysis of data on social networks to, among other things, predict what groups of people could be persuaded through certain forms of contact and content (Takaragawa, 2012). Obama's team even created a specific social network - my.barackobama.com, known as MyBO - that allowed users to create a profile with a personalized description, a list of friends, and a personal blog. They could also participate in fundraising events and organize events linked to the campaign. This was a way to not only keep voters directly involved in the campaign, but also to create a very big and detailed database (Takaragawa, 2012).

Nowadays, organizations, companies, parties and brands know that social media networking is one of the fastest ways to reach consumers. However, being present on these platforms is not synonymous with having a well-designed digital marketing strategy (Deutsch, 2014) To help the brands/organizations in this task, several applications/software have emerged that allow analyzing in detail all that is commented on various social networks about a product, brand, service, public figure, etc. (Flint, 2013). These applications allow not only to monitor what is said, but also to analyze the collected data to identify trends and key topics on the subject that interests us. These tools may help to improve aspects such as customer support, gather information that help to more accurately design the product lifecycle or identify key opinion makers. One of the companies that performs these tasks is Semeon Analytics (semeon.com.) Through semantic contextualization, Semeon records and analyzes content from news, blogs, microblogs, forums, news feeds and articles, allowing the choice of several research parameters. Another company working in this field is the north-american Fizziology (fizziology.com), which has gained recognition for its work with Hollywood producers towards understanding the best marketing strategy for each film. Through datamining exercises on social networks, Fizziology was able to realize that, contrary to what might be expected, there were many men commenting on the movie Pitch Perfect on Twitter. The film studios Universal Pictures, which had initially directed its marketing and communications efforts around the adolescent female audience, adapted its strategies to reach the male audience as well (Ungerleider, 2004). Through this type of analysis, Fizziology can, for example, anticipate what will be the most popular films or extract feedback on new electronic games. Fizziology is also specialized in analyzing the consumer profile based on demographic, psychographic and affinity criteria.

Although the numerous advantages that the analysis of generated content in social networks can bring, it is necessary to consider that there are some dangers when using these techniques. "The use of social networks and other devices are hampered by their inability to source who is writing. With panels, subjects with known demographics are recruited, but social networks and listening platforms have limited ability to track demographics of respondents.." This is one of the main problems pointed out by Pattino et al. (2012, p. 235) on the use of social networks as a tool for marketing research. On the other hand, it seems opportune to refer that this limitation is rapidly disappearing as social networks such as Facebook can now trace very accurate profiles of its users, both with information directly introduced by the user or by tracking its digital movements, which has been provoking heated public debates on privacy and data protection.

However, Pattino refers another challenge that may be more difficult to get around: "(…) researchers are unable to see if the same people are posting on multiple sites. While one may see quantity, it may be the result of continued posting by one fan." The authors question the quality and the difficulty in the external validation of the data. " If the same people are writing numerous postings, the data become suspect, not valid and, thus, not generalizable ." (Pattino et al., 2012, p.235)

Blogs text mining

Blogs, very-well known diary platforms where individuals or groups of individuals share their opinions and impressions on a wide range of subjects, are another tool for collecting data. According to Osman et al. (2009), these unsolicited opinions may prove valuable to market research carried out by organizations intent on measuring reactions to products and services. This type of analysis can be useful, for example, to Governments that want to take the pulse of measures that they intend to implement or future campaigns. In their study, Osman et al. analyze a method, the so-called fusion method, with the aim of increasing the accuracy of automatic detection systems and defend that this system would allow to quantify positive or negative opinions on a certain topic. (Osman et al., 2009)

2.2.7 Web Analytics

Gathering and analyzing data on how a user behaves when navigating a particular site is an activity that began in 1993 with the emergence of the World Wide Web (Zheng, 2015) and allows strategic decisions to be made to increase the efficiency and profitability of a website. For a long time, the concern of the companies was to increase the number of visitors of its pages. Today, it is known that it is more important to understand how the consumer behaves while browsing, so that strategies can be found to increase the conversion rate of those clicks on purchases (Chaffey, 2012).

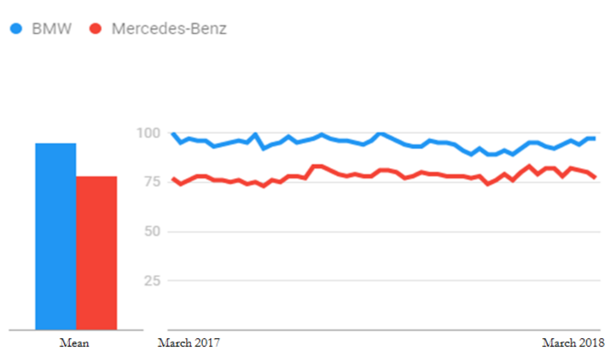
In 2005, the use of Web analytics was democratized with the emergence of Google Analytics, a free software, with features that evolve rapidly and that allows detailed reports. Google Analytics allows, for example, to identify the strengths and weaknesses of a web page or see how mobile devices impact a pages' traffic. In addition, you can evaluate the performance of published ads and know the level of user interaction with buttons that refer to social networks.

2.2.8 Trendspotting

Trendspotting is today an important tool for detecting consumer trends and consumer behavior. This technique can either be applied qualitatively - with trend hunters searching for signs that indicate changes in consumption needs or patterns - or quantitatively, through the analysis of indicators. Through such tools as Google Trends, we can see how many times a keyword has been searched over a period of time.

In Figure 1 we have an example of one of the features of Google Trends. What we did was a very simple exercise of choosing two car brands, BMW and Mercedes, and generate a chart that shows their respective search trends. In this case, we know that there has been a greater interest in BMW for the last one year period, but that the research for both terms remains more or less constant. In this case, the analysis was done regarding a one year period, but Google Trends allows the choice of any time frame for which these keywords have been available. It is possible to filter the search based on the Google search engine, but also through searches made by users on platforms like Youtube or even Google Shopping, a service that aggregates products from several online stores and allows you to compare prices.

Figure1.Trendspotting BMW vs. Mercedes-Benz



Source: Own elaboration (using Google Trends)

2.2.9 Web-Based Survey

According to Malhotra (2012, p. 242), surveys are a "structured technique to collect data that consists in a series of questions, written or oral, that an interviewee must respond to". Online surveys are a technique mainly used for collecting quantitative data and are conducted through a web page containing a set of previously established questions. The researcher can determine the page's appearance and the way the questions are asked. Some of the most well-known web survey platforms today include Survey Monkey (free to use up to one hundred respondents), Google Forms (free to use) or Google Surveys (paid). The latter is a service launched in 2012 by Google that can be used by researchers to target consumers in nearly 60 markets (Sawers, 2018). This feature provided by Google responds to the problem of lack of representativeness of the population, indicated as one of the problems for the validation of an online survey (Furrer and Sudharshan, 2001).

Among the advantages of web-based surveys are the speed at which the completed questionnaires are returned (Couper, 2001), reduction of costs (with the elimination of paper, sending of mail and data transfer), the reduction of the time between the beginning of the collection of data and its analysis, ease in transferring the data to programs of data analysis (Furrer and Sudharshan, 2001).

However, it should be noted that this method requires respondents to have an Internet connection and that it is easy for the respondent to give up halfway through the questionnaire.

2.2.9.1 Adaptive Surveys

In an Era when the discussion around the so-called Attention Economy (Rose, 2015) alerts to the fact that the attention span of consumers is very scarce due to the amount of information circulating in a multiplicity of devices, marketeers and market researchers need to think about strategies that will guarantee efficiency and also return on investment to their studies. Choosing the right method for the right goals is key. That is why next we will present an alternative and more specific form of web-survey, that has already demonstrated to be useful in the market research area.

For example, in a study that aims to analyze several attributes of products or services, the length of the questionnaire can become a burden to the respondent and the complexity of the data can bring difficulties to the researcher. This problem was attenuated by the development of computer-aided procedures like adapted Conjoint Analysis. "Adaptive methods involve developing questions in a sequential manner depending upon the responses from a respondent to previous questions; these methods are essentially a subset of either ratings or choice-based methods" (Rao, 2008, p.27).

2.3 Conjoint Analysis

The emergence of Conjoint Analysis (CA) dates back to the late 1960's, developed by mathematicians and applied in behavioral sciences (Luce and Tukey, 1964). Its application to problems in the marketing field was introduced for the first time in the early 1970's (Green and Rao, 1971). Since then, Conjoint Analysis has become a very popular marketing research tool as it allows gathering and measuring consumer preferences by presenting the respondents a survey that contains hypothetical product profiles (Agarwal et al, 2014). The definition of Conjoint Analysis is summarized by Malhotra (2012, p.531) in the following manner: "Conjoint Analysis seeks to determine the relative importance that consumers give to relevant attributes and the utility that they associate to the levels of attributes".

