Online Healthy Food Experiments: Capturing Complexity by Using Choice-Based Conjoint Analysis

Valdimar Sigurdsson¹ · R. G. Vishnu Menon¹ ·
Asle Fagerstrøm²

Published online: 2 October 2017

© Association for Behavior Analysis International 2017

Abstract The impact of complex environmental factors on consumer choices and preferences can be analyzed through the prism of consumer behavior analysis, whereas variations of marketing attributes and their impact on choice can be measured using conjoint analysis. Considering the case of the constantly growing online food selections, we discuss choice-based conjoint analysis and explore the opportunities for behavior analysts to examine the interrelationships of multiple variables and socially important choice settings, and to promote desired behaviors. We show a few examples of using trade-off analyses in online food retail to understand consumer behavior with respect to healthy food items. As demonstrated in these examples based on our own pilot research, conjoint analysis can be used for complex behavior—that which is not amenable directly to an experimental analysis—or as an efficient initial step before moving into further experiments or analyses using biometrics (e.g., eye-tracking) or web analytics conducted in different settings such as e-commerce, e-mail, social media, or on mobile platforms. This paper summarizes the personalized, data driven economic analysis that is possible with a choice-based conjoint analysis.

Keywords Obesogenic environment · Choice-based conjoint analysis · Online food selection · Health

✉ Valdimar Sigurdsson
valdimars@ru.is

R. G. Vishnu Menon
rgvishnu@ru.is

Asle Fagerstrøm
fagasl@westerdals.no

¹ Reykjavik University, Menntavegur 1, Nautholsvik, 101, Reykjavik, Iceland

² Westerdals Oslo School of Arts, Communication and Technology, Christian Kroghs gate 32, 0186 Oslo, Norway

Introduction

The World Health Organization has been warning of a forthcoming epidemic in noncommunicable diseases such as cancer, heart disease, diabetes, and Alzheimer's since the 1960s. This warning is strengthened as obesity has reached substantial proportions and sedentary activities are widespread (see James 2016, for a detailed discussion). Lake and Townshend (2006) use the term *obesogenic* to describe this state of an environment, and define it as “the sum of influences that the surroundings, opportunities, or conditions of life have on promoting obesity in individuals or populations” (p. 262). Sigurdsson, Saevarsson, and Foxall (2009) show, for example, that it is easy to increase unhealthy choices through a behavioral in-store experiment that investigates the effects of shelf placement on consumers' purchases of potato chips, and Wansink (2016) refers to the hospitable environment and tries to empower consumers by offering them rating scales for different food environments.

The obesity epidemic has been discussed at different levels—from research to health professional policies to general media interest (e.g., Hill, Wyatt, Reed, & Peters, 2003). It is a problem of self-control (Rachlin, 2004) where people recognize behaviors that could be harmful to their health, but where many still continue with these even when the undesired consequences appear. According to Marteau, Hollands, and Fletcher (2012), interventions have traditionally emphasized covert behaviors and reflections; however, these approaches often tend to be ineffective, strengthening the conclusion that most behavior under the influence of the environment is automatic. Arranging the environmental conditions so that people make better decisions, therefore, has the utmost potential for successful obesity prevention (e.g., Hollands et al., 2013; Lake & Townshend, 2006; Sigurdsson, Larsen, & Gunnarsson, 2014); this can hopefully promote the behavior change capabilities of behavior analysis and connect our research with other disciplines. The behavioral changes do not necessarily need to be drastic, as small changes in behavior could add up to significant long-term effects (Wansink, 2007, 2016). However, in order to develop successful interventions, it is of vital importance to understand how environmental conditions influence consumers' food choices, and how they are constantly being altered through new marketing settings and stimuli. In this regard, children and adolescents should be of primary concern, especially given increased sedentary behaviors related to such things as computer games and digital media. Here, behavior analysts have started to contribute by assessing functional relations between environmental events and physical activity (e.g., Hustyi, Normand, & Larson, 2011; Hustyi, Normand, Larson, & Morley, 2012).

Alterations in environments where people either buy or consume food have been successful when healthier choices have been made easier and unhealthier choices have been made less convenient (Wansink, 2016). The environments include people's homes, school, office, restaurants, and grocery retail stores. As shopping is to some extent moving to digital media instead of the traditional brick and mortar retailers, we chose to focus in this paper on the integration of behavioral and digital technology to promote healthy food choices (see also Dallery, Kurti, & Erb, 2014). The ongoing digitalization transforms retail grocery to omni-channel retailing where “the distinctions between physical and online will vanish, turning the world into a showroom without walls” (Brynjolfsson, Hu, & Rahman, 2013 p. 23). Furthermore, realizing that changes happen fast in these dynamic digital marketing settings, it is of the essence to be able to

test and learn in a rapid manner—especially since we want research findings to be current, relevant, and informative to policy making and consumer protection. The purpose of this paper is, therefore, to showcase recent advancements and possibilities within consumer behavior analysis in order to address challenges related to obesogenic environments. We focus on the opportunities related to brief experimental analysis using conjoint analysis within the setting of digital media, as it brings possibilities for prompt answers to issues that are multi-determined and/or possibly complex (Foxall, Oliviera-Castro, James, Yani-de-Soriano, & Sigurdsson, 2006). In addition, we demonstrate the benefit of choice-based conjoint analysis as a methodology that combines operant behavioral economics and marketing science by showing the usefulness of reinforcement value estimates for preferred attributes. Experiments conducted with choice-based conjoint analysis do not only manipulate single attributes when making choices, but also bundles of them for groups or segments of consumers. This reinforcement optimization can also account for individual consumers with repeated measures, as detailed single-subject experimentation is the purview of behavior analysis. As such, choice-based conjoint analysis experiments capture more of the complexity that characterizes consumers' settings in relation to purchasing food. This is especially true because the external validity can be high, given the resemblance between the research setting (making choices on one's own digital devices) and similar choice behaviors in the real marketing place.

The paper has three parts. First, we discuss the applied behavioral economics for healthy interventions, bridging basic and applied research for healthy food promotion. We introduce consumer behavior analysis as a basis for the study of complex online choices. Then, we introduce applied choice-based conjoint analysis and its importance in studying choice architecture and online food selection. The paper concludes with behavioral economic analysis related to healthy food choices with a summary of the personalized, data driven analysis possible with a choice-based conjoint analysis.

