**The Use of Observational Technology to Study In-Store Behavior:**

**Consumer Choice, Video Surveillance, and Retail Analytics**

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**Abstract**

The store is the main laboratory for in-store experimental analysis. This study provides an introduction to a research program aimed at improving research practices in this laboratory, particularly emphasizing the importance of behavioral data and the new opportunities that technology offers. This complex modern-day Skinner box has sets of well-studied stimuli-behavior interactions that constantly adapt to the latest economic environment and as such constantly stretch the boundaries of behavioral analytic theory. However, the retail setting is highly important to applied behavioral analysis for such issues as health, debt, environmental conservation, animal welfare, self-control, and consumer protection in general. This study presents a research strategy that emphasizes key environmental touch points throughout the customer journey in grocery retailing. We highlight the latest development by examining a particular research case and discussing the need for behavioral economic understanding of the start of the grocery journey, that is, the consumer choice of in-store product carrying equipment (e.g., cart, basket, or nothing). The conceptual system consists of a molecular four-term contingency framework as well as a more molar approach with conversion-rate modeling, where actual choice behavior is detected through video surveillance. The data are analyzed using a Shopper Flow© Tracking System in which software is designed to provide automatic data on shopper behavior and to assist human observers in tracking individual shopping trips. We discuss behavioral classifications, methodology, and implications related to the data from consumer tracking efforts.


*Keywords*: In-store experiments, Customer journey, Touchpoints, Video surveillance, Shopping carts, Retail analytics

"We must consider our science immeasurably enriched each time someone brings another sample of behavior under precise experimental control" (Sidman 1960, p. 17).

## Introduction

In-store behavior cannot be placed under rigorous, but artificial, laboratory experimental control. In our view, a behavioral analyst needs to gather empirical data at the point of purchase, measuring the true behavior of interest, and needs to work on transforming the store into a laboratory. Nonetheless, realistic research work in closed settings, such as computer-simulated microworlds (see e.g., Fagerstrøm et al. 2009; Smith and Hantula 2003), can be of value and to some extent, operant laboratory work in behavioral economics (see e.g., Hursh et al. 2013) can build a foundation for research.

At present, video observational technology and retail analytics are creating opportunities for the behavior analysis of shopping behavior, and virtual reality and atomization will likely create further possibilities for experimentation in the future. The current study introduces the possibility of in-store experiments as an important part of the search for a natural science of consumer behavior in the consumer behavior analysis literature. As pointed out by Catania (1998, pp. 6–7), "[E]ven after we've studied behavior in the laboratory, we can't expect to be able to interpret every instance of behavior outside the laboratory. There are limits to what we can know … it's important to recognize what remains out of our reach." Where do the boundaries lie for laboratory work with animals and humans? How far can traditional laboratory work go and what can be gained further by extending natural settings? We do not provide the answers to these weighty questions, nor do we assume that the boundaries are constant, but this work adds to the continuing evaluation of how far consumer behavior analysis can explain the customer journey in retail shopping (Foxall 2016). This should be a new frontier for both basic and applied behavior analysts to interrogate seriously. This includes improvements in behavioral measurements, data analysis, and further opportunities when it comes to behavioral control techniques in everyday open settings. Furthermore, richer and better scientific study of in-store behavior will create more possibilities to apply behavior analysis to problematic consumer choices that occur at the point of purchase. These include such behavior as unhealthy food choices, overspending, and selection of environmentally damaging products.

The current study presents a systematic analysis from a consumer behavior analytic perspective of the in-store environment and discusses recent advances and directions, using the choice of in-store carrying

equipment as a research example. The use or lack of use of shopping carts or baskets can be interpreted as a motivational operation (for particular focus on consumer choice, see Fagerstrøm and Arntzen 2016; Laraway et al. 2003; Michael 1982), as long as punishment attached to carrying products is abolished, and/or there are more reinforcing consequences affecting important behavioral metrics during the shopping journey. We use the example of carrying equipment to highlight in more detail a few critical aspects, such as the general lack of direct measurement focusing on the behavior of interest and the lack of environment–behavior functional analysis in a setting designed to affect consumer choices. This choice of carrying equipment, including the choice to use nothing, might affect the rest of the shopping activity in terms of behavioral consequences and outcomes (e.g., spending, wasting, and eating too much). However, these effects are neither consistently defined nor analyzed in the marketing literature. This and other similar shortcomings seem to be, in large part, caused by the traditional over-reliance in marketing on cognitive theorizing, operationalization, and other indirect measurements, instead of environment-based experimental accounts of "real consumer behavior." Apparently, marketing has weak and limited insights when it comes to one of the main behavior choices at the beginning of the customer journey, although there are recent positive trends in marketing science that behavior analysts should take notice of. Therefore, in this study, we fill a gap in the literature by showing the importance of this choice. More importantly, we show that a behavior analytical account is viable and important. We develop our research based on the emerging field of consumer behavior analysis, especially on the behavior analysis of in-store behavior. In addition, we show how such an environment-based account is becoming stronger through the latest technological changes, with recent growth in in-store analytics and digital technology. This increased behavioral emphasis in marketing science and practice is in desperate need of a sound conceptual system, that is, concepts and methods that can facilitate the improved ability of marketing to better measure the effects of environmental contingencies on consumer behavior.

**Data Beats Opinion: Opportunities for Behavioral Marketing**

In-store behavior can be defined as anything that a consumer does in a store, involving action and response to in-store stimuli. It is safe to conclude that the world is experiencing a new emphasis on "behavioral marketing" through digital technology, analytics, and proliferation of behavioral data. This "digital revolution" has increased, and should continue to do so, thereby strengthening explanations relying on environment–behavior interaction via digital technology and experimentation. Moreover, a sound contextual conceptualization that narrows the gap between explanations and data and that brings evidence-based practices within consumer

behavior analysis should be encouraged. Several authors have called for more experiment-oriented behavioral research in marketing and economic theory, which traditionally has been criticized for armchair theorizing, with little concern for real-world developments (Coase 1998; Smith 1989; Thaler 2000). For example, Deighton et al. (2012) state that existing methods, such as long-form surveys, are hardly consistent with today's modes of communication; the authors call for research that tests new models involving processes that precede and follow transactions, and that can measure marketing actions and contextual factors that drive transactions. Behavior-oriented research that involves manipulation (Wertenbroch 2016), explores "human behaviour in the marketplace" (Wertenbroch 2015, p. 1), and measures "actual behaviour" (Grewal and Levy 2007, p. 450) represents a new avenue for further research in consumer behavior. Monitoring and measuring this *actual behavior* has gained a more prominent role in marketing science lately. A key driving force is new or improved technology that opens up numerous opportunities to study consumer behavior in natural environments, such as retail stores. The value of the new technology lies in its ability to constantly deliver more accurate and nondisruptive accounts of how individual consumers behave in the store and how they react to marketing stimuli. Therefore, there is a real opportunity to stick to and rely on behavioral data at the expense of theoretical, indirect, nonexistent, and even circular constructs.

By studying consumer activity, where customers go in stores, paths, interactions with shelves, and so on, with descriptive observations and interventions, behavior analysts can build an objective science that strives for concrete explanations of consumer behavior. Laboratory experiments certainly can be a guiding light for theory and methods, but they are not enough. There is a need to collaborate further with marketing scientists, economists, health professionals, engineers, practitioners, and consumer spokespeople who are professionals in their fields and can detect marketing problems with store layouts, signage, product organization, and pricing, to mention a few examples. Traffic counters, handheld shopping systems, beacons, radio frequency identification (RFID) tags, infrared sensing devices and high-resolution video surveillance cameras are all examples of new technologies that can be used to study consumer behavior and need to be explored (Larsen and Sigurdsson 2016, Sigurdsson et al. 2016). However, how can this technology be used and evaluated in an experimental science?

It is apparent that the time is ripe for undertaking consumer experiments and analyses from an operant behavioral perspective, in which operant behavior represents an activity that is modified by its environmental consequences, for example, consumer behavior resulting from consequences, such as discounts, reward points, and social attention. This entails, for example, using behavior analysis of the consumers' path to purchase, reinforcing a chain of related behavior shaped towards a particular target activity or end result (e.g., buying).