The basic model of conjoint analysis is represented by the following formula (Malhotra, 2012, p.534):

$$U_x = \sum_{i=1}^{m} \sum_{j=1}^{k_i} \alpha_{ij}\, x_{ij}$$

where Ux =overall utility of an alternative; αij = utility associated with the jth level (j, j=1, 2....ki) of the ith attribute (i, i=1, 2....m); ki = number of levels of attribute i; m =number of attributes; xij =1 if the jth level of the ith attribute is present and=0 otherwise.

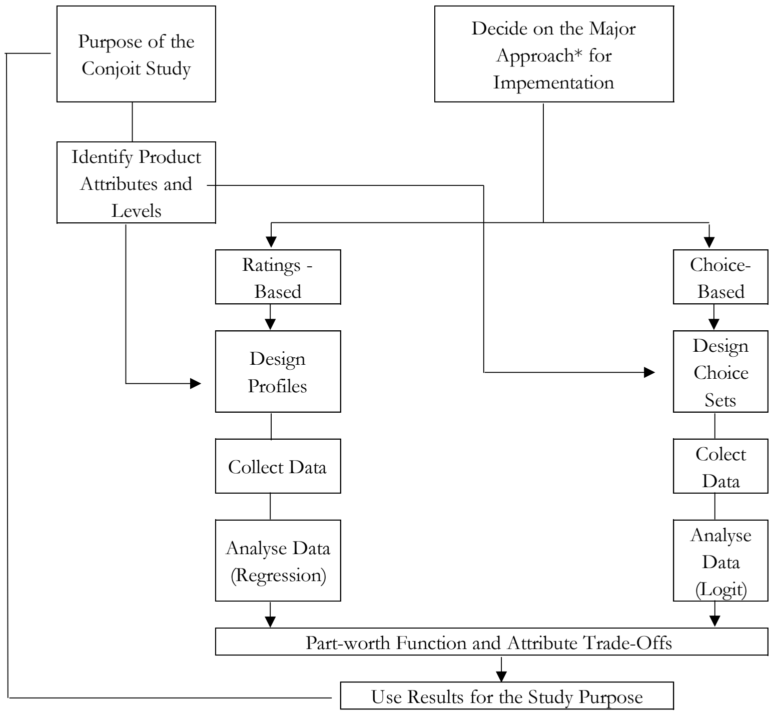
To understand Conjoint Analysis, it is important first to have in mind its most basic terminology:

- Attributes: Characteristics or features that define or can represent a certain product or service.
- Attribute levels: Specific features that can be found within each attribute. For example, if our attribute is Brand, the attribute levels could be Nike, Adidas, Puma, etc.
- Profiles or concepts: Possible combinations of attribute levels that are displayed during the survey to the respondents, who are stimulated to rank these combinations or chose its preferred ones, depending on the CA method adopted by the researcher.
- Utility: Conjoint Analysis estimation of the degree of preference/desirability thar the respondent places upon each level of each atribute. This estimation is computed using the data set that results from the respondent's answers to Conjoint Analysis surveys.

According to Rao (2008), Conjoint Analysis is a very useful tool as it responds to several marketing needs by allowing to quantify buyer tradeoffs and attribute values, predicting buyers' likely reactions to new products/services, identifying groups of buyers that share similar values, assessing new product service ideas, seeking product/service profiles that maximize a pre-specified outcome measure. This technique is, for example, widely used in the automotive industry due to the need of quickly identifying new consumer needs combinations in a cost-effective manner (Urban, 2014). With the advent of Internet, Conjoint Analysis gained new potential and a new environment, with most researchers agreeing that the major developments of this method started in the 1980's with the use of commercial conjoint computer packages (Green et al., 1991). Application of Conjoint Analysis via web has some limitations such as possible interruption of the questionnaire by the impatient respondents (Netzer et al. 2008), noisier data, less observations per respondent, but also has advantages like allowing adaptive and interactive questionnaires that are robust to response error.

As seen in Figure 2, there are several steps that must be considered when conducting a conjoint study.

Figure 2. Major steps in a Conjoint Study



Source: Rao (2008)

* Several alternatives exist here; two are highlighted

2.3.1. Hierarchical Bayes estimation model

Figure 2 indicates two classical techniques to analyze the collected data in Conjoint Analysis: regression for a ratings-based approach and logit for a choice-based approach. Nevertheless, during the last years, an alternative model, Hierarchical Bayes (HB) estimation has become very popular among market researchers and is being considered as highly effective to estimate utilities in studies with both approaches. According to an article published by Qualtrics, "in the context of Conjoint Analysis, HB estimation takes into account the prior knowledge of the features, the individual's preference selections as well as the preferences of all who participated in the survey to derive preference scores." (Qualtrics, 2011). The main objective of this model is to "minimize the difference between the predicted and the actual values of the dependent variable" (Sawtooth, 1999). This method is particularly useful when it comes to conjoint adaptive methods as it collects information from the full data set in order to make estimations for the individual level results (Orme, 2000). This allows shorter questionnaires without compromising the results. Furthermore, Bayesian analysis do not assume large samples (Van de Schoot et al., 2015).

The basics of the algorithm behind HB is explained by Johnson (2000) in the following manner:

If we consider:

- Utility for each individual in a vector b, estimated by calculating the number of times each attribute level is chosen divided by the total number of times that level is presented
- Average utility for the population in a vector a, where the initial estimate has all elements equal to zero
- Variances and covariances for the population in matrix C, where are all initial variances at unity and covariances are set at zero

The algorithm repeats the following three steps thousands of times (iterations):

- Step 1 - Given current estimates of the b's and C, estimate the vector a of means of the distribution.
- Step 2 - Given current estimates of the b's, and a, estimate the matrix C of variances and covariances.
- Step 3 - Given current estimates of a, and C, estimate a new b vector for each respondent.

The iterations are then divided in two groups:

- Group 1 – First thousands of iterations used to achieve convergence, with successive iterations fitting the data in a better way each time.
- Group 2 – Used to estimate b's, a, and C. Usually, the estimation of utilities for each respondent is done by averaging the individual b's of the last thousand iterations.

Next, we will describe the most commonly used types of Conjoint Analysis.

2.3.2. Conjoint Analysis Methods

Adaptive Conjoint Analysis (ACA)

Adaptive Conjoint Analysis (ACA) is a type of Conjoint Analysis that consists on developing a sequence of questions which depend on the respondent's responses to previous questions (Rao, 2008). It was first introduced by Richard M. Johnson in 1987 as a way to collect and analyse preferences regarding a big number of attributes and its most popular implementation was developed by Sawtooth Software (Johnson, 1987; Huertas-García, R., 2016). Johnson's algorithms applied to ACA have allowed researchers to ask more efficient questions (Toubia, 2007). According to Sawtooth (2007), the ACA procedure is composed by four phases.

Table 1. Summary of ACA Survey Phases

Phases	Description	Task Example
1 - Preference for Levels	Respondent rates each level of each attribute being studied in terms of relative preference. This question is usually omitted for attributes (such as price or quality) for which the respondent's preferences should be obvious.	Please rate the following desktop computer Brands in terms of how desirable they are.
2 - Atrribute importance	Respondent ranks attributes in terms of their importance	If two computers were the same in all other ways, how important would this difference be to you? *(screen shows two brand alternatives).*
3 - Paired-Comparison Trade-Off Questions	Respondent is presented a group of paired partial profiles (designed by the software based on previous answers) and indicates his/her preference.	If everything else about these two computers were the same , which would you prefer? *(screen shows two alternative partial-profiles)*.
4 - Calibrating Concepts (Optional Section)	Respondent receives between 2 to 9 profiles composed of several attributes and rates the likelihood of purchase, which can be expressed using a slider scale or by typing a numeric value into a box. .	Now we are going to show you four computers. For each computer, please tell us how likely you are to buy it. Answer using a 100-pt scale, where 0 means not likely and 100 means definitely would buy it.

Source: Adapted from Sawtooth (2007)

Among the advantages of using adaptive Conjoint Analysis is cost efficiency and data quality (Singh et al., 1990), versatility, adaptability and being easy to learn and use (Rao, 2008). It is proved that shorter questionnaires have higher response rates and that the introduction of visual images, such as images of products, enhance the quality of the responses (Deutskens et al., 2004).

