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Enduring Attitudes and Contextual Interest: When and Why Attitude Surveys Still Matter in the Online Consumer Decision Journey

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Abstract

Consumers leave traces of key interest to managers on their journey to purchase. Next to traditional survey-based attitudes, readily available online metrics now show aggregate consumer actions. But how do survey response metrics and online action metrics relate to each other? To what extent do they explain and predict brand sales across consumer categories? This article shows that surveys and online behavior provide complementary information for brand managers. Times series data for 32 brands in 14 categories reveal low correlations but substantial dual causality between survey metrics and online actions. Combining both types of metrics greatly increases the model's power to explain and predict brand sales in low-involvement categories. By contrast, high-involvement categories do not gain much from adding survey-based attitudes to a model including online behavior metrics. The authors synthesize these generalizations in a new framework relating enduring attitudes to the contextual interest expressed by online actions. This new framework helps managers assess both types of metrics to drive brand performance depending on whether their goal is short-term sales or long-term brand health.

Keywords: Marketing metrics; Purchase funnel; Consumer journey; Attitude; Online tracking; Vector autoregression

> Measuring brand effects on the basis of online behavior makes research less dependent on questionnaires and therefore more scalable at less cost.
>
> —Joris Merks, Google (2011, personal communication)

> Online data can help understand some of the WHAT and maybe even the HOW of customer behaviors. But, if the marketer wants to understand WHY people do what they do then they need to get into the mind of the customer.
>
> —Gordon Bruner (2016)

> We need to be able to use predictive modeling to identify when shifts in shopping behavior are most likely to occur, and estimate the direction, magnitude and duration of these shifts.—anonymous manager quoted in Marketing Science Institute 2018–2020 Research Priorities.

The Internet has generated many new metrics recommended to managers when evaluating marketing effectiveness and assessing how consumers think, feel, and act regarding their brand (Colicev, Malshe, Pauwels, & O'Connor 2018; Yadav & Pavlou 2014). Generic and branded search, owned website page views, and social media expressions are key examples of consumers' brand-related actions. To some (e.g., Merks-Benjaminsen 2014), online behavior metrics are the best way to understand brand health and marketing effectiveness. To

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others, such online metrics paint only part of the picture (e.g., Bruner 2016) and are easily faked (e.g., Read 2018). For brand managers, the key question is to what extent both types of metrics are necessary and how they relate to each other and to market outcomes over time. In other words, what are their *separate strengths* and *complementary roles* in driving brand sales?

Marketing literature identifies consumer attitudes as constructs that indicate how consumers think about (cognition), feel about (affect), and act toward (conation) the brand (Vakratsas & Ambler 1999). A rich body of research has clarified the relationships between these constructs and improved their measurement, typically by surveying a representative sample of the prospective customer population (Farris, Bendle, Pfeifer, & Reibstein 2010; Park & Srinivasan 1994). By contrast, despite two decades of research with online behavior metrics, their relationship to consumer attitudes have received little attention. One reason is the challenge to obtain both survey-based attitude and online behavior metrics for the same brands in the same period. Another is conceptual: the few researchers who have attempted to relate behavior to attitudes appear to start from the assumption either that online behavior is a manifestation of attitudes (e.g., Batra & Keller 2016) or that survey-based attitudes simply follow behavior (e.g., Sharp 2010). We challenge these assumptions by showing, for a large variety of brands and categories, a low correlation between survey-based attitude and online behavior metrics.

Importantly, we find: (1) mutual temporal dependencies between metrics of online behavior and survey-based attitudes and (2) that the former excel in explaining same-week brand sales while the latter excel in predicting months-out brand sales. Online behavior metrics are especially important to *explain* same-week sales for brands in high-involvement categories. By contrast, survey metrics move more slowly than sales and tend to perform well in *predicting* sales several months out, especially in low-involvement categories. Based on these findings, we conceptualize online behavioral metrics as *contextual interest* in the product category and/or brand and offer an integrated framework of attitudes and behavior.[1]

While studies have empirically linked marketing and performance to either survey-based attitude (e.g., Hanssens, Yildirim, Srinivasan, Pauwels, & Vanhuele 2014; Kumar, Rajan, Venkatesan, & Lecinski 2019; Petersen, Andrew, Polo, & Javier Sese 2018) or online behavior metrics (e.g., De Vries, Gensler, & Leeflang 2017; Li & Kannan 2014; Srinivasan, Rutz, & Pauwels 2016), none has *combined* comprehensive metrics of attitudes with both online behavior and surveys in the context of sales and marketing activity over time across a wide variety of brands and categories. We do so for 32 brands in 14 categories, including services (Internet, travel, insurance, energy, and lodging), durables (cars), packaged food products (cheese, salty snacks, candy, beer, and soft drinks), and packaged non-food products (toilet tissue and sanitary napkins). We apply Granger-causality tests to show that for most brands, survey metrics drive online behavior and vice versa (mutual temporal dependency). Vector autoregressive (VAR) models compare the in-sample explanation and out-of-sample forecasting accuracy of each metric type for weekly sales.

Our contributions to the literature are threefold. First, we show the correlations and dynamic dependencies between attitude survey metrics and online behavior metrics across a wide variety of business-to-consumer industries. Second, we compare their explanatory and predictive power for brand sales across high- and low-involvement categories. Based on these empirical generalizations, we propose an integrative model of enduring attitudes (also known as the “purchase funnel”) and contextual interest (also known as the “online consumer journey”) on the road to purchase. In doing so, we aim to contribute to calls to rethink “the journey to purchase and beyond” (Marketing Science Institute 2012, p. 3) and to capture customer information to fuel growth by painting a more holistic picture and offering guidance on the research priority “What Key Performance Indices (KPIs)/Metrics Should Be Measured and How**?**”(Marketing Science Institute 2018). Practically, our findings help managers answer key research questions on marketing outcomes, such as “designing dashboards to provide indicators that give feedback on marketing actions and significantly influence returns” (Kannan & Li 2017, p. 20).

Research Background

Starting in the early 1960s (Colley 1961; Lavidge & Steiner 1961), research developed measures of consumer attitudes to evaluate the impact of marketing campaigns and to predict their sales effect. In their theory of buying behavior, Howard and Sheth (1969, p. 14) noted, “Attitude is an input into executive decisions because many marketing decisions, including advertising, can be more adequately evaluated or measured in terms of attitude than of purchase behavior.” However, attitude has proved an elusive concept to measure and to relate to buying behavior. Especially problematic is the link between general attitudes (e.g., toward a brand) and behavior (Ajzen & Fishbein 1977; Wicker 1969).

In marketing, researchers have assessed important concepts such as brand awareness and consideration (cognition), brand preference and liking (affect), and purchase intention and loyalty (conation). Recent market response models have shown that such survey metrics predict sales over and above long-term marketing effects (Bruce, Peters, & Naik 2012; Hanssens et al. 2014; Kumar et al. 2019; Petersen et al. 2018; Srinivasan, Vanhuele, & Pauwels 2010). These studies note, however, that it is costly to continuously track high-quality funnel metrics, which require representative sampling and survey procedures for hundreds of consumers. Therefore, they call for further research on the explanatory power of online behavior metrics relative to that of survey-based measures.

Online behavior metrics have a much shorter history in marketing, with some managers and researchers extolling their virtues and others voicing criticism. To the former, online

[1] Contextual interest can also be called “temporal interest,” as consumers indicate through their online actions that they are at the time interested in the need/want that brand offerings aim to fill.

behavior metrics are inexpensive to collect and unobtrusive to the prospective customer (Lecinski 2011). As such, they are less or not sensitive to the well-documented survey issues of memory, mere measurement, and social desirability biases (Morwitz, Johnson, & Schmittlein 1993; Simmons, Bickart, & Lynch Jr. 1993; Tourangeau, Rips, & Rasinski 2000). Many recent papers have shown that online behavior metrics convert to sales and are responsive to marketing actions (Colicev et al. 2018; De Vries et al. 2017; Srinivasan et al. 2016). Despite the case for online behavior metrics, they have also received several objections, especially as a replacement for attitude survey metrics (Batra & Keller 2016). For one, they do not cover the full potential market for most products and services. Even in the highly connected US market, 39% of all consumers of food products do not consult any online sources (Lecinski 2011). Much of the research demonstrating the sales explanatory power of online metrics involved high-involvement categories such as movies (Onishi & Manchanda 2012), lodging (Li & Kannan 2014), smartphones, electricity services, and automobiles (Dierks 2017; Dotson, Fan, Feit, Oldham, & Yeh 2017). For low-involvement products, only the most dedicated brand advocates and detractors may be consulted online, making several online behavior metrics unrepresentative of the average consumer (and even the average online consumer). Even for high-involvement products, correlations between attitudes and online behavior metrics may not be high (Dotson et al. 2017). As Katsikeas et al. (2016, p. 32) demonstrate for performance, a low correlation between metrics raises the need for "studies linking different aspects of performance and identifying contingency factors that may affect the strength of such relationships."

