Elapsed time on first buying triggers brand choices within a category: A virtual reality-based study

Enrique Bigné, University of Valencia

Carmen Llinares, Polytechnic University of Valencia

Carmen Torrecilla, Polytechnic University of Valencia

June 2015

The authors thank the reviewers for their careful reading and suggestions. Also thanks to Jaime Guixeres, LabHuman, Universitat Politècnica de València for his comments in an earlier version of the paper.

The Spanish Ministry of Economia y Competitividad (Project TIN 2013-45736-R) supported this research.

Send correspondence to Enrique Bigné, Department of Marketing, Universitat de València. Avda. Tarongers s/n, 46022, València, Spain. Tel.: + 34 96 3828312 (enrique.bigne@uv.es); Carmen Llinares, Instituto de Tecnología Orientada al Ser Humano (LabHuman), Universitat Politècnica de València, Camino de Vera, s/n, Valencia, 46022, Spain. Tel: + 96 387 75 18 (Ext. 67042) (cllinare@omp.upv.es); Carmen Torrecilla, Instituto de Tecnología Orientada al Ser Humano (LabHuman), Universitat Politècnica de València, Camino de Vera, s/n, Valencia, 46022, Spain. Tel: + 96 387 75 18 (Ext. 67042) (ctorrecilla@labhuman.i3bh.es)

Abstract

This study integrates neuroscientific tools such as data from eye movements, store navigation, and brand choice in a virtual supermarket into a single source data analysis to examine consumer choice, customer experience, and shopping behavior in a store. Through Qualitative Comparative Analysis the findings suggest that a high level of attention to a brand and slow eye movements between brands lead to additional brand purchases within the product category. This study points out that the key driver of additional brand choices is the time buyers spend on the first choice, showing that the allocation of less for the first choice triggers additional purchases within the product category, and, therefore, increases sales. In addition, this study discusses practical and methodological implications for retailers, manufacturers and researchers.

Keywords: Virtual reality; brand choice; eye tracking; human behavior tracking; CAVE; Qualitative Comparative Analysis.

1. Introduction

Brand choice process at brick-and-mortar store level is still relevant. First, sales volumes are higher offline than online in some product categories (e.g., grocery products account for 80.1% of purchases in UK stores in 2014 (Statista, 2015)). Second, some retailers implement the "buy-online pick-up-in-store" practice, thus pursuing the integration of online and offline retail channels (Gallino & Moreno, 2014).

Although marketing research devotes huge attention to brand choice (Jacoby et al., 1974) and integrative approaches grow in numbers, few of these approaches draw on neuroscientific tools (Van der Laan et al., 2015) or virtual reality (Pfeiffer et al., 2013). However, video tracking emerges as a valid alternative despite the limitations of that tool (Hui et al., 2013; Zhang et al., 2014).

Three main elements may influence shopping behavior in a physical store: (1) brand value as a composite of brand attributes compared with available alternatives; (2) physical variables such as atmospherics, product disposition, and shelf space; (3) consumer paths (Hui et al., 2009); shoppers move dynamically within the store, so brand-choice processes cannot ignore flows, product proximity, physical and visual contact, and space within the store. Prior research in consumer behavior in physical store neglects integrative frameworks because of the complexity of gathering consumer information in a single source data context. Furthermore, conscious decision-making is not always the key driver in purchasing behavior (Walvis, 2008) and unconscious thoughts can even lead to better, more satisfying decisions. With a few exceptions, recent marketing literature does not pay attention to virtual retailing (Pantano & Laria, 2012), choosing to focus, instead, focuses on online retailing and advertising.

Therefore, the aim of this research is to overcome such gaps in brand choice at store level using human behavior tracking (HBT) and eye tracking (ET) in VR. These techniques report consumer paths, seeking behavior, purchase behavior, and the time a person spends on each task. The specific research goals are threefold. First, despite the number of studies explaining variety-seeking behavior, the literature falls short in differentiating between buying and consuming behaviors. Second, to evaluate the influence of the time people spend examining a brand affects subsequent purchase decisions and influences brand choices within the same product category. Third, because the literature considers in-store paths and visual attention explanatory variables for purchase decisions, this study argues that the time people spend on the first brand they purchase influences more purchases within the same product category.