CBC – Choice Based Conjoint Analysis (CBC)

Choice-Based Conjoint Analysis is currently one of the most popular types of Conjoint Analysis. Following a discrete choice approach, the main specificity of this method is that the respondents reveal their preferences by choosing one favourite profile among a set of options, instead of ranking or rating them (Sawtooth, 2017). CBC popularity among marketeers is related to the fact that it creates an environment closer to what happens in a real-life buying experience: the customer that enters a store is confronted with several options and must make a decision. However, this means that the respondent is presented a big amount of information before giving one single answer with not much time to process it, which can be seen as a disadvantage because it is more difficult for the researcher to have enough information to analyse each profile individually. For this reason - and because CBC presents full profiles (meaning that they comprise all attributes under study) - this method is not usually recommended to test a large number of attributes. The general recommendation is that no more than six attributes are tested in the same study. Furthermore, using this method, the researcher has the possibility of including a "none" option in case the respondent is not interested in any of the profiles. Some softwares also offer the possibility to present the profiles in a more visual format, including displaying the products under study as if they were placed in a shelf. In spite of being called "randomized designs", the design of a CBC survey follows several principles and there is more than one strategy that can be followed to construct it.

Table2. CBC principles and design strategies

Design Principles	1 - Minimal Overlap	Each attribute level is shown as few times possible in a single task. If an attribute's number of levels is equal to the number of product concepts in a task, each level is shown exactly once. Nevertheless, allowing some degree of overlap may improve the precision of interactions.
	2 - Level Balance	Each level of an attribute is shown approximately an equal number of times.
	3 - Orthogonality	Attribute levels are chosen independently of other attribute levels, so that each attribute level's effect (utility) may be measured independently of all other effects.
Design Strategies	1 - Complete enumeration	Considers all possible concepts (except those indicated as prohibited) and chooses each one so as to produce the most nearly orthogonal design for each respondent, in terms of main effects. Not recommended when there is a big number of attributes and levels under study.
	2 - Shorcut Method	It attempts to build each concept by choosing attribute levels used least frequently in previous concepts for that respondent. Unlike complete enumeration, which keeps track of co-occurrences of all pairs of attribute levels, shortcut strategy considers attributes one-at-a-time.
	3 - Random Method	Employs random sampling with replacement for choosing concepts. Sampling with replacement permits level overlap within tasks. The random method permits an attribute to have identical levels across all concepts, but it does not permit two identical concepts (on all attributes) to appear within the same task.
	4 - Balanced Overlap Method	It is in a middling position between the random and the complete enumeration strategies. It permits roughly half as much overlap as the random method.

Source: Adapted from Sawtooth (2017)

Adaptive Choice-Based Conjoint Analysis (ACBC)

ACBC is a technique that derives from CBC and integrates an adaptive interviewing experience (Jervis et al., 2015), creating a survey customized to each respondents' preferences. ACBC is composed by three phases, beginning with a "build-your-own" exercise, where the respondent considers and chooses its preferred level for each attribute, this way indicating its ideal product profile.

The second phase, Screening, consists in showing the respondent several profiles considered relevant that take in consideration the answers given in the first phase. Respondents are not asked to give final choices, but to indicate if such profiles are considered a possibility for them. Usually there will be around 3 or 5 profiles in each screen and a total of about 7 screens of concepts. In the unlikely event that all concepts are considered a possibility, then all concepts will be tested in the next phase.

The third phase, Choice Tasks Section, is when the respondent has to make the final choice, in a very similar way to what happens in traditional CBC. The profiles presented take into consideration the answers given in phases one and two. This phase is usually called tournament as the selected profile in each screen compete in the subsequent rounds until the favourite one is identified. "Although it may seem to some that the goal of the tournament section is to identify an overall winning concept, the actual goal is to engage respondents in a CBC-looking exercise that leads to good tradeoff data for estimating partworth utilities". (Sawtooth Software, 2014).

Table 3. Summary of ACBC survey phases

Phases	Description	Task Example
1 - Build Your Own	Respondent answers a "Build Your Own" (BYO) exercise that introduces attributes and levels and asks the respondent to indicate the preferred level for each attribute, this way building the respondents "ideal" profile.	Please describe the beach you would most want to visit during summer vacation. Indicate your preferred option for each feature.
2 - Screening	Respondent answers "screening" questions, where product profiles are shown a few at a time (the number of profiles shown on each screen depends on the design of the survey). In the Screening Section, the respondent is not asked to make final choices, but to indicate if he/she would consider each one "a possibility" or "not a possibility."	Here are a few beaches you might like. Do any of these look like possibilities? For each, indicate wether it is a possibility or not.
3 - Tournament	Respondent is shown a series of choice tasks presenting the surviving product profiles (those marked as "possibilities") in groups of three. The winning profiles from each triple then compete in subsequent rounds of the tournament until the preferred is identified.	Among these three, which beach would you most want to visit for summer vacation? (Identical features are grayed out so that you can only focus on the differences)

Source: Adapted from Sawtooth (2014)

Among the advantages identified for this method is the fact that it could give more accurate data regarding individual-level responses than traditional CBC (Toubia et al., 2003) and provide a decision-making environment more similar to a real life buying experience (Cunningham et al. 2011).

Best/Worst Conjoint

Best/Worst Conjoint is a method based on MaxDiff, a technique developed by Finn and Louviere (1992), Best-Worst Conjoint is a survey method which has been gaining more attention in the last years, especially in health-related studies and consists in asking the respondents to indicate which option is best and which option is the worst among several attribute levels contained in each question. Louviere defends that people are much better at judging items at extremes than in discriminating items of moderate importance. This method is scale-free, which can be beneficial when applying surveys on a sample consisting in individuals from different cultures, who might interpret scales in different ways. In their work, Agarwal et al. (2015), suggest that further research is needed to validate this method.

ACA vs. ACBC

At this point, it is important to clearly define the main differences between the two techniques. ACA is a ratings-based method and presents partial profiles while ACBC is a choice-based method and presents full profiles. ACBC became more popular during the last years because it resembles more to a real-life buying experience (due to its discrete choice approach) and because ACA is usually not recommended to study price (Williams and Kilroy, 2000). Because it presents partial profiles, ACA is often used to study a big number of attributes at the same time, which means the importance of the attribute price can be diminished or unforeseen by the respondents. Given to the fact that it presents partial profiles, ACA tasks may cause less confusion to the respondent than a choice-based survey where the profiles presented could have so much information that it becomes hard to make a choice and may cause fatigue to the respondent (Johnson and Orme, 1996). On the other hand, because ACA presents partial profiles, respondents may not have present on their minds the rest of the attributes under study when they are rating a specific profile.

Table 4. ACA vs. ACBC

<table>
<tr><th></th><th>ACA</th><th>ACBC</th></tr>
<tr><td>Approach</td><td>Ratings-based</td><td>Choice-based</td></tr>
<tr><td>Profiles type</td><td>Partial Profiles</td><td>Full profiles</td></tr>
<tr><td>Recommended attributes number</td><td>Can study up to 30 attributes</td><td>Shouldn't study more than 6 attributes at a time</td></tr>
<tr><td rowspan="3">Advantages</td><td>Cost efficiency and data quality (Singh et al., 1990) - Can also be indicated as advantage of ACBC</td><td>Decision making environment closer to a real life buying experience (Cunningham et. al 2011)</td></tr>
<tr><td colspan="2">Versatility, adaptability and being easy to learn and use (Rao, 2008)</td></tr>
<tr><td colspan="2">Alows to attenuate the problem of studying too many attributes at a time, reducing complexity (Malhotra, 2012)</td></tr>
<tr><td rowspan="2">Disadvantages</td><td>If respondents are not familiar or do not remember all the attributes present in the study, they may have difficulties rating them isolated (in partial profiles) (Sawtooth, 2007)</td><td>Full profiles may be complex to analyse by the respondent in case of a study with many attributes (Johnson and Orme, 1996)</td></tr>
<tr><td>Usually not recommended to study price (Williams and Kilroy, 2000)</td><td>Suitable method for studying the impact of price on choice. (Sawtooth, 2014)</td></tr>
</table>

Source: own elaboration

3. Research Hypothesis, Methodology and Data

Given the focus of this work on digital research techniques, a comparison was made between two Conjoint Analysis methods that demand the aid of a computer in order to be administered. These are the adaptive Conjoint Analysis methods: in this case Adaptive Conjoint Analysis (ACA) and Adaptive Choice-Based Conjoint Analysis (ACBC). An extensive work of literature review – in the databases and other scientific resources available to the author – showed that there are studies comparing different types of ratings-based conjoint methods and others comparing choice-based conjoint methods. However, to the best of our knowledge, a direct comparison between these two adaptive methods (in this case ACA and ACBC) was not made before.

Taking into consideration this context and the literature previously revised, it is important to understand how the two methods work and what similarities and differences exist between them. How comfortable can a researcher be when choosing one instead of the other? Will the results be the same considering a small number of attributes? How long does it take, in average, to answer to each of them?

In an effort to answer these questions, three hypotheses were considered in the frame of this investigation:

H1: Estimated average utilities results in ACA and ACBC methods are the same.

H2: Estimated attribute preferences resulting from ACA and ACBC methods are the same.