Why does a low correlation between attitudes and online behavior metrics challenge common wisdom? We believe it goes against both of the currently dominant views of how consumer attitudes and online behavior should relate. The first view ("attitudes lead action") appears to guide much of the academic research (e.g., Batra & Keller 2016). In this perspective, (online) actions derive from enduring attitudes. In other words, attitude metrics indicate whether the brand is the "brand right" at a next purchase occasion, while contextual interest indicates that it is the "brand right now" as the occasion has arrived. In this perspective, (online) actions derive from enduring attitudes. For example, consumers are more likely to visit websites of brands they know (Dotson et al. 2017; Ilfeld & Winer 2002).

The opposite view ("action leads attitudes") appears to guide much of current marketing practice (Formisano, Pauwels, & Zarantonello 2019; Romaniuk & Sharp 2015). In this perspective, (survey-based) attitude metrics derive from action —for example, consumers report that they know a brand *because* they bought it (Sharp 2010) or came across it online (Lecinski 2011). In other words, "brand right now" becomes "brand right." This allows brand managers to base their decisions exclusively on behavior metrics (which are rather inexpensive to collect online and are also becoming less expensive offline).

Instead, we believe that both survey-based attitudes and online behavior metrics have complementary benefits and drawbacks, which cannot be captured in unidirectional dependence. While survey-based attitude metrics may not adequately capture the when question of consumer action, online behavior metrics may not adequately answer the why question. Note that the when question is key to explaining short-term sales, while the why question is key to predicting sales over longer horizons. Beyond unidirectional dependence, the flow may go both ways: higher attitudes (even when not immediately increasing sales) should on average increase future consumer online action related to the brand. At the same time, more observed consumer actions (even in the limited sample of online-active prospects) may be stored in long-term memory associations (Bjork & Bjork 1996; Keller 1993) and thus increase future attitudes toward the brand, also in the general population (as represented in surveys). To empirically investigate such dynamic patterns, we need both an appropriate methodology and time series data on survey-based attitudes, online behavior and sales.

Methodology

Our analysis focuses on the *dynamic* relationships among *aggregate* metrics *across categories and brands*, which helps "identify when shifts in shopping behavior are most likely to occur, and estimate the direction, magnitude and duration of these shifts" (Marketing Science Institute 2018). This requires a methodology that allows for dynamic effects and is flexible in terms of the temporal sequence among and within each metric type (Srinivasan et al. 2010; Vakratsas & Ambler 1999). Likewise, sequences among online actions may include search–click–visit (starting from a need, the consumer searches for information, clicks on the most relevant link, and visits the website) and click–visit–search (the consumer gets reminded of a need from an online banner ad, visits the website, and then searches for alternatives or a better price). Allowing dynamic sales effects is also important for online metrics, as it may take a while for contextual interest to translate into sales. In summary, our methodology needs to allow for recursive effects among sales, marketing, online behavior metrics, and multiple paths and alternative hierarchies (Kannan & Li 2017). Moreover, effects are likely to emerge between attitudes and online behavior—for example, awareness may drive online search, which then may lead to website visits, enabling development of brand affect (preference), before leading to purchase. Finally, an experience/loyalty loop can shortcut the purchase path for a repeat customer (Court, Elzinga, Mulder, & Vetvik 2009; Deighton, Henderson, & Neslin 1994; Yadav & Pavlou 2014) but also feed the purchase path for another (prospective) customer.

Given the stated requirements, we investigate both survey-based attitude and online behavior metrics at a time interval when both are available so we can compute their correlations and dynamic dependencies. The weekly interval, which is standard in retail marketing models, offers a managerially relevant compromise between the typical measurement intervals of the respective metrics (typically quarterly or monthly for surveys, daily or real time for online behavior metrics). First, we assess the univariate properties of these weekly metrics, such as their coefficient of variation and stationarity. Second, we examine their correlation and Granger causality. Finally, we conduct an econometric time-series analysis, which "combines the merits of econometrics, which focuses on the relationship between variables, with those of time series analysis, which specifies the dynamics in the model" (Franses 1991, p. 240). Table 1 presents an overview of these methodology steps.

In the first step, we verify that each variable has a finite variance with augmented Dickey–Fuller unit-root tests, the most popular test in marketing applications (Bezawada & Pauwels 2013; Dekimpe & Hanssens 1999). In the second step, we conduct Granger-causality tests on each pair of a brand's attitude survey metrics and online behavior metrics (Granger 1969). Granger causality of a variable Y by a variable X means that we can predict Y substantially better by knowing the history of X than by only knowing the history of Y. We perform a series of Granger-causality tests on each pair of variables, paying special attention to the direction of causality between survey-based attitude and online behavior metrics. As in previous applications, we guard against lag misspecification by running the test for lags from 1 up to 13 (i.e., one-quarter of 13 weeks) and report the results for the lag that has the lowest *p*-value for Granger causality (Trusov, Bucklin, & Pauwels 2009).

In the third step, we capture the dynamic interactions, cross-metric influence, and feedback effects from Fig. 1 in Vector Autogressive (VAR) models (Dekimpe & Hanssens 1999). A key difference of this model from, for example, a recursive

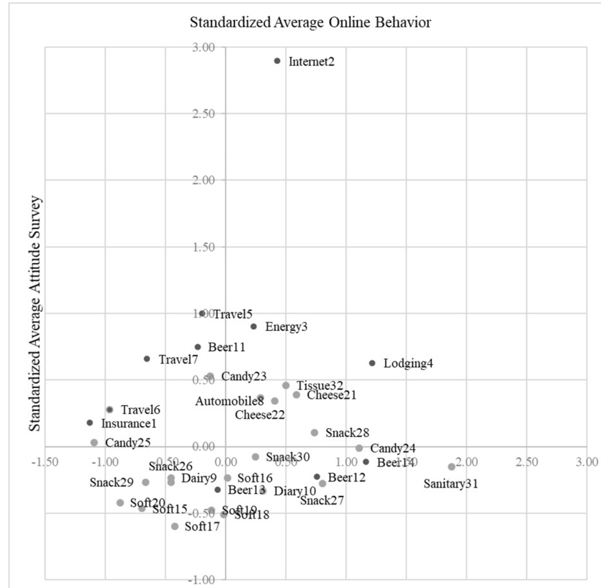

Fig. 1. How brands fall along the online behavior metrics-survey attitude metrics space.* *Note: Brands in low (high) involvement categories have light gray (dark gray) bullets.

system of equations (e.g., Aaker & Day 1971; Ilfeld & Winer 2002) is that we do not need to specify a hierarchy among metrics or assume that survey-based attitude and online behavior metrics precede purchase (Boyd, Ray, & Strong 1972; Vakratsas & Ambler 1999). Moreover, the VAR method offers a unified treatment of short- and long-term effects (Pauwels, Hanssens, & Siddarth 2002). By treating all variables (except the ones mentioned in the box Environment) in Fig. 1 as endogenous (explained by the model),[2] we capture the dynamic relationships among them without imposing a priori restrictions (Sims 1980). Eq. (1) displays the structure of the VAR model in matrix form:

$$Y_t = A + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \Psi X_t + \textstyle\sum_t, \quad t = 1, 2, \quad \ldots, T, \qquad (1)$$

where Y_t is the vector of the endogenous variables, A is the vector of intercepts, p is the number of autoregressive lags (determined by the Akaike information criterion), and X_t is a vector of exogenous control variables. Whether the (endogenous or exogenous) variables enter the model in levels or differences is determined based on the unit-root tests performed in the first step. The full residual variance–covariance matrix Σ contains the contemporaneous effect of each endogenous

Table 1
Overview of the methodological steps.