From the viewpoint of conceptualization and data, this has the aim of making consumer behavior analysis more related and relevant to real-life marketing practice. Table 1 shows a comparison between current behavioral in-store experiments (as introduced in the current paper) and traditional mainstream retail marketing.

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Behavior has antecedents and consequences that often influence action. In a laboratory store with video surveillance, it is possible to observe and analyze the effects of these variables with functional analysis by experimentally controlling and isolating them. Many decades of behavioral analytic research have shown that behavior under study can be built, modified, kept constant, increased, decreased, or eliminated when the environment of the behaving organism is controlled.

## Observing in-store consumer behavior

Consumer behavior analysis occurs in situations of free response (Sidman 1960), in which we have made progress recently in studying a continuous stream of consumer behavior through video surveillance and automatic retail analytics. To address this issue, we collect data using surveillance cameras and Shopper Flow© tracking software. The cameras cover the entire selling space of a typical discount store. Therefore, studies are not bound by a snapshot survey but are rather a behavioral assessment process that is continuous in time. The target behavior can be discrete and independent, but can also be ongoing and dependent on other behavior, such as a cross-promotion in a store. The selection of products or other in-store choices can be substitutional or complementary and it is through the temporal continuity of the consumer's responses that a better picture can be obtained of both molar and molecular accounts of behavior. These can be operants, such as interresponse time, or the time between the selection of products, walking speed, percentage of the store visited, total number of items purchased, or cost matching.

### Capturing the Continuous and Competing Nature of In-Store Behavior

According to Shankar et al. (2011), a critical issue confronting in-store marketing is the lack of generally accepted metrics. The authors argue that traditional metrics, such as store traffic, conversion, and sales increases, are insufficient for understanding what occurs from when a customer enters the store to when he/she has paid for

the items scanned at the checkout. The authors' concern is that many types of in-store behavior can affect choice behavior at an individual level. Shankar et al. (2011) draw a comparison to online shopping, in which browsing-related metrics, such as visits, queries, click-throughs, and conversions, are important and well connected. Among potential new metrics to tap relevant behavior inside physical stores, the authors suggest a few metrics that should be of interest to behavior analysts, such as proximity to the target, dwell time, and product touched. In a similar vein, Hui et al. (2013) suggest in-store travel distance as a new metric to capture product exposure. This presents an opportunity for consumer behavior analysis to grow and contribute in terms of different aspects of marketing–customer relations, including the theory of the marketing firm (Foxall 1999), as innovation in retailing exists in order to reduce transaction costs (Coase 1937; Williamson 1981).

When considering the behavior economic literature on consumer choice (e.g., studies mentioned in DiClemente and Hantula 2003; Foxall 2017; Sigurdsson et al. 2016), studies generally reveal environmental-behavior interaction, such that point-of-purchase stimuli are related to an increase in sales, but progress can be made in capturing the competing and continuous nature of individual behavior taking place inside the store. This means that further progress in basic and applied consumer behavior analysis can be acquired through continuous time series of behavior acquired with video surveillance analyzed through the behavior analytical perspective. It is viable to conceptualize this behavior as the rate of responding (Skinner 1938), responding choice (Herrnstein 1961, 1970), or as time allocation (Baum 2015). The concept of *stimuli* is also important in behavior analysis. Consider a consumer who *walks* into a store. Although the number of possible stimuli in that environment is almost indefinite, there are some pivotal variables in the environment affecting the consumer's choice. For example, the consumer might *observe* some brands while *ignoring* others, and might *touch* some while making his or her choices. A prerequisite for buying a particular brand is that the customer physically visits the zone where that brand is displayed, and further, that he/she not use it as a transit zone but exhibit buying behavior in the form of stopping and looking. This refers to the two conversions customers must undergo to purchase a brand in the double-conversion framework of Sorensen (2009). It is apparent that it is important to be able to analyze how the retail environment affects the continuous nature of consumer behavior. What effects do stimuli promote? What influence do brand price, shelf positioning, in-store stimuli, and store types have on buying behavior? In behavior analytic terminology, some stimuli become "discriminative stimuli" (Skinner 1971), increasing or decreasing the probability of particular behavior, or have motivational operations (Laraway et al. 2003; Michael 1982, 1993), affecting the effectiveness of the reinforcing or punishing stimulus. In the consumer context, the presence of a particular brand can increase the likelihood of being looked at, touched, or even

bought (discriminative stimulus), but this function can be altered by the effect of other variables, like the availability of other brands, their price and placement, in-store advertisements, or the handiness of a shopping cart ready to carry the products (motivational operations). This sounds straightforward, but the generality of behavioral techniques and terminology, when moved from the behavioral laboratory to the real world of the market place, adds complications. This could refute the techniques of behavioral control and make the terminology seem strange and ambiguous.

As mentioned previously, in-store behavior can be defined as anything that a consumer does in a store involving action and response to stimuli. Table 2 represents an attempt to categorize a wide range of basic behavior taking place in the retail environment to illustrate the range and diversity of in-store consumer behavior.

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Table 2 contains a much wider spectrum of behavior than simply traditional shopping behavior. Many of these types of behavior are relevant when developing new metrics or functional explanations in consumer behavior analysis, or when analyzing the competing forces within this environment and its effects on consumer behavior, as operant behavior is choice behavior. Four-term contingency entails molecular-discrete analysis suitable to describe simple environment–behavior relationships; for instance, in this setting, it might be the effects of the price of brand A on the brand being touched or purchased (see e.g., Sigurdsson et al. 2011). This analysis reveals more than "a block of sloping straight lines" (see the arguments of Skinner 1976, p. 218 for a molecular analysis against molar), for identifying changes in the probability of responding, but does not handle competing environmental influences (the effects of the price of brand Y on the purchase of brand X) very well (e.g., Herrnstein 1997). This is an important limitation, as it is possible to have implicitly the same effect on consumer behavior, similar to direct reinforcement and punishment of the target behavior, by increasing the reinforcement or punishment of other competing behavior compared to the target behavior. This is difficult to conceptualize from the standpoint of the four-term contingency alone, but can be represented from a behavior economic point of view (Hursh 1984) which considers all behavior as choice (Herrnstein 1997), for example, measured with time allocation (Baum 2015). The aforementioned principles and techniques developed in basic behavior analysis have been transferred from animal laboratories to the analysis of patterns of consumer choice in open real settings (e.g., Foxall 2007). This has mostly occurred within the framework of the matching law, and has dominated research on choice in behavior analysis for decades. The matching law (Herrnstein 1961, 1970)

states that relative behavior (e.g., response rate) matches its relative reinforcement in equilibrium. In consumer behavior analysis, price and other marketing variables are analyzed, for instance, using relative buying behavior analysis (Sigurdsson et al. 2009) or cost matching analysis/relative demand analysis (Foxall and James 2001). Relative buying behavior analysis has developed from the concept of relative response rate in behavior analytical work (Herrnstein's dependent variable, e.g., Herrnstein 1961) and visual inspections of moment-to-moment changes in response rate (Skinner's dependent variable, e.g., Skinner 1976). In fact, relative buying behavior analysis is a combination of these, as it represents *changes* in *relative* behavior related to a particular target brand (analogues to the experimental key in the behavioral laboratory) as a function of particular environmental contingencies. This gives the data its relativity and makes it usable for comparison in terms of market share and in terms of brand competition. For relative buying behavior analysis, the units sold of the target brand are divided by the total units sold in the relevant product category in each store (Equation 1 shows an example for sales):

$$\text{Relative sales} = \frac{U_t}{\sum U}, \tag{1}$$

where $U$ represents units sold of brands and $t$ the target brand. However, this can be extended to measure the effects of price in consumer behavior analysis, revealing the relative quantity obtained of a brand as a function of relative price. This is introduced to consumer behavior analysis by Foxall and James (2001), who adapt it to the realms of human consumer behavior analysis building on experimental economic studies on animal behavior by Kagel et al. (1980). It is defined as:

