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Customer journey analyses in digital media: exploring the impact of cross-media exposure on customers' purchase decisions

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Abstract

Purpose – In the age of digital media, customers have access to vast digital information sources, within and outside a company's direct control. Yet managers lack a metric to capture customers' cross-media exposure and its ramifications for individual customer journeys. To solve this issue, this article introduces media entropy as a new metric for assessing cross-media exposure on the individual customer level and illustrates its effect on consumers' purchase decisions.

Design/methodology/approach – Building on information and signalling theory, this study proposes the entropy of company-controlled and peer-driven media sources as a measure of cross-media exposure. A probit model analyses individual-level customer journey data across more than 25,000 digital and traditional media touchpoints.

Findings – Cross-media exposure, measured as the entropy of information sources in a customer journey, drives purchase decisions. The positive effect is particularly pronounced for (1) digital (online) versus traditional (offline) media environments, (2) customers who currently do not own the brand and (3) brands that customers perceive as weak.

Practical implications – The proposed metric of cross-media exposure can help managers understand customers' information structures in pre-purchase phases. Assessing the consequences of customers' cross-media exposure is especially relevant for service companies that seek to support customers' information search efforts. Marketing agencies, consultancies and platform providers also need actionable customer journey metrics, particularly in early stages of the journey.

Originality/value – Service managers and marketers can integrate the media entropy metric into their marketing dashboards and use it to steer their investments in different media types. Researchers can include the metric in empirical models to explore customers' omni-channel journeys.

Keywords Digital media, Individual-level data, Experience tracking, Customer journey, Media synergies

Paper type Research paper

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Digital media have dramatically changed how customers communicate with brands. Rather than being passive recipients of information, modern customers actively co-create brand meaning through social media channels such as Facebook, Twitter or YouTube (Hennig-Thurau *et al.*, 2010; Leeflang *et al.*, 2014). Whereas company-controlled advertising previously dominated, currently peer-to-peer media, such as consumer reviews, social media activities and word of mouth (WOM) represent equally important sources of brand information (Jahn and Kunz, 2012). Such media fragmentation requires service managers to rely on customer journey analyses, conducted by internal departments (e.g. marketing, data science) or external service providers (e.g. marketing agencies), to understand what they can do to create superior customer experiences (Homburg *et al.*, 2017; Lemon and Verhoef, 2016). Customer journey analysis accordingly has emerged as a distinctive service offered by marketing agencies (e.g. Custellence), consultancies (e.g. Bain and Company) and software as a service (SaaS) platforms (e.g. SAS). These service providers go beyond identifying series of touchpoints and instead provide relevant, actionable metrics that promise to capture the overall journey and experience (Bain and Company, 2018; McKinsey and Company, 2019).

Yet popular metrics such as the Net Promoter Score or assessments of customer satisfaction typically adopt an aggregated, "end of pipe" perspective that does not specify specific stages of individual customer journeys. Managers strive for a deeper understanding of customer decision-making processes, especially in omni-channel environments characterized by a plethora of touchpoints (Verhoef *et al.*, 2015). For example, understanding decisions along customer journeys requires insights into customers' pre-purchase information status. It not only shapes their subsequent information search behaviour (Verhoef *et al.*, 2007) but also informs the level of difficulties consumers likely will have in predicting the quality of complex products and service with salient experience and credence qualities (Voorhees *et al.*, 2017; Zeithaml, 1981). An inability to assess quality levels prior to purchase, due to a lack of information, may prevent customers from buying a product or service in the first place.

To capture customers' information status in the pre-purchase stage, we propose a new metric that assesses cross-media exposure at the individual customer level. Beneficial media synergies might result from customers' exposures to company-controlled "paid media" and peer-driven "earned media" touchpoints. Thus, we propose assessing the effects of cross-media exposure on the basis of media entropy – defined as variation in paid and earned media sources within a customer journey. To the best of our knowledge, individual-level metrics that capture cross-media exposure and its effects on customers' purchase decisions remain scarce. This is surprising, considering the bottom-line importance of media synergies assessed based on aggregated market-level data (e.g. Naik and Raman, 2003; Pauwels *et al.*, 2016) and the increasing availability of individual-level data gathered from customer journey tracking tools (Baxendale *et al.*, 2015).

We empirically test the impact of cross-media exposure on customer purchase decisions based on individual-level customer journey data. This data was collected in cooperation with a marketing agency and encompasses more than 25,000 digital and traditional media touchpoints reported by 1,831 participants from five countries (China, France, Germany, United Kingdom and United States), through a smartphone application.