Methodological step	Relevant literature	Research question
1. Univariate properties	Schultz (1985)	How much do metrics vary over time?
Coefficient of variation	Enders (2004)	Are variables stationary or evolving?
Unit-root test Cointegration test	Johansen, Mosconi, and Nielsen (2000)	Are evolving variables in long-term equilibrium?
2. Granger Causality	Granger (1969) Trusov et al. (2009)	Which variable's changes precede another variable's changes over time?
3. Dynamic system model	Sims (1980)	How do all endogenous variables interact over time, when accounting for the unit-root and cointegration results?
VAR model	Slotegraaf and Pauwels (2008)	What is the relative importance of each variable's past in driving sales?
VAR in differences	Dekimpe and Hanssens (1999)	
Vector error correction Forecast error variance decomposition (FEVD)	Hanssens (1998)	
4. Forecasting accuracy Out-of-sample forecast error	Theil (1966)	What is the forecasting error of the model compared with a naive model?

[2] To have the same number of variables in the Attitude survey vs. Online behavior boxes, we use three variables for each box, dropping generic search but keeping branded search as a variable in the VAR models. Thus, the most elaborate VAR model (the dual model) has 10 endogenous variables (sales, 3 attitude metrics, 3 online behavior metrics and 3 marketing actions) and 3 exogenous variables (intercept, trend and either temperature or the Consumer Confidence Index). Because the VAR is efficiently estimated equation-by-equation (Leeflang, Wieringa, Bijmolt, & Pauwels 2016), it uses all observations against the parameters for each equation. We further guard against overfitting by predicting out-of-sample.

variable on the others. We estimate the model in logs of the raw data (i.e., the multiplicative model yielding a constant elasticity) for each brand, as typical for previous VAR models in marketing (Pauwels et al. 2002; Srinivasan et al. 2010; Srinivasan, Pauwels, Hanssens, & Dekimpe 2004) and to accommodate the different periods and different variable operationalizations across brands (see "Data Description" section).

To assess the sales explanatory power of survey-based attitude and online behavior metrics, we estimate four versions of the VAR model for each brand. For the all-metric full model (hereafter the "dual model"), the vector of endogenous variables includes, alongside volume sales and marketing actions, both survey-based attitude and online behavior metrics. In separate models, we leave out, respectively, the attitude survey metrics or the online behavior metrics to obtain the "online behavior model" and the "attitude survey model" (so marketing actions are still included in both of these models). Finally, we leave out both survey-based attitude and online behavior metrics to obtain the "marketing-only model." Volume sales and marketing actions are endogenous variables in each model. Because the four models have a different number of variables, we display and evaluate the adjusted R^2 of the sales variable to compare them for each brand.

To compare the power of individual metrics to drive sales, we derive for each brand the sales forecast error variance decomposition (FEVD) from the VAR estimates. Similar to a "dynamic R^2," FEVD provides a measure of the relative impact over time of shocks initiated by each of the individual endogenous variables in a VAR model (Hanssens 1998). Following previous research, we evaluate the FEVD at 10 weeks, which reduces sensitivity to short-term fluctuations. The standard errors obtained with Monte Carlo simulations allow us to evaluate statistical significance (Srinivasan et al. 2010).

In the fourth step, we assess out-of-sample forecasting performance of each VAR model. First, we estimate the four VAR models on the total sample, excluding the last three months (i.e., the estimation sample). Second, we use the estimated coefficients to make a dynamic forecast of sales on the last three months of data (the holdout sample). To compare models on out-of-sample forecasting accuracy, we calculate Theil's inequality coefficient (TIC), which has the dual advantages (Lindberg 1982; Theil 1966) of scale invariance and normalizing the forecast error by that of a naive model (a random walk), so the TIC varies between 0 (perfect forecast) and 1 (if the model forecasts only as well as the naive model).

Data Description

To focus the scope of our study, we obtained data from the Netherlands. With help of AiMark, we contacted Dutch clients of the metric providers GfK, Google, Metrix Lab, and Millward Brown with an invitation to participate in the study. If they were interested in participating, we checked with the brand managers whether data were available for sales and marketing metrics, and both survey-based attitude and online behavior metrics for at least eight months. Given our desire to assess our framework across industries, we gave priority to category and brand coverage over exact comparability of survey-based attitude metrics, which are often customized to the category and the brand in question. In other words, we included brands that differ among one another in the exact metrics covered in the classic purchase funnel. Of 79 brands contacted, 32 were able to deliver the required time series (response rate = 41%). The average number of data points is 108, within the time frame of February 2008 to September 2011. We did not detect substantial differences between responding and non-responding brands in sales growth/decline (33% of studied brands show declining sales), or fraction of marketing budget spent online (this figure varied between 0.5% and 84% in our sample, with an average of 30%). Although the included brands may differ in other dimensions from brands not participating in the study, our substantive findings are based on a broad sample in terms of online activity, and sales growth.

Our sample of 32 brands covers 14 business-to-consumer categories, including services (Internet, travel, insurance, energy, and lodging), durables (automobiles), packaged food products (cheese, salty snacks, candy, beer, and soft drinks), and packaged non-food products (toilet tissue and sanitary napkins). These categories differ on many dimensions, including consumer involvement. We operationalize category involvement using expert judges from GfK on a 7-point scale for the sole purpose of distinguishing our findings for relatively low-involvement products (receiving 3 or lower out of 7 ratings) and relatively high-involvement products and services (receiving 4 or higher out of 7 ratings). The former category consists of 20 brands, the latter of 12 brands.

The data derive from several sources. First, the 32 brands provided us with volume sales (e.g., number of milliliters sold for brands in the beer category, number of cars sold for the automobile brand),[3] marketing communication expenditures by channel (i.e., offline advertising like print, radio, outdoor, and television vs. online advertising like Google Display); and, for fast-moving consumer goods, price (average per volume unit), and promotion pressure (% of volume sales sold on promotion). The market shares (in volume) of the brands who provided us this information (19 brands in packaged food products) range from 0.06% to 20.10%, with an average of 5.68%. Second, the brands provided us survey data representative for the Netherlands consisting of the attitude metrics of brand awareness, consideration, preference, purchase intention, user status (stable), usage, and pleasantness of the brand. Table 2 shows a typical survey administered by GfK.

These surveys were answered by a random sample (of 150–350 households) drawn from a nationally representative panel of 90,000 households. The use of repeated cross-sections instead of continuous samples (asking the same respondent frequently about the same brand) is best practice to avoid survey fatigue and mere measurement bias, as practiced by competing market research firms whose data was used in, e.g.,

[3] For insurance and Internet providers, we received the number of new contracts as the metric for sales.

Table 2
Survey questions on attitude metrics.

Brand awareness

Which brands of <product category> **do you know?**
Please write down all the brands you know.

1. …
2. …
3. …
4. …
5. …
6. …
7. …
8. …
9. …

Consideration

Which of the following brands of <product category> **would you consider?**
More answers possible
<Show logo's>

1. <Brand>
2. …
3. …
4. none of these brands

Preference

Which brands of <product category> **would you prefer?**
<Show logo's>

1. <Brand>
2. …
3. …
4. none of these brands
5. don't know

Intention

<Randomize brands>
Below are some brands of <product category>**.**

How likely would you buy <brand> **in the future?**

<Brands, grid rows><show logo's>

- <Brand>
- ...
- ...

<answers, grid columns>

1. Would definitely buy
2. Would buy
3. Would not buy
4. Would definitely not buy
5. Don't know

Intention: % of respondents who answer 1 or 2.

Trial, Repeat, Stable

<Randomize brands>
Below are some brands of <product category>**.**

Could you please indicate which of the following statements best applies to below mentioned brands?

<Brands, grid rows> < show logo's>

- <Brand>
- ...
- ...

<answers, grid columns>

1. never heard of
2. only know the name
3. I know this brand and would like to try it
4. have used it, but not anymore
5. ...
6. use sometimes
7. use regularly
8. use most lt;solo>

Trial: % of respondents who answer 3, 4, 5, or 6.
Repeat: % of respondents who answer 4, 5, or 6.
Stable: % of respondents who answer 5 or 6.

Usage

Which of the following brands of <product category> **have you ever eaten?**
More answers possible
<Show logo's>

5. <Brand>
6. …
7. ...
8. none of these brands

Closeness

<Randomize brands>
Below are some brands of <product category>**.**

Could you please indicate which of the following statements best applies to below mentioned brands?