> "the ratio of amount bought of the dominant brand (A) to the amount bought of the remaining brand in that category (B) as a function of the ratio of the relative average prices of the dominant brand to the average price of other brands purchased from the appropriate product category."
> (Foxall et al. 2004, p. 241)

This is ratio analysis, and as such, departs from more standard demand calculations in economics, by showing the quantity that consumers are willing and able to buy at a given price. This method is unlike traditional economic demand analysis, as it takes into consideration competition among competing brands in the

product category, and uses the x-axis to represent price instead of the y-axis (see a discussion of how psychological and economic demand curves are drawn in different ways in Lea et al. 1987). In line with the matching standpoint, in which all behavior is choice, the relativity of the quantity bought of the target brand as a function of relative prices gives an economic account of the competition between brands in the same product category. This reveals the target brand's market share as a function of its relative price against the prices of the other brands, making it possible to analyze the effects of the target brand price positioning against its product category. To perform this analysis, two parameters are used: the ratio of quantity bought (reinforcers earned) and the relative price ratio (reinforce cost). This relationship is shown in Equation 2:

$$\log \frac{M_1}{\sum M_2} = a \log \frac{P_1}{AP_2} + \log c , \qquad (2)$$

where $P_1$ is the price of the target brand (or average price if there is a brand line); $AP_2$ is the average price of the other brands in the product category; $M$ represents the magnitude bought of the brand(s), and the subscripts *1* and *2* stand for the target brand and other brands, respectively. Cost-matching analysis states the connections between relative average prices and the relative quantity bought as a consequence. The results from previous cost-matching analyses (e.g., Foxall et al. 2004) reflect this empirical foundation by showing mixed relative demand curves for purchasing data aggregated across purchasers and stores, in which the regression lines show either neutral, downward-sloping, or upward-sloping demand curves. The dependent variable, the relative quantity bought, is best represented as being maintained on concurrent ratio schedules, inverse to quantity matching (Curry et al. 2010); ceteris paribus, as price (aversive) declines, the quantity bought should increase. However, things are not this simple in the animal laboratory and are even less so in retail experiments. In the animal laboratory, when reinforcement rates are increased from moderate to high, response rates do not necessarily increase (Catania and Reynolds 1968; Hall and Lattal 1999). Even under certain conditions, increasing the rate of reinforcement can lead to reductions in response (Hursh 1978, 1980, 1984, 1991; Hursh and Silberberg, 2008). The results from previous cost-matching analysis (e.g., Foxall and James 2001, 2003; Foxall et al. 2004) reflect this empirical foundation by showing mixed relative demand curves for purchasing data from individuals as well as aggregated data across purchasers and stores, in which the regression lines show either neutral, downward-sloping, or upward-sloping demand curves. This might be because consumers usually spend only a small part of their discretionary income on individual items in retail stores, and therefore, the

aversive consequence of paying a higher price for a product might be comparably weak compared with the habitual consequence of saving time and effort of searching for a product. Consequently, the open retail setting (e.g., supermarkets) creates behavioral consequences that are quite different from closed settings, such as token economies (for a review of token economies, see Hackenberg 2009). Furthermore, marketing studies show that pricing can have a motivating function on consumer buying behavior. Shiv et al. (2005) demonstrate that such factors as the price of brands can change the effectiveness of products for consumers; for example, consumers who pay discounted prices for products (e.g., an energy drink thought to increase mental acuity) might derive less actual benefit from consuming those products (e.g., they can solve fewer puzzles). Price apparently can affect consumer behavior negatively (budget constraint leading to downward-sloping demand) as well as positively by sometimes signaling better quality and even enhancing the experience and efficiency of the brand (i.e., price can lead to upward-sloping demand; see Rao 1984; Rao and Monroe 1988; Sigurdsson et al. 2010, 2011b).

To study these effects on in-store behavior in more detail, researchers can draw on technology that makes it possible to observe and intervene in consumer behavior. With reference to Table 1, data in mainstream marketing research is generally only aggregated, discrete, measurements are indirect, and competing factors are generally not taken into account. This introduces vulnerability, as the methodology does not generally accommodate the characterization of basic behavior taking place inside a retail store. Table 2 shows both a classification and a list for important dependent variables occurring in such an environment. In the behavioral in-store experiments introduced in the current study (Figure 1, right), the continuity of consumer behavior, conversely, is analyzed using video surveillance and data analysis with machines, like the Shopper Flow©️ system, and also with human observers with high inter-observer agreement for more flexibility. Our research strategy is in line with that of Dallery et al. (2015), as we believe that advances in digital technology bring opportunities for behavior analysis that need to be explored better. In fact, engineering and innovation have intervened in the history of behavior analysis, from the pigeon chamber in the mid-twentieth century (see e.g., Sakagami and Lattal 2016; Sidman 1960) to modern-day digital technology (see e.g., Dallery et al. 2013; Twyman, 2010, 2011). The intervention of behavior analytical terminology, methodology, and emerging technology developed along these lines invites behavior analysts to conduct a much more thorough examination of consumers' in-store behavior. This is more inductive than traditional marketing research. This comes at a time when a range of new technologies has expanded the possibilities for measuring and collecting behavioral data more reliable and thoroughly. Such technologies include RFID-based tracking, eye-tracking devices, handheld

scanners, eye cameras, video tracking, and biometrics (e.g., heart-rate monitoring). Conducting behavioral experiments using these technologies might take behavior analyses one-step further to find out why consumers behave as they do in terms of behavior–environmental contingencies, beyond simply addressing what they do (choice) or even less informatively, say they will do. That said, various methods and technologies differ in their capability to capture the basic behavior we have categorized (Table 2). For example, RFID technology can capture only walking behavior, such as direction, path, and speed. In addition, eye tracking has limitations in that it is difficult in natural settings and scanner data captures only purchase data but not the data relevant to the purchase path. On the other hand, video tracking or camera surveillance is needed to capture socializing behavior, assistance-related behavior, and such behavior as touching, holding, switching, and buying; combined with path-tracking software, it is possible to obtain a rich data set on in-store behavior. Shopper Flow©️ automatically registers such data as the number of meters walked, the percentage of the store visited, walking speed (m/s), and total time spent in the store. In addition, we register both instances in which a customer touches an item (item interaction), when the customer picks an item and buys it (item purchase), the choice of carrying equipment, as well as basic demographic data.

Another advance in consumer science application involves the use of neurological measurement tools, such as a portable electroencephalogram (EEG). Such technology makes it possible to study the unconscious processes of the human brain (Agarwal and Xavier 2015). Since consumers largely evaluate in-store stimuli (e.g., promotional displays) subconsciously, portable EEG applications offer the opportunity to gain a better understanding of how the brain responds to such stimuli and its connections to behavior. Researchers can recruit shoppers and ask them to wear mobile EEG applications and send them on well-designed shopping tasks or perform their usual shopping activities. In addition, the integration of neuromarketing tools and nanodevices seems promising. As such, traditional issues associated with immovable instruments could be overcome, thereby increasing our ability to carry out relatively noninvasive and nonintrusive experiments in natural shopping environments (Mileti et al. 2016).

**Automatic Retail Analytics and Trained Human Observers**

Although our research utilizes a tracking software, Shopper Flow©️, developed by Flow Insights, there is steady growth in other consumer technology at the moment waiting to be analyzed and tested. Our research strategy for the behavioral in-store experiments is in line with Johnston and Pennypacker (1993, p. 112) position that:

"[m]achines should be preferred for the task of detecting and recording the behavioral data required by the experiment, and humans should serve a supplementary observational function of monitoring the operation of machine transducers and looking for any features of the subjects behavior, the behavior of others, or the experimental environment that may be important in managing the experiment."

