Journal of Retailing 91 (2, 2015) 235–253

Journal of Retailing

The Impact of Different Touchpoints on Brand Consideration

Shane Baxendale[a], Emma K. Macdonald[a,b,*], Hugh N. Wilson[a]

[a] Cranfield School of Management, Cranfield University, United Kingdom
[b] School of Marketing, University of South Australia, Australia

Abstract

Marketers face the challenge of resource allocation across a range of touchpoints. Hence understanding their relative impact is important, but previous research tends to examine brand advertising, retailer touchpoints, word-of-mouth, and traditional earned touchpoints separately. This article presents an approach to understanding the relative impact of multiple touchpoints. It exemplifies this approach with six touchpoint types: brand advertising, retailer advertising, in-store communications, word-of-mouth, peer observation (seeing other customers), and traditional earned media such as editorial. Using the real-time experience tracking (RET) method by which respondents report on touchpoints by contemporaneous text message, the impact of touchpoints on change in brand consideration is studied in four consumer categories: electrical goods, technology products, mobile handsets, and soft drinks. Both touchpoint frequency and touchpoint positivity, the valence of the customer's affective response to the touchpoint, are modeled. While relative touchpoint effects vary somewhat by category, a pooled model suggests the positivity of in-store communication is in general more influential than that of other touchpoints including brand advertising. An almost entirely neglected touchpoint, peer observation, is consistently significant. Overall, findings evidence the relative impact of retailers, social effects and third party endorsement in addition to brand advertising. Touchpoint positivity adds explanatory power to the prediction of change in consideration as compared with touchpoint frequency alone. This suggests the importance of methods that track touchpoint perceptual response as well as frequency, to complement current analytic approaches such as media mix modeling based on media spend or exposure alone.

Keywords: Retailing; Advertising; Integrated marketing communications; In-store communications; Word-of-mouth (WOM)

Introduction

There is a stream of research comparing the impact of various paid-for media, which is helpful to marketers in determining their overall media spend and its allocation across media (Naik and Peters 2009). Brand owners have a bigger challenge, however: how to allocate budgets and management time across the wider range of touchpoints that occur in the customer decision journey (Court et al. 2009). These broader touchpoints go beyond the brand advertising which is generally referred to as paid media (or owned media where the firm does not have to pay directly), to include for example traditional earned media such as editorial coverage. Peer-to-peer encounters with the brand such as word-of-mouth (WOM) conversation can also be regarded as earned touchpoints (Stephen and Galak 2012). In the case of consumer goods sold through retailers, the focus of this article, the retailer may also pay for advertising that mentions the brand. Furthermore, the store itself is far more than a fulfillment channel to convert pre-existing intentions to purchases. In-store communications can also bring new brands into active consideration (Court et al. 2009; Goodman et al. 2013) and influence immediate or subsequent purchase irrespective of channel (Verhoef, Neslin, and Vroomen 2007). Of these touchpoints, the brand owner only directly controls brand advertising, but all are potentially within the brand owner's influence. The resulting resource allocation challenge in turn leads to a measurement challenge: assessing the relative importance of these diverse touchpoints in evolving the customer's brand attitudes and hence behaviors.

* Corresponding author at: Cranfield School of Management, Cranfield University, Cranfield, Bedofrdshire MK43-0AL, United Kingdom.
Tel.: +44 07788 543 905.
E-mail addresses: S.Baxendale@Cranfield.ac.uk (S. Baxendale), Emma.Macdonald@Cranfield.ac.uk (E.K. Macdonald), Hugh.Wilson@Cranfield.ac.uk (H.N. Wilson).

http://dx.doi.org/10.1016/j.jretai.2014.12.008
0022-4359/

Despite widespread agreement that the customer decision journey needs to be understood across all touchpoints (Wiesel, Pauwels, and Arts 2010), most research focuses on parts of this journey in isolation, such as brand advertising, in-store communications, or WOM. Such focused studies are undoubtedly necessary, providing granular insight into these parts of the journey. However, managers also have an interest in understanding comparative effects of diverse touchpoints in an equivalent manner in order to inform the complete marketing plan. Multiple touchpoints in the consumer search process, including customer interactions with 'sales' channels, can be viewed symmetrically until final choice occurs, as the search process may iterate indefinitely while consumers revise brand/channel utilities (Neslin et al. 2014). Such a holistic view of touchpoints is particularly important as media fragmentation sees brand managers increasingly allocate their budgets to what are still often described as "unmeasured media" such as news media coverage and in-store communications (Ailawadi et al. 2009, p. 50).

We speculate that the paucity of empirical studies across multiple touchpoints is in large part due to data availability. In Table 1 we show representative examples of research that does assess the impact of multiple touchpoints. While rich individual-level data are available for retail transactions and promotions from loyalty-card holders and consumer panels (Ngobo 2011), these data sources do not reach other parts of the journey such as WOM. Aggregate-level data such as media spend can be used to model the relative impact of some market mix variables on consumer response (Naik and Peters 2009), but again there are parts of the journey such as peer-to-peer touchpoints that this method cannot reach. In the online context, automatically captured data can allow a rich picture of the customer journey (Trusov, Bucklin, and Pauwels 2009), but there is no ready equivalent for offline brand encounters. Surveys can in theory ask about touchpoints holistically, but respondents find it difficult to remember touchpoints accurately (Wind and Lerner 1979); in particular, affective response decays rapidly and is recalled poorly (Aaker, Drolet, and Griffen 2008). Marketing practitioners tend, therefore, to use brand tracking surveys only for a few frequent and memorable touchpoints such as television advertisements.

In this article, we therefore apply the emerging real-time experience tracking (RET) method to understand how a range of touchpoints impacts on brand consideration. Adopted by a number of companies such as BSkyB, Energizer, Microsoft and Intercontinental Hotels (Macdonald, Wilson, and Konuş 2012), the RET method involves asking a panel of consumers to send a structured text (SMS) message by mobile phone whenever they encounter one of a set of competitive brands within a category for a period of a week. This has the benefit of allowing a wide range of touchpoints to be reported, including those such as offline WOM that leave no behavioral trace. It also allows touchpoint positivity, the valence of the customer's affective response to the touchpoint (Kahn and Isen 1993), to be captured. By pooling multiple RET samples, we study four categories: electrical goods, technology products, mobile phone handsets, and soft drinks. These categories provide a spread of high involvement, extended decision journeys in mobile handsets, and in technology products such as laptops, cameras, and televisions; somewhat lower involvement journeys in electrical goods, such as blenders and dishwashers; and repertoire brands in the case of soft drinks

Through these data, we hence address two objectives. First, we examine the impact on change in brand consideration of six broad touchpoints: brand advertising; retailer advertising; in-store communications; peer-to-peer conversation; traditional earned media; and peer observation (observing other customers). Second, we examine the roles of both touchpoint frequency and touchpoint positivity in forming this impact.

This study thereby makes three contributions to multichannel and brand choice literature. First, we evidence the relative role of multiple touchpoints in evolving brand consideration. All six touchpoints are significant in at least three categories. While relative touchpoint effects vary somewhat by category, a pooled model suggests the positivity of in-store communication is in general more influential than that of other touchpoints including brand advertising. Furthermore, an almost entirely neglected touchpoint, peer observation, is both pervasive and persuasive. Overall, our findings evidence the relative impact of retailers, social effects and third party endorsement in addition to brand advertising. Second, we highlight the roles of both touchpoint positivity and frequency across this wide range of touchpoints. In particular, we find that positivity adds to the explanatory power of a model predicting consideration change based on frequency alone. This suggests a limitation of media mix modeling based on media spend as a proxy for frequency. Third, we propose and exemplify a RET-based approach by which both the positivity and the frequency of multiple touchpoints can be assessed in further categories and with further touchpoints.

In the following sections, we develop a conceptual framework, describe the data collection and data analysis in more detail, present findings, and discuss implications for practice as well as research directions.

Conceptual Framework

We view the customer search process as consisting of a number of discrete encounters with varying touchpoints, such as advertisements, WOM, and so on. See Fig. 1. Drawing on Court et al. (2009), we define a touchpoint as an episode of direct or indirect contact with the brand. Thus touchpoints include but are not limited to channels as defined by Neslin et al. (2006, p. 96) as: "a customer contact point, or a medium through which the firm and the customer interact". We suggest an expansion of this definition is required, as the emphasis here on interaction commonly excludes one-way communications such as television advertising, while the emphasis on the firm may exclude brand encounters such as WOM in which the firm is not directly involved.

Our choice of touchpoints emphasizes breadth in the stakeholder who the customer touches, from the brand owner (brand advertising) and the retailer (retailer advertising and in-store communications) to peers (WOM and peer observation) and independent third parties such as editorial and expert reviews (traditional earned media). In the interests of parsimony we combine subtypes within each of these touchpoints: online and

Table 1
Illustrative studies on the impact of multiple touchpoint types.

	Context	Data collection	Main dependent variable(s)	Touchpoints						Real-time encounter recording	Perceptual response
				Brand advertising	Retailer advertising	In-store comms.	WOM	Peer observation	Traditional earned media		
Stephen and Galak (2012)	Lending	Search, media scanning	Sales				*		*	*	
Ngobo (2011)	Grocery	Panel data	Preference, purchase intention		*	*					
Stammerjohan et al. (2005)	Credit cards	Experiment	Attitude to brand	*					*		*
Trusov, Bucklin, and Pauwels (2009)	Social network	Transaction data	Member growth	*			*			*	
van der Lans et al. (2010)	Viral marketing	Online form	Participation in the campaign	*			*				
O'Cass (2002)	Politics	Survey	Attitude to brand	*			*		*		
Ataman, van Heerde, and Mela (2010)	Multiple	Panel data	Sales	*		*					
This paper	*Multiple consumer goods*	*Real-time experience tracking*	*Consideration*	*	*	*	*	*	*	*	*

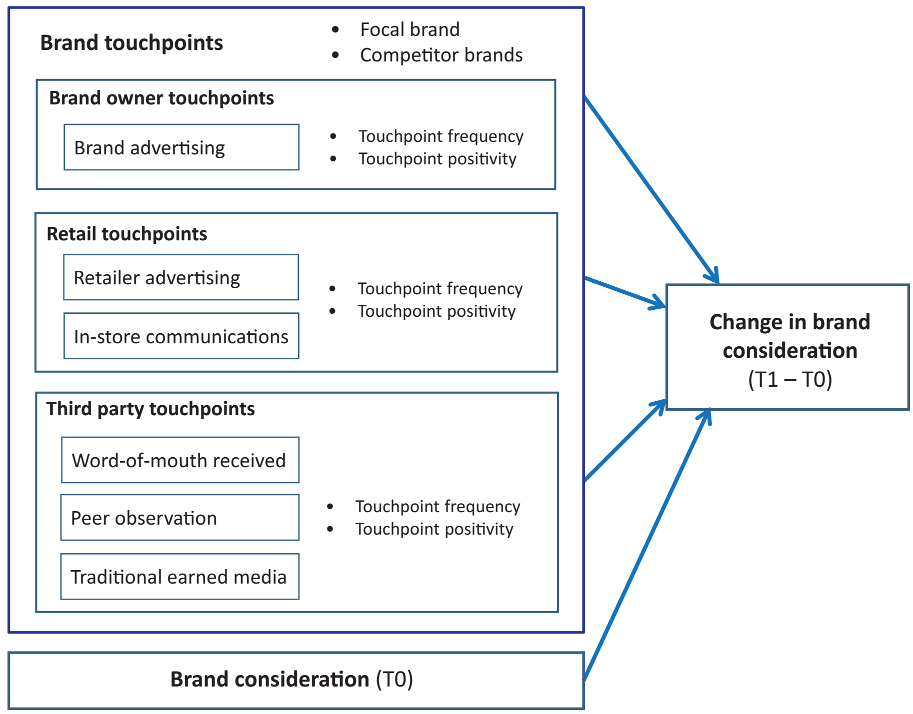

Fig. 1. Conceptual framework.

offline WOM, for example. We model the impact of these touchpoints on change in consideration, taking account of prior consideration.