<Brands, grid rows><show logo's>

- <Brand>
- ...
- ...

<answers, grid columns>

1. A brand where I feel comfortable with
2. I share interests, activities and style with this brand
3. ...
4. This brand has high quality
5. This brand has good taste
6. ...

Closeness: % of respondents who answer 1 or 2.

Srinivasan et al. (2010) and Hanssens et al. (2014) and by YouGov, whose data were used in Colicev et al. (2018).

Online behavior metrics were sourced from Google's "Insights of Search" and consisted of the weekly number of *generic search* terms: (consumer searches for category/need), and the number of *branded search* terms (consumer searches for brand by name). Moreover, we obtained directly from the brand manager the number of website visits (single-user session, coming from any source), and the number of page views per visitor (ratio of the total number of pages viewed to the total number of visitors to the website). As environmental control variables, we used a time trend, temperature for fast-

Table 3
Categories, involvement, and available metrics for each brand.

Brand	Category (Involvement [a])	Sales and marketing [b]	Survey`trics [c]	Online behavior metrics [d]
1	Insurance (5/7)	Sales, Adv	Aware, Cons, Pref	BS, GS, WV, PV
2	Internet (5/7)	Sales, Adv	Aware, Cons, Pref	BS, GS, WV, PV
3	Energy (4/7)	Sales, Adv	Aware, Cons, Pref	BS, GS, WV, PV
4	Lodging (7/7)	Sales, Adv	Aware, Cons, Pref	BS, GS, WV, PV
5–7	Travel (7/7)	Sales, Adv	Aware, Pref	BS, GS, WV, PV
8	Automobile (7/7)	Sales, Adv	Aware, Cons, Pref	BS, GS, WV, PV
9, 10	Dairy (3/7)	Sales, Adv, Pri, Pro	Aware, Intention	BS, GS, WV, PV
11	Beer (4/7)	Sales, Adv, Pri, Pro	Aware, Cons, Pref	BS, GS, WV, PV
12–14	Beer (4/7)	Sales, Adv, Pri, Pro	Aware, Pleasant	BS, GS, WV, PV
15–20	Soft drinks (2/7)	Sales, Adv, Pri, Pro	Aware, Stable Buyers	BS, GS, WV, PV
21, 22	Cheese (2/7)	Sales, Adv, Pri, Pro	Aware, Intention	BS, GS, WV, PV
23–25	Candy (3/7)	Sales, Adv, Pri, Pro	Aware, Intention, Pref	BS, GS, WV, PV
26–30	Salty snacks (3/7)	Sales, Adv, Pri, Pro	Aware, Cons, Pref	BS, GS, WV, PV
31	Sanitary napkins (3/7)	Sales, Adv, Pri, Pro	Aware, Usage	BS, GS, WV, PV
32	Toilet tissue (2/7)	Sales, Adv, Pri, Pro	Aware, Cons, First Choice	BS, GS

[a] Involvement scale from 1 (“lowest”) to 7 (“highest”).
[b] Sales = volume sales (for insurance and Internet providers, we received the number of new contracts as the metric for sales), Adv = marketing communication expenditures by channel (i.e., offline vs. online advertising), Pri = average price per volume unit, Pro = promotion pressure (% of volume sales sold on promotion).
[c] Aware = % respondents who are aware of Brand X, Cons = % respondents who consider buying Brand X, Intention = % respondents who would (definitely) buy Brand X in the future, Pleasant = % respondents who feel pleasant with Brand X, Stable = % respondents who use Brand X regularly or often/always, Usage = % respondents who have used Brand X in the last 4 weeks, First Choice = % respondents who say that Brand X is their first choice, Pref = % respondents who prefer Brand X.
[d] BS = branded search (number of branded search terms), GS = generic search (number of generic search terms), WV = website visits (total number of visits, where a visit consists of a single-user session), PV = page views per visitor (ratio of the total number of pages viewed (where repeated views of a single page are counted) to the total number of visitors to the website).

moving consumer goods (obtained from Royal Netherlands Meteorological Institute) and the Dutch Consumer Confidence Indicator for durables and services (obtained from Statistics Netherlands). For each brand, Table 3 lists the category (involvement) and available metrics.

Note that specific metrics available differ by brand, sometimes even within the same category (e.g., the first beer brand measures awareness, consideration, and preference, while the others measure awareness and “pleasant”). Moreover, several metrics are only available for a few brands: purchase intent and the loyalty metric of user status (stable), pleasant, first choice, and usage. Rather than restricting our analysis to the few brands with exactly the same metrics, we maintain broad coverage and assess our framework for each brand.

Findings

Distribution of Brands in Online Behavior Metrics-Survey-Based Attitude Metrics Space

Fig. 1 plots the average of the survey-based attitude metrics against the average of the online behavior metrics for all brands (after standardizing the individual metrics across all brands). The lack of a strong correlation between the two dimensions is evident from the spread of brands across this space. Brands in the upper-right quadrant score on average relatively high on both types of metrics: consumers have high enduring attitudes for these brands, while showing a lot of contextual interest as well. Such brands are typically in high involvement categories (as indicated by the darker color) such as Automobile (Brand 8) and Lodging (Brand 4). The opposite holds for brands in the lower-left quadrant, which suffer from double jeopardy: they score low on average on attitude and consumers generally do not show much contextual interest. Brand 15 in Soft Drinks and Brand 26 in Salty Snacks are in this category. Brands in the upper-left quadrant have low contextual interest but high enduring attitudes. Such brands are typically in low involvement categories (indicated by the lighter color), such as Sanitary Napkins (Brand 31) and Dairy (Brand 10). Conversely, brands in the lower-right quadrant enjoy lots of contextual interest, but brand attitudes are relatively low. Brand 1 in Insurance and Brand 7 in Travel share this fate.

Metric Variation and Correlations

Table 4 shows the across-brand average of each metric's coefficient of variation and its correlation[4] with the other metrics, for each metric we have at least 10 brands (sales, awareness, consideration, preference, generic search, branded search, website visits, page views per visit). As expected from our conceptual framework, survey-based attitude metrics show the lowest week-to-week variation, online metrics the highest, with brand sales in between. In other words, survey-based attitude metrics change more slowly than brand sales, which change more slowly than the online behavior metrics (the only

[4] The coefficient of variation is calculated for each variable in levels, regardless of whether the variable has a unit root. Among stationary variables only, the values of the coefficient of variation are 0.37 for sales, 0.15 for awareness, 0.11 for consider, 0.31 for preference, 0.36 for generic search, 0.86 for branded search, 1.54 for website visits, and 0.19 for page views per visitor.

Table 4
Coefficient of variation and correlations between metrics (averaged across 32 brands).

	Sales	Awareness	Consider	Preference	Generic search	Branded search	Website visits	Pageviews per visitor
Coefficient of variation	0.34	0.18	0.14	0.32	0.32	0.59	1.21	0.44
Awareness	0.07	1.00						
Consider	0.04	0.31	1.00					
Preference	0.12	0.24	0.43	1.00				
Generic search	0.06	−0.03	−0.03	−0.05	1.00			
Branded search	0.14	0.08	0.08	0.05	0.33	1.00		
Website visits	0.15	0.10	0.04	0.02	0.18	0.47	1.00	
Page views per visitor	0.14	−0.06	−0.16	−0.09	0.05	−0.04	−0.05	1.00

exception is that preference and generic search have the same coefficient of variation). This is consistent with the notion that survey metrics express more enduring attitudes while online behavior metrics express more fickle contextual interest.

Regarding the correlations, all metrics show a positive correlation with brand sales. To assess whether metrics load on the same construct, note that all correlations between enduring attitudes and contextual interest metrics are at most 0.10, which indicates an almost negligible relationship because they are below 0.20 (Cha 1977; Warrington & Shim 2000). This is inconsistent with the competing theory that online behavior metrics are simply a manifestation of attitudes. Two recent publications find similar low correlations between online and offline metrics, though for different data. First, Fay, Keller, Larkin, and Pauwels (2019) show the absence of significant correlations between online and offline word-of-mouth metrics. Second, using individual data for smartphones and automobiles, Dotson et al. (2017) report similarly low correlations in their appendix. Instead, correlations are higher within each metric type, up to 0.43 for survey-based attitude metrics (0.49 in Dotson et al. 2017) and up to 0.47 for online behavior metrics. Consistent with these low correlations, factor analysis of all metrics does not yield satisfactory results. The low correlations between any survey metric and any online behavior metric indicate that they reflect *different information* instead of measuring the same attitude construct. However, the metrics could drive each other across periods, as we investigate in our analysis.