H3: ACA surveys have the same average response time than ACBC surveys.

3.1 Design Generation Strategy

It is important to understand – regarding both methods - the procedure behind the software's 'decision' of what questions should be asked to the respondents taking in consideration their previous answers.

As mentioned in literature review, ACA method is divided in several phases and the first ones are used to learn about the opinion of the respondent regarding all the attributes presented. This information is used to build initial utility estimates. After that, the paired-comparison tasks begin. According to Sawtooth (2007), given that the possible number of concepts is very high, several steps are followed in order to choose the concepts shown to the respondent at this phase: (1) Count the number of times each pair of attributes appeared together in any concept. Pick a set of attributes at random from among those whose members have previously appeared together the fewest times; (2) For each of the chosen attributes, repeat similar logic to find levels that have been paired least frequently; (3) Examine all possible ways of combining these levels into concepts. Find the pair of concepts most nearly equal in attractiveness, using current estimates of the respondent's utilities. (4) Randomly determine which concept will appear on each side of the screen. Brian Orme explains[1] that "ACA estimates utilities (updates them) after each pairs question is answered; It does not do this to discard levels going forward, it does this to know how to arrange the attribute levels within the partial-profile concepts shown in the pairs questions to ensure there is a trade-off".

In the case of ACBC, there is a different approach. This method does not estimate utilities during the interview to 'decide' which question comes next. The process is explained by Sawtooth (2014) in the following manner: (1) Respondent provides initial input in the BYO phase, defining a vector (C_0) that contains as many elements as attributes included in BYO, describing which levels were included; (2) Researcher provides inputs that control the design such as the number of total concepts to generate (T), the minimum number of attributes to vary from the BYO profile (A_{min}), the maximum number of attributes to vary from the BYO profile ($A_{\max}$).

The design is then generated through an algorithm. The procedure of selecting each concept is the following:

[1] This explanation was given as an answer to an inquiry made via email in the scope of this dissertation to Sawtooth Software team, that Bryan Orme integrates.

(1) Randomly select a number ($A_{i)}$ from (A_{min}) to $(A_{\max)}$ that specifies how many attributes within (C_0) will be modified to create a new (near-neighbour) concept (C_i);

(2) Randomly select ($A_{i)}$ elements within (C_0) to modify;

(3) Randomly select new (non-BYO selected) levels for the attributes chosen in step 2;

(4) Ensure that prohibitions defined by the researcher are respected and that concepts previously chosen are not duplicated. In that case, concept should be discarded and return to step one.

During this process a "counts array" is maintained in order to guarantee much more balance than this process would have if it was a strictly randomized design. Sawtooth explains that "counts array keeps track of how many times each element has been selected or modified" allowing more control of, for example, how many times each level is included across concepts.

3.2 Data collection

To compare the two aforementioned methods, primary data was collected through a quantitative approach. Two surveys were designed using Sawtooth Software (Lighthouse Studio 9.5.3., 2017) and uploaded to a server in order to allow remote responses. This software is the most popular form of implementation of adaptive conjoint methods.

The responses were collected during a one-month period – from June 23rd to July 25th, 2018. All respondents had access to the surveys via two different links and ACA was presented as questionnaire 1 and ACBC as questionnaire 2.

3.2.1 Sampling

Given that the main objective of the study was to compare research methods rather than getting to know preferences regarding Cola consumption, a convenience sample was constituted by 48 respondents with ages ranging from 20 to 60 years-old (mainly close friends and family), who were approached individually (via telephone and e-mail) in order to make sure that the importance of answering to both surveys in a coherent way was fully understood, therefore guaranteeing a comparable data set. There was the need to assure that all respondents had a level of literacy skills that guaranteed a proper interpretation of the questions.

Sawtooth Software allows the researcher to know what kind of device was used by the respondents to answer the surveys and from this data we can conclude that 56,3% of respondents used mobile devices and the remaining used laptops or PCs.

Table 5. Demographic sample information

	% (n=48)
Male	52,1
Female	47,9
Under 18 years old	4,2
18-29 years old	35,4
30-39 years old	33,3
40 -49 years old	14,6
50-60 years old	12,5

3.4. Surveys design

With the objective of comparing the two methods under study, two surveys (one using ACA method and the other using ACBC method) were built using the same subject – the widely popular soda Cola, more specifically the 33cl Cola can - and were configured using the same set of attributes and levels (see table 6). These attributes were brand, quantity of sugar per can, quantity of calories per can and price per can.

The reason for choosing the 'Cola' soda as a subject of study derives from the fact that Cola is a product consumed universally, therefore guaranteeing that respondents are very familiar with the product and are most probably able to give coherent answers on both surveys

Table 6. Attributes and attribute levels for the ACA and ACBC conjoint studies

Attribute	Level
Brand	Coca-Cola
	Pepsi
	Cola Pingo Doce
Quantity of sugar	0g
	35g
Quantity of calories	1kcal
	125kcal
	160 kcal
Price	0,35 €
	0,66 €
	0,80 €
	1,00 €

The surveys structure followed the method presented in literature review and every respondent was shown a personalized questionnaire that takes into consideration the answers given throughout the survey. The questions were displayed in Portuguese language in order to facilitate its understanding, given that all the respondents were from Portuguese nationality.

The ACA exercise comprised one 'preference for levels' task, four 'attribute importance' tasks, ten 'paired-comparison' tasks (with concepts with two attributes each in the first stage and three attributes in the second stage) and five 'calibration' tasks. For 'preference for levels' task a 7-point Likert scale was used where 1=Not Desirable and 7=Extremely Desirable. For 'attribute importance' phase a 7-point Likert scale was used where 1=Not important and 7=Extremely Important. For 'paired comparison' phase a 9-point Likert scale was used where 1=I undoubtedly prefer the combination on the left and 9= I undoubtedly prefer the combination on the right. Naturally, the combinations were shown above the question. In the calibration phase, the respondent evaluated the concept presented with a number between 0 and 100, where 0= I would definitely not buy and 100= I would definitely buy.

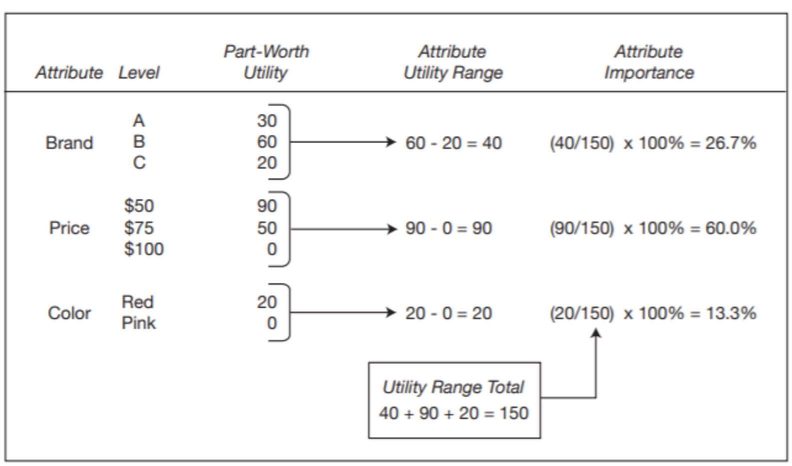
It was defined an *a priori* ranking for the attributes price, quantity of calories and quantity of sugar because, in theory, consumers prefer cheaper and healthier products, even if in a real-life buying experience that does not always happen. This *a priori* settings avoids inquiring respondents questions with an obvious answer in the 'preference for levels' tasks and that it why there was only one task at this phase, regarding the attribute "brand".

The ACBC exercise comprised a BYO (Build-your-own) configurator task, 6 screening tasks of 4 concepts each, a choice tournament with a maximum of 16 product concepts with 3 concepts shown in each group. It also contained two “unacceptable” tasks, where respondents indicate if a certain attribute level is completely unacceptable for them and two “must have” tasks, where respondents indicate if a certain feature is indispensable for them. Just like in ACA exercise, a priori rankings of levels were established to avoid obvious answers. However, it was decided to maintain all attributes in the BYO phase in order to guarantee that the respondent would be totally free to make is preferred combination of attributes. Several prohibitions were introduced in both surveys to avoid impossible profile combinations (e.g. can of Cola with 35g of sugar and 1kcal or Cola with 0g of sugar with 160 kcal).