This study tests the effects of store navigation and gaze behavior on purchase decisions within a budget in the context of fast-moving consumer goods (FMCG) using a neuroscientific approach based on human behavior tracking (HBT) (Gonzalez et al., 2008) and eye tracking (Wedel & Pieters, 2014) in a VR store. This research contributes to the existing literature by integrating HBT and eye tracking to overcome the limitations of prior neuroscientific studies based solely on eye tracking (Van der Laan et al., 2015) or video tracking approaches which do not capture the scan path and fixations of shoppers' eye movements (Hui et al., 2013). In addition, this study introduces new metrics of interest in consumer choice at store level that link with brand choice and consumers' paths and attention to specific brands foster shoppers' decisions and different behavioral responses such as time spent at the store, time spent on first purchase or number of eye fixations on each brand on the shelf.

As far as the literature goes, this is the first study to use Qualitative Comparative Analysis (QCA) drawing on neuroscientific information.

2. Literature review and hypotheses

Individual preferences, past experience, and marketing mix elements influence consumers' brand choice (Shin et al., 2012). At store level, retailer's decisions also play a key role. This study integrates individual preferences and manufacturer and retailer policies in a virtual store to capture consumer responses to an integrated stimulus from the brand and shelf space (i.e., manufacturer and retailer policies).

Khan (1995) defines variety-seeking in purchase behavior as the tendency of individuals to seek diversity in their choices of services or goods. Consumer behavior is goal-oriented and draws on deep reasoning (Kopetz et al., 2012). Consumers may differ from buyers in many product categories and more interestingly may differ in their behavior goals. Consumers may pursue variety-seeking to achieve emotional goals or new experiences, whereas utilitarian tasks such as saving money, saving time or following orders is what drives buyers. Although researchers argue that experiential or hedonic motives explain variety-seeking, (Van Trijp et al., 1996) studies tend not to differentiate buying and consuming.

This study argues that consumers are more variety-seeking than buyers, and because purchase frequency also affects repeat purchasing (Van Trijp et al., 1996):

H1: Usual consumers differ from usual buyers in their variety-seeking behavior, showing more diversity in their brand choice.

Turley and Milliman (2000) summarize the atmospheric effects on shopping behavior, positing a bundle of influences on consumer evaluations and subsequent behaviors. This research replicates store elements using VR. Prior research posits the influence of atmospheric elements on traffic paths within the store. More interestingly consumers' visual attention to brands is the key driver of potential purchases through perception in different parts of the brain, like the fovea and brain area V1 (Orquin & Loose, 2013). Therefore, choice modeling begins to incorporate objective measures of visual attention that derive from eye movement research (Orquin & Loose, 2013).

Human behavior studies define fixation as the point in time and space when the eyes are relatively stationary and virtually all visual input occurs (Rayner, 1998). Almost all human decisions involve acquisition of visual information but decision-making is a special kind of task where the valuation of information is different depending on each case and user (Just & Carpenter, 1985). Russo and LeClerc (1994) find that the decision process in a prototypical physical store involves orientation, evaluation, and verification with different fixation patterns at each stage. This study uses two measures from eye tracking studies: "Average fixation duration (AFD)" to capture attention to one specific stimulus in seconds, and "fixations per second" to reflect the speed of attention. Pieters and Warlop (1999) argue that time pressure may lead customers to accelerate information acquisition, filter part of the available information, and/or shift the information acquisition strategy.

Therefore, at store level, on the one hand, customers who spend more time (i.e., non-accelerated processes) and/or do not filter much of the brand information, purchase more products; in addition, this behavior may stem from emotional goals and occurs in variety-seeking behaviors. On the other hand, customers with less time and a high level of

filtering make fewer purchases and their behavior relates to brand loyalty, through a retrieval of the main features of their regular brand.

H2a: A high level of attention to a brand and slow eye movements between brands lead to additional brand purchases within the product category.

H2b: A low level of attention to a brand and quick eye movements between brands lead to few brand choices within the product category.

Time at the store is an exogenous variable with various influences on consumer behavior. When consumers spend more time in a store, they become more goal-oriented, spend less time on exploration and are more likely to buy (Hui et al., 2009). Time pressure also limits the ability to process information (Suri & Monroe, 2003) and therefore of fostering the choice of additional brands.

H3: When less time is spent on the first purchase, more purchases of other brands within the same category emerge.