Granger-Causality Results

How do survey-based attitude and online behavior metrics drive each other over time? Table 5 shows the Granger causality results. For almost all brands (30 of the 32 brands, i.e., 94%), at least one online behavior metric Granger causes a survey-based metric. Across brands, the average percentage of online behavior metrics Granger causing a survey-based metric is 41%. Thus, we find support for the perspective that online behavior metrics (contextual interest) drive survey metrics (enduring attitudes). Likewise, for all brands, at least one survey-based attitude metric Granger causes an online behavior metric. The average percentage of survey metrics that Granger cause online behavior metrics is 53%. Thus, we also find support for the perspective that attitude survey metrics (enduring attitudes) drive online behavior metrics (contextual interest).

In summary, the mutual temporal dependence between survey-based attitude and online behavior metrics is consistent

Table 5
Granger causality between online behavior and survey-based attitude metrics. [a]

Brand	Category	Do online behavior metrics granger cause survey-based attitude metrics?	Do survey-based attitude metrics granger cause online behavior metrics?
1	Insurance	50.00%	58.33%
2	Internet	16.67%	75.00%
3	Energy	16.67%	50.00%
4	Lodging	25.00%	41.67%
5	Travel	50.00%	37.50%
6	Travel	50.00%	75.00%
7	Travel	50.00%	12.50%
8	Automobile	0.00%	58.33%
9	Dairy	75.00%	100.00%
10	Dairy	12.50%	50.00%
11	Beer	25.00%	50.00%
12	Beer	62.50%	75.00%
13	Beer	62.50%	50.00%
14	Beer	75.00%	62.50%
15	Soft drinks	25.00%	37.50%
16	Soft drinks	50.00%	37.50%
17	Soft drinks	25.00%	25.00%
18	Soft drinks	0.00%	100.00%
19	Soft drinks	50.00%	66.67%
20	Soft drinks	37.50%	12.50%
21	Cheese	12.50%	50.00%
22	Cheese	50.00%	75.00%
23	Candy	58.33%	91.67%
24	Candy	25.00%	25.00%
25	Candy	22.22%	44.44%
26	Salty snacks	16.67%	33.33%
27	Salty snacks	58.33%	25.00%
28	Salty snacks	50.00%	75.00%
29	Salty snacks	33.33%	44.44%
30	Salty snacks	75.00%	41.67%
31	Sanitary napkins	87.50%	100.00%
32	Toilet tissue	50.00%	16.67%

[a] The percentages show the number of times one or more of the online behavior metrics (attitude survey metrics) Granger cause one or more of the attitude survey metrics (online behavior metrics), relative to the total number of pairs possible. For example, for Brand 1 (insurance), three attitude behaviors can Granger cause five online behavior metrics (and vice versa), leading to 15 pairs possible. In total, 9 online behavior-survey-based attitude pairs are significant (60.00%), and 10 survey-based attitude–online behavior pairs are significant (66.67%).

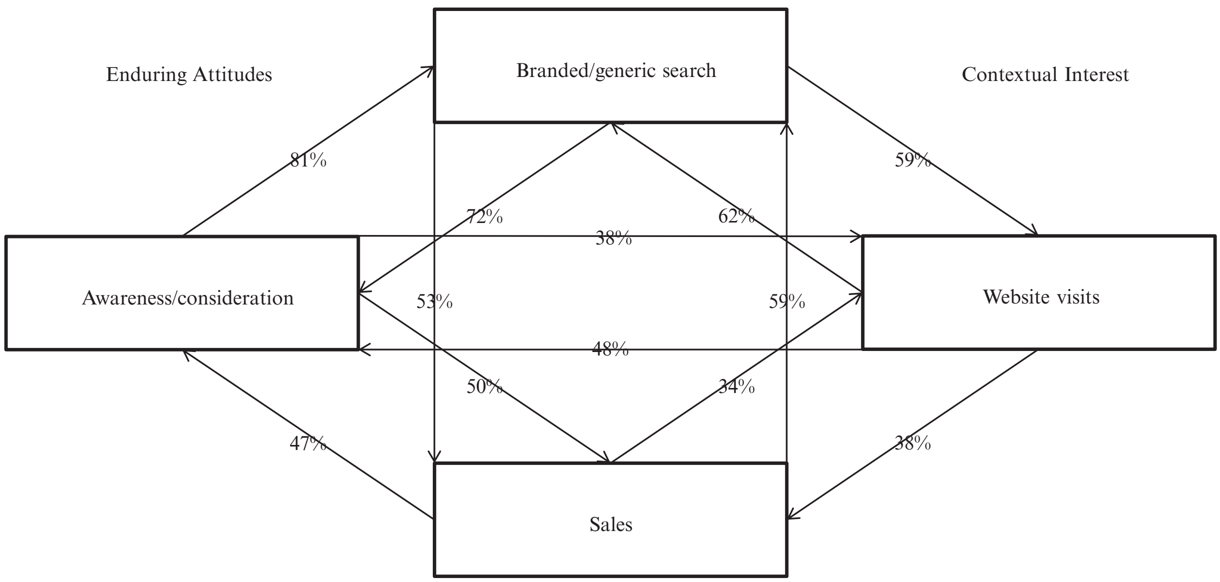

Fig. 2. Temporal causality* of aggregate metrics of attitude survey and online behavior. *Percentage of brands for which the arrow-starting metric Granger causes the arrow-receiving metric, close to which the percentage of brand cases is displayed (note: this has nothing to do with the effect size, which is estimated in the VAR models instead). For ease of exposition, and consistent with Court et al. (2009)'s "online consumer decision journey," we combined awareness and consideration in the left hand box, and branded and generic search in the top box, even though the Granger Causality tests were executed separately for each of these variables.

Table 6
Sales explanatory power across models: R^2 (adjusted R^2).

Brand	Category	Dual model	Online behavior model	Attitude survey model	Marketing-only model
1	Insurance	0.91 (0.88)	0.88 (0.88)	0.88 (0.88)	0.89 (0.88)
2	Internet	0.84 (0.77)	0.82 (0.77)	0.8 (0.74)	0.77 (0.74)
3	Energy	0.33 (0.25)	0.3 (0.24)	0.28 (0.22)	0.26 (0.22)
4	Lodging	0.44 (0.14)	0.39 (0.14)	0.27 (0.02)	0.23 (0.04)
5	Travel	0.9 (0.71)	0.88 (0.75)	0.76 (0.58)	0.68 (0.56)
6	Travel	0.91 (0.8)	0.88 (0.77)	0.87 (0.8)	0.83 (0.76)
7	Travel	0.95 (0.79)	0.86 (0.66)	0.81 (0.61)	0.66 (0.47)
8	Automobile	0.64 (0.09)	0.49 (0.09)	0.46 (0.05)	0.3 (0.05)
9	Dairy	0.6 (0.45)	0.59 (0.46)	0.5 (0.38)	0.48 (0.38)
10	Dairy	0.23 (0.02)	0.22 (0.04)	0.19 (0.03)	0.17 (0.05)
11	Beer	0.69 (0.44)	0.6 (0.4)	0.54 (0.31)	0.49 (0.34)
12	Beer	0.72 (0.58)	0.69 (0.57)	0.63 (0.5)	0.59 (0.49)
13	Beer	0.22 (0.1)	0.14 (0.04)	0.16 (0.07)	0.09 (0.03)
14	Beer	0.55 (0.5)	0.55 (0.51)	0.52 (0.49)	0.52 (0.49)
15	Soft drinks	0.18 (0.12)	0.17 (0.12)	0.17 (0.12)	0.16 (0.12)
16	Soft drinks	0.39 (0.16)	0.35 (0.16)	0.33 (0.16)	0.3 (0.18)
17	Soft drinks	0.84 (0.64)	0.77 (0.58)	0.76 (0.6)	0.69 (0.55)
18	Soft drinks	0.77 (0.22)	0.69 (0.31)	0.76 (0.36)	0.66 (0.35)
19	Soft drinks	0.53 (0.42)	0.48 (0.38)	0.5 (0.41)	0.46 (0.39)
20	Soft drinks	0.51 (0.41)	0.44 (0.36)	0.46 (0.39)	0.41 (0.36)
21	Cheese	0.67 (0.29)	0.59 (0.3)	0.56 (0.34)	0.48 (0.33)
22	Cheese	0.22 (0.07)	0.22 (0.1)	0.17 (0.06)	0.17 (0.09)
23	Candy	0.53 (0.36)	0.5 (0.37)	0.48 (0.35)	0.44 (0.36)
24	Candy	0.17 (0.09)	0.16 (0.1)	0.13 (0.07)	0.12 (0.08)
25	Candy	0.31 (0.25)	0.3 (0.26)	0.31 (0.26)	0.3 (0.27)
26	Salty snacks	0.48 (0.34)	0.43 (0.33)	0.46 (0.34)	0.4 (0.32)
27	Salty snacks	0.37 (0.2)	0.27 (0.13)	0.36 (0.23)	0.27 (0.16)
28	Salty snacks	0.74 (0.62)	0.62 (0.49)	0.7 (0.6)	0.58 (0.49)
29	Salty snacks	0.41 (0.24)	0.32 (0.19)	0.38 (0.24)	0.3 (0.2)
30	Salty snacks	0.48 (0.11)	0.38 (0.09)	0.39 (0.1)	0.32 (0.1)
31	Sanitary napkins	0.17 (0.03)	0.15 (0.05)	0.17 (0.04)	0.14 (0.06)
32	Toilet tissue	0.08 (0.001)	0.08 (0.01)	0.07 (0.01)	0.07 (0.02)