Applied Behavioral Economics for Healthy Interventions

According to Gerteis et al. (2014), the World Health Organization's Global Health Observatory data now indicate that over two thirds of the 56 million global deaths were attributed to noncommunicable diseases in 2012. Such chronic health conditions come in the form of type 2 diabetes, obesity, heart disease, stroke, and cancer, and account for 86% of all healthcare spending in the United States. In recent decades, the prevalence of obesity has been linked to dramatic changes in choice behavior as it is well documented that the majority of chronic health conditions results from unhealthy behaviors. According to the Center for Disease Control and Prevention, these behaviors include choosing sedentary activities and choosing to eat high calorie food (James 2016). Numerous interventions and governmental guidelines have therefore been introduced to promote the consumption of more healthy food products, but results have been inconsistent (e.g., Yeh et al. 2008). According to James (2016), some high-income countries experienced reductions in heart disease during the last decades of the twentieth century. For example, based on established data there were 70,000 fewer deaths from heart disease in England in the 20 years from 1980. The question is, what was, for instance, responsible for that substantial reduction? Was it due to innovation in

medical healthcare? Improvements in medicine did indeed contribute to increased life expectancy, but it is only estimated as 20% of the total benefit. The larger benefit of 80% is deemed to be due to changes in behavior. The most important factors were reduced smoking and changes in diet (see behavior analytical research on smoking in Kurti & Dallery, 2014; Dallery, Raiff, & Grabinski, 2013). It seems to be to a large extent question about choice architecture as health in all societies results more from environmental-behavioral contingencies than from biomedical factors (James 2016) or social-cognitive programs (Sigurdsson, Larsen, & Gunnarsson, 2011a; b). However, the possibilities of a natural science of behavior have still received relatively little attention in this regard. Why is this the case when the primary explanans lies in the environment?

Toward a Natural Science of Consumer Behavior

The famous behaviorist John B. Watson was the first to bring behavior analytical techniques to the area of consumer behavior. Watson wanted to use behavioral methods, such as classical conditioning, to control consumers' buying behavior and did not hesitate to extrapolate, prematurely, from the animal laboratory (Buckley 1982). Since the time of Watson, consumer psychology (see e.g., Foxall, 1990, 2016) has advanced considerably from a behavioral perspective (for a review of consumer choice research in behavior analysis see DiClemente & Hantula, 2003; Foxall, 2016). Despite these efforts, behavior analysis is unfortunately lacking in the field of marketing, and in consumer research in general, and it can be concluded that there are signs of growing isolation of behavior analysts over the spectrum of fields during the last decades. Freedman (2016, p. 89) even declares that "[o]utside of autism, behavior analysis is unfamiliar to most people, in spite of the field's many active application domains." This can no doubt be attributed to several factors. One of these is the predomination of research traditionally carried out with animals as subjects in basic behavior analysis. This is mostly known from former students of Skinner at Harvard University, as well as their students, such as Herrnstein (e.g., 1997), Rachlin (e.g., 1982), and Baum (e.g., 1979). From these and other behavior analysts at the Harvard Pigeon lab, we have learned a lot about environmental contingencies that influence behavior—from rigorous animal experimental research to mathematical treatment of behavior. This has stimulated Foxall at Cardiff University, his collaborator Oliveira-Castro at the University of Brasilia, Hantula at Temple University as well as their students, collaborators, and other interested researchers to explore to what extent these behavior principles and this methodology are applicable and useful in the realm of consumer behavior. Furthermore, this research has also been connected to, supported, and challenged by the basic disciplines, that is, behavior analysis and economics (e.g., Foxall, 2001; Oliveira-Castro et al. 2006). Moreover, another explaining factor for increasing isolation may be a restriction on rather closed and limited experimental environments in behavior analysis (see Foxall, 1998) for the sake of traditional experimental designs.

Other factors for the unfamiliarity of behavior analysis can also be pinpointed, such as how intense and time-consuming single subject research can be, and how costly it is on a large-scale basis. See a discussion of these issues in Smith (2016), who proposes among other things that behavior analysts need to rely on technological

systems that sample behavioral data as easily as possible. Moreover, it is important to reconcile that the term “single” in single-subject experimentation refers to the experimental comparison, but not to the few subjects generally used (Perone 1991). Smith (2016) also mentions the importance of detecting multiple variables that influence behavior. However, behavioral experiments struggle with many factors and intervening effects, and some factors simply are not at all amenable to strict experimental analysis. The aforementioned factors all include subjects that behavior analysts can work on; however, issues like traditional demand for cognitive constructs in marketing (as well as generally in the social sciences) are more difficult. In summary, researchers in the behavioral economics field of consumer choice should work more on research that:

studies human behavior;
can deliver rapid results;
allows advanced statistical treatment;
can be conducted in open natural settings;
connects our science to other disciplines working on behavior;
can deal with price sensitivity and the rest of the marketing mix
extends individual data easily and inexpensively to large populations;
can handle interrelationships of multiple variables influencing behavior;
allows realistic interpretation for factors that are not easily open for experiments

Therefore, we are arguing for a behavioral science of consumer and marketer behavior for its own sake, not as a symbol or sign of something else—a field where there is a bridge between behavior analysis and marketing science, and the emphasis is on direct measurements of the choice behavior in a more natural setting.

Krapfl (2016) pinpoints, and we agree, that behaviorists need to specialize, that is, they need a deep understanding of one or a few business domains such as health care, financial services, or academic institutions so that it is possible to engage in serious discussions and analyses. Behavior analysis also needs to bridge over to other disciplines (Hantula 2016). When it comes to consumer behavior, there are interactions with marketing (the Behavioral Perspective Model, Foxall, 1987) and ecology (Behavioral Ecology of Consumption, Rajala & Hantula, 2000); both perspectives are complementary and both have been converged with the matching law (DiClemente & Hantula, 2003). Consumer behavior analysis—the application of behavioral economics to the sphere of human consumer choice—attempts to explore the nature of behaviorist explanation and methodology and its capacity to illuminate consumer research, particularly in the context of advanced marketing-oriented economies (Foxall, 1998).

In this paper, we showcase consumer behavior analysis in e-commerce, as the rapidly changing digital environment has redefined the way in which most companies interact with their customers. Search engines, websites, Internet databases, and social media enable consumers to exploit new opportunities—whether information exchange or price/product comparison—and allow them to create content and spread their message. This “digital revolution” is at the same time a real opportunity for descriptive behavioral science that wants to stay close to data, as increased environmental-behavior interaction via digital technology consumes data and enhances the possibilities for

sound contextual explanation and practice. For behavior analysts, it is therefore more critical than ever to understand, predict, and influence the changing behavior of “digital consumers” from a sound empirical foundation. We see choice-based conjoint analysis as an important tool in this development, as it can be used to study consumer behavior, which is directly under the simultaneous effects of multiple environmental factors. Furthermore, it can also be used to test the effects of variables that cannot easily be manipulated directly, or where it is not efficient for some reasons. An example of such variables are the color and design of carpets at a hotel chain or other aspects such as shown in Wind, Green, Shifflet, and Scarbrough (1989) in their successful application of conjoint analysis to the development of the Courtyard sub-brand for the Marriott hotel chain.