Shopper Flow© automatically captures basic data from individual customer shopping trips (e.g., number of meters walked, areas visited, and time spent in areas). We use this software in conjunction with observations from surveillance cameras covering the entire selling space of the store. The cameras enable our trained observers to "follow" each targeted customer from the entrance to the exit, and thus, to perform real-time tracking of the customer's movements and behavior in the store. This solution prevents consumers from being affected by the immediate presence of observers. Our observation room is equipped with two computers and two large monitors. While one of the monitors display the live images from the store (see Figure 1), the other is involved simultaneously in tracking the customer's movements and behavior using Shopper Flow©.

Pairs of trained observers undertake the tracking. Shopper Flow© has been adapted to the store's floor plan and distances. Since the tracking occurs in real time, the time-based measures automatically registered by the software follow the customer's movements in the store. This includes time in a specific area, average walking speed, and total amount of time spent in the store. In addition, the software automatically registers the start time of each shopping trip, the date, and when the trip ends. Furthermore, based on the customer's movements in the store, the software automatically keeps track of the exact product area from which a targeted customer interacts with or purchases a product, as well as the number of areas the customer visits. Shopper Flow© allow observers to register the customer's choices in real time, for example, every instance in which the customer touches an item (item interaction) and picks an item without returning it to the shelf (item purchase). Touch can occur in many forms, ranging from taking the product off the shelf for further inspection to touching the product on the shelf without moving it. The procedure we follow is to study customers' arm movements when they slow their pace and start interacting with the shelf/display. Arm movements differ for customers taking products off shelves without putting them in baskets/carts and customers moving products from shelves to baskets or carts (Liu et al. 2016). Thus, the action of the arm and hand reveal much information about the consumer's interaction with and purchase of products. Figure 2 presents a graphical illustration of a shopping

trip we track using Shopper Flow© ("P" and "I" in Figure 2 represents a purchase and a product interaction, respectively).

The shopping trip illustrated in Figure 2 belongs to a female customer (age 31–40 years) who entered the store at 13:08:49 on a Wednesday. She chose a large basket, walked a total of 234 meters in the store at an average speed of 0.3 m/s, visited 36% of the total store area, interacted with 6 items without purchasing them, purchased a total of 12 items on her entire trip, and spent a total of 772 seconds before queuing at the cashier desk.

The starting point for activating tracking is the same across the targeted shopping trips, except for those customers who choose to take a shortcut by going through the checkout zone on their way into the store, but generally, there is a particular standard path, or customer journey, that the retailer tries to facilitate. For these instances, our procedure is to activate the tracking approximately 2 meters before the customer reaches the passage between two of the cashier desks. We stop the tracking of a shopping trip when either the customer starts queuing (when there was a queue at the cashier desk) or when he/she places the first item on the belt at the cashier desk. This prevents the time spent standing in a queue from having any influence on the total amount of time spent in the store. Queuing time could be very different from one customer to another. Thus, in order to make the shopping trip data as comparable as possible across individual cases, we stop tracking as soon as the customer starts queuing. Our procedures involve neither the storage of any video images, nor the registration of personal data. All data consist of anonymous numeric identifications that cannot be related to any physical person. Furthermore, a poster at the entrance of the experimental store informs customers that this particular store is participating in a research project involving the use of surveillance cameras.

Since in-store behavior depends on the time of the day and the day of the week the shopping trip occurs, we use a proportionate stratified sampling approach in our research. This is in line with Malhotra and Birks (2007), who recommend proportionate stratified sampling when there are reasons to believe that the relative size of a stratum in the total population is different from the relative size of another stratum. We select customers following a systematic sampling process, involving selecting random starting points and then picking the i*th* visitor entering the store. Such a procedure does not require knowledge of the elements of the sampling frame, but requires very strict control of the flow of potential study objects (Malhotra and Birks 2007).

## Developing the Store as a Behavioral Laboratory

To perform in-store consumer behavior analysis, researchers either need to develop their own experimental store, which is difficult and expensive, or they need permission from a retailer to use one or more stores as a research setting. There are some examples of developing experimental stores, although it is understandably quite uncommon. For example, Proctor & Gamble (P&G) built a consumer village in St. Bernard (USA), and included a convenience-sized store that stocked its own as well as other products (Fasig 2009). Thousands of shoppers volunteer each year to visit the village to shop as they do at their regular grocery stores at home, but in front of a camera and two-way mirror. The P&G village conducts as many as 450 studies a year (Fasig 2009). Retailers will probably fairly soon also experience a fundamental shift in the employment of advanced technologies in their physical stores, bringing further opportunities for behavior analysts. A strong signal for such a shift is the Amazon Go store in Seattle, which provides a checkout-free shopping experience made possible by the same types of technologies used in self-driving cars: computer vision, sensor fusion, and deep learning (Amazon.com). For example, products that customers take from or return to Amazon Go shelves are automatically detected, and the store keeps continuous track of the customer's purchased products in a virtual cart.

The variety of potential in-store promotional (motivational) instruments/vehicles, discrimination stimuli, and consequences found in the physical retail environment provide endless opportunities for in-store experimental efforts. Therefore, there have been calls in the marketing literature for more controlled experiments in real physical store environments. For instance, Shankar et al. (2011, p. 34) claim that it is unclear which of the new technology-based in-store promotional instruments (e.g., shopping carts, shelf-talkers, and in-store TVs) are effective, to what extent, and under what conditions. The authors further note that controlled experiments in natural environments can better ascertain the effectiveness of different aisle placements and shelf positions. The problem then arises of selecting an experimental store in which to run the studies. In line with other traditional experimentation, in-store experiments automatically imply a certain degree of restriction on both the activity of the consumer and the types of observations open to the behavior analyst. This is to some degree akin to the traditional behavioral laboratory (e.g., as explained by Sidman 1960). When a consumer enters an experimental store, in a metaphorical sense, he or she places himself or herself in an enclosed chamber, that is, an environmental setting to learn about behavior as well as to modify it. The setting restricts the consumer's area of activity and possibilities, but not his or her freedom of activity within the store. In line with Sidman's (1960) paramount concerns about evaluating experimental findings (1960), when selecting an experimental store, the

researchers should consider the potential for the setting to generate important scientific data as well as the highest possibilities of reliability and generalization.

Previous in-store experiments (e.g., Sigurdsson et al. 2010) have revealed experimental control with increased potential to diminish or regulate behavioral variability. There are usually clearer behavioral patterns when the laboratory store is larger in terms of number of consumers and transactions, and when the target brand is a true fast-moving consumer good. Furthermore, it is important to be able to locate the marketing intervention (e.g., promotion) and behavioral measurement (sales). This is a strength of in-store experiments, in which there are no or few intermediaries, compared to measuring the effectiveness of mass advertising, in which there can be time lapses, changes in budget, advertisements from other manufacturers, or word of mouth, between consumers noticing the intervention and the response (see e.g., Sigurdsson et al. 2010). Finally, it is all about control, as it is important to have as many opportunities as possible to control the setting and assess the situation frequently. The external factors within the marketing mix (McCarthy 1960) that need the most experimental consideration are brand quantity, quality, packaging, shelf space and placements, availability of brands, prices of other brands, and in-store promotions. In other words, for successful in-store experiments, the product category needs to be kept constant (see e.g., Sigurdsson et al. 2009).

In terms of generalization, it would be beneficial to conduct a similar experiment in one or more comparable retail stores in order to check if similar trends can be observed elsewhere and if they are consistent (see e.g., Sigurdsson et al. 2009, 2016). In addition, a researcher can conduct an identical experiment in other types of retail stores (e.g., size, store type, and location—mall, rural, or downtown) to one used as an experimental setting for the initial study to observe if similar trends can be observed. The only way to verify whether the results derived from experiments conducted in one store format also apply for other formats is to run similar experiments in stores belonging to different retail formats. This is utilized in the studies by Sigurdsson et al. (e.g., 2011a, 2014), who run identical in-store experiments in both convenience stores and discount stores. In addition, researchers are encouraged to validate trends detected in data sets from one country market with results from data sets acquired from other country markets using the same method, as well as to validate the results across products. Sigurdsson et al. (2011a, 2011b, 2014) use the latter approach extensively in their in-store marketing studies. They run experiments in both Iceland and Norway and experiment with different types of target brands to examine the effects of their manipulations and in-store interventions.