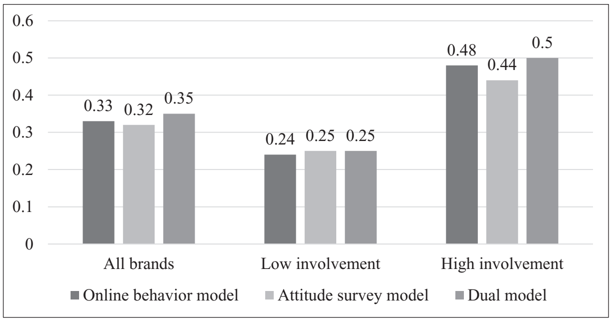

Fig. 3. Adjusted R^2 for the attitude survey, online behavior, and dual models.

with our framework and inconsistent with the competing theories that online behavior unidirectionally follows from attitudes or that survey-based attitudes unidirectionally follow from (online) behavior. Instead, more complex feedback loops exist among enduring attitudes and online expressions of contextual interest. We illustrate in Fig. 2 the prepurchase metric aggregates (awareness/consideration, branded/generic search, and website visits) that Granger cause sales for the majority of studied brands.

Brand attitudes both drive and are driven by online branded/generic search and website visits. Moreover, online branded/generic search leads to more website visits and vice versa. For more than 44% of brands, awareness/consideration, branded/generic search, and website visits drive brand sales, which in turn drive these metrics.

VAR Model Specification and Fit

The unit-root tests showed that 12 brand sales series are trend stationary, while 20 brand sales series show a unit root and thus need to be first differenced before inclusion in the model (we do the same for other endogenous variables that show a unit root, as no cointegration was detected). This also means that, for most brands, the (adjusted) R^2 results represent the explanatory power of sales *growth*, which is harder to explain and predict than sales levels. For the number of lags, the Akaike information criterion indicates one lag for about one-third of the brands and two, three, or four lags for the remaining brands.

The VAR models show acceptable fit for brand sales, with an average explanatory power of 0.47 (the average adjusted R^2 is 0.33) and average forecasting accuracy (TIC) of 0.44. Lindberg (1982) considers TIC values around 0.55 and below "very good," and therefore we conclude that the models are usable for forecasting sales. Table 6 shows the explanatory power (R^2 and adjusted R^2) for each brand and each of the four alternative models.

For 7 out of 32 brands (22%), adding either online behavior or attitude metrics does not increase the adjusted R^2 in the marketing-mix VAR model, which already accounts for long-term marketing effects. However, most brands (78%) do see significantly higher sales explanation from adding metrics – and the type of beneficial metric depends on involvement. Fig. 3 shows the average adjusted R^2 for the attitude survey model, the online behavior model, and the dual model, across all brands as well as by involvement type. The explanatory power of the online behavior model is lowest for low involvement brands, consistent with the notion that few consumers take online action in such categories. On average though, the online metrics-only model explains sales better than the attitude survey-only model does.

Our findings of the higher explanatory power of online behavior metrics are also reflected in the FEVD (dynamic R^2) results, which show that survey-based attitudes explain 15.8% in sales while online behavior metrics explain 23.2% in sales for the average brand. Fig. 4 shows the average FEVD for each metric in explaining brand sales. Awareness, branded search, and website visits stand out as most important across categories. Website visits can be expected to matter most, as they are the owned media that allows brands to provide consumer information and often to sell directly (Ilfeld & Winer 2002; Pauwels, Aksehirli, & Lackman 2016). Moreover, branded search indicates active interest of the consumer in the brand (Rutz & Bucklin 2011), while awareness retains a prominent place in models of the consumer journey (Court et al. 2009; Ilfeld & Winer 2002). Fig. 4 illustrates that most

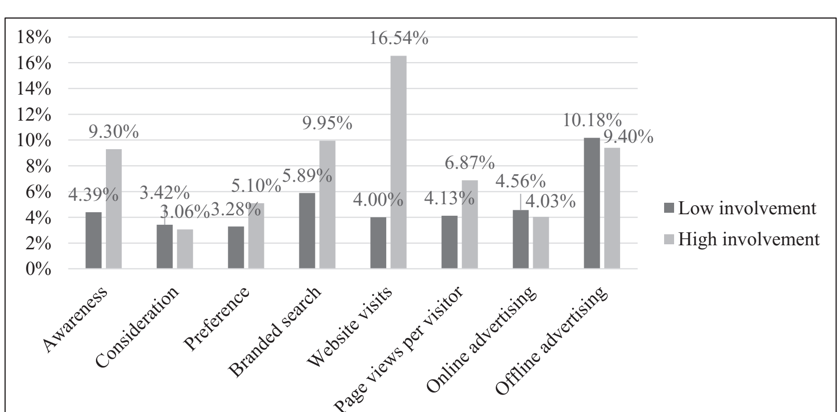

Fig. 4. How each metric and online and offline marketing drive sales.* *Forecast Error Variance Decomposition (FEVD) of brand sales; the remainder percentage is past sales, averaged across brands.

Table 7
Sales predictive power across models: TIC. [a]

Brand	Category	Dual model	Online behavior model	Attitude survey model	Marketing-only model
1	Insurance	0.01	0.01	0.01	0.01
2	Internet	0.01	0.01	0.01	0.005
3	Energy	0.82	0.86	0.83	0.87
4	Lodging	0.02	0.02	0.02	0.02
5	Travel	0.02	0.01	0.01	0.01
6	Travel	0.01	0.004	0.01	0.01
7	Travel	0.25	0.35	0.64	0.67
8	Automobile	0.73	0.71	0.71	0.77
9	Dairy	0.76	0.77	0.77	0.75
10	Dairy	0.79	0.79	0.79	0.79
11	Beer	0.88	0.66	0.77	0.76
12	Beer	0.64	0.71	0.68	0.64
13	Beer	0.03	0.03	0.03	0.03
14	Beer	0.71	0.75	0.71	0.76
15	Soft drinks	0.01	0.01	0.01	0.01
16	Soft drinks	0.01	0.01	0.01	0.01
17	Soft drinks	0.63	0.95	0.51	0.83
18	Soft drinks	0.97	0.68	0.76	0.76
19	Soft drinks	0.71	0.74	0.73	0.74
20	Soft drinks	0.63	0.69	0.78	0.79
21	Cheese	0.61	0.67	0.76	0.81
22	Cheese	0.05	0.05	0.05	0.05
23	Candy	0.62	0.65	0.62	0.67
24	Candy	0.01	0.01	0.01	0.01
25	Candy	0.88	0.88	0.88	0.88
26	Salty snacks	0.85	0.86	0.84	0.85
27	Salty snacks	0.83	0.81	0.73	0.75
28	Salty snacks	0.56	0.67	0.68	0.67
29	Salty snacks	0.04	0.04	0.04	0.04
30	Salty snacks	0.66	0.74	0.78	0.78
31	Sanitary napkins	0.01	0.01	0.01	0.01
32	Toilet tissue	0.01	0.01	0.01	0.01

[a] Three months out dynamic forecast, with lower errors reflecting better models.