3. Method

3.1 Research design and study context

This study uses VR and neuroscientific techniques, which have proven their suitability in other contexts (Bohil et al., 2011). The virtual environment (VE) was a high-quality 3-D simulation of a supermarket aisle projected into a Cave Automated Virtual Environment, CAVE, set-up, an 3x3x3 immersive reality room with three walls and a floor capable of displaying stereo images (Carlson et al., 2011). Position tracking is also available in CAVE. Graphic programming and natural interfaces allow the user to navigate

freely through the store and interact with 3D products. In addition, CAVE records eye movements, gaze time, and fixations.

This study focuses on fast-food product category. The criteria for this choice were high brand assortment, price and package sensitivity, and a wide range of varieties and formats. Beer meets the above criteria and also shows brand-switching in brand choice studies (Van Trijp et al., 1996). This study invited purchasers of beer at a supermarket within the last three months to participate in the research. Participants do not suffer from claustrophobia, epilepsy and / or anxiety. Participants had a fixed budget of 15 euros to spend on any type or amount of beers, following their regular shopping pattern. To reflect reality as much as possible, the study limited the time at the virtual store to eight minutes, following previous experience in similar VR studies. Participants could move through the supermarket aisle, examine and return the product or put it into the shopping trolley.

This study collected user behavior through HBT technology, a monitoring layer that runs in background, and grouped the data into: (1) product interaction and choice; that is, data on products that consumers took off the shelf, viewed, and had information on their attributes, in-depth information on the depth of the interaction (viewed vs. taken off the shelf), viewing time, and final selection of products for the virtual shopping basket, taking into account order of purchase and personal budget evolution. (2) In-store navigation; that is, data on how shoppers navigate, time spent in areas of interest (AOI), proportion of AOI visited, stops inside the space, and paths into the virtual store.

An eye-tracking system embedded in the HBT technology monitored eye movements. Participants had wireless SMI eye tracking glasses with a video-based pupil and corneal reflex system and head-tracking system inside CAVE, which recorded data at 50Hz and scene video at 25Hz with over-laid gaze cursor. Two cameras recorded

participants' eye movements and the virtual scene at which participants were looking. The study coded eye tracking recordings from each participant by using the video player functionality in analytical software SMI BeGaze. The main metrics extracted were: (1) average duration of all fixations for each user during the session; (2) number of fixations per second.

3.2. Selection and measurement of variables

This study used a data set comprising data from three complementary sources. The first source was a questionnaire to obtain consumer pattern profiles. This set used dichotomous self-reported questions to assess the relationships between product category and consumer brand behavior: (1) Usual buyer of product category; (2) Usual consumer in product category; (3) brand loyalty.

The second data source is HBT and comprises the number of products bought, total time spent shopping within the product category, and time used to purchase the first product and total shopping time within the product category.

The third data set comprises common eye tracking measurements like average fixation duration and fixation in seconds (Wedel & Pieters, 2014).

3.3. Sample

This study gathered information on customer shopping patterns through an online self-administered questionnaire before the virtual shopping experiment. This research pre-tested the questionnaire and the virtual shopping experience in CAVE to refine the questionnaire and adjust calibration for HBT and eye tracking in the virtual store. The

pretest compromised 15 participants: two marketers, three researchers in marketing, five experts in VR, and five consumers of the target population.

From December 2014 to February 2015, this study gathered customer data with non-probabilistic sampling. Of 105 participants, only 41 successfully completed the three data sets (i.e., self-reported questionnaire, HBT, and eye tracking) to form a valid sample. Participants were between 23 and 61years old, 54% were females, 73% had a university degree, 42% were employed, 31% were students, and 7 unemployed.

3.4. Data analysis

Qualitative Comparative Analysis (QCA) enables the identification of associations that determine causality (Ragin, 2000; 2008). This study uses this method because this method can explain causally complex structures through equifinality and asymmetric causality and identify combinations of attributes that link a particular outcome, thus detecting patterns of causation (Hsu et al., 2013).

Fuzzy-set Qualitative Comparative Analysis (fsQCA) needs the calibration of all data into set membership values ranging from 0 to 1 (Ragin, 2008). The data from the questionnaires were dichotomous and the calibration was 0-1. For user behavior in the virtual store this study identified the thresholds for full membership (fuzzy score = 0.95), crossover point (fuzzy score = 0.50) and full non-membership (fuzzy score = 0.05). This study calibrated the conditions following Woodside (2012). Table 1 shows the cutoff values for each condition and the outcome.

Table 1 here.