**Applied Behavior Analysis**

According to Foxall (1998), "[t]o explain consumer behavior is to *locate* it—in space and time, at the intersection of a learning history and a current behavior setting" (p. 322). This entails the use of behavior analysis that offers researchers on consumer behavior a conceptual and methodological system that makes extensive behavior–environmental analysis possible. The law of effect and experiments has allowed the creation of behavioral techniques and terminology. Research in behavior analysis has produced many useful applications of methods to predict or affect behavior. Applied behavior analysis is now used effectively in many important and diverse areas, like developmental disabilities, problem behavior, education, and organizations. Nevertheless, many behavior analysts have acknowledged that behavior analysis has had some problems in moving to the real world (see e.g., Kunkel 1987; Logue 2002) and that the time is right for an extension of theoretical explanations, concepts, and methods, demonstrating their importance (e.g., Logue 2002; Mazur 2010). The key problem in the field is to what extent the terms and techniques of behavior analysis can be used profitably in the real consumer environment. This is important from the perspective of determining the impact of situational factors on consumer behavior from the standpoint of behavior analysis, which utilizes well-researched behavioral principles. Nevertheless, there are concerns that applied behavior analysis has to some degree become stuck in developmental disabilities. For example, 60% of data-based articles published in the *Journal of Applied Behavior Analysis*, the flagship periodical for applied work in the field of behavior analysis, from 2001 to 2005 were in this area (Woods et al. 2006). The accomplishments within autism and developmental disabilities are remarkable and important for the field but, nevertheless, an extension of behavior analysis to other settings and populations should be encouraged (see also Normand and Kohn 2013).

Therefore, applied behavior analysis is unfortunately not as relevant to society as many professionals in the field would like. Behavior analysts would not appreciate the notion that their behavior principles and methods are mainly applicable to animals and developmentally disabled people. Applied behavior analysis has its origins in the animal laboratory and closed settings that can be considered as resembling a laboratory environment (e.g., classrooms and institutions). There is nothing wrong with putting internal validity, acquired with extensive and precise laboratory experimentation, before external validity. However, further examination and conceptualization in more complex open environments would be helpful to broaden the scope and interpretation of human behavior. It has been 30 years since Kunkel (1987, pp. 329–330) stated:

"one gets the impression that applied behavior analysis is in something of a rut...The rut has deepened over the years, and we will get out of it only by boldly venturing beyond today's methodological parameters. Applied behavior analysis can be considerably more than the

endlessly repeated use of effective techniques to modify activities of individual children and patients. Such uses are laudable and necessary, and they may well remain central to applied behavior analysis."

Kunkel (p. 331) puts forward ten questions, including two that are vital for consumer behavior analysis as a field and the relevance and importance of behavioral in-store experiments to applied behavior analysis in general. These are how complex the activities subject to applied behavior analysis could be, and to what extent applied behavior analysis can occur outside the laboratory and institutional setting. The agenda of consumer behavior analysis is to add the realism of effects of a real consumer environment to basic behavioral laws and principles. It is genuinely assumed that doing so would make these laws and principles more able to describe, predict, and affect consumer behavior. Nevertheless, as a consequence, the models would become more complicated and it would be necessary to stretch the boundaries of behavioral analytical theory as well as to connect it to other fields (see e.g., Hantula 2015). One of the fundamental directions of behavior analysis is that measurements should be direct, measuring exactly the behavior of interest (e.g., Johnston and Pennypacker 1993). Despite the value of laboratory experiments, it is not possible to generalize the findings from basic laboratory experiments to consumer behavior without testing them in that realm. In our view, the goal of scientific inquiry in this field is to test the efficiency of the store as a laboratory. This research has been made possible by progress in behavior analysis and technology.

In recent years, many behavior analysts have worked on the "rut," as portrayed by Kunkel (1987). Steps have been taken to broaden the relevance of behavior analysis and link it to other disciplines. Consumer behavior analysis is an important sub-discipline bridging behavior analysis, marketing, and economics. This research searches for proper methods to find the norms and principles of consumer choice in naturally occurring environments. There is now increased and broader research in consumer behavior analysis (e.g., Foxall 2016) and behavioral marketing (Foxall 2015), conducted in such divergent areas as brand choice (e.g., Oliveira-Castro et al. 2015), matching (e.g., Curry et al. 2010), foraging (Hantula 2012), drug consumption (Foxall and Sigurdsson 2011), gambling (Foxall and Sigurdsson 2013), environmental conservation and corporate social responsibility (Fagerstrøm et al. 2015; Foxall 2016, Oliveira-Castro et al. 2006), e-mail marketing (Sigurdsson et al. 2013), social media marketing (Menon et al. 2016), and credit card use (Fagerstrøm and Hantula 2013).

There is still a further need for applied behavior analysis in stores, such as for health promotion at the point of purchase. Despite the recent popularity of nudging and choice architecture, Adam and Jensen (2016), in

their literature review on the effectiveness of obesity-related intervention in retailing, make special note that only three studies (Foster et al. 2014; Holmes et al. 2012; Sigurdsson et al. 2014) have been published on the effects of using shelf space management to promote healthy food. Adam and Jensen (2016) encourage researchers to undertake more experiments and in particular to study both healthy and unhealthy food, as well as their substitution and final basket sales. They also encourage researchers to rely more on objective sales data. It is necessary to work with retailers on these issues, as they can give access to their premises and who decides what is placed on the shelves in the first place. Without the benefits offered by these gatekeepers to the end customer, it would be much more difficult to facilitate lasting healthy behavior change, or even just to get a chance to try it. *Push* and *Pull* strategies are common terms in marketing science that can be used in behavior analytical terminology. In terms of healthy food promotion, it is important to promote healthy food products in the best retail placements with as many shelf facings (how many packages are presented on a shelf) as possible in the brick and mortar store, or with a large part of the "online real estate" (the visible screen) in e-commerce. Also of interest is the strength of the push and pull for unhealthy food products. Here, we can consider such aspects as stacking products on the lowest or middle shelves in a store (e.g., Sigurdsson et al. 2009 show this has a large effect on sales of a particular brand of potato chips). Retailers use choice architecture to shape consumer behavior for their own benefit, for example the effectiveness of the middle shelf is influenced by whether a store organizes its products horizontally on the shelves, which is a common choice architecture for discount stores that want to promote certain products. A *pull strategy* works for getting consumers to seek out products or ask for them, which then increases sales of those products and can affect the further promotion of those products by retailers. For example, it is common knowledge that sweets and products with high glycemic carbohydrates are most commonly situated in highly visible areas, and sweets are almost always situated at the checkout. Hence, owing to the critical importance of exposure, retailers have been pressured by consumers to put more emphasis on maximizing accidental exposure to more healthy food products in the retail environment along with more active promotion of such products. Therefore, a retailer collaborating with our research group was considering making every other checkout sugarless, by placing such products as fruit and vegetables at the checkout instead of sweets. Sigurdsson et al. (2014) examine both the immediate and enduring effects on consumer behavior of modifying the typical in-store shelf placement of food items at the checkout (the grand finale of shoppers' journeys through the store), with or without in-store advertisements. Instead of unhealthy items (e.g., candy and high glycemic carbohydrates), healthier items were rotated at the checkout lines in different types of stores. The results demonstrate that placing healthy food items at the checkout (prominent discriminative stimuli) in stores

can lead to a substantial impact on sales of these products. They identify healthy food items (e.g., dried fish and nuts) whose sales have potential to increase by about 400–500% if placed at pivotal places within the store. These sales levels were not maintained during withdrawal conditions or during the follow-up stage (return to baseline).