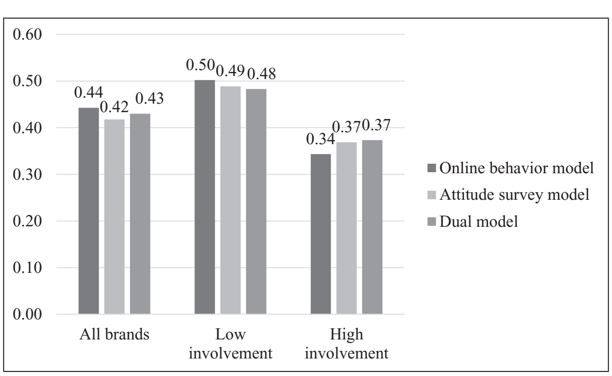

Fig. 5. Forecast error for the attitude survey, online behavior, and dual models.* *Theil's Inequality Coefficient (TIC) for three months out-of-sample dynamic forecasting (0 = perfect, 1 = naive forecast; i.e., random walk), averaged across brands.

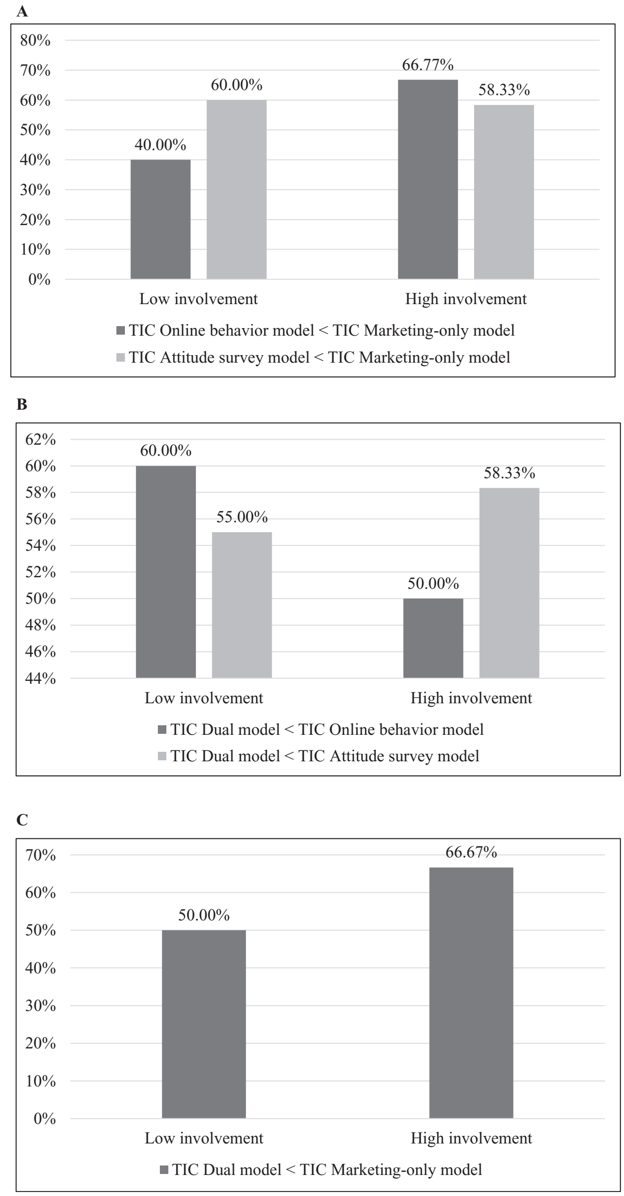

Fig. 6. Model comparison out-of-sample forecasting accuracy.* A: Percentage of brands for which metric models outpredict marketing-only model. B: Percentage of brands for which dual model outpredicts the metric type models. C: Percentage of brands for which dual model outpredicts the marketing-only model. *Percentage of brands for which TIC model A (e.g., Online behavior model) is lower than TIC model B (e.g., Marketing-only model) for brands in high vs. low involvement categories.

metrics explain sales more in high-involvement categories, while consideration, pages per visit, and advertising explain sales more in low-involvement categories. Important to managers, offline advertising has twice the sales explanatory power of online advertising. Thus, the high explanatory power of *online metrics* does not mean that brands should shift all their dollars to *online ads*, as discussed in several studies showing the ability of offline ads to drive online behavior (Fay et al. 2019; Pauwels et al. 2016; Wang & Goldfarb 2017).

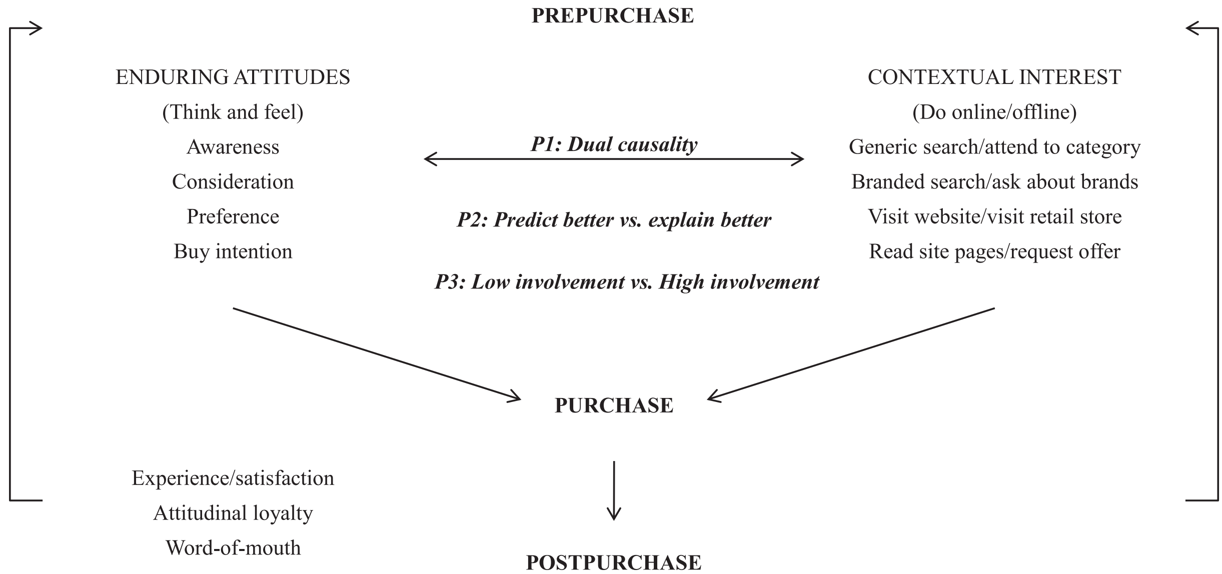

Fig. 7. Proposed framework of enduring attitudes and contextual interest.

In summary, we find that online behavior metrics, representing contextual interest, perform better in explaining short-term sales than attitude survey metrics do. Given their complementary roles, however, the dual model with both types of metrics has the strongest explanatory power. We next turn to the metrics' predictive power.

Survey-Based Attitude and Online Behavior Metrics in Sales Prediction

Table 7 and Figs. 5 and 6 show the out-of-sample dynamic forecast error (TIC) three months out for sales of the attitude survey model (marketing plus attitude survey metrics), the online behavior model (marketing plus online behavior metrics), and the dual model (marketing plus attitude survey metrics and online behavior metrics).

The online behavior model performs worst (higher forecast error three months out) and the dual model best in low-involvement categories. Thus, we find some support for the notion that attitude survey metrics are crucial to forecasting sales in low-involvement categories. Although online behavior metrics perform better in-sample, attitude survey metrics do better in forecasting out-of-sample for low-involvement categories. Fig. 6 (Panel A) visualizes this contrast: adding attitude metrics to the marketing-only model improves sales prediction for the majority of low-involvement brands, but adding online behavior metrics does not. By contrast, the online behavior model performs best in high-involvement categories in general (Fig. 5), and adding online behavior metrics improves over the marketing-only model for most brands (Fig. 6, Panel A). As Panel B of Fig. 6 shows, the dual model has better predictive power than the online behavior model for 60% of low-involvement and 50% of high-involvement brands. Finally, Panel C of Fig. 6 shows that, compared to the marketing-only model, the dual model improves sales prediction for the majority of high-involvement brands, but for only half of of the low-involvement brands. Thus, for many brands in our sample, we observe no additional value of collecting aggregate metrics of attitudes and online behavior for predicting sales in a model that already includes long-term marketing effects.