4. Results

The first step in an fsQCA is to test for the conditions necessary to achieve the outcome. This study considers a consistency threshold of 0.90 (Ragin, 2008; Schneider & Wagemann, 2012), so at least 90% of brands present a necessary condition, allowing for ten deviant cases. For brand diversity, the condition of usual consumer of beer (CONS) is necessary with coverage of 0.46 and consistency of 0.917. Usual buyer of beer (COM) is a necessary condition for absence of brand diversity because the consistency threshold exceeds 0.9 (see Table 2). This finding supports the first hypothesis because of the different forms of seeking-variety in buyers and consumers.

Table 2 here.

The sufficiency test aims to identify configurations of conditions that are quasi-sufficient to explain brand choice. Ragin (2008) recommends a consistency threshold of 0.75. Tables 3 and 4 show the results for the QCA solutions for both outcomes; this study adopts and the intermediate solution. This solution includes all the logical remainders that the literature considers lead to the outcome (Ragin, 2008).

Table 3 here.

The truth table analysis identifies 6 causal configurations, which provide a solution that explains brand diversity in the purchase (Table 3). The solution covers 71% of the sample, with a consistency of 0.81, which indicates that the configurations are sufficient to produce the outcome. The variable usual consumer (CON) is relevant and is present in all the configurations; the preliminary analysis identifies this variable as necessary.

In addition, a common pattern in all configurations exists. Diversity of brands relates to buyers and regular consumers of beer who are not loyal to a particular brand of beer. Purchasing a large number of items, and speed of purchase seem to be relevant in

brand diversity. Furthermore, visual attention to the shelf is a fast sweep (due to a high number of fixations per second), and also shows attention only to certain areas or brands (due to a high average fixation duration). These results confirm H2a.

The configuration with the highest coverage (0.379) (*Ybrand.diversity= (COM * CONS * NUMBER * ~FIRST * AFD * ~FIX_S*) is a usual consumer and buyer of beer who buys a large number of items, makes the first purchase quickly, and makes a quick limited visual sweep of the shelf but with attention on the desired brands. This configuration is sufficient for brand diversity in 38% of the cases. The next configuration (*Ybrand.diversity= (COM * CONS * NUMBER * ~FIRST * ~TIME*) is a usual consumer and buyer of beer, who buys a large number of brands, and makes the first purchase quickly. This configuration is sufficient for brand diversity in 34% of the cases. This condition seems to associate with compulsive consumption. Table 4 shows the analysis for “absence of diversity in purchases".

Table 4 here.

The truth table analysis offers 6 configurations covering 75.6% of the sample with a consistency of 0.88. Again, usual buyer (COM) is important in 5 of the 6 configurations. Usual buyer and usual consumer also associate with lack of brand diversity. Purchasing fewer items over a longer period of time and with a slower sweep response to specific brands behaviors associate with the absence of brand diversity. These results confirm H2b.

The configuration with the highest coverage (0.44) is *Y ~brand.diversity= (COM * CONS * ~NUMBER * ~AFD * FIX_S*, which shows that usual consumers and usual buyers who buy fewer items and look at many products but lack of AFD do not show brand diversity. The next configuration in coverage *Y ~brand.diversity= (COM * ~NUMBER * FIRST * TIME*, shows that usual buyers, who buy fewer items but need more time to

decide, also buy fewer brands in 36.5% of the cases. These two configurations show that customers who focus on specific brands showing a more reflective process that leads to the purchase of only a few brands.

Tables 3 and 4 jointly to support H3. When customers or buyers spend less time on the first purchase, more purchases of other brands within the same category emerge, whereas when customers or buyers spend more time on the first choice, additional brand purchases are lower.

Therefore, retailers should consider encouraging less time on first-brand choice to stimulate additional purchases of other brands to receive higher revenues. Manufacturers should also consider this idea because consumers are more likely to buy a powerful brand as their first choice. However, customers or buyers taking a shorter time to choose non-leading brands triggers additional purchases and, therefore, increases sales.

5. Conclusions and future research

Prior consumer choice research does not clearly differentiate between buyers and consumers. According to the findings of this research, the emotional and experiential aspect of consumption, which may foster sensory reactions in some product categories, is what motivates consumers. Buyers, however, concentrate on shopping lists and exhibit fewer emotional influences.