3.4 Statistical Analysis

Individual utility scores were computed using Hierarchical Bayesian method, aforementioned and described, and utilities were rescaled using zero-centered differences method, which means that utilities sum zero within each attribute in order to facilitate the interpretation of results. Attribute relative importance’s are calculated “by considering how much difference each attribute could make in the total utility of a product. That difference is the range in the attribute’s utility values.” (Orme, 2010, p.80)

Figure 3. Relative importance of attributes calculation



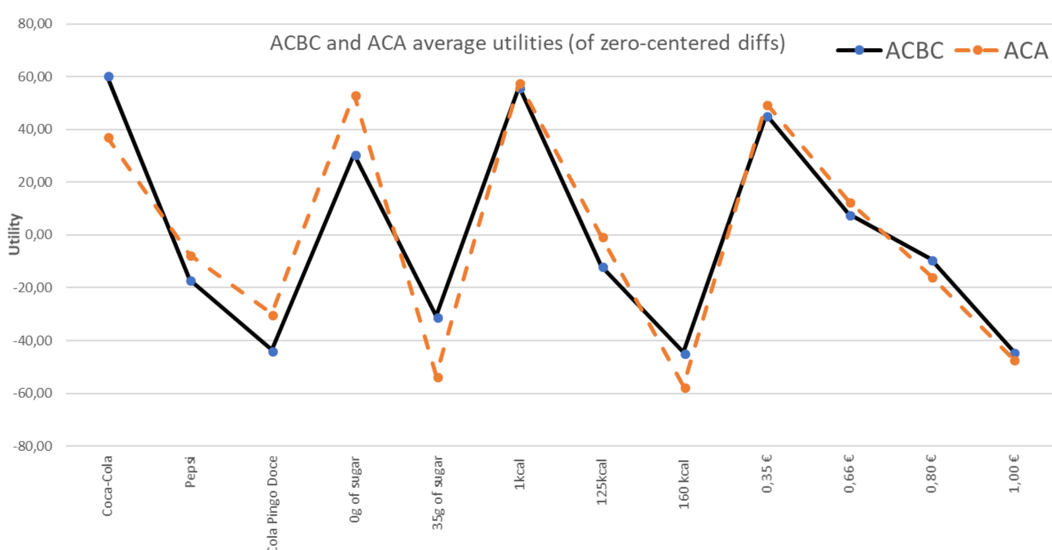
Source: Orme, 2010

4. Results

H1: Estimated average utilities results in ACA and ACBC methods are the same.

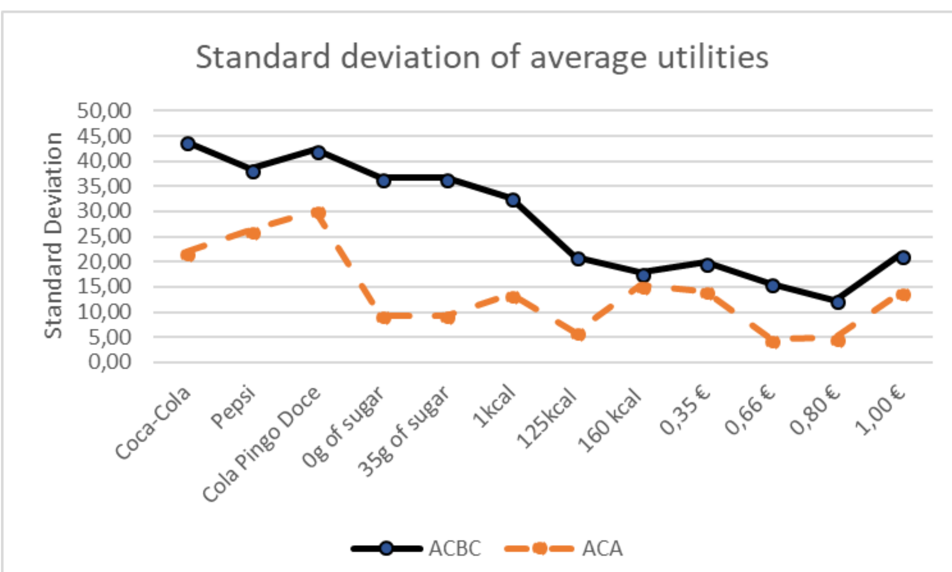
Given that the same attribute levels were tested in both exercises using the same sample, it was expected that average utilities resulting from ACA and ACBC methods would be very similar. To test this hypothesis, a Wilcoxon test was run. This non-parametric test, which is suitable to compare paired samples (Marôco, 2018), revealed that there were no significant differences regarding the values of ACA and ACBC average utilities (p-value higher than 0,05). By analysing figure 4, one can better understand the similarities between utilities results. Regarding brand, both surveys revealed that Coca-Cola is the most preferred soda among the ones under study, while Pepsi is the second preferred and Cola Pingo Doce is the least preferred. Utilities regarding sugar quantity were also very similar in both studies, but in ACA the desirability for a zero-sugar soda was more accentuated. In terms of the attribute levels regarding Quantity of Calories and Price, the results were practically the same. Because there were no big discrepancies between average utility results, we can conclude that, despite ACBC being nowadays a more popular conjoint method than ACA between researchers, they are both reliable methods to use in case we are considering a small number of attributes (we cannot extrapolate this conclusion to studies with more attributes. This would imply the construction and testing of two more surveys).

Figure 4. ACBC and ACA average utilities



In the case of Conjoint Analysis, what standard deviation of average utilities (Figure 5) tells us is how heterogeneous the responses regarding a certain utility level are (this is useful because marketing managers need to know how heterogeneous consumer opinions are regarding a certain feature in order to do an accurate market segmentation). Standard deviation for price attribute levels were lower, which means that there was little discrepancy in the opinions of the respondents regarding this variable. It is interesting to note that standard deviation for the "0g of sugar" level is much lower in ACA study than in ACBC study. In the ACA study, respondents evaluated the attribute levels independently while in ACBC they had to choose them in conjugation with other attributes (as mentioned before, full profiles are presented in ACBC), so this might mean that when considering sugar quantity isolated most respondents easily indicate that they prefer a zero sugar soda, but when evaluating it together with other attributes like price or brand, there is more dispersion in the answers and heterogeneity of the responses grows. The same happened with quantity of calories, apart from the level "160 kcal", where standard deviation is the same, both in ACA and ACBC which means that no matter the approach of the method (ratings-based or choice-based) consumers converge in their opinions when considering that 160kcal is not a desirable feature. By running a Wilcoxon test, it was possible to conclude that the differences between ACA and ACBC standard deviation of average utilities are significant (p-value lower than 0.05).

Figure 5. ACBC and ACA standard deviation of average utilities



H2: Estimated attribute preferences resulting from ACA and ACBC methods are the same.

Figure 6. ACBC average attribute importance

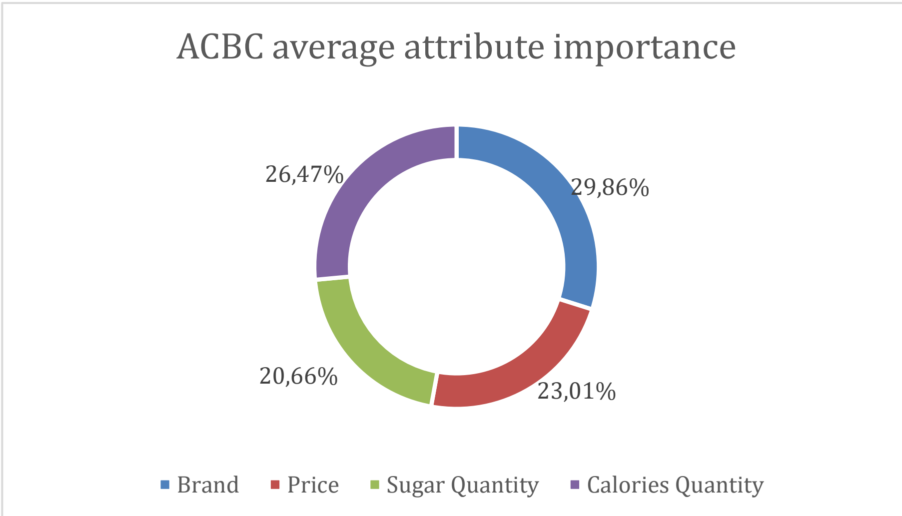
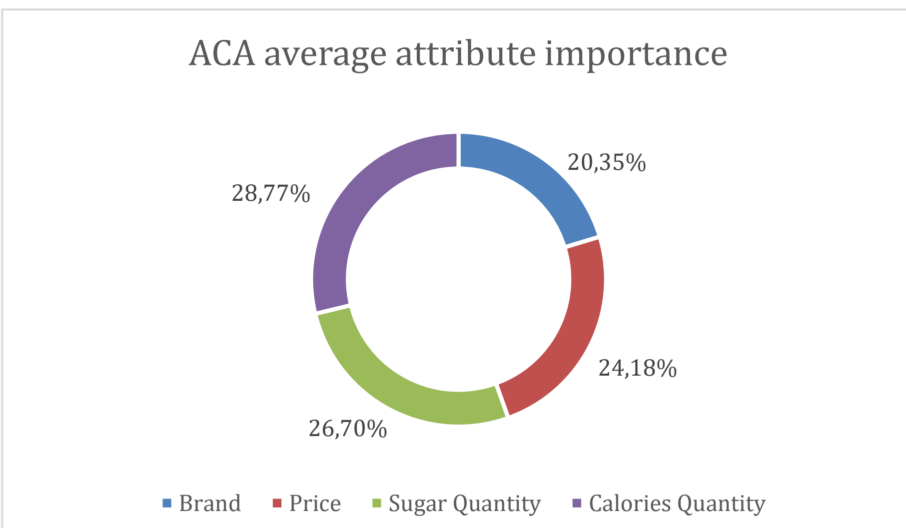


Figure 7. ACA average attribute importance



Average attribute importance values were very similar regarding the attributes price and calories quantity but showed slight differences regarding brand and sugar quantity. A Wilcoxon test showed that the difference between ACA and ACBC average attribute importance's is not significant (p-value higher than 0.05) in this case.