Touchpoint Frequency and Positivity

Unlike many time-series media mix studies (Thomas and Sullivan 2005), our study allows for customer heterogeneity in touchpoint frequency. Frequency may impact brand attitudes by increasing brand awareness (Yaveroglu and Donthu 2008). Repetition can also improve learning (Goh, Hui, and Png 2011). In addition, we consider perceptual response to touchpoints. Despite experimental findings that perceptual response to advertisements impacts attitudes (Briñol, Petty, and Tormala 2004), many models of field data, particularly in the case of paid media, focus purely on frequency or media spend, presumably because perceptual response data are frequently unavailable. This makes it difficult to untangle the effect of the medium from that of the message. Inspired by WOM research, we model perceptual response with touchpoint positivity, which we define as the valence of the customer's affective response to the encounter (Kahn and Isen 1993). Affective response has been shown to impact on spending and repeat purchase intentions (Arnold and Reynolds 2009; Liu 2006). While affective response can be viewed multidimensionally (Chitturi, Raghunathan, and Mahajan, 2008), qualitatively different emotions can be related to the unidimensional construct of affective valence or positivity (Kahneman and Krueger 2006; Westbrook and Oliver 1991). Positivity is associated with outcomes including satisfaction (Westbrook and Oliver 1991), commitment (Ahluwalia, Burnkrant, and Unnava 2000), variety seeking (Kahn and Isen 1993), and consideration (Desai and Raju 2007). We adopt positivity here in the interests of model parsimony. Post-touchpoint affect forms part of the customer's evaluative response as affective markers remain in episodic memory thereafter (Westbrook and Oliver 1991), influencing future brand-related cognitions (Baumeister et al. 2007). After a period of time, however, affective response may be not just imperfectly recalled but also reconstructed for reasons such as self-justification (Cowley 2008). This suggests that touchpoint positivity should be assessed immediately after the encounter, rather than retrospectively in surveys.

Brand Consideration

We focus for parsimony on one brand attitude construct: brand consideration. Following Roberts and Lattin (1997), we define consideration as the extent to which the customer would consider buying the brand in the near future. It is hence closely related to purchase intention, but allows for the observation that customers evoke a set of brands, which may evolve over time, between which they then choose based on a comparison of utility (Neslin et al. 2014). Priester et al. (2004) provide experimental support for the mediating role of consideration between evolving attitudes to the brand on the one hand and purchase on the other. Brand consideration is hence useful as an intermediate outcome variable when purchase data are not available. Court et al. (2009), in particular, conceive of the consumer decision journey as an interplay between multiple touchpoints and the consumer's evolving brand consideration. We add to this work more granularity of method description, real-time data collection, the distinction between touchpoint frequency and positivity, and further touchpoints such as peer observation. Another reason for adopting consideration is that it is in common use among practitioners for evaluating consumer response, as it is readily studied through brand tracker surveys.

Touchpoints

See Fig. 1 for the touchpoints captured in this study. First, we examine separately advertisements by the brand owner and the retailer. Media spend models do not necessarily pick up the latter (Naik and Peters 2009). Next, we examine in-store communications, including touchpoint subtypes such as viewing in-store posters and seeing prominent display of the product on the shelf (Ailawadi et al. 2009). In a bar or restaurant, subtypes include posters, beer mats, and seeing display of the product behind the bar.

The first of two peer-to-peer touchpoints is peer observation. The impact of other customers in the retail or consumption environment has been explored relatively sparsely as compared with customer-firm interactions (Verhoef et al. 2009). Nonetheless, both qualitative (Borghini et al. 2009) and a few quantitative (Sweeney and Soutar 2001) studies suggest that other customers can impact brand attitudes through observation alone without the explicit recommendation or criticism of WOM. Observing peers may impact service satisfaction (Grove and Fisk 1997); the similarity of others may increase purchase intentions (Thakor, Suri, and Saleh 2008); and consumers who purchase products with the support of others may form more enduring brand relationships (McAlexander, Schouten, and Koenig 2002). The influence of others is higher in environments where consumption is public (Bearden and Etzel 1982); this is the case to differing extents in our four categories. The second peer-to-peer touchpoint is WOM, defined as any conversation (whether online or offline) with other individuals in which the brand is mentioned. The impact of WOM has often been examined in isolation from other touchpoints (East, Hammond, and Lomax 2008). Exceptions largely concern WOM in social media which has been the focus of much recent attention (Archak, Ghose, and Ipeirotis 2011; Liu 2006).

Finally, earned media such as editorial and news coverage has been recently rebranded as traditional earned media to distinguish it from social media (Stephen and Galak 2012). Such earned communications have been the subject of some dedicated time series studies (Goh, Hui, and Png 2011), though as Stephen and Galak (2012, p. 626) document in their extensive literature review on earned media, “often only one source of publicity is examined, precluding comparisons between different types of channels”. Overall, these authors observe, “The effects of paid media on sales have been extensively covered in the marketing literature. The effects of earned media, however, have received limited attention”.

Method

Data Collection Approach and Sample

See Fig. 2 for our operationalization of the RET method. Data were collected by MESH, a market research firm which pioneered the method, on behalf of multiple sponsoring brand owners over the four categories. Data were collected in Northern America and Europe. First, an online survey was used to collect demographics and brand consideration for a set of competitive brands at time T0; consideration was collected again at the end of the week (time T1). Second, participants were asked to send a text message whenever they encountered one of the brands during the seven days of the study. Each participant was sent an initial text message which documented the code frame in Fig. 2 so they always had the required information to hand. This enabled the capture of touchpoints as they occurred as well as participants’ real-time affective response in a positivity measure.

Within each category, a sample of consumers looking to purchase within the next three to twelve months (depending on the category) was recruited via an online panel (Table 2). In the case of soft drinks participants were regular drinkers of carbonated drinks. The data were collected over a period of several months (dependent on the category) through weekly samples in each category, with a new set of participants recruited each week. This approach was adopted in order to expand the sample and to allow sponsoring firms to track trends over time.

Each SMS message recorded the brand, the touchpoint, and the participant’s real-time assessment of touchpoint positivity. Participants were briefed with a coding scheme for the message, with a letter for each brand, a letter for each touchpoint, and a Likert-scale number for positivity; so, for example, “BA5” might represent a brand named “Quench” (name amended for confidentiality); a TV advertisement; and a positivity rating of 5 (very positive) on a 5-point scale (measures are described below). The conciseness of the message had the aim of minimizing the disruption to the participant’s life. While touchpoints were collected in detail (such as television, radio, billboards and so on), they were aggregated into the broad touchpoints (such as brand advertising) shown in Fig. 1, for analysis purposes. To enhance validity in this coding, participants were asked to visit an on-line diary at their convenience (typically in the evening) every two days, where the texts they had sent were displayed. In the diary, they were asked to provide further details about each touchpoint through a pull-down menu containing touchpoint sub-types. This allowed checking, for example, whether a magazine touchpoint was an advertisement from the brand, an advertisement from a retailer, editorial material, and so on.

We excluded from analysis any participants where pre-consideration or post-consideration was missing. We also excluded those who did not report any brand encounters at all, as these participants either did not engage with the process and hence constitute missing data, or genuinely had no encounters which is of limited interest to our research objectives. We also cleaned the data to ensure validity of entries; if any touchpoint was recorded with invalid codes then the participant was removed. We used listwise deletion as imputation methods can lead to bias in coefficients and as the sample size was regarded as sufficient to allow a slight loss of power. 265 (6.0%) electrical goods participants were excluded from the final dataset, 260 (4.4%) technology products participants, 204 (10.7%) mobile handset participants, and 62 (2.5% of sample) soft drinks participants. Table 2 shows the base sizes after excluding these participants, ranging from 1709 for mobile phones to 5632 for technology products.

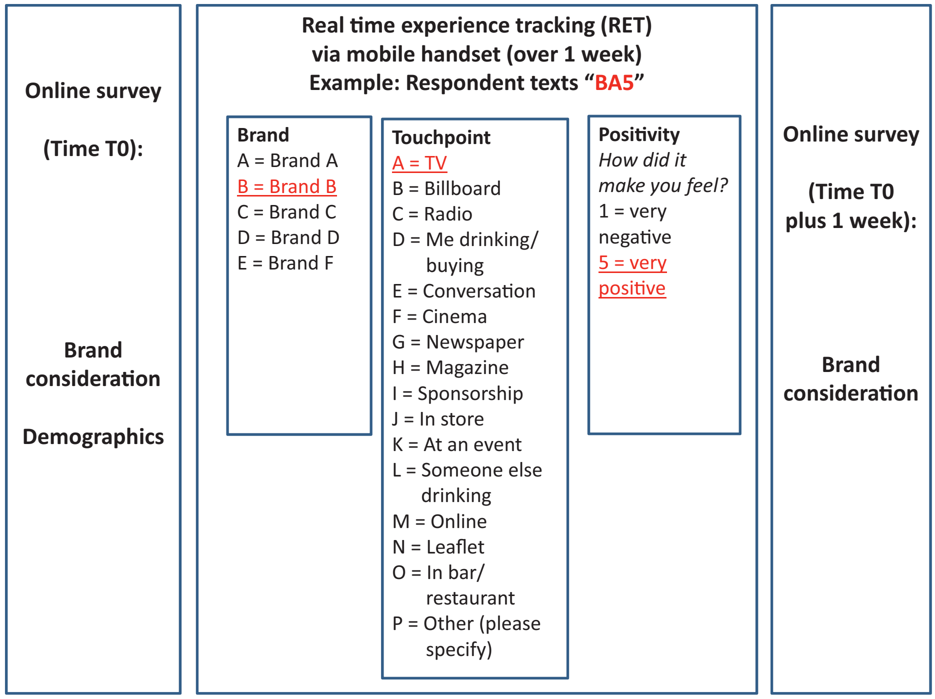

Fig. 2. Method.