Chandon et al. (2009) also use eye tracking to explain brand choice at store level. However the integrative approach that this research uses grants robustness and expands prior research in two ways: (1) Eye-fixation duration accounts for visual attention on a focal point or area of interest, and the number of brands that consumers or buyers purchase appears to increase with duration. (2) In contrast, looking at different products on the shelf

but without allocating specific time to brands leads to less diversity of brand purchase. Customers appear to look quickly at the offers, looking for a specific brand. Gidlöf and Holmqvist (2013) develop a natural decision segmentation model with three stages (observation, evaluation and verification) and find that a longer observation phase correlates more closely with a high number of fixations, whereas a longer evaluation phase correlates with high average fixation duration. Therefore, this study argues for two patterns of behavior: People who conduct a deeper observation phase, and people who make more effort in the evaluation phase, which is closer to the purchase.

The time spent on the first choice appears to be a condition for subsequent purchases within the product category. Complex decision heuristics deplete resources, resulting in diminished visual attention during subsequent choices (Wästlund et al., 2015). This study shows a new effect. A shorter time to the first buying determines more buying within the same product category.

In addition, factors such as having a pleasant experience or the sensory influence that the packaging or brand elicit in the consumer drive variety-seeking. No empirical proof of the direct effect of specific cues such as packaging exists in this study, but the emotional aspect of the brand is likely to influence the purchase of additional brands. Fixing eye attention on brands may also show a willingness to purchase new brands in the same product category, an idea that non-loyal customer behavior also supports. Apparently, when buyers or customers spend less time on the first choice, they tend to purchase more brands. Retailers should consider this influence when pursuing additional sales by considering product location and time of buying jointly. Future research should address the physical distance of a brand to the chosen brand; that is, further research could examine the distance and time between chosen and non-chosen brands in relation to the first-choice brand.

References

Bohil, C. J., Alicea, B., &, Biocca, F. A. (2011). Virtual reality in neuroscience research and therapy. *Nature Reviews Neuroscience, 12*(12), 752–762.

Carlson, P. Kirpes, C., Pavlik, R. A., Vance, J. M., Yin, L., Scott-Cooper, T., & Lambert, T. (2011). Comparison of single-wall versus multi-wall immersive environments to support a virtual shopping experience. In *ASME 2011 World Conference on Innovative Virtual Reality* (pp. 287-291). American Society of Mechanical Engineers.

Chandon, P., Hutchinson, J. W., Bradlow, E. T., & Young, S. H. (2009). Does in-store marketing work? Effects of the number and position of shelf facings on brand attention and evaluation at the point of purchase. *Journal of Marketing, 73*(6), 1–17.

Gallino, S., & Moreno, A. (2014). Integration of online and offline channels in retail: The impact of sharing reliable inventory availability information. *Management Science, 60*(6), 1434–1451.

Gidlöf, A. W., & Holmqvist, R. D. K. (2013). Using eye tracking to trace a cognitive process: Gaze behaviour during decision making in a natural environment, *Journal of Eye Movmenet Research, 6*(1), 1–14.

Gonzalez, M. C., Hidalgo, C. A., & Barabasi, A. L. (2008). Understanding individual human mobility patterns. *Nature, 453*(7196), 779–782.

Hsu, S.Y., Woodside, A.G., & Marshall, R. (2013). Critical tests of multiple theories of cultures' consequences: Comparing the usefulness of models by Hofstede, Inglehart and Baker, Schwartz, Steenkamp, as well as GDP and distance for explaining overseas tourism behavior. *Journal of Travel Research, 52*(6), 679–704.

Hui, S. K., Bradlow, E. T., & Fader, P. S. (2009). Testing behavioral hypotheses using an integrated model of grocery store shopping path and purchase behavior. *Journal of Consumer Research, 36*(3), 478–493.

Hui, S. K., Huang, Y., Suher, J., & Inman, J. J. (2013). Deconstructing the "First Moment of Truth": Understanding unplanned consideration and purchase conversion using in-store video tracking, *Journal of Marketing Research, 50*(4), 445–462.

Jacoby, J., Speller, D. E., & Kohn, C. A. (1974). Brand choice behavior as a function of information load. *Journal of Marketing Research, 11* (February), 63–69.

Just, M. A., & Carpenter, P. A. (1985). Cognitive coordinate systems: Accounts of mental rotation and individual differences in spatial ability. *Psychological Review, 92*(2), 37–172.

Kahn, B. E. (1995). Consumer variety-seeking among goods and services: An integrative review. *Journal of Retailing and Consumer Services*, *2*(3), 139–148.