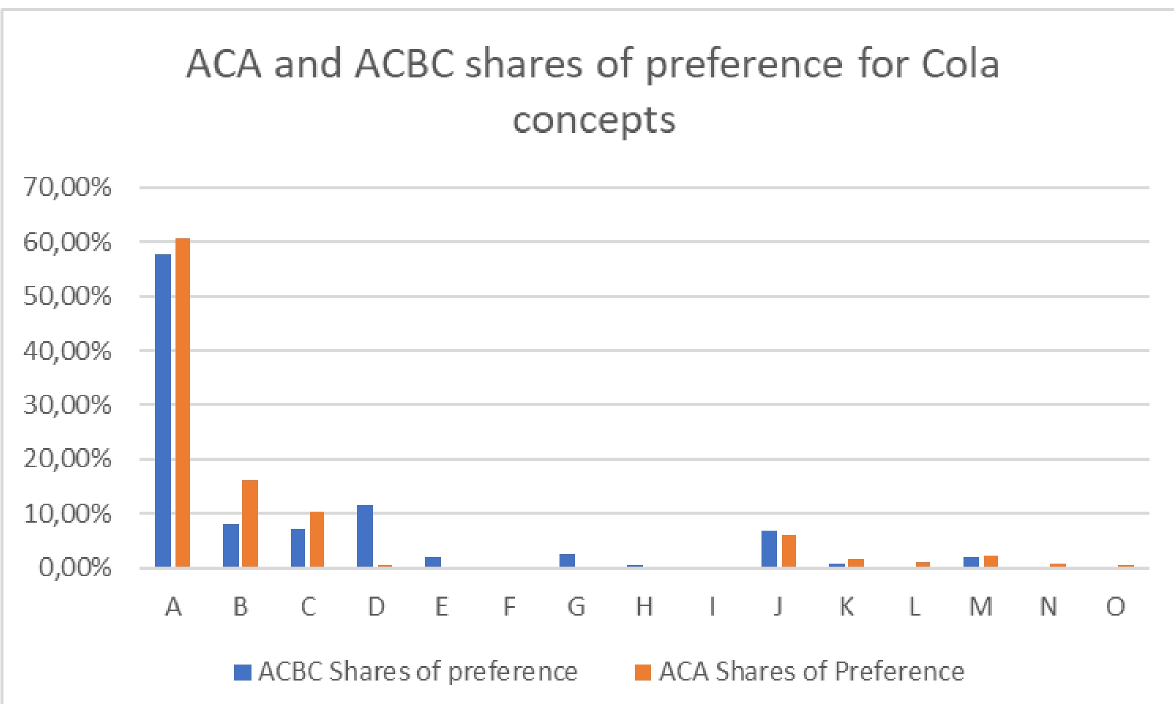
However, further discussion is needed regarding these results. As seen previously, both in ACA and ACBC studies, the average utilities with highest standard deviations were the ones of Brand and Sugar Quantity attribute levels, which denotes more heterogeneity in opinion across respondents and might have affected the coherence between surveys. Respondents could be undecided about what they value most. It is important to note that attribute average importance is often disregarded by researchers, as there are some problems attached to its calculation: "one of the problems with standard importance analysis is that it considers the extremes within an attribute, irrespective of whether the part-worth utilities follow rational preference order. The importance calculations capitalize on random error, and attributes with very little to no importance can be biased upward in importance" (Orme, 2010, p.81). That is why most market researchers rely on market simulators to test attribute importance. Market simulators are often the preferred method of market researchers to present results to company managers as it facilitates the interpretation of results. For example, it is sometimes confusing for a manager to see negative values results associated with certain features (due to zero-centered differences method) and understand that those negative values do not mean that a specific feature is unattractive. They just mean that they were considered less attractive when compared to the other features of a certain attribute but might even have been considered acceptable by all respondents.

Taking this into consideration, we did two tests for fifteen 'Cola' concepts - that have different variations in terms of attribute levels - in the market simulator integrated in Sawtooth Software. One test used the data set obtained from the ACBC study and the other used the data set obtained from the ACA.

Table 7. Share of preferences resulting from ACA and ACBC market simulations

Cola concept	Brand	Price	Sugar Quantity	Calories Quantity	ACBC Shares of preference	ACA Shares of Preference
A	Coca-Cola	0,35€/un.	0g	1kcal	57.7 %	60.7 %
B	Pepsi	0,35€/un.	0g	1kcal	8.1 %	16.1 %
C	Cola Pingo Doce	0,35€/un.	0g	1kcal	7.2 %	10.5 %
D	Coca-Cola	0,35€/un.	35g	125kcal	11.5 %	0.4 %
E	Pepsi	0,35€/un.	35g	125kcal	2.1 %	0.1 %
F	Cola Pingo Doce	0,35€/un.	35g	125kcal	0.3 %	0.0 %
G	Coca-Cola	0,80€/un.	35g	125kcal	2.4 %	0.0 %
H	Pepsi	0,80€/un.	35g	125kcal	0.5 %	0.0 %
I	Cola Pingo Doce	0,80€/un.	35g	125kcal	0.0 %	0.0 %
J	Coca-Cola	0,80€/un.	0g	1kcal	6.9 %	5.9 %
K	Pepsi	0,80€/un.	0g	1kcal	0.7 %	1.8 %
L	Cola Pingo Doce	0,80€/un.	0g	1kcal	0.3 %	1.0 %
M	Coca-Cola	1,00€/un.	0g	1kcal	1.9 %	2.2 %
N	Pepsi	1,00€/un.	0g	1kcal	0.3 %	0.8 %
O	Cola Pingo Doce	1,00€/un.	0g	1kcal	0.1 %	0.4 %

Figure 8. ACA and ACBC shares of preference histogram



From comparison between the results of both simulations, we conclude that the Cola concepts that contain sugar have barely no desirability in the opinion of the respondents, with the exception of concept D, where the brand is "Coca Cola". However, the importance of D concept is only significant in the ACBC study (11.5%) while in ACA it has a preference close to zero. The other important difference between results regards concept B, that has a share of preference of 8.1% in ACBC while in ACA it has a share of preference of 16.1%. Brand and quantity of sugar (the latter is deeply connected to quantity of calories) seem to be the most determinant attributes in the preferences of the respondents regarding the tested concepts, a result that goes in line with ACBC average preference results. Price, despite being important, seems less determinant. For example, price in profile J is 0,80€ and still gets a share of preference of 5,9% in ACA and 6,9% in ACBC. Also the concepts with 1€ price get a share of preference above zero, which says that there might be some space in the market for more expensive products as long as they have low quantities of sugar and calories. Regarding the comparison of the two methods, we note that ACBC might be a more sensitive method because it detected a positive share of preference for concepts F,G and H while ACA reports 0% share of preference.

The market simulator is an important tool for correctly interpreting results and understanding which concepts could be successful or not and what combinations of attributes are desirable or not in the eyes of the consumer.

H3: ACA surveys have the same average response time than ACBC surveys

The differences between the two methods regarding response times is minimal. The mean of response time for ACA was 5,2 minutes while for ACBC it was 4,9 minutes. A Wilcoxon test revealed no significant differences between the average response times of ACA and ACBC surveys (p-value higher than 0,05). Nevertheless, we must alert that these times relate to this specific study, which analyzed a small number of attributes and attribute levels. However, from our conclusions, response time shouldn't be a determinant factor when choosing between ACA and ACBC methods as they are practically the same. This calculation was possible because the software used keeps track of how long each respondent takes to answer the full survey.

5. Discussion of Results and Conclusions

Every day, consumers are more connected and informed, have more power of choice and less time available. The rapid evolution of information societies is reshaping the way companies act towards their target markets. The challenges and opportunities created by new technologies and new channels of communication demand an accurate analysis of the fast changes occurring in several activity sectors, in consumption trends and consumer profiles. This analysis can only be done if marketeers and market research companies, who are deeply impacted by this environment of permanent change and evolution, have the right tools to do so.