Applying Conjoint Analysis

Choice Architecture, Conjoint Analysis, and Online Food Selection

The launch of the online market for food products, currently being developed by online grocers, provides potential benefits for consumers’ diet and new business opportunities for both retailers and producers (see a behavior economic analysis of how consumers and firms influence each other in Vella and Foxall (2011)). As a consequence, new digital sites are developed with different structures and content to promote and sell food through digital media, and competition has considerably increased (Desai, Potia, & Salsberg, 2012). However, there is limited knowledge (at least academic) on customers’ preferences when selecting healthy food, such as fish, using digital media. As the multitude of contingencies related to complex real world consumer behavior creates complexities that can preclude or complicate a direct experimental analysis, we want to explore a methodology that can test the combined effects of marketing factors and the economical trade-off. Our quest is to enlarge the capacity of behavioral economics to elucidate human activity in a more natural setting. This is an extension of behavioral economics toward understanding how consumers’ choices of different bundles of attributes work in the affluent economic system of e-commerce. Specifically, we are concerned with the ways in which behavioral economics can be taken a step further to embrace the analysis of complex consumer choices in the natural settings provided by market economies. For these reasons, we use choice-based conjoint analysis to explore the effects of price and shipping cost and other non-monetary reinforcement or punishment factors—such as reinforcement quality estimate and delay—and their impact on healthy online food choices.

Conjoint analysis is a measurement technique with its origin in the field of mathematical psychology, and covers models and techniques that are used to map and analyze preference hierarchies (Green & Srinivasan, 1978). For example, buying fish involves evaluating a variety of choice attributes such as the quality of the fish, price, and health benefit, and it is not always known which attributes are preferred and selected. Since consumers do not assign an equal preference to any attributes, some attributes are more important than others. The conjoint technique starts with the participant’s overall evaluation of a set of attributes. It then performs the job of decomposing the participant’s original choice evaluation into separate and compatible

impact scales by which the original overall evaluation can be reconstituted (Green and Wind 1975). The ability to separate an overall evaluation into components in this manner provides researchers and practitioners with information about the relative impact of various attributes for each individual or for segments. The attributes can be arranged in a hierarchy, where the most important one (or most preferred choice) comes first, then the second most important one, and so on. As such, it is possible to arrange a preference hierarchy on the individual level (e.g., consumer X prefers mostly a favorable price when buying fish) or segment level (consumers with a high income, living in urban areas, prefer mostly high quality fish). Previous studies have used conjoint analysis to understand consumer preferences for fruits and vegetables (Van der Pol & Ryan, 1996), to assess consumer evaluation of probiotic functional foods (Annunziata & Vecchio, 2013), and to understand consumer responses to food packaging (Silayoi & Speece, 2007).

Online grocery shopping have emerged significantly across the globe. In a recent study conducted by Nielsen (2015), one-quarter of the 30,000 global surveyed are already ordering grocery products online, and more than half are willing to use it in the future. However, the form of online sales differs by both retailers and countries (e.g., online website of a store in India might be different from the one in the UK). Some retailers emphasize certain attributes or online tools such as ranking and reviews (e.g. Marks & Spencer), while others focus on pricing (e.g. Aldi). Form refers to different online tools and structure, while content differs as some retailers try to sell the “whole experience” by using for instance words such as “succulent” with elaborate pictures, while other online retailers retain minimalism by showing the fish and the price. For online grocery shopping and healthy food purchase to develop, retailers need to understand the key factors that influence consumer purchase behavior, and the extend to which the online shopping environment reinforces consumer behavior (Hand, Riley, Harris, Singh, & Rettie, 2009).

Choice and Concatenated Matching

We believe that it is imperative to study relevant consumer behavior directly, and that the behavior of social interest should be particularly emphasized. According to MacDonall (2016), it is ironic that behavior analysts have supported the notion that multifaceted environmental contingencies account for the diversity of human behavior, while mostly experimenting with a limited range of behaviors. Modern human behavior consists of social media, search engine and e-commerce activity, and we can just imagine the complexity of behavior analysis if it thoroughly examined all of those interesting behaviors and the functional effects of the environments. There are opportunities that need to be explored; as such we propose choice-based conjoint analysis as a tool, building on behavior economic models, concepts, and methods.

Therefore, it should be safe to conclude that behavior analytical influences have much potential currently, given recent trends in technology (see also Dallery et al., 2014; Overskeid, 2008). Marketing scientists should be interested in behavior analysis, as they work on advancing the environmental experience as the primary engine of behavior to develop science and practice. Thus, if we want to analyze complex choice behavior it is good to start with the factors in the concatenated generalized matching equation, choices, and relativity, as there we can use many competing factors

accounting for choices. These can, for example, be the variables that research has shown to affect behavior, such as rate, amount, immediacy, and quality of the reinforcers or response effort (for a review see Fisher & Mazur, 1997). We can account for this within the framework of the generalized matching equation (Baum, 1974) by using a concatenated generalized matching equation (Eq. 1):

$$\log \frac{B_1}{B_2} = a_r \log \left(\frac{R_1}{R_2} \right) + a_m \log \left(\frac{M_1}{M_2} \right) + a_q \log \left(\frac{Q_1}{Q_2} \right) + a_d \log \left(\frac{D_1}{D_2} \right) + \log c \quad (1)$$

Where B , R , M , Q , and D represents behavior frequencies, reinforcer frequencies, amount, quality, and delay respectively for alternatives 1 and 2, and a and c are empirical constants. If it is possible to assume that the effects of the independent variables do not interact, then the concatenated generalized matching law can be relevant and useful when researching the effects of two or more independent variables ((Landon, Davison, & Elliffe, 2003). However, the variables possibly interact and the reality soon becomes very complicated. It would for example be difficult to do an experiment or a traditional functional analysis on all the attributes and study their combined effects on choice behavior. As Krapfl (2016) points out, behavior analysis is unlikely to flourish unless behavior analysts understand a good deal more about the cultural and other contextual features of the environments in which they work. That field is complicated and therefore, instead of extrapolating merely laboratory results or interpreting a need for an extra layer to behavior analytical work in complex (“real world”) situations, we propose choice-based conjoint analysis as a method to do so.