Kopetz, C. E., Kruglanski, A. W., Arens, Z. G., Etkin, J., & Johnson, H. M. (2012). The dynamics of consumer behavior: A goal systemic perspective. *Journal of Consumer Psychology*, *22*(2), 208–223.

Orquin, J. L., & Loose, S. M. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica, 144*(1), 190–206.

Pantano, E., & Servidio, R. (2012). Modeling innovative points of sales through virtual and immersive technologies. *Journal of Retailing and Consumer Services, 19*(3), 279–286.

Pantano, E., & Laria, G. (2012). Innovation in retail process: From consumers' experience to immersive store design. *Journal of Technology Management & Innovation, 7*(3), 198–206.

Pfeiffer, T., Pfeiffer, J., & MeiBner, M. (2013). Mobile recommendation agents making online use of visual attention information at the point of sale. *Proceedings of the Gmunden Retreat on NeuroIS 2013*. Retrieved April, 2015 from http://pub.uni-bielefeld.de/publication/2578942

Pieters, R., & Warlop, L. (1999). Visual attention during brand choice: The impact of time pressure and task motivation. *International Journal of Research in Marketing, 16*(1), 1–16.

Ragin, C. (2000) *Fuzzy-Set Social Science*. Chicago, IL: University of Chicago Press.

Ragin, C. (2008) *Redesigning Social Inquiry: Fuzzy Sets and Beyond*. Chicago, IL: University of Chicago Press.

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychological Bulletin, 124*(3), 372–422.

Russo, J. E., & LeClerc, F. (1994). An eye-fixation analysis of choice processes for consumer nondurables. *Journal of Consumer Research, 21*(2), 274–290.

Schneider, C. Q., & Wagemann, C. (2012). *Set-Theoretic Methods for the Social Sciences: A Guide to Qualitative Comparative Analysis*. Cambridge: Cambridge University Press.

Shin, S., Misra, S., & Horsky, D. (2012). Disentangling preferences and learning in brand choice models. *Marketing Science, 31*(1), 115–137.

Statista. (2015). Online and offline share of shopping channels in the United Kingdom Distribution of consumer goods purchases in the United Kingdom (UK) in 2014, by online/offline channel. Retrieved February 23rd, 2015 from Statista website, http://www.statista.com/statistics/320099/online-and-offline-share-of-shopping-channels-in-the-united-kingdom-uk/

Suri, R., & Monroe, K. B. (2003). The effects of time constraints on consumers' judgments of prices and products. *Journal of Consumer Research*, *30*(1), 92–104.

Turley, L. W., & Milliman, R. E. (2000). Atmospheric effects on shopping behavior: A review of the experimental evidence. *Journal of Business Research, 49*(2), 193–211.

Van der Laan, L. N., Hooge, I. T. C., De Ridder, D. T. D., Viergever, M. A., & Smeets, P. A. M. (2015). Do you like what you see? The role of first fixation and total fixation duration in consumer choice. *Food Quality and Preference*, *39*, 46–55.

Van Trijp, H. C., Hoyer, W. D., & Inman, J. J. (1996). Why switch? Product category: level explanations for true variety-seeking behavior. *Journal of Marketing Research*, *33*(3), 281–292.

Vlaskamp, B. N., & Hooge, I. T. C. (2006). Crowding degrades saccadic search performance. *Vision Research, 46*(3), 417-425.

Walvis, T.H. (2008). Three laws of branding: Neuroscientific foundations of effective brand building. *Journal of Brand Management*, *16*(3), 176-194.

Wästlund, E., Otterbring, T., Gustafsson, A., & Shams, P. (2015). Heuristics and resource depletion: eye-tracking customers' in situ gaze behavior in the field. *Journal of Business Research*, *68*(1), 95-101.

Wedel, M., & R. Pieters (2014). Looking at vision: Eye/face/head Tracking of Consumers for Improved marketing decisions. In L. Moutinho, L. Bigné, & A. K. Manrai (Eds.), *Routledge Companion on Future of Marketing.*New York: Routledge, 177-189.

Woodside, A.G. (2012). Proposing a new logic for data analysis in marketing and consumer behavior: Case study research of large-N survey data for estimating algorithms that

accurately profile X (extremely high-use) consumers. *Journal of Global Scholars of Marketing Science*, *22*(4), 277–289.

Zhang, X., Li, S., Burke, R. R., & Leykin, A. (2014). An examination of social influence on shopper behavior using video tracking data. *Journal of Marketing*, *78*(5), 24–41.