## The Case of Consumer Carrying Equipment in Stores

Consumer carrying equipment represents one of the first instances of direct contact consumers have with a retailer's product or service when visiting a grocery store. Such contact is what Meyer and Schwager (2007) define as a consumer touch point. Although there are numerous potential touch points that consumers might be exposed to from the store entrance to the exit, the first touch point at the beginning and the last touch point at the end often tend to be among the most important. Earlier studies conduct in-store experiments on consumer choice of healthy versus unhealthy food at the grand finale of a shopping trip, as described in the previous section (shelves at or near the checkout) (see Sigurdsson et al. 2011a, 2014). We now turn our focus to the entrance, represented by the consumer's choice of carrying equipment. As mentioned in the previous section, Adam and Jensen (2016) encourage greater focus on the total effects of consumer behavior. The reason for our interest in carrying equipment is that the choices consumers make at the entrance apparently have important consequences for how they act thereafter as well as on final sales and even substitution between healthy and unhealthy food products. Behavior analysis of these consumer choices cannot be limited to choice behavior itself, but needs to take account of relevant behavioral incidents that occur throughout the entire shopping trip, or what we here call the in-store customer journey. The in-store journey is a linear, time-based representation of the behavioral process and flow that a customer goes through when visiting a grocery store. The concept of the in-store consumer journey is valuable for behavior analysis due to the emphasis on continuous measurement of consumer behavior and consumers' interactions with the environment.

Despite the prominent role that carrying equipment has in retail environments, there is surprisingly limited literature involving such equipment in grocery retailing. Therefore, little is known about customers' choices regarding carrying equipment (e.g., cart, basket, or nothing) in terms of how frequently the different choice alternatives are preferred in different settings, why consumers choose as they do, and the consequences of these choices. See Table 3 for an overview of relevant studies pertaining to carrying equipment in grocery retailing.

The procedure we use for category development (the research issues as reflected in Table 3) was to work through each relevant study with the aim of deducing, step by step, tentative categories reflecting issues of relevance for consumer carrying equipment in retailing. Following a feedback loop, the initial research categories are revised and then reduced to the main categories. In addition, Table 3 includes a short description of the main research methods employed in each of the studies. Only a few of the relevant studies listed in Table 3 (De Groot et al. 2013; Gil et al. 2009) report grocery shoppers' actual choice behavior when it comes to the choice between a cart, a type of basket, or no equipment. The vast majority of studies are concerned with elderly consumers' experiences and challenges of using a shopping cart or basket, and shopping cart-related injuries among children. Only two of the reviewed studies examine carrying equipment-related effects on buying behavior. An example is Bergh et al. (2011), who examines whether customers carrying shopping baskets have greater preference for products providing immediate benefits (e.g., "vice" products) than do customers pushing shopping carts.

Most of the studies listed in Table 3 employ research methods that draw heavily on consumers' personal accounts. None of the relevant studies involves experiments conducted in natural store environments. This includes a growing number of observational studies (in-store or video-surveillance) and those using path-tracking technology, such as RFID tags affixed under shopping carts (e.g., Larson et al. 2005) and consumers wearing belts with RFID tags (e.g., Hui et al. 2013). This demonstrates a general lack of behavioral in-store experiments in this area that are more inductive and that consist of a continuous stream of observations of direct behavior.

Our ongoing experimental research on consumer carrying equipment in the store demonstrates why behavior insight at the point of purchase requires data covering complete in-store customer journeys. In addition, this research points to the need to observe consumers' actions along their entire journey as well as the benefits of applying tracking software, such as Shopper Flow©, in this endeavor. Through a *continuous stream of observations*, we can identify, register, and describe incidents that occur along the customer journey, from the entrance to the exit point, which would be difficult to achieve otherwise. There are many such incidents relevant to the context of consumer carrying equipment. The most obvious is the consumer's choice of carrying equipment itself, defined in this study as the entrance act. One of our observational studies, a part of the present

research covering 635 complete individual in-store customer journeys conducted in a typical discount store located in a suburb of a smaller European city, reveals many other critical incidents. One rather relevant incident is when the consumer reaches his/her maximum carrying capacity (the basket cannot handle more items or the capacity of the customer's arms is stretched to the limit). We observe that customers carrying baskets respond differently to such a constraint. Some walk straight to the checkout, while others carry additional items in their hands or go back to the entrance and switch to a larger item of carrying equipment. Other relevant observations involve incidents in which carts are used for carrying children, returning empty bottles, or as a walking aid for elderly consumers, and not as vehicles to make larger purchases more convenient. In addition, it is quite common for consumers to park their carts, and in some incidents also their baskets, in one zone while they visit different zones of the store. These are just examples of incidents that might occur along the in-store customer journey. Since disconnected incidents hardly explain behavior in the retail environment, there is progress in being able to connect incidents occurring at different points in a journey. This involves describing the incidents, looking for interconnections, searching for patterns, and developing explanations. In other words, by applying an *inductive approach*, we conclude that the consumer is always right.

In order to discover such patterns, it would be necessary to examine a larger number of in-store journeys, and thus, to perform analyses on a more aggregated level. Figure 3 provides an example of a pattern obtained from analyzing the 635 in-store customer journeys through the use of a multinomial logistic regression.

--- Put in Figure 3 about here ---

The vertical axis (y-axis) represents the probability of customers choosing a cart, a basket, or no equipment ("nothing") at any given level of purchased items. The given estimates are conditional on other variables kept on average. The vertical spikes on each category line represent the 95 % confidence interval (Cis) at the given estimate. The figure shows that the number of items customers purchase on their in-store journeys is strongly related to their choice of carrying equipment. A shopping cart is chosen at an increasing level as number of purchases increase, and being the dominant choice for consumers buying more than 15 items. Further, a basket is the preferred carrying equipment for number of purchases between 5 and 14 items, while entering the store without any consumer carrying equipment, labeled as "nothing", is the main choice for those purchasing less than 5 items. Similarly, multinomial logistic regression could be employed to detect the probability of customers choosing a cart, a basket, or no equipment at any given level of healthy food items purchased, such as fruit and vegetables. Items such as fresh berries, tomatoes etc. are easily damaged if other products are placed on

top of them, which makes the choice of carrying equipment a very relevant issue. The placement of such items in the store, early versus late in the customer journey, have also relevance, especially for consumers carrying a basket with limited capacity. Herein, plenty of opportunities for in-store experiments exist.

Table 4 lists a broader range of positive and negative consequences associated with choosing a cart and walking into the store without any carrying equipment, respectively.

--- Put in Table 4 about here ---

As shown in Table 4, there are several *positive consequences* associated with carts. Carts offer consumers less "restrictions" on the type of goods and the number of items consumers are able to purchase (large carrying capacity), make consumers more capable of acting on attractive in-store promotions (monetary consequences), make it easier and safer to transport heavy items around the store (less effort), offers space to place handbags, backpacks or other personal belongings (convenience), and are suitable as a walking aid. The latter apply in particular for consumers with restricted mobility (Yin et al. 2013; Meneely et al. 2009). Prior research has for instance found carts to offer a balance and something consumers with restricted mobility can lean on (Meneely et al. 2009). In this respect, our analyses of the 635 customer journeys using a multinomial logistic regression also reveal an age-related pattern as shown in Figure 4. The vertical axis (y-axis) represent the probability of the consumer choosing a cart, a basket or no equipment, at the given levels of age. Similar to Figure 3, the given estimates are conditional on other variables kept on average. The vertical spikes on each category line represent the 95 % confidence interval (Cis) at the given estimate.

--- Put in Figure 4 about here ---

As shown in Figure 4, both no equipment and a basket are popular choices. While entering the store without any carrying equipment are preferred for consumers younger than 40 years of age, it has a decreasing popularity as age increases. At this point, consumers 41 years and older are more likely to choose a basket, only beaten by the cart for consumers in the oldest category. The latter choice however, gradually increases in popularity as age increase.