Choice-Based Conjoint Analysis for Complex Situations

According to Krapfl (2016), marketers tend to think of a marketing bifurcation that divides efforts into two foci, one pertaining to benefits and the other to attributes. Attributes describe characteristics of provider behavior or product features, whereas benefits describe what the customer gets. Marketing has a lot to offer to behavior analysis and vice versa. An established thought of modern marketing is that consumer behavior results not only from price, as is usually focused on by economists, or from different individual factors such as price, product attributes, advertising, or other promotional means, but by a combination of all these influences on demand that constitute the marketing mix (McCarthy, 1960). Furthermore, all these stimuli can have utilitarian and/or informational reinforcement or punishing consequences according to the Behavioral Perspective Model of consumer choice (e.g., Foxall, 1990, 2010). The Behavioral Perspective Model is built on the extensive empirical research done by applied behavior analysts on consumer behavior modification. It offers behavior analysts and marketing scientists a conceptual and methodological system that makes it possible to analyze the interplay between consumer settings, learning history, and behavioral consequences. The Behavioral Perspective Model’s characterization of reinforcing and punishing consequences into utilitarian (functional, hedonic) and informational (social and symbolic) is consistent with our perspective on the adoption of digital shopping behavior of food products. In the utilitarian view, consumers are concerned with purchasing products in an efficient and timely manner to achieve their

goals with a minimum of effort. Utilitarian consequences lead directly to hedonic and personal gain and are linked to pleasure, fun, and positive emotional outcomes. These consequences primarily have in common that they are tangible. Chocolate, pizza, and hamburgers are physical items, and this carbohydrate-intensive consumption generally motivates further ingestion in the future. In contrast, informational consequences include feedback on performance such as an admiration of one's fitness, the number of miles walked, and weight reduction seen on the scale. This communication or feedback is largely symbolic and is often conveyed verbally. The attainment of such rewards often confers social status since they are objectively demonstrable and generally linked to a known level of performance. Studies (see e.g., Foxall et al., 2006) have shown that it is important to consider both utilitarian and informational consequences, and that they may often operate most effectively to influence consumer behavior when presented in combination (see e.g., Sigurdsson, Menon, Sigurdarsson, Kristjansson, & Foxall, 2013a, b).

To initiate our understanding of the effects of digital media on behavior, we draw upon response cost (or punishment), delay, reinforcement quality, and magnitude (Landon, Davison, & Elliffe, 2003). Response cost postulates in this setting the ease of technology use. While reinforcement quality refers to the outcome of the shopping experience, "ease of use" refers to the process leading to the final outcome. When shopping on the web, ease of use can be thought of as the process of using new media while engaging in shopping behavior. Another addition is utilitarian reinforcement, or the extent to which the activity of using the technology is perceived to provide reinforcement in its own right, apart from any performance consequences that may be anticipated (see e.g., Davis, Bagozzi, & Warshaw, 1989). At a molar level of analysis, the Behavioral Perspective Model (Foxall, 2010) comprehends consumer choices, as they are distributed over time, as a function of the rates of both utilitarian and informational reinforcement (Foxall, 1997) and punishment (Foxall, 1999). This is expressed algebraically in Eq. 2:

$$\frac{B_1}{B_2} = \frac{(({}_uR_1 + {}_iR_1) - ({}_uP_1 + {}_iP_1))}{(({}_uR_2 + {}_iR_2) - ({}_uP_2 + {}_iP_2))} \quad (2)$$

This is the Behavioral Perspective Model's matching equation, in which the consequences of behavior are divided into utilitarian (${}_uR$) and informational (${}_iR$) reinforcements and utilitarian (${}_uP$) and informational (${}_iP$) punishments. Equation 2 is shown to characterize the consumer behavior analytical standpoint; this equation however, has not been empirically quantified. It captures the complexity of consumer behavior as subject matter for consumer choice research. As this confounds all analyses, and since the above-mentioned attributes are not on a common scale, we use choice-based conjoint analysis to price out non-monetary stimuli through economic trade-offs in monetary terms (e.g., a free shipping or better customer rating is worth a particular trade-off value in monetary terms to the consumer).

Conjoint analysis was originally proposed by mathematical psychologists (Luce & Tukey, 1964), but has been used extensively in marketing, starting with the academics Green and Rao in 1971 (for an introduction to conjoint analysis, see Orme, 2014) it has since also been used for commercial purposes (Wittink, Vriens, & Burhenne, 1994). Behavior analysis has been adopted and has grown through an implementation of suitable terminology and methods from economics and other disciplines, and further

opportunities should arise to adopt and translate this to marketing. In conjoint analysis (Green & Rao, 1971; Green, 1974; Green & Srinivasan, 1978; Green & Srinivasan, 1990), consumers are asked to make trade-offs between different reinforcers and economic goods, because a single product bundle may offer the preferred levels for one attribute (e.g., good customer ratings), while offering less preferred levels for other attributes (e.g., higher price). It provides good realism as the analysis closely mimics what buyers do in the complex natural setting—choose among available offerings. Including “none” as an option enhances the realism, and allows those respondents who are not likely to purchase to choose accordingly (Orme, 2014). One of the goals of consumer behavior analysis is to predict choice; it is therefore only natural that we would value choice-based data, which is exactly one of the major objectives in conjoint analysis—that is, to predict the choices made by a sample of individuals for a new item described in terms of a set of attributes used in a conjoint study (Rao, 2014). Choice-based conjoint analysis pursues the path of choice experiments where each individual makes a choice from several choice sets, each of which is described by a set of attributes. These choice data, across all the choice sets and all individuals, are then analyzed using a choice model to obtain a function that relates the attribute levels to the probability of choice. One of the advantages of choice-based conjoint experiments is that it can be designed to simulate choices that are made in a similar way to actual marketplace choices. Rather than collecting evaluations on hypothetical attribute profiles and estimating utility models to predict choices for new products as in the ratings-based approaches, this approach directly collects stated choice data and develops a model giving the probability of choice of an alternative in terms of a set of attributes and their respective attribute levels. To emulate the idea that individuals make choices in the marketplace among a subset of products, this approach involves presenting several choice sets of hypothetical profiles, each set consisting of a few product profiles described by a finite number of attributes.

Application of Conjoint Analysis

One of the main applications of conjoint analysis is in helping managers with pricing decisions (Rao, 2014). The part-worth utilities can be used to conduct trade-off analyses, the results of which can be used to enhance a firm’s value proposal. Through trade-off analysis, it is possible to understand how much consumers value one attribute over the other. Identifying the optimum price that consumers are willing to pay for a product is one of the main objectives of many market research instruments like pricing surveys and conjoint tasks (Green & Rao, 1971; Green & Srinivasan, 1990; Johnson, 1974; Nagle, Hogan, & Zale, 2010; Winer, 2006). To elaborate on the applicability of conjoint analysis to understand healthy food choices, we illustrate an online healthy food choice-based conjoint study (fish purchase) where we derived utility estimates and importance score for 7 attributes, and conducted a sensitivity analysis on price and quantity by deriving the shares of preference levels. A detailed explanation is provided below.