This work aimed to give a comprehensive perspective of what are the digital tools currently available and what can be expected from each of them in terms of its advantages and limitations. This is precisely what the literature review tried to achieve, by exploring several research methods that are currently used by companies and others that are just emerging and need further investigation such as "in the moment" research or research games. It is very important for marketeers and managers to be informed of the options available so that they can choose the right tool for the right purpose.

One of the most popular methods used for collecting data are web-based surveys. Its use is very common due to several factors, such as the short period of time it is needed to gather information, the easy access to web-based survey platforms that carry no costs or how easy it is to treat and analyse the data after it is collected. However, this advantages does not mean that a traditional web-survey is the best method to apply in all cases. What we tried to do with this investigation was to go one step ahead and see what other options exist within web-based surveys that can be of value in a managerial perspective. Through an extensive literature review, we realized that for more specific purposes, such as preparing the launch of a new product or service, segmenting the market or simply assessing the appeal of a certain campaign, the survey-based multivariate statistical technique called Conjoint Analysis can be of great help. In this specific case and given the importance of avoiding do burden respondents with long questionnaires, our analysis was focused on adaptive methods of conjoint analysis, that have proven before to have efficiency gains.

By comparing two of these adaptive methods and understanding how they work and how they can be built, we concluded that despite some complexity, if correctly used, this tool can is useful to marketeers who want study and compare several attributes of a product or service. The fact that this technique is usually aided by software that integrates market simulators makes it more appealing to managers.

In this context, we designed two surveys, one with the Adaptive Conjoint Analysis (ACA) method and the other with the Adaptive Choice-Based Conjoint Analysis (ACBC) method and concluded that for a few number of attributes (in this case four) both reach the same results in terms of the utilities estimated for attribute levels and also the attribute relative importance, with ACBC showing – through a market simulator exercise - to be more sensitive and detecting smaller shares of preference than ACA. For both surveys the response time was the same.

It was also very interesting to notice that more than half of the respondents used mobile devices to answer the surveys, which stands out a warning to companies who still haven't reached the point to adapt their tools to face this new reality. To get good response rates, market research companies need to face the fact that adapting contents to mobile is no longer optional.

As a limitation to this study, it is important to say that it would have been optimal to do two more surveys using the same sample but a higher number of attributes and analyse if there would be any differences when comparing to a study with a short number of attributes and attribute levels.

Many other research methods are arising, and further investigation is needed to understand which ones will become relevant in the future. The fact that new types of data are now starting to be collected through several apps, for example biodata (the Health app that comes as default on iPhones is just an example), is a theme that needs to be addressed from a marketing point of view on how to use this information for business purposes, but always keeping in mind the ethics questions related to this new opportunities.

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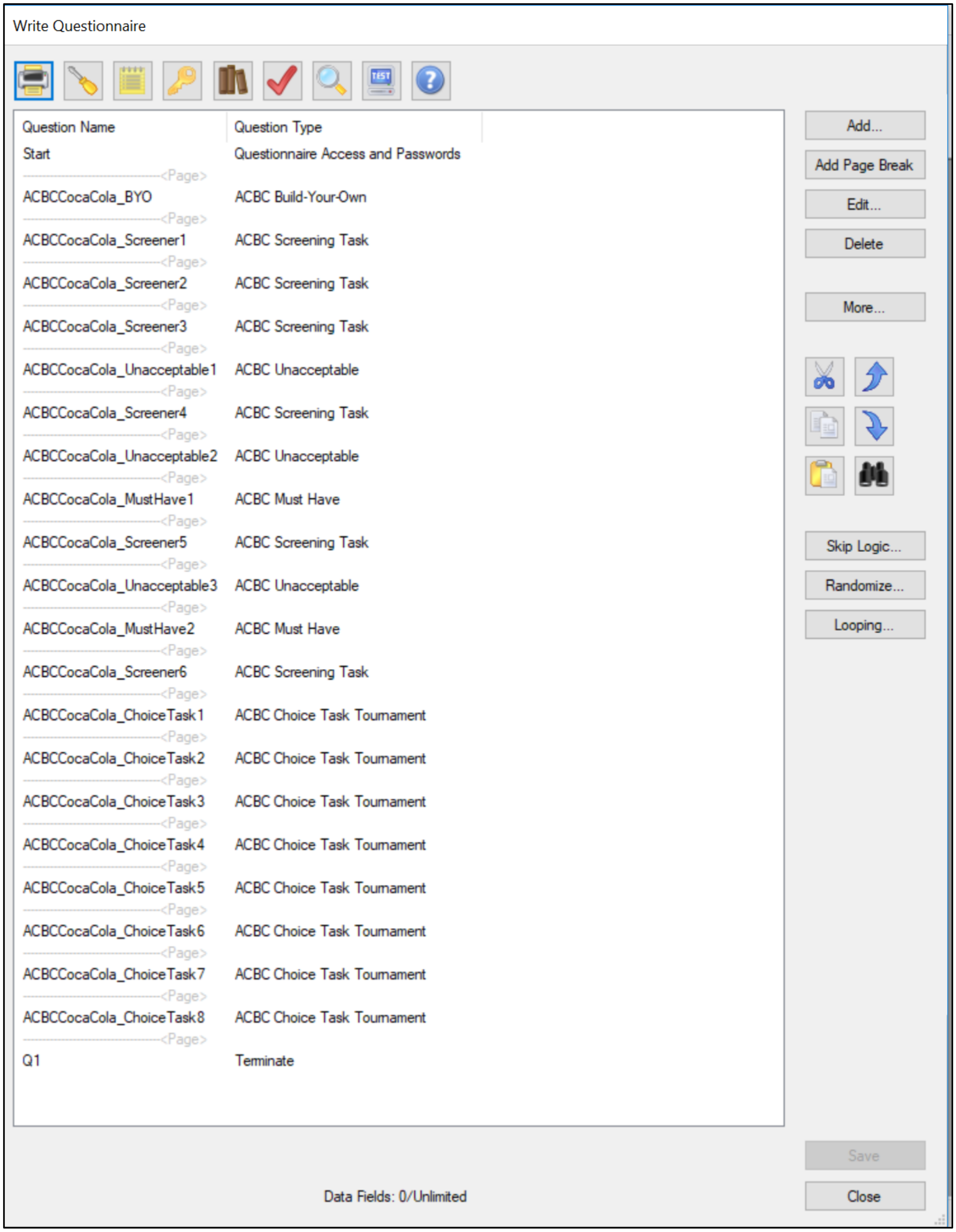
7. Appendices

Appendix 1. ACBC Questionnaire Structure



Appendix 2. ACBC Build-Your-Own (BYO) task (example)

Entre as opções abaixo, indique as características preferidas numa Cola (refrigerante).

Feature	Select Feature
Marca	Select Feature ▼
Preço	Select Feature ▼
Quantidade de Açucar	Select Feature ▼
Quantidade de Calorias	Select Feature ▼

Appendix 3. ACBC Screening task (example)

Apresentados abaixo estão perfis de algumas Colas de que poderá gostar. Para cada um deles indique se os considera ou não uma possibilidade.

(1 of 6)

Marca	Pepsi	Cola Pingo Doce	Coca-Cola	Coca-Cola
Preço	0,35€/un.	0,80€/un.	0,35€/un.	0,66€/un.
Quantidade de Açucar	0g de açucar	0g de açucar	35g de açucar	0g de açucar
Quantidade de Calorias	1kcal por lata	1kcal por lata	160 kcal por lata	1kcal por lata
	◯ É uma possibilidade ◯ Não me agrada	◯ É uma possibilidade ◯ Não me agrada	◯ É uma possibilidade ◯ Não me agrada	◯ É uma possibilidade ◯ Não me agrada