Measures

Brand consideration was measured using a 6-point scale, anchored by: '*This is the only brand that I would consider purchasing*' and '*I would definitely not consider purchasing it*'. This is similar to Bian and Moutinho (2009). Positivity was measured with a single Likert-scale item "*How did it make you feel about the brand?*" on a 5-point scale anchored by '*very positive*' and '*very negative*', similarly to McFarland and Buehler (1998) amongst others. Touchpoint frequency was calculated by counting the touchpoints of a given type: so, if a respondent sees two advertisements for a brand over the week, the touchpoint frequency is 2. Positivity was re-centered around 0, such that 0 represented neutral encounters, +2 very positive and −2 very negative encounters. This was then averaged for each respondent and touchpoint type: so, if the respondent rates one brand advertisement as 4 and another as 5, the average positivity (after re-centering) is 1.5. If the participant did not report a touchpoint (i.e., frequency is zero), average positivity was coded as zero. Hence in a regression the impact of neutral touchpoints (or if the average positivity is zero) is equivalent to the impact of frequency. Hence the impact of positivity can be interpreted as the impact above the neutral baseline of frequency, aiding interpretation. We return later to some robustness checks on this approach to modeling frequency, positivity, and our decision to code positivity as zero where a touchpoint did not occur during the week.

Models

We combine the data from our four categories in a pooled model to further increase the sample size and deliver generalized results. We weight the data such that each brand is represented in the dataset equally to prevent any bias toward those categories

Table 2
Sample definition.

	Electrical goods	Technology products	Mobile handsets	Soft drinks
Sample definition[a]				
Age	18–64	18–64	18–64	16–44
Number of encounters				
Brand advertising	4446	4227	3033	4198
Retailer advertising	7254	7003	1096	736
In-store communications	4202	7002	1890	5402
WOM	1132	1706	1403	659
Peer observation	2201	2689	2550	2693
Traditional earned media	795	2462	299	104
Respondents	4176	5632	1709	2445

[a] Either a current user or purchasing within the next few months, depending on the study.

with a greater sample size. We model the change in consideration (T1 consideration minus T0 consideration) at the customer level for each brand by using prior (T0) brand consideration, demographics, brand dummies, and time of year as control variables. We then explain additional variability through incorporating touchpoint frequency and positivity variables for both the focal brand and competitor brands. As we observe multiple responses per customer (one response for each brand in their study), there is likely to be unmodeled heterogeneity across each set of customer responses caused, for example, by unobserved covariates at the customer level. To account for this, we include a respondent-level random intercept via a linear mixed-effects model.

The correlation matrix in Table 3 indicates no severe multi-collinearity problems; however, we do notice high correlations between the frequency and positivity of each touchpoint, which we return to in an exploratory analysis below. As a further check we calculated the variance inflation factors (VIF) for the explanatory variables in each model. All VIF values (summarized in Table 4) fall below the recommended cut off of 5 (O'Brien, 2007), suggesting multi-collinearity is not of concern.

Our model formulation is as follows:

$$
\begin{aligned}
Consid\ Post_{i,k} - ConsidPre_{i,k} &= \alpha + b_i + \beta^{pre} ConsidPre_{i,k} \\
&+ \beta^{brand} Brand_k + \beta_1^{time} Quarter_i + \beta_2^{time} Year_i + \beta_1^{dem} Age_i \\
&+ \beta_2^{dem} Sex_i + \sum_{j=1}^{J} \{\beta_j^{freq} \ln(Freq_{i,k,j} + 1) + \beta_j^{pos} AvgPos_{i,k,j} \\
&+ \gamma_j^{freq} \ln(Freq_{i,-k,j} + 1) + \gamma_j^{pos} AbgPos_{i,-k,j}\} + \in_{i,k}
\end{aligned}
$$

where $ConsidPost_{i,k}$ and $ConsidPre_{i,k}$ are the consideration scores of individual i for brand k after and before the week of texting, respectively, $Brand_k$ is a dummy variable accounting for heterogeneity across brands, $Quarter_i$ and $Year_i$ are dummy variables identifying when individual i was tracked, Age_i and Sex_i are variables for the age and sex of individual i. Age is treated as a continuous variable and Sex is a dummy variable taking 1 for male and 0 for female, $Freq_{i,k,j}$ and $AvgPos_{i,k,j}$ are the frequency and average positivity of encounters individual i has through touchpoint j for brand k, and J is the total number of touchpoints in the model, $Freq_{i,-k,j}$ and $AvgPos_{i,-k,j}$ are the frequency and average positivity of encounters individual i has through touchpoint j for all brands other than k (i.e., competitors to the focal brand).

We build this model sequentially and summarize the model fit for each in Table 4:

Model 1: Only the control variables are included. This is to identify how respondent-level data can measure consideration shifts and to provide a baseline for future models.[1]

Model 2: As we anticipate that changes in consideration will also be a function of brand touchpoints, Model 2 builds on the previous model by adding touchpoint frequency with a natural logarithmic decay.

Model 3: We then add touchpoint positivity to distinguish touchpoint frequency from touchpoint perceptual response.

Model 4: While Model 3 only looks at same-brand effects, such as brand A's touchpoints impacting on brand A consideration, in Model 4 we add competitor touchpoint frequency and positivity; we would expect these to have a negative effect on the focal brand's consideration.

Model Selection

We compared and selected models on the basis of their AIC (Akaike's Information Criterion) and BIC (Bayesian Information Criterion), with BIC preferring simpler models (fewer parameters) than AIC. Improved model fit is evidenced by decreases in information criterion between models; however, neither AIC or BIC gives an absolute indication of fit (Burnham and Anderson 2004). We also therefore use the marginal and conditional r^2 values for mixed-effects models (Nakagawa and Schielzeth, 2013). Marginal r^2 demonstrates the amount of variability explained by only the fixed effects in our models, and conditional r^2 demonstrates the variability explained by both fixed and random effects.

Further, we calculated model fit statistics for each category in isolation, to understand which model best fits individual category data. If we were to take the full data for each category then we might expect the categories with a higher sample size to prefer more complex models due to the formula used to calculate AIC and BIC. To avoid this bias we restricted the sample to 1,500 respondents per category when calculating fit statistics. Using a bootstrapping technique, we took a random sample with replacement of 1,500 respondents from each category and calculated AIC, BIC, and r^2 values for Models 1–4 using that sample. We performed 5,000 iterations of this procedure and took the average of the model statistics. See Table 4.

In the case of the pooled data, according to both AIC and BIC the full Model 4 is preferred. Fixed effects explain 19.6% of the variability in a respondent's change in consideration, with unobserved individual-level covariates (random intercept) accounting for a further 12.2%. By contrast, AIC indicates Model 3 is preferred for the individual categories, likely due to the lower sample size when compared to the pooled data. BIC also favors Model 3, except in soft drinks where Model 1 is preferred. This could be due to the higher price-tag and extended purchase journey for electrical goods, technology products, and mobile handsets when compared to soft drinks, more factors hence influencing consideration. Given that r^2 continues to rise until Model 4 in soft drinks, for simplicity we will only consider Model 3 when reporting individual category results.

[1] We also tested alternatives to Models 1 to 3 in which the dependent variable was post-study consideration and not change in consideration. Naturally, the pre-consideration coefficient was substantial and positive (β ranging from 0.52 in electrical goods to 0.71 in soft drinks in Model 3) as pre-consideration acts as an initial estimate for post-consideration. However, substantive results regarding the role of touchpoint frequency and positivity, including which variables were significant and coefficient magnitudes, were very similar to those reported here, suggesting robustness of the model with respect to this choice of dependent variable. We therefore do not report these in full.

Table 3
Correlation matrix: pooled data.

	Mean	Standard deviation	Conside-ration (pre)	Age	Sex	Frequency						Average positivity					
						Traditional earned	Brand advertising	WOM	Peer observation	In-store communica-tions	Retailer advertising	Traditional earned	Brand advertising	WOM	Peer observation	In-store communica-tions	Retailer advertising
Consideration (post–pre)	−0.02	*1.12*	-0.38^{**}	-0.02^{**}	-0.01^{*}	0.02^{**}	0.06^{**}	0.02^{**}	0.03^{**}	0.07^{**}	0.03^{**}	0.05^{**}	0.03^{**}	0.05^{**}	0.06^{**}	0.08^{**}	0.06^{**}
Consideration (pre)	3.79	*1.17*	1.00														
Age	37.11	*11.41*	0.04^{**}	1.00													
Sex (male)	43%		0.01	-0.01^{*}	1.00												
Frequency																	
Traditional earned	0.04	*0.23*	0.04^{**}	0.00	0.00	1.00											
Brand advertising	0.17	*0.56*	0.02^{**}	-0.03^{**}	0.03^{**}	0.05^{**}	1.00										
WOM	0.05	*0.30*	0.03^{**}	-0.04^{**}	0.02^{**}	0.06^{**}	0.1^{**}	1.00									
Peer observation	0.10	*0.43*	0.03^{**}	-0.05^{**}	0.00	0.02^{**}	0.05^{**}	0.08^{**}	1.00								
In-store com-munications	0.19	*0.57*	0.05^{**}	0.01^{*}	0.00	0.01^{**}	0.03^{**}	0.05^{**}	0.08^{**}	1.00							
Retailer advertising	0.16	*0.56*	0.07^{**}	0.11^{**}	-0.03^{**}	0.02^{**}	0.03^{**}	0.02^{**}	0.00	0.04^{**}	1.00						
Average positivity																	
Traditional earned	0.02	*0.20*	0.06^{**}	0.00	-0.01^{*}	0.54^{**}	0.00	0.02^{**}	0.01^{**}	0.01^{**}	0.01^{*}	1.00					
Brand advertising	0.10	*0.39*	0.07^{**}	-0.01^{*}	0.01^{**}	0.01	0.55^{**}	0.03^{**}	0.02^{**}	0.02^{**}	0.02^{**}	0.01^{**}	1.00				
WOM	0.03	*0.25*	0.06^{**}	-0.01^{**}	0.01	0.02^{**}	0.04^{**}	0.44^{**}	0.04^{**}	0.04^{**}	0.02^{**}	0.03^{**}	0.05^{**}	1.00			
Peer observation	0.05	*0.32*	0.09^{**}	-0.02^{**}	-0.01^{**}	0.03^{**}	0.02^{**}	0.04^{**}	0.46^{**}	0.04^{**}	0.00	0.04^{**}	0.02^{**}	0.05^{**}	1.00		
In-store com-munications	0.12	*0.44*	0.12^{**}	0.04^{**}	-0.01^{**}	0.02^{**}	0.01^{**}	0.04^{**}	0.02^{**}	0.52^{**}	0.02^{**}	0.04^{**}	0.03^{**}	0.06^{**}	0.06^{**}	1.00	
Retailer advertising	0.08	*0.34*	0.09^{**}	0.07^{**}	-0.03^{**}	0.01^{**}	0.02^{**}	0.01^{**}	0.00	0.03^{**}	0.48^{**}	0.02^{**}	0.05^{**}	0.03^{**}	0.03^{**}	0.06^{**}	1.00

Significant parameters:
** $p < .01$.
* $p < .05$.