There are also *negative consequences* associated with a shopping cart. Consumers risk buying too much food which might lead to excessive spending (monetary consequence), wasteful behavior, and/or, if repeated over time, a higher food intake than optimal (weight increase). Prior research in the US has identified consumers

as one of the largest contributors of the total generated food waste and that consumers shopping routines largely could explain food waste (Griffin et al. 2009; Stefan et al. 2013) Similarly, Graham-Rowe et al. (2014) report that consumers may buy in bulk or in excess of their needs to avoid unnecessary trips to the store (avoidance of inconvenience). A cart also reduces the consumer's shopping efficiency (decelerates consumers) and has a negative effect on consumers' moving flexibility. Carts therefore hinder consumers who wish to complete their shopping trip as fast as possible. Furthermore, carts represent a clash between seeing and moving (Underhill 1999). Since walking require a tight coordination of attentional, cognitive, and motor abilities (Gidlöf et al. 2013), consumers must gather visual information to control foot placement and to avoid obstacles or hazards while searching for products (Gottlieb et al. 2014). Some consumers might find this difficult or uncomfortable (Dulsrud and Jacobsen 2009). Furthermore, younger consumers might view a cart as not particular trendy (embarrassment), while others might find it difficult to load and unload a cart due to its depth (Yin et al. 2013; Pettigrew et al. 2005; Leighton and Seaman 1997). A cart might also cause distress, frustration, or even annoyance due to the physical difficulty of handling them. Finally, some consumers might be concerned with how clean shopping carts really are (e.g. the presence of dirt and bacteria). This should not come as any surprise since smaller children often stand in carts (Smith et al. 1996) with their dirty shoes while parents are shopping. Carts therefore pose a risk of contaminating the products put in them. This is particularly relevant for fresh products such as F&V that comes without any packaging protecting them against contamination. Perhaps more severe, having children standing in the cart may cause injuries. Prior research show that the most common mechanism of shopping cart-related injury was children falling out from the cart basket (Smith 2006; Smith et al. 1996).

Walking into the grocery store without any carrying equipment may also have consequences. Some, but not all, relate to the limited carrying capacity such a behavior represents, which might lead to both negative and positive consequences. The limited capacity results in consumers not being able to purchase so many products (limit consumers' total spending on groceries). There is a limit on how much a person can carry in his/her arms, and consumers entering a store without any carrying equipment tend to select additional products only as long as their hands can hold them (Underhill 2009). A limited capacity also increases the likelihood that purchases the customer makes are necessary and not excessive, thereby minimizing household food waste. Inman et al. (2009) recommend consumers to make "fewer-item trips" more frequent. Consumers without any carrying equipment can furthermore maximize their shopping efficiency. It is a very convenient strategy for customers in a hurry.

Negative consequence of not choosing any carrying equipment is that the consumer miss great deals in form of in-store promotions valid only for a short time (monetary and psychological costs), as well as an increased likelihood of having to make a new trip soon to the store. Research has shown that minimizing trips to grocery stores is a strategy consumers use to cope with inconvenience (Graham-Rowe et al. 2014). Consumers trying to exploit their arm carrying capacity to its maximum might also experience carrying a heavy load (effort), which at worst can lead to accidents, for instance when the consumer loses one or more products on the floor. Such accidents can cause liability (financial loss) and/or lead to embarrassment. Carrying a heavy load can also affect a person's thoughts and emotional state. Zhang and Li (2012), for instance, found that carrying a heavy load could activate corresponding semantic concepts in a person's associate network (heavy, weight), and thereby potentially having some negative psychological effects on the consumer.

## Conclusions

In the swamp of theoretical development within marketing it is of primary importance to consumer behavior analysis to develop behavioral control techniques suitable for discovering functional relations, which will form the basis for an inductive behavioral theory and applied analysis of consumer and marketer behavior.

A behavior analysis begins with complex behavior and breaks it down into its components, and functional analysis holds the stimuli and responses of interest constant, while changing their relations (Catania 1998). Our aim with the in-store experiments is to describe, predict, and affect behavior. Acknowledging this, we have a criterion to appraise different ways of performing them. When comparing different descriptions of behavior it is important to focus on the invented concepts and try to use those which make for economical and comprehensible descriptions of behavior (Baum 2005). By focusing on control, the effectiveness of different methodologies is assessed by looking at the degree of control over the target behavior that can be produced by each approach (Johnston and Pennypacker 1993). Foxall (1998, p. 338) asks the important question; "How far can the control of behaviour be attributed to the environment when the setting is relatively open?" The sufficient condition for identifying functional relationships is the experimental manipulation of an independent variable (Johnston & Pennypacker 1993). To answer Foxall's question, it is thus necessary to manipulate the retail environment and see how it affects consumer behavior. The aim is to control, or hold constant, important variables of the concatenated generalized matching equation (e.g., reinforcement magnitude, effort, and quality) or the sole effects of marketing mix variables; like price, shelf placements, and in-store advertisements, to detect

the effects of the store environment on consumer choice. The research strategy is to gain ground in terms of control with experimental methodology and also to look for opportunities in terms of emerging technology.

Over recent decades, important steps in analyzing more complicated forms of human behavior have been taken. This research is pioneering in its search for more control over important human behavior in open real environments. In-store behavioral experiments have been unexplored territory up to a few years ago and it is in steady progress. In addition to the general marketing management application of this kind of research, it is possible to claim socially important aspects to the study, such as analyzing the access to goods which society considers harmful in some way over a long period, or because of their excessive consumption (cigarettes, wine, and unhealthy food items). These are products which society has tried to regulate by controlling access, handling, price, and advertising, but a more scientific approach is needed. These problems consist of behavioral excesses and shortages, which applied behavior analysis is ideally suited to deal with (see e.g. Hursh 1991), especially consumer behavior analysis.

By taking consumer in-store carrying equipment as a case, we have shown that inductive research involving continuous observations of individual customers actual in-store behavior over some time (such as over the entire customer journey), provides the opportunity to detect interconnected incidents, some perhaps not even on the experimental agenda. We have also discussed the value of new or improved technology when undertaking in-store experiments from an operant behavioral perspective, and how technological development have opened up totally new avenues for studying consumer behavior in the natural environments where the behaviors occur. This research is crucial in establishing further methodological grounds for the application of operant behavioral economics to consumer and social marketing.

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*Table 1*: A comparison of the research strategy characteristics of behavioral in-store experiments, as presented in the current paper, and a more traditional marketing approach

| Dimension | Behavioral In-store Experiments | Traditional Marketing Research |
|---|---|---|
| Number of subjects | *Few*, segmented or aggregated | Segmented or aggregated |
| Research design | *Primarily Within-subject* | Between-subjects |
| Data collection | *Direct, repeated measures of behavior* | Various methods, often indirect and non-repeated measures of behaviors |
| Data analysis | *Graphical and statistical* | Statistical |
| Approach to variable data | *Consider the variability as imposed; isolated and control of the responsible extraneous variables* | Consider the variability as intrinsic; use statistics to detect the effects of the independent variable despite the variability |
| Observations | *Continuous stream* | Snap shots |
| Approach to research | *More inductive* | *More deductive* |

*Table 2*: Categorization of basic behaviors occurring inside a retail store

| In-store behaviours | | | | |
|---|---|---|---|---|
| Walking behavior | Choice behavior | Socializing behavior | Assistance related behavior | Other behaviors |
| Direction | Browsing | Talking (phone) | Consulting smartphone | Redeeming coupons |
| Speed | Fixating (eye) | Speaking (with other consumers) | Consulting store personnel | Collecting empty bottles |
| Paths | Touching | Speaking (with store personnel) | Using hand-held scanners | Parking carts and baskets |
| Navigating | Holding | | Choosing a carrying equipment | Placing and arranging items in the cart/basket |
| Visiting | Tasting | | Using a shopping list | Eating |
| Stopping | Switching | | Using a shopping bag | Littering |
| Facing shelf Display | Buying | | Bringing to the store his/her own Shopping bag | |
| Queuing | | | | |

Note: Relevant metrics include occurrence/non-occurrence, where it occurs, number of occurrences, patterns, distance, area coverage, time measures etc.