Seven attributes and its related levels were identified for this study (Table 1). Price, quantity, delivery time, product quality rating by customers, and environmental impact were operationalized at three level; secure checkout, and health benefit info were operationalized at two levels as shown in the table. Table 1 shows the utility estimates

and relative importance of attributes. The utilities were estimates using an Hierarchical Bayes estimation model (for a review on HB models, see Allenby & Ginter, 1995; Lenk, DeSarbo, Green, & Young, 1996). The first column shows attributes and levels. The attributes contrast with the base impact (constant) in either positive or negative direction. From Table 1, we see that product quality rating has the highest importance score of 30.211, followed by delivery time (14.909), secure checkout (14.262), environmental impact (12.751), price (11.287), and quantity (8.461). Health benefit info is least influential with an importance score of 8.118.

Figure 1 shows an example of the partial utility plots for six individual consumers, calculated for different attributes and their corresponding levels. From Fig. 1, we see at an individual level, the varying impact of different levels of attributes on the likelihood of purchasing the product. From the figure we see that utilities for the attributes are

Table 1 Conjoint impact estimate and relative importance of attributes

Utilities	Utility Estimate	Importance score
Price		11.287
Low price	35.713	
Medium price	−3.080	
High price	−32.633	
Quantity		8.461
250 g package	7.464	
500 g package	−1.625	
750 g package	−5.839	
Delivery time		14.909
Same day collection	24.935	
Next day collection	14.982	
Collect in 3 days	−39.705	
Product quality rating by costumers		30.211
1 star	−107.922	
3 star	9.218	
5 star	98.705	
Secure checkout		14.262
Securely checkout	38.163	
No additional security	−38.163	
Health benefit info		8.118
Health benefit info provided	20.988	
Health benefit info not provided	−20.988	
Environmental impact		12.751
Responsible sourcing and minimal environmental impact	41.942	
No info on environmental impact	−41.942	
(Constant)	37.173	

Averaged importance score

different for each consumer. For example, for consumer 10, a 500 g package has a higher utility than 750 g, whereas consumer 16 prefers a 750 g package. This is particularly important, as it is possible to examine the impact of multiple variables on consumer behavior at individual level. This also supports the behavioral analytic focus on behavior at an individual level rather than only group averages.

Conjoint analysis is often used to assess how consumers trade off product attributes with price (Orme, 2014). Researchers can conduct sensitivity analyses (e.g. price sensitivity) of consumers for different potential product configurations using simulation models based on conjoint results. Sensitivity analyses refers to running a simulation scenario multiple times and observing the change in share of preference due to changing product specifications. Figure 2 presents the sensitivity analysis on price. Here, we see that the share of consumers' choice preferences falls as the price increases. This is in line with the law of demand, which posits that, *ceteris paribus*, as the price of a commodity increases, the consumption of that commodity decreases the consumption of a commodity decreases as the price of that commodity increases.

Figure 3 shows the sensitivity analysis on price with respect to the package quantity offered. For the lowest package quantities of 250, and 300 g, the shares of preference initially drops as price increases, then stabilizes. However, for the remaining package quantities, the shares of preference decreases as price increases. This shows an interesting aspect of consumer choices. In a stark contrast to other package quantities offered, for 700, and 750 g, the shares of preference increases with an increase in

Fig. 1 An example of partial utility estimates for each of six consumers

Fig. 2 Sensitivity analysis on price

price. This points to the conclusion that price affects consumer choice, both as a budget constraint, and as a signal of quality (Sigurdsson, Engilbertsson, & Foxall, 2010a, b; Zeithaml, 1988).

From an organizational standpoint, if a firm wants to assess incremental demand generated from different product offerings, it should be estimated using market simulations within a realistic competitive context, and based on specific objectives (Orme, 2014). For example, the objective of the firm may be to determine how much price can

Fig. 3 Sensitivity analysis on price with respect to package quantity offered

be increased if an additional feature is provided. In the example given below, we demonstrate a trade-off analysis between price and information on environmental impact, that is, how much money are consumers willing to give up if information on environmental impact is provided.

Consider three hypothetical product scenarios which represents the current products in the marketplace, as shown in Table 2. The first two products are more expensive than the third one and both have information on environmental impact. In response to the competition, the firm that sells product 3 wants to change their product offering by adding information on environmental impact, and wants to estimate the new price that can be charged, while maintaining the same shares of preference. Using conjoint analysis simulator, we obtained (simulation 1) base case shares of preference for product scenarios shown in Table 2. The shares of preference obtained were 31.37%, 29.41%, and 25.49% respectively for products 1, 2, and 3.

In simulation 2, we changed product 3 by adding information on environmental impact (see Table 3), while holding product 1 and 2 constant. The new shares of preference obtained were 23.53%, 27.45%, and 37.25% respectively for products 1, 2, and 3. From the two simulations, we see that, for product 3, the shares of preference increased from 25.49% to 37.25% when the information on environmental impact was added. We performed additional simulations raising the price of product 3, until the shares of preference dropped again to the initial 25.49%. The difference in price between the more expensive improved product 3 that captured 25.49%, and the old product 3 that captured the same shares of preference gives the price change that can be implemented. In this example, the price of \$13.99 can be increased to \$18.1.

Conjoint analysis market simulations such as this are conducted using individual-level utilities, as such simulations focuses the trade-off analysis on a reference product and critical individuals rather than the market as a whole (Orme, 2014). Such market

Table 2 Product scenarios for simulation 1

	Price	Quantity	Delivery time	Product quality rating by consumers	Secure checkout	Health benefit info	Environmental impact
Product 1	14.99	500 g package	Same day collection	3 star	No additional security	Health benefit info provided	Responsible sourcing and minimal environmental impact
Product 2	15.99	500 g package	Collect in 3 days	5 star	Securely check out	Health benefit info not provided	Responsible sourcing and minimal environmental impact
Product 3	13.99	500 g package	Next day collection	3 star	Securely check out	Health benefit info provided	No info on environmental impact

Table 3 Product scenarios for simulation 2

	Price	Quantity	Delivery time	Product quality rating by consumers	Secure checkout	Health benefit info	Environmental impact
Product 1	14.99	500 g package	Same day collection	3 star	No additional security	Health benefit info provided	Responsible sourcing and minimal environmental impact
Product 2	15.99	500 g package	Collect in 3 days	5 star	Securely check out	Health benefit info not provided	Responsible sourcing and minimal environmental impact
Product 3	13.99	500 g package	Next day collection	3 star	Securely check out	Health benefit info provided	Responsible sourcing and minimal environmental impact

simulations are also helpful to understand various factors such as degree of substitution (cross-effects), and differences in consumer price sensitivity to each product.

Concluding Remarks

According to a McKinsey report by Desai et al. (2012); see also Verhoef, Kannan, & Inman, 2015), it seems that we are in a new major period in the evolution of retail grocery—the digital and omni-channel retailing. Technology is driving the industry, and we can already see some experimentation with ecosystems for the future of online retail grocery. From this, our approach to understanding healthy food choices has been in an online food retail setting. One of the reasons for using digital media is to address the concerns that have been raised about the relevance of operant behavioral economics and behavior analysis to natural, everyday behavior (e.g., Kunkel, 1987; Nevin, 2008; Woods, Miltenberger, & Carr, 2006; Mace & Critchfield, 2010). Another, and perhaps the most important, reason for our focus on digital media is its richness and increased importance in modern consumer behavior.