Table 4
Model statistics.

Model	AIC	BIC	r^2 marginal	r^2 conditional	Average VIF	Maximum VIF
Pooled data						
Model 0: Null	248,999	249,027	0.0%	16.7%	NA	NA
Model 1: Baseline	235,861	236,186	14.6%	26.6%	2.02	2.49
Model 2: Frequency	233,931	234,330	16.7%	29.4%	1.91	2.60
Model 3: Positivity	231,244	231,717	19.4%	32.0%	1.92	2.62
Model 4: Competitor effects	230,905[a]	231,527[a]	19.6%	31.8%	1.84	2.67
Electrical goods[b]						
Model 0: Null	26,029	26,051	0.0%	18.6%	NA	NA
Model 1: Baseline	24,584	24,705	17.1%	28.5%	1.44	1.82
Model 2: Frequency	24,337	24,513	19.8%	32.2%	1.37	1.86
Model 3: Positivity	24,036[a]	24,269[a]	22.7%	35.1%	1.55	2.04
Model 4: Competitor effects	24,068	24,414	23.3%	34.9%	1.55	2.08
Technology products[b]						
Model 0: Null	19,241	19,262	0.0%	17.0%	NA	NA
Model 1: Baseline	18,152	18,253	17.8%	25.9%	1.30	1.62
Model 2: Frequency	17,962	18,117	20.6%	30.5%	1.30	1.81
Model 3: Positivity	17,734[a]	17,943[a]	23.8%	34.3%	1.61	2.18
Model 4: Competitor effects	17,737	18,055	24.8%	34.1%	1.62	2.22
Mobile handsets[b]						
Model 0: Null	20,060	20,081	0.0%	15.4%	NA	NA
Model 1: Baseline	18,840	18,947	18.8%	30.1%	1.53	1.80
Model 2: Frequency	18,710	18,871	21.2%	33.3%	1.38	1.84
Model 3: Positivity	18,499[a]	18,715[a]	24.1%	36.2%	1.60	2.19
Model 4: Competitor effects	18,549	18,872	24.5%	36.0%	1.64	2.82
Soft drinks[b]						
Model 0: Null	16,869	16,890	0.0%	19.6%	NA	NA
Model 1: Baseline	16,332	16,420[a]	9.6%	25.4%	1.39	1.71
Model 2: Frequency	16,300	16,442	10.7%	26.7%	1.40	1.90
Model 3: Positivity	16,243[a]	16,438	12.0%	27.6%	1.42	1.93
Model 4: Competitor effects	16,318	16,621	12.6%	27.7%	1.38	1.99

[a] Preferred model.
[b] 1500 bootstrap sample.

Robustness Checks

To check robustness we tested a number of competing models and reformulations of frequency and positivity variables, and also checked our decision to code the positivity of non-occurring touchpoints as 0. We discuss these in turn.

Frequency

The models above assume that frequency has a natural log relationship with change in consideration. This is to account for communication wearout through over-exposure which results in diminishing returns (Bass et al. 2007). To check this transformation of frequency we try four competing models, each with a different formulation of frequency:

Model Freq1: With dichotomous variable (where at least one instance of the touchpoint occurs): $\beta_j^{freq} I_{[Freq_{i,k,j}>0]}$.

Model Freq2: With a linear term: $\beta_j^{freq} Freq_{i,k,j}$.

Model Freq3: With a quadratic decay term: $\beta_{1,j}^{freq} Freq_{i,k,j} + \beta_{2,j}^{freq} Freq_{i,k,j}^2$.

Model Freq4: With a natural log decay term: $\beta_j^{freq} \ln(Freq_{i,k,j} + 1)$.

The fit statistics in Appendix show that the log decay term (Model Freq4) provides the best fit.

Positivity

We investigated different ways of incorporating positivity by devising several competing models: again, see Appendix. The inclusion of average positivity (Model Pos1) leads to a potential loss of information. For example, it treats an individual who has a very negative, a neutral, and a very positive (−2, 0, 2) encounter the same as an individual who has three neutral (0, 0, 0) encounters because both average to 0. To check the robustness of this approach, we introduced a term for the variance of touchpoint encounters (Model Pos2) following Archak, Ghose, and Ipeirotis (2011). We alternatively separated the frequency of negative, neutral, and positive encounters (Model Pos3) following Liu (2006). We also investigated a term for the positivity of the last touchpoint instead of (and as well as) average positivity (Models Pos4 and Pos5). We conclude from the fit statistics that

Table 5
Touchpoint impacts on consideration change (pooled data).

	Model 1		Model 2		Model 3		Model 4	
	β	SE	β	SE	β	SE	β	SE
(Constant)	**0.07****	0.02	**−0.14****	0.02	**−0.10****	0.02	0.01	0.02
Pre-consideration[a]	**−0.39****	0.00	**−0.40****	0.00	**−0.43****	0.00	**−0.43****	0.00
Frequency								
Traditional earned			**0.14****	0.03	−0.01	0.03	0.02	0.03
Brand advertising			**0.26****	0.01	**0.08****	0.02	**0.09****	0.02
WOM			**0.18****	0.02	−0.03	0.02	−0.01	0.02
Peer observation			**0.24****	0.02	**0.05****	0.02	**0.07****	0.02
In-store communications			**0.29****	0.01	**0.06****	0.02	**0.10****	0.02
Retailer advertising			**0.19****	0.01	**0.06****	0.02	**0.08****	0.02
Positivity[a]								
Traditional earned					**0.04****	0.00	**0.04****	0.00
Brand advertising					**0.07****	0.00	**0.07****	0.00
WOM					**0.06****	0.00	**0.06****	0.00
Peer observation					**0.08****	0.00	**0.08****	0.00
In-store communications					**0.10****	0.00	**0.10****	0.00
Retailer advertising					**0.06****	0.00	**0.06****	0.00
Competitor frequency								
Traditional earned							−0.02	0.02
Brand advertising							**−0.04****	0.01
WOM							**−0.06****	0.01
Peer observation							**−0.05****	0.01
In-store communications							**−0.08****	0.01
Retailer advertising							**−0.04****	0.01
Competitor positivity[a]								
Traditional earned							**−0.01***	0.00
Brand advertising							−0.01	0.00
WOM							0.00	0.00
Peer observation							**−0.01****	0.00
In-store communications							**−0.02****	0.00
Retailer advertising							−0.01	0.00

Significant parameters ($p < 0.05$) are bolded.
* $p < .05$.
** $p < .01$.
[a] Standardized coefficients.

the most effective way to include positivity is indeed to use a simple average.

Positivity When no Touchpoint Occurs

When a respondent does not encounter a particular touchpoint with a brand during the week, its frequency is zero. In the main Models 1–4 we coded positivity as zero in this case; however, an alternate approach would be mean imputation. We tested both approaches on Model 4. Both AIC and BIC indicate that zero-coding gives the best model fit (Appendix). Further, while zero-coding gives VIFs below the recommended cut-off of 5, mean imputation gives six VIF scores above this cut-off with the largest being 18.2. Hence using zero coding seems the most appropriate approach to reduce multi-collinearity and improve model fit.

Findings and Discussion

Results for the pooled data, using Models 1–4, are shown in Table 5. In Table 6 we show Model 3 estimated for each category. We report standardized coefficients for positivity to aid comparison of relative impact across touchpoints, but leave dummy and frequency (count) variables unstandardized for ease of interpretation. We begin with these main results, focusing primarily on Model 4 in the case of the pooled data, before turning to the exploratory analyses.

Initially, we briefly discuss non-touchpoint terms. First we note that prior consideration is negatively associated with shift in consideration ($p < 0.01$, standardized $\beta = -0.43$ for the pooled model and ranging from −0.33 to −0.46 for category models). This is presumably an expected regression to the mean effect, as the higher a respondent's pre-consideration, the more likely it is that any shift will be down rather than up.

While the study focus is primarily brand neutral, some additional explanatory power is obtained through consideration of individual brands. The coefficients of these dummy variables correlate highly with prior consideration ($r = 0.84$). One possible explanation is that higher levels of consideration represent not just a more positive attitude but also higher attitude strength, which provides resistance against change to attitude (Priester et al. 2004).

Table 6
Touchpoint impacts on consideration change by category (Model 3).

	Electrical goods		Technology products		Mobile handsets		Soft drinks	
	β	SE	β	SE	β	SE	β	SE
(Constant)	**−0.31****	0.02	**−0.12****	0.02	0.02	0.04	0.06	0.04
Pre-consideration[a]	**−0.45****	0.01	**−0.45****	0.01	**−0.46****	0.01	**−0.33****	0.01
Frequency								
Traditional earned	0.02	0.06	−0.02	0.04	−0.06	0.11	−0.02	0.14
Brand advertising	**0.14****	0.03	**0.14****	0.03	0.05	0.04	0.02	0.03
WOM	**−0.13***	0.05	−0.04	0.05	−0.06	0.06	0.08	0.06
Peer observation	−0.07	0.04	−0.03	0.05	0.04	0.04	**0.10****	0.03
In-store communications	0.04	0.03	−0.01	0.03	0.06	0.05	**0.08****	0.02
Retailer advertising	**0.06****	0.02	**0.06***	0.03	0.10	0.07	−0.05	0.07
Positivity[a]								
Traditional earned	**0.03****	0.01	**0.06****	0.01	**0.02***	0.01	**0.02***	0.01
Brand advertising	**0.08****	0.01	**0.06****	0.01	**0.09****	0.01	**0.08****	0.01
WOM	**0.05****	0.01	**0.05****	0.01	**0.09****	0.01	**0.04****	0.01
Peer observation	**0.09****	0.01	**0.09****	0.01	**0.10****	0.01	**0.04****	0.01
In-store communications	**0.12****	0.01	**0.15****	0.01	**0.09****	0.01	**0.06****	0.01
Retailer advertising	**0.08****	0.01	**0.08****	0.01	**0.02****	0.01	0.02	0.01

Significant parameters ($p < 0.05$) are bolded.
* $p < 0.05$.
** $p < 0.01$.
[a] Standardized coefficients.