Table 1. Calibration of the conditions for continuous indicators and the outcome

	0.05 Full Non-Membership	**0.5 Crossover Point**	**0.95 Full Membership**
Number of SKU purchased (NUMBER)	3	6	10
First Choice/Time spent shopping (FIRST)	0.08	0.18	0.50
Time spent shopping (TIME)	172	296	495
Average Fixation Duration (AFD)	130	158	215
Number of fixations per second (FIX_S)	4.6	6.3	7.6
Outcome: Brand Diversity (BRAND_DIV)	2	4	6

Table 2. Analysis of necessary conditions

	Outcome_BRAND_DIV		**Outcome_~BRAND_DIV**	
Conditions tested	**Consistency**	**Coverage**	**Consistency**	**Coverage**
COM	0.849760	0.443056	0.901934	0.556944
~COM	0.150240	0.564000	0.098066	0.436000
CONS	0.917421	0.465405	0.889789	0.534595
~CONS	0.082579	0.387500	0.110211	0.612500
LOYAL	0.384656	0.424706	0.439946	0.575294
~LOYAL	0.615344	0.481250	0.560054	0.518750
NUMBER	0.825253	0.807191	0.437247	0.506514
~NUMBER	0.495472	0.426410	0.833558	0.849610
FIRST	0.445924	0.435937	0.706703	0.818229
~FIRST	0.814065	0.700917	0.512821	0.522936
TIME	0.624401	0.574792	0.580747	0.633154
~TIME	0.601492	0.547792	0.609987	0.657933
AFD	0.649973	0.610916	0.672200	0.636955
~AFD	0.613745	0.547789	0.650472	0.687589
FIX_S	0.603090	0.546596	0.638327	0.685176
~FIX_S	0.652637	0.603746	0.577598	0.632824

Table 3. Analysis of sufficient conditions for the outcome “brand diversity” (Outcome_BRAND DIVERSITY)

fs_Outcome_BRAND DIVERSITY = f (COM, CONS, LOYAL, BRAND, NUMBER, FIRST, TIME, DF, FIX_S) **Intermediate Solution**											
Config. nº	**Antecedent Conditions**								**Coverage**		**Consistency**
	COM	**CONS**	**LOYAL**	**NUMBE**	**FIRST**	**TIME**	**AFD**	**FIX_S**	**Raw**	**Unique**	
1	●	●		●	○		●	○	0.379862	0.022376	0.860072
2	●	●		●	○	○			0.353756	0.100693	0.823821
3	●	●	○	●	○				0.348428	0.075120	0.899587
4	●	●	○	●			●	○	0.293554	0.033564	0.790531
5		●	○	●		○			0.212573	0.057006	0.801205
6	●	●	●		●	○	●	○	0.1111348	0.033564	0.933036
solution consistency: 0.817791; solution coverage: 0.710176											
frequency cutoff: 1.00 / consistency cutoff: 0.805668											
Note: black circles “●” indicate the presence of antecedent conditions. White circles “○” indicate the absence or negation of antecedent conditions. The blank cells represent ambiguous conditions.											

Table 4. Analysis of sufficient conditions for the outcome “absence of brand diversity” (Outcome_~BRAND DIVERSITY)

~fs_Outcome_BRAND DIVERSITY = f (COM, CONS, LOYAL, BRAND, NUMBER, FIRST, TIME, DF, FIX_S) **Intermediate Solution**											
Config. nº	**Antecedent Conditions**								**Coverage**		**Consistency**
	COM	**CONS**	**LOYAL**	**NUMBE**	**FIRST**	**TIME**	**AFD**	**FIX_S**	**Raw**	**Unique**	
1	●	●		○			○	●	0.446694	0.084570	0.928037
2	●			○	●	●			0.365722	0.062078	0.920725
3		●			●	○	○	●	0.316689	0.045884	0.928037
4	●	●		○	○	○			0.271705	0.038237	0.838889
5	●		●	○	●		○	●	0.210076	0.006748	0.979036
6	●	●	○	○	●		●	○	0.209627	0.027440	0.917323
solution consistency: 0.887131; solution coverage: 0.756635											
frequency cutoff: 1.00 / consistency cutoff: 0.825503											
Note: black circles “●” indicate the presence of antecedent conditions. White circles “○” indicate the absence or negation of antecedent conditions. The blank cells represent ambiguous conditions.											