*Figure 1*: Live pictures from the experimental store

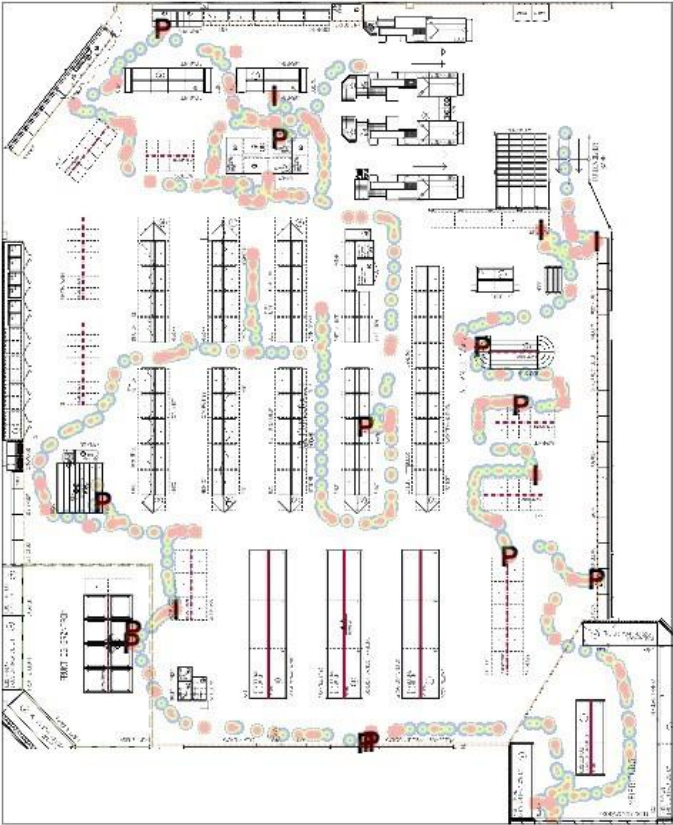*Figure 2*: Output graphics from a shopping trip in Shopper Flow©

*Table 3*: An overview of relevant research involving carrying equipment in grocery retailing

| Research issues | Studies | Research methods |
|---|---|---|
| Shopping cart history | Cochoy (2009) | Content analysis |
| Cart and basket usage | De Groot et al. (2013)<br>Gil et al. (2009) | In-store observation<br>Survey and video observation |
| Quality, availability and importance for store loyalty | Pandey and Darla (2012)<br>Moutinho and Hutcheson (2007) | Survey<br>Survey |
| The amount of items in carts, cart users' group size, organization of items in carts | Cochoy (2008) | Quantitative observations and focus group interviews |
| Facilitating communication | Van Ittersum et al. (2013) | Survey, iPad on carts, receipts |
| Facilitating tracking of in-store behavior | Hui et al. (2009)<br><br>Larson et al. (2005)<br>Sorensen (2003) | RFID-tags on carts and scanner data<br>RFID-tags on carts<br>RFID-tags on carts |
| Effect on buying behavior | Wagner et al. (2014)<br><br>Bergh et al. (2011) | In-store observation, PDA, shadowing software<br>In-store observation, PDA, receipts |
| Experiences of elderly consumers | Yin et al. (2013)<br><br>Angell et al. (2012)<br>Kohijoki (2011)<br>Meneely et al. (2008, 2009)<br>Pettigrew et al. (2005)<br>Geuens et al. (2003)<br>Leighton and Seaman (1997) | In-store observation (video, cameras), personal interviews<br>Survey<br>Panel data and GIS<br>Personal interviews<br>Focus group interviews, survey<br>Focus group interviews<br>Survey |
| Consumers' opinions/views | Kwong et al. (2010)<br>Aylott and Mitchell (1998) | Survey<br>Focus group interviews |
| Cleanness and litter | Trinkaus (2004) | In-store observation |
| Shopping cart related injuries | Smith (2006)<br>Parry et al. (2002)<br>Smith et al. (1996) | Secondary data<br>Secondary data<br>Secondary data |

*Figure 3:* The choice of carrying equipment relative to number of purchased items
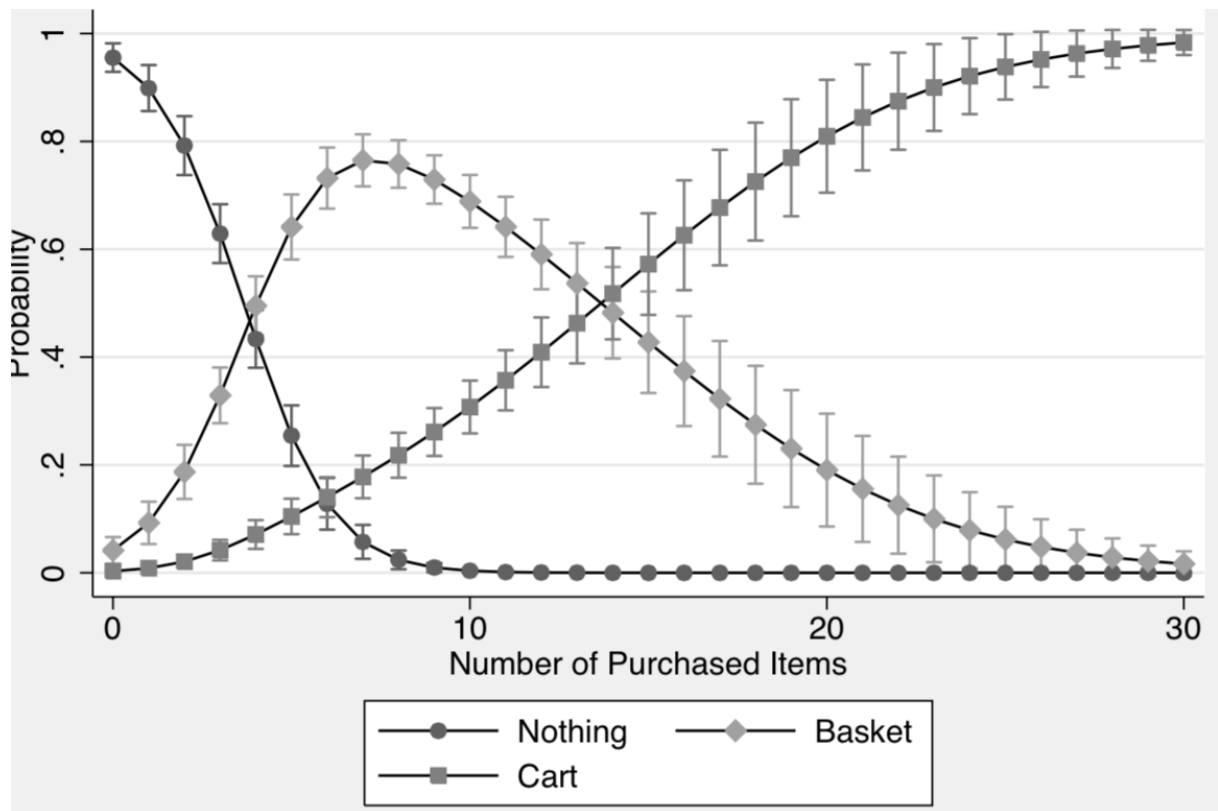
*Table 4*: Consequences associated with using a cart versus not using any equipment

| | | Consequences | |
|---|---|---|---|
| | *Positive consequences* | | *Negative Consequences* |
| *Carts* | Large capacity | | Monetary (spending too much) |
| | Monetary | | Increasing food waste |
| | Less effort | | Shopping efficiency |
| | Convenience | | Moving flexibility |
| | Walking aid | | Embarrassment |
| | | | Frustration |
| | | | Difficulties to load/unload |
| | | | Inconvenience |
| | | | Product contamination |
| | | | Injuries |
| | | | |
| *No equipment ("Nothing")* | Monetary (save money) | | Inconvenience |
| | Fast walking | | Heavy load |
| | Shopping speed | | Embarrassment |
| | Moving flexibility | | Monetary (miss out great deals) |
| | Convenience | | Accidents (losing products on the floor) |
| | Minimizing food waste | | |

*Figure 4*: The choice of carrying equipment relative to age