With regard to the temporal dummy variables, we find that respondents are likely to report a higher shift in consideration during Quarters 2–4 compared to Quarter 1. We conjecture that this may be due to a post-Christmas dip, with fewer people able to make discretionary expenditure and hence lower brand attention levels. We also see that years 2011 and 2012 lead to significantly higher shift than 2010 ($\beta = 0.08$ and 0.10, respectively), which could coincide with an increase in consumer confidence following the recession.

There are also some demographic predictors, which are not our focus here.

Touchpoint Frequency and Positivity

The pooled analysis suggests that touchpoint frequency and positivity both play a role in shaping consideration. While we cannot compare these coefficients directly (as the scale of data is radically different), we do see that touchpoint positivity adds substantial explanatory power (Model 2 vs. Model 3). We also see the coefficients for touchpoint frequency change substantially between Model 2 and Model 3. It appears that as frequency is naturally somewhat correlated with positivity (due, for example, to the liking effect), its separate effect (due, for example, to awareness increases) is over-estimated if positivity is not also considered. This supports work on advertising affect that suggests that emotional appeals may have a strong effect despite low recall (Bülbül and Menon 2010). It suggests the need to supplement existing methods of measurement that rely purely on touchpoint frequency, such as the respondent-level frequency approach (Havlena, Cardarelli, and De Montigny 2007) and media spend modeling (Naik and Peters 2009). These methods for assessing touchpoint impact struggle to tease out the difference between an encounter that does not work because of the touchpoint choice and one where the execution is flawed. Our findings show that this difference matters. A practical implication is that measurement techniques focusing purely on touchpoint frequency, even putting aside the well-known validity problems associated with recall (Wind and Lerner 1979), will not provide the specificity of insight provided by techniques that track positivity.

Relative Touchpoint Impacts

We next consider the relative impacts of different touchpoints, both by examining which terms are significant and by comparing coefficients. To check for significance in the latter case, we use the method proposed by Wooldridge (2009, pp. 140–143). We define a new coefficient $\Delta\beta_{pq}$ (= $\beta_p - \beta_q$), representing the difference in the positivity coefficients of touchpoints p and q. Our null hypothesis is that $\Delta\beta_{pq} = 0$, that is, that there is no difference in the coefficients, against the alternate $\Delta\beta_{pq} \neq 0$. We reparameterize the model to ensure that $\Delta\beta$ is estimated as a coefficient (by simple algebraic manipulation), enabling us to calculate the standard error associated with the difference and hence the p-value for the hypothesis test. We summarize the resulting coefficient comparisons in Table 7. The table shows detailed results for the pooled analysis, and summarized results for the category-specific analysis. The touchpoints are ranked by the impact of their *positivity* on consideration change.

While we followed a similar process to examine the relative impact of touchpoint *frequency*, examination of Tables 5 and 6 shows that only some touchpoints have significant frequency coefficients in any case, and the coefficient comparison showed few significant differences amongst these. Hence, we suppress these results for brevity (except occasionally in the text) and refer

Table 7
Comparative impacts of touchpoint positivity.

Touchpoints	Pooled data: rank	Pooled data: coefficient differences (Model 4)												Category-specific: rank (Model 3)			
		In-store communications		Peer observation		Brand advertising		WOM		Retailer advertising		Traditional earned		Electrical goods	Technology products	Mobile handsets	Soft drinks
		$\Delta\beta$	SE	$\Delta\beta$	SE	$\Delta\beta$	SE	$\Delta\beta$	SE	$\Delta\beta$	SE	$\Delta\beta$	SE				
In-store communications	**1**	***0.099*****	*0.004*	**−0.024****	0.006	**−0.025****	0.006	**−0.039****	0.005	**−0.042****	0.006	**−0.063****	0.006	1	1	1=	1=
Peer observation	**2=**			***0.075*****	*0.004*	−0.002	0.005	**−0.016****	0.005	**−0.018****	0.006	**−0.040****	0.006	2=	2=	1=	3=
Brand advertising	**2=**					***0.074*****	*0.004*	**−0.014****	0.005	**−0.016****	0.006	**−0.038****	0.006	2=	5=	1=	1=
WOM	**4=**							***0.060*****	*0.004*	−0.002	0.005	**−0.024****	0.006	5	5=	1=	3=
Retailer advertising	**4=**									***0.057*****	*0.004*	**−0.022****	0.006	2=	2=	5=	3=
Traditional earned	**6**											***0.036*****	*0.004*	6	2=	5=	3=

Significant parameters ($p < 0.05$) are bolded.
** $p < .01$.
Off-diagonal elements show the difference in positivity coefficients and their associated standard error.
On-diagonal elements (in italics) show the touchpoint positivity coefficients from Model 4.
Touchpoints are ranked by the relative impact of their touchpoint positivity on consideration change.
Rankings are derived from significant differences between touchpoints' positivity coefficients.

the reader instead to the frequency coefficients and significance levels in Tables 5 and 6.[2]

We begin with the pooled model and consider the touchpoints in turn, in order of decreasing positivity impact, as summarized in the ranking of Table 7. Highest-ranked is in-store communications, for which frequency is also significant. In-store communications such as shelf and display make the brand more salient at the point of purchase (Van Nierop et al. 2010), potentially leading to unplanned purchases (Cobb and Hoyer 1986). They are aided by their multi-sensory nature, as well as by high attention levels in a store environment (Peck and Wiggins 2006). However, this effect on sales is not direct but via consideration (Van Nierop et al. 2010; Zhang 2006) and is the case not just for such in-store communications, such as feature ads and display but also for price-based promotions, which also play a role in consideration set evolution. This is in addition to the role of discounted price in the customer's judgment of utility at the moment of final choice (Van Nierop et al. 2010). The empirical importance of in-store communications in our data is consistent with recent arguments that in-store touchpoints are important in influencing consideration irrespective of where and when the purchase is made (Court et al. 2009; Verhoef, Neslin, and Vroomen 2007).

Second-ranked are two touchpoints, brand advertising and peer observation. It is notable that while brand advertising is influential in determining consideration through both frequency and positivity effects, it is not the most influential touchpoint in terms of positivity. This supports the wider agenda for a touchpoint-neutral view of the customer decision journey (Neslin et al. 2014), and in particular a touchpoint-neutral approach to customer insight (Macdonald, Wilson, and Konuş 2012).

While WOM positivity is significant, in line with the contemporary emphasis on social effects, it is notable that the positivity of the rarely studied peer observation touchpoint is significantly more influential. Furthermore, its frequency coefficient is significantly higher than that for WOM ($\Delta\beta = 0.07$, $SE = 0.03$, $p < 0.01$). Seeing someone else drinking a branded drink was a common case in point in the soft drinks category. This observation led to marketing strategies in a sponsoring firm to increase the frequency and positivity of such touchpoints, for example through the prominence and positioning of the brand on the product.

Retailer advertising also has a significant role in complementing advertising by the brand owner, impacting consideration via both frequency and positivity. Its impact via frequency is not significantly different to brand advertising ($\Delta\beta = 0.01$, $SE = 0.02$, ns), but the impact of its positivity is somewhat lower. Retailer advertising is frequently missing from practitioners' media mix models due to the lack of available data (Macdonald, Wilson, and Konuş 2012), but this result shows that it has an important role and should be tracked.

Finally, traditional earned media plays a significant role via touchpoint positivity, though we could not detect an effect via frequency. In this respect, traditional earned media are similar to WOM. The absence of frequency effect may be related to the low mean positivity of these two touchpoints, and in Model 2 where positivity is not considered, both terms become significant. This suggests that careful attention to both frequency and positivity is required in earned media evaluation too, in order to diagnose how the impact of earned media can be increased, or whether efforts should be focused elsewhere.

Competitor Effects

Competitor touchpoint effects are accounted for in Model 4. Competitor frequency and positivity variables test for any direct competitor influence on consideration for the focal brand.

We find that the effect of several competitor touchpoints is significant (and in the expected, negative, direction on consideration change for the focal brand). However, in comparison to focal brand effects, the effect size is moderate, as indicated by somewhat modest coefficients and a modest increment to r^2.

Again, in-store communication is important, ranking as the most influential competitor touchpoint via both frequency and positivity. The ability for the consumer to compare multiple brands simultaneously in a store may contribute to this as compared with touchpoints where brands are seen in isolation. Also as with the focal brand, peer observation is significant, its positivity being significantly more influential than that of WOM. Again, this highlights the need to track and, where feasible, optimize peer observation.

The frequency of competitor advertising (from either the brand or retailer) is significant but its positivity is not, implying that mere exposure rather than perceptual response may decrease focal brand consideration. However, these are ranked 4th and 5th in terms of the impact of competitor touchpoint frequency, behind peer influence and in-store communications.

Comparing Touchpoint Impacts by Category

Next we consider briefly similarities and differences to the pooled model in the category-specific analysis: see Table 6 and the category-specific ranks in Table 7 for details. In-store communications is consistently the most important touchpoint across categories in terms of positivity. Its frequency is also significant in soft drinks, a sector with rich opportunities for brand encounters out of the home. Peer observation positivity is also significant in each category, and while it is less so than brand advertising in the case of soft drinks, peer observation frequency is nonetheless significant in this category in which consumption is readily observed. Overall, then, peer observation retains its importance across categories.

The relative impact of brand advertising is fairly consistent across categories, being ranked the equal most influential touchpoint via positivity in two categories (mobile handsets and soft drinks), and the most influential via frequency in the others. Its

[2] Equivalents of Table 7 for frequency and for competitor effects are available from the authors on request.

importance relative to retailer advertising varies, however, in the positivity analysis. Whereas in soft drinks and mobile handsets brand advertising has a higher coefficient, consistent with the pooled analysis, the reverse is true is technology products, an area where high margins lead to intense competition among retailers.