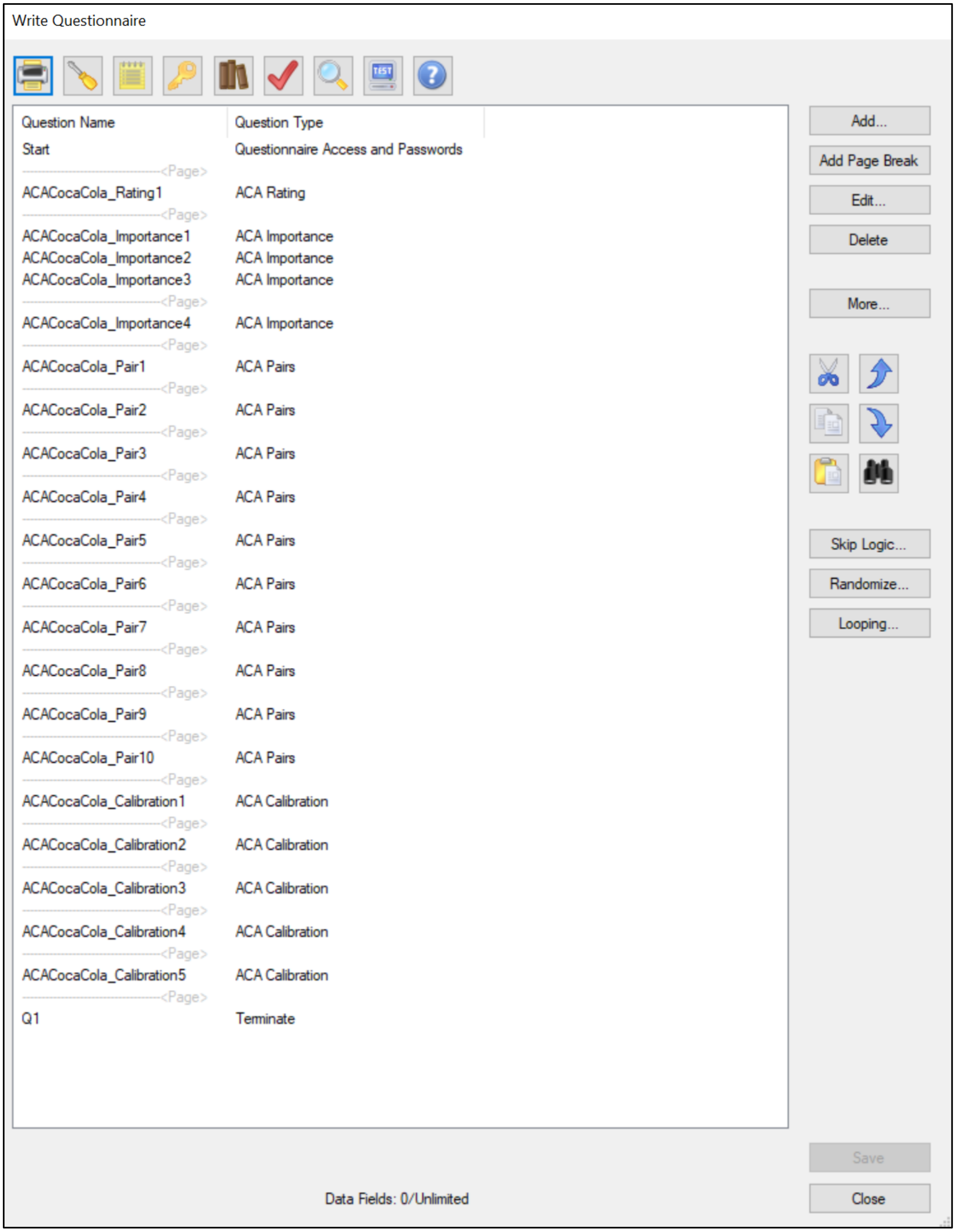
Appendix 4. ACBC Choice Task Tournament (example)

Entre estas opções, qual considera ser a melhor? (A cizento estão sublinhadas as características que são iguais em todas as opções para que se possa focar apenas nas diferenças.)

(7 of 8)

Marca	Cola Pingo Doce	Pepsi	Cola Pingo Doce
Preço	0,66€/un.	0,66€/un.	1,00€/un.
Quantidade de Açucar	0g de açucar	0g de açucar	0g de açucar
Quantidade de Calorias	1kcal por lata	1kcal por lata	1kcal por lata
	◯	◯	◯

Appendix 5. ACA Questionnaire Structure



Appendix 6. Preference for levels task (ACA Rating) example

Indique quão desejáveis são, na sua opinião, as seguintes Marcas ?

	Nada desejável		Ligeiramente desejável		Muito desejável		Extremamente desejável
Coca-Cola	○	○	○	○	○	○	○
Cola Pingo Doce	○	○	○	○	○	○	○
Pepsi	○	○	○	○	○	○	○

Appendix 7. Attribute importance task example

Se duas Colas fossem aceitáveis em todos os outros aspetos, quão importante seria esta diferença para si?

	Não é importante		Ligeiramente Importante		Muito Importante		Extremamente Importante
0g de açucar *---em vez de---* 35g gramas de açucar	○	○	○	○	○	○	○

Se duas Colas fossem aceitáveis em todos os outros aspetos, quão importante seria esta diferença para si?

	Não é importante		Ligeiramente Importante		Muito Importante		Extremamente Importante
1kcal *---em vez de---* 160kcal	○	○	○	○	○	○	○

Se duas Colas fossem aceitáveis em todos os outros aspetos, quão importante seria esta diferença para si?

	Não é importante		Ligeiramente Importante		Muito Importante		Extremamente Importante
0,35€/un. *---em vez de---* 1€/un	○	○	○	○	○	○	○

Appendix 8. Paired Comparison Trade-Off Questions (ACA pairs) example

Se estas duas Colas fossem idênticas em todos os outros aspetos, qual preferiria?

0,35€/un. 160kcal	ou	1€/un 1kcal

○	○	○	○	○	○	○	○	○
Prefiro sem dúvida a combinação da esquerda		Prefiro ligeiramente a combinação da esquerda		Indiferente		Prefiro ligeiramente a combinação da direita		Prefiro sem dúvida a combinação da direita

Appendix 8. ACBC/HB Report Results Summary

ACBC/HB Report Results Summary		
Number of Respondents	48	
Average Utilities (Zero-Centered Diffs)	**Average Utilities**	**Standard Deviation**
Coca-Cola	60,55286	43,84879
Pepsi	-16,94843	38,43747
Cola Pingo Doce	-43,60442	42,23636
0,35€/un.	45,45865	19,90118
0,66€/un.	7,88869	15,71451
0,80€/un.	-9,12889	12,38002
1,00€/un.	-44,21846	21,38204
0g of sugar	30,72030	36,61727
35g of sugar	-30,72030	36,61727
1kcal	56,19033	32,73943
125kcal	-11,76028	21,01318
160 kcal	-44,43006	17,88071
Average Importances	**Average Importances**	
Brand	29,85874	
Price	23,00831	
Sugar Quantity	20,66242	
Calories Quantity	26,47052	

Appendix 9. ACA/HB Report Results Summary

ACA/HB Run Results Summary		
Number of Respondents	48	
Average Utilities (Zero-Centered Diffs)	**Average Utilities**	**Standard Deviation**
Coca-Cola	37,34358	21,87324
Pepsi	-7,43401	26,27210
Cola Pingo Doce	-29,90957	30,11998
0,35€/un.	49,70531	14,13717
0,66€/un.	12,83718	4,64566
0,80€/un.	-15,51339	4,85741
1€/un	-47,02910	13,83618
0g of sugar	53,39216	9,29146
35g of sugar	-53,39216	9,29146
1kcal	57,79666	13,52143
125kcal	-0,49386	5,97029
160kcal	-57,30280	15,25214
Average Importances	**Average Importances**	
Brand	20,34545	
Price	24,18360	
Sugar Quantity	26,69608	
Calories Quantity	28,77486	

Appendix 10. Wilcoxon tests

- Wilcoxon test comparing “ACA and ACBC average utilities”
- Wilcoxon test comparing “ACA and ACBC standard deviation of average utilities”

Test Statistics[a]

	ACA_Average_Utilities - ACBC_Average_Utilities	ACA_Standard Deviation - ACBC_Standard Deviation
Z	-,118[b]	-3,061[c]
Asymp. Sig. (2-tailed)	,906	,002

a. Wilcoxon Signed Ranks Test.

b. Based on negative ranks.

c. Based on positive ranks

- Wilcoxon test comparing “ACA and ACBC average attribute importance”

Test Statistics[a]

	ACA_Average Importances - ACBC_
Z	-,365[b]
Asymp. Sig. (2-tailed)	,715

a. Wilcoxon Signed Ranks Test.

b. Based on negative ranks.

- Wilcoxon test comparing ACA and ACBC “average response time”

Ranks

		N	Mean Rank	Sum of Ranks
ACBC - ACA	Negative Ranks	27[a]	25,74	695,00
	Positive Ranks	21[b]	22,90	481,00
	Ties	0[c]		
	Total	48		

a. ACBC < ACA

b. ACBC > ACA

c. ACBC = ACA

Test Statistics[a]

	ACBC - ACA
Z	-1,097[b]
Asymp. Sig. (2-tailed)	,272

a. Wilcoxon Signed Ranks Test.

b. Based on positive ranks

Pearson Correlation

		ACA	ACBC
ACA	Pearson Correlation	1	,208
	Sig. (2-tailed)		,156
	N	48	48
ACBC	Pearson Correlation	,208	1
	Sig. (2-tailed)	,156	
	N	48	48