Conjoint analysis is a fast, relatively inexpensive method to measure individual consumer choices in open natural settings. It bridges behavior analysis to other disciplines working on social issues as it derives utilities from consumer choices, thereby aiding in analyzing the interrelationships of multiple variables influencing behavior. While conjoint pricing experiments for digital media are not as realistic as real-world events, they resemble these closely. These experiments can test price ranges or new products outside of current offerings. They offer the advantage of directly measuring unique price sensitivities by brand. Furthermore, price elasticity can be quantified for each brand by examining the ratio of preference at the highest price versus preference at the lowest price. Choice-based conjoint analysis has proven useful

and generally accurate for pricing decisions, especially when it comes to fast moving consumer goods (Orme, 2014). As an example, price sensitivity measurements by conjoint analysis for various Procter & Gamble products were shown to match well (on average) the price sensitivities calculated from econometric models applied to actual sales data (Renkin, Rogers, & Huber, 2004). Although choice-based conjoint analysis has its advantages and show promise for behavior analysis, this method also has some limitations. Disadvantages of the use of choice-based conjoint analysis can be related to participants' limited capability to evaluate a number of attributes, attribute levels, or a number of concept tasks. Moreover, the conjoint method has been considered complex in nature, and there is a lack of clear instructions how to select a satisfactory preference structure measurement model.

From a behavioral perspective, the most important task for a firm focused on the demand side is to identify the brand's stimulus and reinforcement classes, seen as different stimuli or bundles of stimuli (e.g., packaging and price promotion) and consequences (e.g., amount or duration), that increase the likelihood of the brand's product or service being bought. Taking the emerging online food retail setting as a case, this paper aimed to contribute to the understanding of the complexity of online healthy food choices by the use of recent advancement in conjoint analysis and consumer behavior analysis in general. The paper demonstrates how to capture the complex behavior by comparing different consumer choices for different marketing attributes involved in online healthy food purchase by placing them on a comparable pricing scale, or pricing out non-monetary stimuli (e.g. price, quantity, delivery time etc.).

Acknowledgements The authors thank The Icelandic Centre for Research (RANNIS) for funding the study.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

References

- Allenby, G. M., & Ginter, J. L. (1995). Using extremes to design products and segment markets. *Journal of Marketing Research*, 32, 392–403. doi:[10.2307/3152175](https://doi.org/10.2307/3152175).
- Annunziata, A., & Vecchio, R. (2013). Consumer perception of functional foods: a conjoint analysis with probiotics. *Food Quality and Preference*, 28, 348–355. doi:[10.1016/j.foodqual.2012.10.009](https://doi.org/10.1016/j.foodqual.2012.10.009).
- Baum, W. M. (1974). On two types of deviation from the matching law: bias and undermatching. *Journal of the Experimental Analysis of Behavior*, 22, 231–242. doi:[10.1901/jeab.1974.22-231](https://doi.org/10.1901/jeab.1974.22-231).
- Brynjolfsson, E., Hu, Y. J., & Rahman, M. S. (2013). Competing in the age of Omnichannel retailing. *MIT Sloan Management Review*, 54(4), 23–29.
- Buckley, K. W. (1982). The selling of a psychologist: John Broadus Watson and the application of behavioral techniques to advertising. *Journal of the History of the Behavioral Sciences*, 18, 207–221. doi:[10.1002/1520-6696\(198207\)18:3<207::AID-JHBS2300180302>3.0.CO;2-8](https://doi.org/10.1002/1520-6696(198207)18:3<207::AID-JHBS2300180302>3.0.CO;2-8).
- Dallery, J., Raiff, B. R., & Grabinski, M. J. (2013). Internet-based contingency management to promote smoking cessation: a randomized, controlled study. *Journal of Applied Behavior Analysis*, 46, 750–764. doi:[10.1002/jaba.89](https://doi.org/10.1002/jaba.89).
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management Science*, 35, 982–1003. doi:[10.1287/mnsc.35.8.982](https://doi.org/10.1287/mnsc.35.8.982).