Exploratory Analyses

We investigate extensions to Model 4 via three exploratory analyses. The first considers the possible interaction between touchpoint frequency and positivity, the second examines the impact of pre-consideration on touchpoint impact, and the third investigates the impact of competitor touchpoints on brand touchpoint performance. Each analysis is now briefly discussed.

Frequency/Positivity Interaction

In Exploratory Analysis 1, we consider the possibility that touchpoint frequency and positivity may interact. For example, while attitude to a single message can influence brand attitude, attitude strength may be boosted by repeated positive (or negative) messages (Erdem and Keane 1996).

Interacting the frequency and positivity of touchpoints, whether for the focal brand or for both the focal and competitor brands, does not lead to an increase in model fit as calculated by AIC or BIC (Appendix). Furthermore, VIF scores substantially increase, most likely due to the collinearity we are introducing through interaction terms. With this warning, we briefly highlight preliminary results without reporting them in full for the sake of brevity.[3] Future research may better isolate these interaction effects, if they exist. First, interaction effects are all in the expected direction (positive for focal brand and negative for competitors). Second, the competitor interactions which are significant are WOM, in-store communications, and retailer advertising. These are the three environments where multiple brands are perhaps most likely to be experienced in close proximity, which may invoke a more complex relationship between these touchpoints and consideration. Finally, the significant focal brand interactions are precisely those which have significant frequency-only effects, namely peer observation, retailer advertising, in-store communications, and brand advertising, again suggesting that there may be a more complex relationship at play between frequency and positivity. This finding is consistent with work on attitude strength (Erdem and Keane 1996), and shows another respect in which taking account of positivity and not just frequency may be important.

Touchpoint Interaction With Pre-Consideration

In Exploratory Analysis 2 (models Exp2a/b in Appendix), we suggest that an individual's pre-disposition to the brand may affect how touchpoints influence his/her shift in consideration.

[3] Results tables for exploratory analyses are available from the authors on request.

Hence, we allow *ConsidPre* to interact with the touchpoint variables by reformulating the touchpoint coefficients, such that:

$$\beta_{i,k,j}^{freq} = \beta_{1,j}^{(freq\times pre)} + \beta_{2,j}^{(freq\times pre)} ConsidPre_{i,k}$$

And similar for β_{-}^{pos}, γ_{-}^{freq}, and γ_{-}^{pos}.

Model Exp2b provides an improvement over Model 4 (Appendix). This model includes the interaction of initial focal brand consideration with touchpoint variables (for both focal and competitor brands). However, due to the large number of interactions, VIF scores are high (average 8.79). While our data suggest that this interaction exists, further investigation is therefore needed to establish its exact strength and significance. Hence again we do not report results in detail but instead provide an overview. In general, as an individual's pre-consideration increases, the impact of touchpoint frequency and positivity on their change in consideration decreases. This suggests that consumers who have a more favorable predisposition to the brand are less impacted by brand encounters. This could be a straightforward case of regression to the mean, where consumers who already hold a very positive opinion are more likely to move down the scale or stay where they are rather than further increase their opinion. This is managerially interesting when deciding targets for touchpoints such as addressable media, particularly where the aim of the communication is attitudinal rather than directly behavioral.

We also see that as an individual's pre-consideration increases, the impact of competitor frequency and positivity increases: that is, the pulling power of competitor touchpoints is greater for those who have a favorable predisposition to the focal brand. Again, we conjecture that this is a regression to the mean effect.

Competitor Effects on Consideration

In Exploratory Analysis 3 (Exp3a/b/c/d), we attempt to measure the indirect effect of competitor touchpoints on focal brand consideration via an interaction with focal brand touchpoints. We investigate the impact of competitor clutter on focal brand touchpoint performance (Danaher, Bronfer, and Dhar 2008). We include an interaction term between focal and competitor touchpoint frequency and, as proposed by Danaher, Bonfrer, and Dhar (2008), attempt to moderate this by the proportion of competitors experienced. We do this using the reparameterization of:

$$\beta_{i,k,j}^{freq} = \beta_{1,j}^{comp} + \beta_{2,j}^{comp} \frac{\sum_{\rho}^{\rho \neq k} I_{[Freq_{i,p,j}>0]}}{B_i - 1} Freq_{i,-k,j}$$

where $I_{[f(x)]} = 1$ if the statement $f(x)$ is true, that is, if respondent i has an experience with brand ρ through touchpoint j, and zero otherwise; and B_i is the total number of brands which individual i was asked to report on – that is, we are calculating the proportion of competitor brands which respondent i has experienced. We also investigate whether competitor positivity ($AvgPos_{i,-k,j}$) moderates focal touchpoint frequency, and further, the moderating effect on focal touchpoint positivity (a reparameterization of β_{-}^{pos}). Appendix shows model fit for each of these explorations.

Whilst none of these models decreases BIC, Model Exp3b is preferred over Model 4 by AIC although there is no real increase in the r^2. With this warning, we briefly report preliminary results to aid future research. In each model, the significant interactions are all in the expected negative direction: an improvement in competitor touchpoints (whether frequency or positivity) results in a lower impact from focal brand touchpoints. In the preferred Model Exp3b, competitor positivity reduces the impact of focal brand frequency for four touchpoints: brand advertising, peer observation, in-store communications, and retailer advertising. This is consistent with Danaher et al. (2008) who found that when competitors and focal brands advertise concurrently the elasticity of the focal brand's advertising reduces. Our results show that this could also extend into retailer advertising and into positivity.

Conclusion

In this study, we tracked the impact of contemporaneously reported touchpoints on brand consideration across four consumer goods categories. We examined the impact on brand consideration change of six touchpoints. In our main, pooled Model 4 (Table 5), we found that touchpoint positivity significantly impacts consideration change for all six touchpoints, and touchpoint frequency does so for all but WOM and traditional earned media. We further rank the touchpoints by the touchpoint positivity coefficients (Table 7) and find that in-store communications are most influential, followed by peer observation and brand advertising, then WOM and retailer advertising. Finally, traditional earned media are the least influential. The impact of competitor touchpoints on a focal brand was also examined (Table 5). Again, in-store communications are most influential (via both frequency and positivity), and as with the focal brand, peer observation has a significant effect, its positivity being significantly more influential than that of WOM.

We hence make three contributions. First, the study is to our knowledge one of the first, if not the first, on the relative impact of brand, retailer, peer and earned touchpoints on the customer's brand relationship. Notably, peer observation, predominantly the focus until now of qualitative research (Grove and Fisk 1997), is both frequent and influential, suggesting that this touchpoint requires far more attention from both scholars and practitioners. A recent line of research (Nitzan and Libai 2011; Risselada, Verhoef, and Bijmolt 2014) shows the importance of social connections on consumer behavior. Our research sheds light on the mechanisms underpinning these social effects by empirically distinguishing WOM (recommendation or criticism) from simply observing peers. Earned media are somewhat less influential but are nonetheless significant. While the role of retailer advertising is somewhat category contingent, in-store communications are consistently impactful.

Our second contribution is to propose and demonstrate that the assessment of touchpoint impact needs to take into account touchpoint positivity and not just frequency. We find that positivity adds explanatory power as compared with frequency alone when predicting brand consideration. This generalizes findings from long-standing experimental advertising research (MacKenzie, Lutz, and Belch 1986) to a multi-touchpoint context. Positivity by definition is a real-time affective response which can only be recalled imperfectly and with significant known biases (Aaker, Drolet, and Griffen 2008; Cowley 2008). This makes the survey problematic for such research, while behavioral measures mostly fail to capture positivity entirely. We have illustrated one method for addressing this, through the RET texting approach; alternative methods may be possible. Real-time reporting takes the logic of mall intercepts (and variants such as exit surveys as customers leave a website) and generalizes it to the challenge that decision journeys play out in real time across diverse touchpoints.

This brings us to our third contribution, which is to propose and exemplify an RET-based approach by which the impact of multiple touchpoints can be assessed. This approach treats symmetrically touchpoints with the brand owner, the retailer, peers and the media. We hence respond to calls for research which acknowledges that the consumer decision journey extends beyond firm-owned media and channel contacts (Ailawadi et al. 2009; Court et al. 2009). Customers integrate learning from multiple sources in order to achieve their objectives (Neslin et al. 2014). In our study, touchpoints significantly associated with brand consideration included those from four stakeholders: the brand owner, retailers, peers, and the public media. Yet there are other stakeholders who the customer may touch, and whose touchpoints could be included within further applications of this approach, such as sponsors (Court et al. 2009) and service personnel (Grove and Fisk 1997).

Practitioner Implications

As classic market research is increasingly complemented by database analytics, managers are hardly short of customer data. But these data are fragmented, hiding key insights on the customer's holistic relationship with the brand. They are also frequently incomplete, as empowered customers take less notice of company-driven communication, choosing instead to learn from the experience of other customers and doing their own research online. Marketers need to know which parts of the customer journey have most impact on attitudes and behaviors, and which of these crucial encounters are not working well. Methods such as real-time experience tracking may prove a useful addition to the methodological armory to complement both ethnographic approaches on the one hand and, on the other, focused quantitative work within subsets of the touchpoint mix. Whether or not data collection follows the SMS-based approach we have described, we tentatively suggest three guidelines to practitioners for providing holistic customer insight.

First, we suggest widening the scope of insight to all direct and indirect touchpoints, as an input into the overall marketing plan. For instance, should a company invest in advertising or in improving call center standards, in product design improvement or online advice, in supporting customer communication through channel partners or in social media? While a company's overall positioning and competencies will inform such decisions, we suggest that holistic insight across multiple touchpoints can help.

Second, we suggest tracking the customer's perceptual response to touchpoints contemporaneously. Even if objective data were available on all touchpoints, it would not include this important information. To get closer to customers, one might ideally walk along with them, asking how they feel at the moment when they encounter the brand. Asking this at the end of the month in a tracker survey may be too late to capture the problem or opportunity. As mobile handsets tend to travel with the customer, they seem a natural place to start in seeking this real-time feedback.

Third, we suggest assessing the impact of encounters on key outcomes. These may be attitudinal, as in this study, or behavioral, as we discuss further below. A bank might wish to know, for example, whether it should invest further in marketing communications, or whether improvement in service levels would have a higher impact on consideration and purchase.