Discussion: Enduring Attitudes and Contextual Interest on the Road to Purchase

Based on these empirical generalizations across consumer categories, we propose the integrated Road to Purchase framework in Fig. 7. On the sides, we distinguish enduring attitudes (as measured by surveys) from contextual interest (as manifested in either online behavior or offline or online behavior, such as visiting a retail store).

Three main propositions derive from our framework. First, enduring attitudes and contextual interest metrics show mutual temporal dependence (P1). Second, both enduring attitude and contextual interest metrics drive sales but the former excel in sales prediction (P2a) and the latter in sales explanation (P2b). Third, survey-based attitudes should be most informative in low-involvement categories (P3a), which are characterized by inertia/habitual buying (Ehrenberg 1974) and show less online behavior (Lecinski 2011). By contrast, online behavior metrics should be especially informative in high-involvement categories (P3b). To close the post-purchase loop, customers' experience with the product/service may induce them to update their attitudes and online/offline behavior (bottom of Fig. 7). Moreover, their purchase and word-of-mouth may inspire other consumers to consider, search for, and buy the brand (e.g., Pauwels et al. 2016).

Conceptually, we propose that survey metrics represent *enduring attitudes* that fundamentally differ from the *contextual interest* measured by online behavior metrics. Just as with the distinction between enduring involvement and situational importance (Bloch & Richins 1983), attitude metrics should barely change over time (Hanssens et al. 2014), while contextual interest depends on the specific situation of the consumer. Unlike "situational importance" though, this contextual interest need not reflect an urgent buying need (e.g., the refrigerator broke down) but may reflect the consumer's need to explore, escape, and/or entertain (Holbrook & Hirschman 1982). Indeed, people often browse the Internet to escape their problems and improve their mood (Abrantes, Seabra, Lages, & Jayawardhena 2013; Grant 2005). While doing so, they may stumble on a reference to a category or product that peaks their interest. Brand managers may capitalize on new online advertising forms to reach such audiences, e.g., Amazon's DSP program allows advertisers to buy display and video ads reaching audiences on and off the ecommerce platform (Amazon 2020).

Conclusion

In this article, we show that online behavior metrics are distinct from the attitudinal constructs previously developed as part of the purchase funnel. These actions provide complementary information that excels in explaining short-term sales but not in predicting long-term sales, especially in low-involvement settings. Specifically, we find a low correlation between weekly attitudinal and online metrics but a mutual dependence over time. Moreover, attitudinal metrics change more slowly but online metrics change more quickly than brand sales do, across a wide variety of categories of consumer durables, services, and packaged goods. While online behavior metrics excel in explaining (same-week) sales, survey-based attitude metrics excel in predicting sales, especially in low-involvement categories.

In terms of substantive theory contributions, our study helps explain a key puzzle in marketing literature. Why do "old-fashioned" survey-based attitude metrics still have explanatory sales power and forecasting performance if they change more slowly than sales do (Merks-Benjaminsen 2014) and when "the first thing people do when they hear about a product is search for it online" (Tobaccowala, as quoted in Lecinski 2011, p. 9)? The slower change in survey-based attitude metrics likely reflects the enduring attitudes toward the brand, and therefore they are suited to capture long-term movements that affect a brand's fortune. In other words, frequent shifts in weekly online activity may fit sales well in-sample but contain a substantial amount of noise that masks the long-term signal. In addition, survey metrics have evolved over decades of marketing research and are often customized for specific brands in an iterative process (Pauwels et al. 2009). Marketing literature has well documented their measurement errors for decades, and managers have learned over time which ones are most useful to their decision making. By contrast, both researchers and managers are still trying to figure out which online metrics to trust, concerned by studies that show that less than 60% of web traffic is human based and worried that "years of metrics-driven growth, lucrative manipulative systems, and unregulated platform marketplaces have created an environment where it makes more sense to be fake online" (Read 2018). If brand managers are getting better at customizing online metrics as well (Pauwels 2014), the advantage of survey metrics might diminish over time. Furthermore, many product categories are characterized by habitual and stable buying patterns (Ehrenberg 1974), which attitude survey metrics capture well (Srinivasan et al. 2010).

As a further contribution to literature, our finding that both survey-based attitude and online behavior metrics help explain sales is consistent with the claim that consumers increase activity to accommodate new information rather than merely substitute old for new information sources (Lecinski 2011). Such increased total search activity logically flows from a consumer model in which the online activity reduces search costs but consumers expect relatively high gains from additional search (Ratchford, Lee, & Talukdar 2003). Even when the expected benefit from online activity is rather small (e.g., salty snacks), the low cost of online information gathering makes it worthwhile for at least some consumers to do so.

For managers, our integrated framework provides a more comprehensive picture of brand health and the road to purchase. The low correlations between survey-based attitude and online behavior metrics mirror those between offline and online WOM (Fay et al. 2019) and indicate the danger of limiting the brand's measurement focus to one side of our conceptual framework. Both types of metrics can be leading key performance indicators (i.e., Granger cause performance; Pauwels 2014) and show both marketing responsiveness and sales conversion (Hanssens et al. 2014). Quantifying these conversions for their own brand enables managers to address weak links and take remedial action with both offline and online marketing instruments.

Our specific managerial recommendations are threefold. First, our mutual temporal dependence findings show that inducing changes to online behavior can change attitudes down the road. Empirically confirming McKinsey's "consumer decision journey" (Court et al. 2009), we find that online exposure can increase brand awareness and other attitudes. Businesses have caught on. For instance, over 40% of advertising on Amazon.com is geared toward awareness (Christe 2019). Second, when do attitude metrics still matter? When the consumer product is in a low-involvement category. We find the largest benefit of survey-based attitudes in explaining and predicting brand sales for lower-involvement categories, also known as fast moving consumer goods. Third, which specific metrics should managers track? The relatively high correlations within the survey attitude metrics and online behavior metrics respectively (and the low correlations between them), suggest that managers do not need to track all attitude survey metrics, and all online behavior metrics in short time intervals – which is expensive. Rather, they should select those that are leading indicators of sales but not highly correlated with each other. Based on our data and analysis, benchmark candidate metrics are awareness and preference for the attitude survey metrics, and branded search and pageviews per visitor for the online metrics. The other metrics could then be tracked and analyzed on a monthly or even quarterly interval. Managers aiming to influence sales in the short term (e.g., to reach tactical weekly or monthly targets) should put more weight on online behavior metrics. This holds especially for managers of brands in high involvement categories. By contrast, managers with a long term focus (e.g., when making strategic plans for the coming year) should include both metric types, but put more weight on attitude survey measures, especially in low-involvement categories. Coming back to the priorities of the Marketing Science Institute, such attitude metrics help “identify when shifts in shopping behavior are most likely to occur, and estimate the direction, magnitude and duration of these shifts.”

Limitations of our empirical work include the aggregated and weekly nature of our data. Aggregating in itself is not atypical for studies on online activity, as privacy concerns limit access to individual-level information. Regarding the data interval, online metrics are typically available at finer frequencies than attitude survey metrics, which allows for faster assessment of the tactical successes of specific campaign executions. Our study does not consider this benefit of online behavior metrics and thus is likely to underestimate their value to managers who want real-time information on, for example, how much online behavior a specific television campaign generates. Our methodology has the benefit of offering a dynamic and flexible description of data patterns and of forecasting the effects of marketing actions similar to those in the estimation period, but it does not allow for a structural interpretation of the parameters or an optimization of the marketing effects. Finally, our data are a few years old and from the Netherlands; a developed market with high internet penetration. We invite further research in other countries and time periods.

In summary, we find that attitude survey metrics still have power in predicting sales across brands and categories. However, we find high explanatory power for online behavior metrics, especially for high-involvement goods and services. Our empirical analysis quantifies the sales explanatory power of both types of metrics and thus helps managers understand and drive their brand's success in the digital age.

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