- Desai, P., Potia, A., & Salsberg, B. (2012, December). Retail 4.0: the future of retail grocery in a digital world. Retrieved from <http://www.mckinseyonmarketingandsales.com/retail-4-0-the-future-of-retail-grocery-in-a-digital-world>
- DiClemente, D. F., & Hantula, D. A. (2003). Optimal foraging online: increasing sensitivity to delay. *Psychology & Marketing*, 20(9), 785–809. doi:10.1002/mar.10097.
- Fisher, W. W., & Mazur, J. E. (1997). Basic and applied research on choice responding. *Journal of Applied Behavior Analysis*, 30, 387–410. doi:10.1901/jaba.1997.30-387.
- Foxall, G. R. (1987). Radical behaviorism and consumer research theoretical promise and empirical problems. *International Journal of Research in Marketing*, 4, 111–129. doi:10.1016/0167-8116(87)90003-6.
- Foxall, G. R. (1990). *Consumer psychology in behavioral perspective* (First ed.). New York/Maryland: Routledge/Beard Books.
- Foxall, G. R. (1997). Affective responses to consumer situations. *International Review of Retail, Distribution and Consumer Research*, 7, 191–225. doi:10.1080/095939697342996.
- Foxall, G. R. (1998). Radical behaviorist interpretation: generating and evaluating an account of consumer behavior. *The Behavior Analyst*, 21(2), 321–354.
- Foxall, G. R. (1999). Putting consumer behavior in its place: The behavioral perspective model research programme. *International Journal of Management Reviews*, 1, 133–158. doi:10.1111/1468-2370.00009.
- Foxall, G. R. (2001). Foundations of consumer behavior analysis. *Marketing Theory*, 1, 165–199. doi:10.1177/147059310100100202.
- Foxall, G. R. (2003). The behavior analysis of consumer choice. *Journal of Economic Psychology*, 24, 581–588. doi:10.1016/S0167-4870(03)00002-3.
- Foxall, G. R. (2010). Invitation to consumer behavior analysis. *Journal of Organizational Behavior Management*, 30, 92–109. doi:10.1080/01608061003756307.
- Foxall, G. R. (Ed.). (2016). *The Routledge companion to consumer behavior analysis*. New York, NY: Routledge.
- Foxall, G. R., Oliviera-Castro, J. M., James, V. K., Yani-de-Soriano, M. Y., & Sigurdsson, V. (2006). Consumer behavior analysis and social marketing: the case of environmental conservation. *Behavior and Social Issues*, 15, 101–125. doi:10.5210/bsi.v15i1.338.
- Freedman, D. H. (2016). Improving public perception of behavior analysis. *The Behavior Analyst*, 39, 89–95. doi:10.1007/s40614-015-0045-2.
- Gerteis, J., Izrael, D., Deitz, D., LeRoy, L., Ricciardi, R., Miller, T., & Basu, J. (2014) *Multiple chronic conditions chartbook: 2010 Medical expenditure panel survey data* (AHRQ publication no. Q14-0038). Rockville, MD: Agency for Healthcare Research and Quality.
- Green, P. E. (1974). On the design of choice experiments involving multifactor alternatives. *Journal of Consumer Research*, 1, 61–68 <http://www.jstor.org/stable/2489108>.
- Green, P. E., & Rao, V. R. (1971). Conjoint measurement for quantifying judgmental data. *Journal of Marketing Research*, 8, 355–363. doi:10.2307/3149575.
- Green, P. E., & Srinivasan, V. (1978). Conjoint analysis in consumer research: issues and outlook. *Journal of Consumer Research*, 5, 1023–1033. doi:10.1086/208721.
- Green, P. E., & Srinivasan, V. (1990). Conjoint analysis in marketing research: new developments and directions. *Journal of Marketing*, 54, 3–19. doi:10.2307/1251756.
- Green, P. E., & Wind, Y. (1975). A new way to measure consumer judgment. *Harvard Business Review*, 53(7), 107–117.
- Hand, C., Riley, F. D., Harris, P., Singh, J., & Rettie, R. (2009). Online grocery shopping: the influence of situational factors. *European Journal of Marketing*, 43, 1205–1219. doi:10.1108/03090560910976447.
- Hantula, D. A. (2016). Editorial: A very special issue. *The Behavior Analyst*, 39, 1–5. doi:10.1007/s40614-016-0066-5.
- Hill, J. O., Wyatt, H. R., Reed, G. W., & Peters, J. C. (2003). Obesity and the environment: where do we go from here? *Science*, 299, 853–855. doi:10.1126/science.1079857.
- Hollands, G. J., Shemilt, I., Marteau, T. M., Jebb, S. A., Kelly, M. P., Nakamura, R., Suhrcke, M., & Ogilvie, D. (2013). Altering micro-environments to change population health behaviour: towards an evidence base for choice architecture interventions. *BMC Public Health*, 13(1), 1218. doi:10.1186/1471-2458-13-1218.
- Hustyi, K. M., Normand, M. P., & Larson, T. A. (2011). Behavioral assessment of physical activity in obese preschool children. *Journal of Applied Behavior Analysis*, 44, 635–639. doi:10.1901/jaba.2011.44-635.
- Hustyi, K. M., Normand, M. P., Larson, T. A., & Morley, A. J. (2012). The effect of outdoor activity context on physical activity in preschool children. *Journal of Applied Behavior Analysis*, 45, 401–405. doi:10.1901/jaba.2012.45-401.
- James, J. (2016). *The health of populations* (1st Ed.). Academic Press.

- Johnson, R. M. (1974). Trade-off analysis of consumer values. *Journal of Marketing Research*, 11, 121–127. doi:10.2307/3150548.
- Krapfl, J. E. (2016). Behaviorism and society. *The Behavior Analyst*, 39, 123–129. doi:10.1007/s40614-016-0063-8.
- Kunkel, J. H. (1987). The future of JABA: a comment. *Journal of Applied Behavior Analysis*, 20, 329–333. doi:10.1901/jaba.1987.20-329.
- Kurti, A., & Dallery, J. (2014). Effects of exercise on craving and cigarette smoking in the human laboratory. *Addictive Behaviors*, 39, 1131–1137. doi:10.1016/j.addbeh.2014.03.004.
- Lake, A., & Townshend, T. (2006). Obesogenic environments: exploring the built and food environments. *The Journal of the Royal Society for the Promotion of Health*, 126, 262–267. doi:10.1177/1466424006070487.
- Landon, J., Davison, M., & Elliffe, D. (2003). Concurrent schedules: reinforcer magnitude effects. *Journal of the Experimental Analysis of Behavior*, 79, 351–356. doi:10.1901/jeab.2003.79-351.
- Lenk, P. J., DeSarbo, W. S., Green, P. E., & Young, M. R. (1996). Hierarchical bayes conjoint analysis: recovery of partworth heterogeneity from reduced experimental designs. *Marketing Science*, 15, 173–191. doi:10.1287/mksc.15.2.173.
- Luce, D. R., & Tukey, J. W. (1964). Simultaneous conjoint measurement: a new type of fundamental measurement. *Journal of Mathematical Psychology*, 1, 1–27. doi:10.1016/0022-2496(64)90015-X.
- MacDonall, J. S. (2016). Learning, the sole explanation of human behavior: review of *The marvelous learning animal: what makes human nature unique*. *The Behavior Analyst*, 39, 175–182. doi:10.1007/s40614-016-0056-7.
- Mace, F. C., & Critchfield, T. S. (2010). Translational research in behavior analysis: historical traditions and imperative for the future. *Journal of the Experimental Analysis of Behavior*, 93, 293–312. doi:10.1901/jeab.2010.93-293.
- Marteau, T. M., Hollands, G. J., & Fletcher, P. C. (2012). Changing human behavior to prevent disease: the importance of targeting automatic processes. *Science*, 337(6101), 1492–1495. doi:10.1126/science.1226918.
- McCarthy, J. (1960). *Basic marketing: a managerial approach*. Homewood: Irwin.
- Nagle, T. T., Hogan, J. E., & Zale, J. (2010). *The strategy and tactics of pricing: a guide to growing more profitably*. Pearson Education Inc: Upper Saddle River, NJ.
- Nevin, J. A. (2008). Control, prediction, order, and the joys of research. *Journal of the Experimental Analysis of Behavior*, 89, 119–123. doi:10.1901/jeab.2008.89-119.
- Nielsen (2015). The future of grocery: e-commerce, digital technology and changing shopping preference around the world [white paper]. Retrieved April 14, 2016, from The Nielsen Company (US), LLC: [https://www.nielsen.com/content/dam/nielsen-global/vn/docs/Reports/2015/Nielsen%20Global%20E-Commerce%20and%20The%20New%20Retail%20Report%20APRIL%202015%20\(Digital\).pdf](https://www.nielsen.com/content/dam/nielsen-global/vn/docs/Reports/2015/Nielsen%20Global%20E-Commerce%20and%20The%20New%20Retail%20Report%20APRIL%202015%20(Digital).pdf)
- Oliveira-Castro, J. M., Foxall, G. R., & Schrezenmaier, T. (2006). Consumer brand choice: individual and group analyses of demand elasticity. *Journal of Experimental Analysis of Behavior*, 85, 147–166. doi:10.1901/jeab.2006.51-04.
- Orme, B. (2014). *Getting started with conjoint analysis: strategies for product design and pricing research* (3rd ed.). Manhattan Beach, CA: Research Publishers LLC.
- Overskeid, G. (2008). They should have thought about the consequences: the crisis of cognitivism and a second chance for behavior analysis. *The Psychological Record*, 58(1), 131–151.
- Perone, M. (1991). Experimental design in the analysis of free-operant behavior. In I. H. Iverson & K. A. Lattal (Eds.), *Experimental analysis of behavior: part 1* (pp. 135–172). Elsevier: New York.
- Rachlin, H. (2004). *The science of self-control*. Cambridge, MA: Harvard University Press.
- Rajala, A. K., & Hantula, D. A. (2000). Towards a behavioral ecology of consumption: delay- reduction effects on foraging in a simulated Internet mall. *Managerial and Decision Economics*, 21(3–4), 145–158. doi:10.1002/mde.979.
- Rao, V. R. (2014). *Applied conjoint analysis*. Berlin: Springer-Verlag.
- Renkin, T., Rogers, G., & Huber, J. (2004). A comparison of conjoint and scanner data-based price elasticity estimates. In *Presented at Advanced Research Techniques Forum 2004*. Whistler: BC.
- Sigurdsson, V., Engilbertsson, H., & Foxall, G. (2010a). The effects of a point-of purchase display on relative sales: an in-store experimental e experimental evaluation. *Journal of Organizational Behavior Management*, 30, 222–233. doi:10.1080/01608061.2010.499028.
- Sigurdsson, V., Foxall, G., & Saevarsson, H. (2010b). In-store experimental approach to pricing and consumer behavior. *Journal of Organizational Behavior Management*, 30, 234–246. doi:10.1080/01608061.2010.499029.