Limitations and Research Directions

While we have employed some robustness checks, future studies might usefully further explore the strengths and weaknesses of real-time experience tracking in focused research efforts, analogous to the methodological studies of survey methods (Chandon, Morwitz, and Reinartz 2006). First, for some touchpoint types, self-reports could be checked against objective sources such as CRM data. Second, a comparison against retrospective surveys might allocate respondents randomly to one method. We might expect real-time reporting to be fuller and more accurate – given Wind and Lerner's (1979) findings when comparing surveys with purchase diaries, of which RET can be thought of as a variant – as well as more differentiating in perceptual response. These conjectures could be tested using a field experiment. Such pairwise comparisons of methods might also examine the relative explanatory power of different methods on an attitudinal or behavioral outcome, to test the extent to which real-time experience tracking captures encounters that prove to be significant. Third, touchpoints mentioned in post-study interviews could be compared against data from real-time tracking.

Such methodological studies would amongst other things enable the estimation of mere measurement effects. As with survey methods, the act of asking respondents to respond is itself an intervention which may influence brand attitudes (Chandon, Morwitz, and Reinartz 2006). Unlike some company surveys, however, our respondents were not aware of any particular brand sponsoring the study. We conjecture, therefore, that study participants may be to some extent hot-housed, paying more attention to the whole category than they might otherwise, and perhaps thereby exhibiting greater shifts in brand attitudes than non-participants. Any such effect might be expected, though, to be equal across brands. An experimental design in which a control group fills in only pre-study and post-study surveys without SMS messaging in-between could perhaps check this conjecture. Hot-housing might also cause respondents to notice and hence report greater touchpoint frequencies than a control group. Conversely, the agency problem may lead to respondents not reporting all touchpoints due to laziness. Again, experiments are needed to check any downward or upward bias in reporting.

Another research opportunity concerns the tracking period. We found that even with around 1700–5600 respondents, the sheer breadth of touchpoint types led to some touchpoints being relatively sparsely represented for some brands within the study period of one week. While a greater number of respondents might help, a powerful option would be longitudinal studies covering a longer tracking period of perhaps one month. In addition to raising the statistical power for relatively infrequent touchpoints, this might also increase the statistical power for further exploration of interactions (Naik and Peters 2009). Furthermore, longitudinal data structured in panel data format could allow the examination of the time-variant dynamic effects of touchpoints, such as the recency, frequency and sequential order of encounters. Such longitudinal data might also be the key to bringing customer initiated touchpoints into the analysis, such as product use, product purchase, or visiting a brand website. These might be modeled as resulting from the impact of prior encounters as well as pre-study attitudes.

A further limitation and research direction concerns the possibility of touchpoint endogeneity. In common with most research on the impact of touchpoints from advertising to WOM (Archak, Ghose, and Ipeirotis 2011; Bass et al. 2007; Goh, Hui, and Png 2011; Liu 2006), we have treated touchpoints as independent. However, this simplification may bias coefficients. For example, those individuals who are more likely to increase their consideration for a brand may also be more likely to notice touchpoints for that brand or perceive them as positive. Therefore their shift in consideration is not wholly due to their experience but also a result of some unobserved engagement with the brand. Or there may be psychographic or lifestyle variables that impact touchpoint frequency or positivity. Hence there may be omitted variable bias affecting coefficient estimates. Related, firm actions are tacit within our model: while our analysis is primarily brand neutral, brand strategies may target a segment who are naturally more likely to increase their consideration for the brand, in which case a participant's segment membership is correlated with both their frequency of exposure and their change in consideration. By omitting any relevant segment variables we may be introducing bias into the estimate of frequency, as frequency is correlated with an omitted variable.

We do not have available suitable instrumental variables to adequately identify whether and to what extent this endogeneity issue exists, and we prefer not to use weak or ill-defined instrumental variables as they are likely to introduce further bias rather than remove it (Larcker and Rusticus 2010; Wooldridge 2009). This issue deserves focused attention in future research. Again, one-month datasets may help, where psychographic and socio-demographic variables with potential conceptual links to touchpoints would need to be included. While we have reported an exploratory analysis of the interaction between prior consideration and touchpoint impact, conceptually the best measure of prior brand relationship in predicting touchpoints might be the recently clarified construct of brand engagement (Brodie et al. 2011). Another potential predictor of touchpoints might be the respondent's involvement in the study, as this may impact on the level of the potential biases we have discussed in touchpoint recording.

A final limitation concerns unobserved customer heterogeneity. The gap between marginal r^2 and conditional r^2 for the preferred models suggests that around 8–14% of variability in consideration change could be explained by unobserved, individual level data. Again, careful consideration of relevant psychographic, socio-demographic or brand health variables may shed further light and be managerially useful.

Concluding Remarks

There was perhaps a time when customers learned about products and services through what the brand owner told them. If this time ever existed, it is certainly not the case now, as our data make plain. A focus purely on optimizing the spend within the brand-owner's control would be myopic. Instead, we suggest listening to customers in real time to understand how they construe their customer journey. The range of touchpoints they encounter in this journey is undoubtedly broad but perhaps not intractably so. Managers take decisions every day based on their working assumptions about their relative importance and efficacy. The research challenge is to support these holistic decisions with holistic insight.

Acknowledgements

The authors gratefully acknowledge the financial support provided by the Technology Strategy Board (UK) and the Economic and Social Research Council (UK) via a Knowledge Transfer Partnership grant. The authors also gratefully acknowledge the support and data access provided by research agency MESH Experience.

Appendix.

Fit statistics for robustness checks and exploratory models (based on pooled data Model 4)

Model	AIC	BIC	r^2 marginal	r^2 conditional	Average VIF	Maximum VIF
Robustness checks						
Model Freq1: Frequency – Dichotomous Incidence Variable	231,091	231,713	19.5%	31.7%	1.90	2.66
Model Freq2: Frequency – Linear Frequency	231,010	231,633	19.5%	31.7%	1.75	2.64
Model Freq3: Frequency – Quadratic Decay	231,150	231,921	19.6%	31.8%	2.10	3.10
Model Freq4: Frequency – Natural Log (ln) decay	230,905[a]	231,527[a]	19.6%	31.8%	1.84	2.67
Model Pos1: Positivity – Arithmetic Mean	230,905[a]	231,527[a]	19.6%	31.8%	1.84	2.67
Model Pos2: Positivity – Mean and Variance	230,926	231,697	19.7%	31.8%	1.77	2.67
Model Pos3: Positivity – Frequency of positive, negative, and neutral experiences	231,958	232,729	18.6%	30.6%	2.17	3.45
Model Pos4: Positivity – Last experience positivity	233,445	234,067	17.2%	29.1%	1.72	2.63
Model Pos5: Positivity – Mean and last experience positivity	230,988	231,758	19.7%	31.8%	2.28	5.71
Model Imp1: Positivity imputation – using zero-coding	230,905[a]	231,527[a]	19.6%	31.8%	1.84	2.67
Model Imp2: Positivity imputation – using mean	231,022	231,644	19.4%	31.5%	2.92	18.21
Exploratory models						
Model 4: Preferred model for pooled data	230,905	231,527	19.6%	31.8%	1.84	2.67
Model Exp1a: Focal brand frequency and positivity interaction	230,916	231,613	19.7%	31.8%	4.31	19.53
Model Exp1b: Focal brand and competitor frequency and positivity interaction	230,936	231,707	19.7%	31.8%	5.19	19.91
Model Exp2a: Focal initial consideration interaction with focal brand touchpoints	230,321	231,092	20.2%	32.2%	6.75	21.02
Model Exp2b: Focal initial consideration interaction with focal and competitor touchpoints	230,119[a]	231,038[a]	20.8%	32.7%	8.98	21.19
Model Exp3a: Competitor frequency interaction with focal brand frequency	230,969	231,665	19.7%	31.8%	1.82	2.67
Model Exp3b: Competitor positivity interaction with focal brand frequency	230,865[a]	231,561	19.7%	31.8%	1.85	2.67
Model Exp3c: Competitor frequency interaction with focal brand positivity	230,974	231,670	19.7%	31.8%	1.79	2.67
Model Exp3d: Competitor positivity interaction with focal brand positivity	230,925	231,622	19.7%	31.8%	1.85	2.67

[a] Preferred model.

References

Aaker, Jennifer, Aimee Drolet and Dale Griffen (2008), "Recalling Mixed Emotions," *Journal of Consumer Research,* 35 (2), 268–78.

Ahluwalia, Rohini, Robert E. Burnkrant and H. Rao Unnava (2000), "Consumer Response to Negative Publicity: The Moderating Role of Commitment," *Journal of Marketing Research,* 37, 203–14.

Ailawadi, Kusum L., J.P. Beauchamp, Naveen Donthu, Dinesh K. Gauri and Venkatesh Shankar (2009), "Communication and Promotion Decisions in Retailing: A Review and Directions for Future Research," *Journal of Retailing,* 85 (1), 42–55.

Archak, Nicolay, Anindya Ghose and Panagiotis G. Ipeirotis (2011), "Deriving the Pricing Power of Product Features by Mining Consumer Reviews," *Management Science,* 57 (8), 1485–509.

Arnold, Mark and Kristy Reynolds (2009), "Affect and Retail Shopping Behavior: Understanding the Role of Mood Regulation and Regulatory Focus," *Journal of Retailing,* 85 (3), 308–20.

Ataman, M. Berk, Harald J. van Heerde and Carl F. Mela (2010), "The Long-term Effect of Marketing Strategy on Brand Sales," *Journal of Marketing Research,* 47 (1), 866–82.

Bass, Frank M., Norris Bruce, Sumit Majumdar and B.P.S. Murthi (2007), "Wearout Effects of Different Advertising Themes: A Dynamic Bayesian Model of the Advertising-Sales Relationship," *Marketing Science,* 26 (2), 179–95.

Baumeister, Roy F., Kathleen D. Vohs, C. Nathan DeWall and Liqing Zhang (2007), "How Emotion Shapes Behavior: Feedback, Anticipation, and Reflection, Rather Than Direct Causation," *Personality and Social Psychology Review,* 11, 167–203.

Bearden, William O. and Michael J. Etzel (1982), "Reference Group Influence on Product and Brand Purchase Decisions," *Journal of Consumer Research,* 9 (2), 183–94.

Bian, Xuemei and Luiz Moutinho (2009), "An Investigation of Determinants of Counterfeit Purchase Consideration," *Journal of Business Research,* 62 (3), 368–78.

Borghini, Stefania, Nina Diamond, Robert V. Kozinets, Mary Ann McGrath, Albert M. Muñiz Jr. and John F. Sherry Jr. (2009), "Why Are Themed Brandstores So Powerful? Retail Brand Ideology at American Girl Place," *Journal of Retailing,* 85 (3), 363–75.

Briñol, Pablo, Richard E. Petty and Zakary L. Tormala (2004), "Self-Validation of Cognitive Responses to Advertisements," *Journal of Consumer Research,* 30 (4), 559–72.