- Sigurdsson, V., Larsen, N. M., & Gunnarsson, D. (2011a). An in-store experimental analysis of consumers' selection of fruits and vegetables. *The Service Industries Journal*, 31, 2587–2602. doi:[10.1080/02642069.2011.531126](https://doi.org/10.1080/02642069.2011.531126).
- Sigurdsson, V., Larsen, N. M., & Gunnarsson, D. (2011b). The behavioral economics of neutral and upward sloping demand curves in retailing. *The Service Industries Journal*, 31, 2543–2558. doi:[10.1080/02642069.2011.531127](https://doi.org/10.1080/02642069.2011.531127).
- Sigurdsson, V., Larsen, N. M., & Gunnarsson, D. (2014). Healthy food products at the point of purchase: an in-store experimental analysis. *Journal of Applied Behavior Analysis*, 47, 151–154. doi:[10.1002/jaba.91](https://doi.org/10.1002/jaba.91).
- Sigurdsson, V., Saevarsson, H., & Foxall, G. (2009). Brand-placement and consumer choice: an in-store experiment. *Journal of Applied Behavior Analysis*, 42, 741–745. doi:[10.1901/jaba.2009.42-741](https://doi.org/10.1901/jaba.2009.42-741).
- Sigurdsson, V., Khamseh, S., Gunnarsson, D., Larsen, N. M., & Foxall, G. R. (2013b). An econometric examination of the behavioral perspective model in the context of Norwegian retailing. *The Psychological Record*, 62, 277–294. doi:[10.11133/j.Tpr.2013.63.2.004](https://doi.org/10.11133/j.Tpr.2013.63.2.004).
- Sigurdsson, V., Menon, R. G. V., Sigurdarsson, J. P., Kristjansson, J. S., & Foxall, G. R. (2013a). A test of the behavioral perspective model in the context of an E-mail marketing experiment. *The Psychological Record*, 63, 295–308. doi:[10.11133/j.Tpr.2013.63.2.005](https://doi.org/10.11133/j.Tpr.2013.63.2.005).
- Silayoi, P., & Speece, M. (2007). The importance of packaging attributes: a conjoint analysis approach. *European Journal of Marketing*, 41, 1495–1517. doi:[10.1108/03090560710821279](https://doi.org/10.1108/03090560710821279).
- Smith, J. M. (2016). Strategies to position behavior analysis as the contemporary science of what works in behavior change. *The Behavior Analyst*, 39, 75–87. doi:[10.1007/s40614-015-0044-3](https://doi.org/10.1007/s40614-015-0044-3).
- Van der Pol, M., & Ryan, M. (1996). Using conjoint analysis to establish consumer preferences for fruit and vegetables. *British Food Journal*, 98, 5–12. doi:[10.1108/00070709610150879](https://doi.org/10.1108/00070709610150879).
- Vella, K. J., & Foxall, G. R. (2011). *The marketing firm: economic psychology of corporate behaviour*. Cheltenham: Edward Elgar.
- Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From multi-channel retailing to omni-channel retailing: introduction to the special issue on multi-channel retailing. *Journal of Retailing*, 91(2), 174–181. doi:[10.1016/j.jretai.2015.02.005](https://doi.org/10.1016/j.jretai.2015.02.005).
- Wansink, B. (2007). *Mindless eating: why we eat more than we think*. New York: Bantam Books.
- Wansink, B. (2016). *Slim by design: mindless eating solutions for everyday life*. London: Hay House UK.
- Wind, J., Green, P. E., Shifflet, D., & Scarbrough, M. (1989). Courtyard by Marriott: designing a hotel facility with consumer-based marketing. *Interfaces*, 19, 25–47. doi:[10.1287/inte.19.1.25](https://doi.org/10.1287/inte.19.1.25).
- Winer, R. S. (2006). *Pricing*. Cambridge, MA: Marketing Science Institute.
- Wittink, D. R., Vriens, M., & Burhenne, W. (1994). Commercial use of conjoint analysis in Europe: results and critical reflections. *International Journal of Research in Marketing*, 11, 41–52. doi:[10.1016/0167-8116\(94\)90033-7](https://doi.org/10.1016/0167-8116(94)90033-7).
- Woods, D. W., Miltenberger, R. G., & Carr, J. E. (2006). Introduction to the special section on clinical behavior analysis. *Journal of Applied Behavior Analysis*, 39, 407–411. doi:[10.1901/jaba.2006.intro](https://doi.org/10.1901/jaba.2006.intro).
- Yeh, M. C., Ickes, S. B., Lowenstein, L. M., Shuval, K., Ammerman, A. S., Farris, R., & Katz, D. L. (2008). Understanding barriers and facilitators of fruit and vegetable consumption among a diverse multi-ethnic population in the USA. *Health Promotion International*, 23, 42–51. doi:[10.1093/heapro/dam044](https://doi.org/10.1093/heapro/dam044).
- Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *Journal of Marketing*, 52(3), 2–22. doi:[10.2307/1251446](https://doi.org/10.2307/1251446).