Brodie, Roderick J., Linda D. Hollebeek, Biljana Juric and Ana Ilic (2011), "Customer Engagement: Conceptual Domain, Fundamental Propositions, and Implications for Research," *Journal of Service Research,* 14 (3), 252–71.

Bülbül, Cenk and Geeta Menon (2010), "The Power of Emotional Appeals in Advertising: The Influence of Concrete Versus Abstract Affect on Time-Dependent Decisions," *Journal of Advertising Research,* 50 (2), 169–80.

Burnham, Kenneth P. and David R. Anderson (2004), "Multimodel Inference: Understanding AIC and BIC in Model Selection," *Sociological Methods Research,* 33 (2), 261–304.

Chandon, Pierre, Vicki G. Morwitz and Werner Reinartz (2006), "Do Intentions Really Predict Behavior? Self-Generated Validity Effects in Survey Research," *Journal of Marketing,* 69 (2), 1–14.

Chitturi, Favindra, Rajagopal Raghunathan and Vijay Mahajan (2008), "Delight by Design: The Role of Hedonic Versus Utilitarian Benefits," *Journal of Marketing,* 72 (May), 48–63.

Cobb, Cathy J. and Wayne D. Hoyer (1986), "Planned Versus Impulse Purchase Behavior," *Journal of Retailing,* 62 (4), 384–409.

Court, David, Dave Elzinga, Susan Mulder and Ole J. Vetvik (2009), "The Consumer Decision Journey," *McKinsey Quarterly,* 3, 96–107.

Cowley, Elizabeth (2008), "Looking Back at an Experience Through Rose-Colored Glasses," *Journal of Business Research,* 61, 1046–52.

Danaher, Peter J., André Bonfrer and Sanjay Dhar (2008), "The Effect of Competitive Advertising Interference on Sales for Packages Goods," *Journal of Marketing Research,* 45 (April), 211–25.

Desai, Kalpesh K. and Sekar Raju (2007), "Adverse Influence of Brand Commitment on Consideration of and Preference for Competing Brands," *Psychology & Marketing,* 24 (7), 595–614.

East, Robert, Kathy Hammond and Wendy Lomax (2008), "Measuring the Impact of Positive and Negative Word of Mouth on Brand Purchase Probability," *International Journal of Research in Marketing,* 25, 215–24.

Erdem, Tülin and Michael P. Keane (1996), "Decision-Making Under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets," *Marketing Science,* 15 (1), 1–20.

Goh, Khim-Yong, Kai-Lung Hui and Ivan Png (2011), "Newspaper Reports and Consumer Choice: Evidence from the Do Not Call Registry," *Management Science,* 57 (9), 1640–54.

Goodman, Joseph K., Susan M. Broniarczyk, Jill G. Griffin and Leigh McAlister (2013), "Help or Hinder? When Recommendation Signage Expands Consideration Sets and Heightens Decision Difficulty," *Journal of Consumer Psychology,* 23 (2), 165–74.

Grove, Stephen J. and Raymond P. Fisk (1997), "The Impact of Other Customers on Service Experiences: A Critical Incident Examination of "Getting Along"," *Journal of Retailing,* 73, 63–85.

Havlena, William, Robert Cardarelli and Michelle De Montigny (2007), "Quantifying the Isolated and Synergistic Effects of Exposure Frequency for TV, Print, and Internet Advertising," *Journal of Advertising Research,* 45 (2), 255–68.

Kahn, Barbara E. and Alice M. Isen (1993), "The Influence of Positive Affect on Variety Seeking among Safe, Enjoyable Products," *Journal of Consumer Research,* 20, 257–70.

Kahneman, Daniel and Alan B. Krueger (2006), "Developments in the Measurement of Subjective Well-Being," *Journal of Economic Perspectives,* 20 (1), 3–24.

Larcker, David F. and Tjomme O. Rusticus (2010), "On the Use of Instrumental Variables in Accounting Research," *Journal of Accounting and Economics,* 49, 186–205.

Liu, Yong (2006), "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing,* 70 (July), 74–89.

Macdonald, Emma K., Hugh N. Wilson and Umut Konuş (2012), "Better Customer Insight – In Real Time," *Harvard Business Review,* 90 (9), 102–8.

MacKenzie, Scott B., Richard J. Lutz and Beorge E. Belch (1986), "The Role of Attitude Toward the Ad as a Mediator of Advertising Effectiveness: A Test of Competing Explanations," *Journal of Marketing Research,* 23, 130–43.

McAlexander, James H., John W. Schouten and Harold F. Koenig (2002), "Building Brand Community," *Journal of Marketing,* 66 (January), 38–54.

McFarland, Cathy and Roger Buehler (1998), "The Impact of Negative Affect on Autobiographical Memory: The Role of Self-Focused Attention to Moods," *Journal of Personality and Social Psychology,* 75 (6), 1424–40.

Nakagawa, Shinichi and Holger Schielzeth (2013), "A General and Simple Method for Obtaining R^2 From Generalized Linear Mixed-Effects Models," *Methods in Ecology and Evolution,* 4 (2), 133–42.

Naik, Prasad A. and Kay Peters (2009), "A Hierarchical Marketing Communications Model of Online and Offline Media Synergies," *Journal of Interactive Marketing,* 23, 288–99.

Neslin, Scott A., Dhruv Grewal, Robert Leghorn, Venkatesh Shankar, Marije L. Teerling, Jacquelyn S. Thomas and Peter C. Verhoef (2006), "Challenges and Opportunities in Multichannel Customer Management," *Journal of Service Research,* 9 (2), 95–112.

Neslin, Scott A., Kinshuk Jerath, Bodapati Anand, Eric T. Bradlow, John Deighton, Sonja Gensler, Leonard Lee, Elisa Montaguti, Rahul Telang, Raj Venkatesan, Peter C. Verhoef and Z. John Zhang (2014), "The Interrelationships Between Brand and Channel Choice," *Marketing Letters,* 25 (3), 319–30.

Nitzan, Irit and Barak Libai (2011), "Social Effects on Customer Retention," *Journal of Marketing,* 75 (November), 24–38.

Ngobo, Paul V. (2011), "What Drives Household Choice of Organic Products in Grocery Stores?," *Journal of Retailing,* 87 (1), 90–100.

O'Brien, Robert M. (2007), "A Caution Regarding Rules of Thumb for Variance Inflation Factors," *Quality and Quantity,* 41 (5), 673–90.

O'Cass, Aron (2002), "Political Advertising Believability and Information Source Value During Elections," *Journal of Advertising,* 31 (1), 63–74.

Peck, Joanne and Jennifer Wiggins (2006), "It Just Feels Good: Customers' Affective Response to Touch and its Influence on Persuasion," *Journal of Marketing,* 70 (4), 56–69.

Priester, Joseph, Dhananjay Nayakankuppam, Monique A. Fleming and John Godek (2004), "The A^2SC^2 Model: The Influence of Attitudes and Attitude Strength on Consideration and Choice," *Journal of Consumer Research,* 30 (4), 574–85.

Risselada, Hans, Peter C. Verhoef and Tammo H.A. Bijmolt (2014), "Dynamic Effects of Social Influence and Direct Marketing on the Adoption of High-Technology Products," *Journal of Marketing,* 78 (March), 52–68.

Roberts, John H. and James M. Lattin (1997), "Consideration: Review of Research and Prospects for Future Insights," *Journal of Marketing Research,* 34, 406–10.

Stammerjohan, Claire, Charles M. Wood, Yuhmiin Change and Esther Thorson (2005), "An Empirical Investigation of the Interaction Between Publicity, Advertising, and Previous Brand Attitudes and Knowledge," *Journal of Advertising,* 34 (4), 55–67.

Stephen, Andrew T. and Jeff Galak (2012), "The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace," *Journal of Marketing Research,* 49 (5), 624–39.

Sweeney, Jillian C. and Geoffrey N. Soutar (2001), "Consumer Perceived Value: The Development of a Multiple Item Scale," *Journal of Retailing,* 77 (2), 203–20.

Thakor, Mrugank V., Rajneesh Suri and Katayoun Saleh (2008), "Effects of Service Setting and Other Consumers' Age on the Service Perceptions of Young Consumers," *Journal of Retailing,* 84 (2), 137–49.

Thomas, Jacquelyn S. and Ursula Y. Sullivan (2005), "Managing Marketing Communications with Multichannel Customers," *Journal of Marketing,* 69 (4), 239–51.

Trusov, Michael, Randolph Bucklin and Koen Pauwels (2009), "Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site," *Journal of Marketing,* 73 (September),90–102.

van der Lans, Ralf, Gerrit Van Bruggen, Jehoshua Eliashberg and Berend Wierenga (2010), "A Viral Branching Model for Predicting the Spread of Electronic Word of Mouth," *Marketing Science,* 29 (2), 348–65.

Van Nierop, Erjen, Bart Bronnenberg, Richard Paap, Michel Wedel and Philip Hans Franses (2010), "Retrieving Unobserved Consideration Sets From Household Panel Data," *Journal of Marketing Research,* 47 (1), 63–74.

Verhoef, Peter C., Scott A. Neslin and Bjorn Vroomen (2007), "Multi-channel Customer Management: Understanding the Research Shopper Phenomenon," *International Journal of Research in Marketing,* 24 (2), 129–48.

Verhoef, Peter C., Katherine N. Lemon, A. Parasuraman, Anne Roggeveen, Michael Tsiros and Leonard A. Schlesinger (2009), "Customer Experience Creation: Determinants, Dynamics and Management Strategies," *Journal of Retailing,* 85 (1), 31–41.

Westbrook, Robert A. and Richard L. Oliver (1991), "The Dimensionality of Consumption Emotion Patterns and Consumer Satisfaction," *Journal of Consumer Research,* 18, 84–91.

Wiesel, Thorsten, Koen Pauwels and Joep Arts (2010), "Marketing's Profit Impact: Quantifying Online and Off-line Funnel Progression," *Marketing Science,* 30 (4), 604–11.

Wind, Yoram and David Lerner (1979), "On the Measurement of Purchase Data: Surveys Versus Purchase Diaries," *Journal of Marketing Research,* 16 (February), 39–47.

Wooldridge, Jeffrey M. (2009), *Introductory Econometrics: A Modern Approach,* 4th ed. Boston: South Western College.

Yaveroglu, Idil and Naveen Donthu (2008), "Advertising Repetition and Placement Issues in On-line Environments," *Journal of Advertising,* 37 (2), 31–44.

Zhang, Jie (2006), "An Integrated Choice Model Incorporating Alternative Mechanisms for Consumers' Reactions to In-Store Display and Feature Advertising," *Marketing Science,* 25 (3), 278–90.