Introducing and validating this individual-level metric to capture cross-media exposure yields several contributions to research and managerial practice. First, our proposed media entropy metric addresses calls for new metrics of customer experiences in general (Bolton *et al.*, 2018; Lemon and Verhoef, 2016; McColl-Kennedy *et al.*, 2015) and for assessments of the "pre-core service encounter" in particular (Voorhees *et al.*, 2017). Second, we make a methodological contribution to customer journey analyses in service research (e.g. Halvorsrud *et al.*, 2016; Tax *et al.*, 2013; Zomerdijk and Voss, 2010) and to studies of media synergies (e.g. Naik and Raman, 2003; Pauwels *et al.*, 2016; Srinivasan *et al.*, 2016). Current studies tend to focus on media exposure or media volume, whereas our metric accounts for the increasing variety of media touchpoints in omni-channel systems and thereby captures the information structures of customer journeys. Third, we investigate the effectiveness of cross-media exposure in light of heterogeneous customer characteristics. By accounting for pre-existing brand strength and current brand ownership, this study provides an extension of the rarely considered influence of customer characteristics on media type effectiveness (Ho-Dac *et al.*, 2013; Leeflang *et al.*, 2014). Accordingly, we advance research into the effectiveness of media synergies in brand-related conditions (Pauwels *et al.*, 2016). For companies and marketing agencies, this study establishes an actionable metric they can integrate directly into their marketing dashboards and use to select their marketing investments in different media types.

Research background

Customer journey, media touchpoints and purchase decisions

Unlike impulsive or habitual purchases, service purchases typically require customers to proceed along different stages of the customer journey. Theoretically, this requirement stems from the experience and credence qualities that typically dominate services and hamper customers' quality assessments prior to a purchase (Zeithaml, 1981). In general, when consumers identify a need to buy a service in a certain category, they start their decision-making process with an initial consideration set of brands. This consideration set is usually formed on the basis of their past purchase experiences and previous encounters with marketing campaigns by the category's brands (Baxendale *et al.*, 2015). Then during the subsequent pre-purchase stage, customers start to obtain and review brand information and evaluate the available brands. They next decide which service to purchase or whether to forgo purchase completely (Court *et al.*, 2009; Edelman and Singer, 2015).

From a service research perspective, the pre-purchase stage thus significantly shapes the relationship between the firm and the customer. It is mainly characterized by customers' information search, through which they gather information from company-controlled and peer-driven sources in traditional and digital media channels (McColl-Kennedy *et al.*, 2015). This puts a focus on the design and management of the customer journey to provide the customer with relevant information across different media channels (Lemon and Verhoef, 2016).

Despite its importance for the eventual purchase decision, the pre-purchase stage has received relatively little attention in service research, especially compared with the focus on the core service delivery (Voorhees *et al.*, 2017). Exposure to different information sources or media touchpoints before making a purchase decision is a key feature of customer journeys though, especially in the digital age (Lemon and Verhoef, 2016; Voorhees *et al.*, 2017). Media touchpoints include various encounters that provide information about a firm. Most prominently, literature differentiates between company-controlled "paid" and customer- or peer-driven "earned" media, which can appear either in the offline or in the online channel. Paid media encompass activities undertaken directly by the company itself or its agents (e.g. retailers), such as television advertising, online advertising or sponsoring. Earned media refer to indirect encounters with the brand, through other customers or third parties. This category includes peer-to-peer interactions such as WOM, consumer reviews and published content (e.g. expert reviews) (Stephen and Galak, 2012). In contemporary media environments, peers' communication efforts exert a growing influence on purchase decisions, in addition to company-initiated communication activities (Hennig-Thurau *et al.*, 2010). Capturing the overall influence of digital media requires investigating patterns of interactions that determine customers' information structures and measuring the consequences of their exposure to different media in their customer journey (McColl-Kennedy *et al.*, 2015). Particularly, insights on cross-media synergies between different information sources might help reveal the influence of the information structure.

Research on media synergies

Exposures across multiple media should be more informative for customers than receiving information from a single medium. Extensive research also suggests a positive effect of such media synergies on sales (e.g. Jayson *et al.*, 2018; Naik and Raman, 2003; Pauwels *et al.*, 2016; Srinivasan *et al.*, 2016). These studies distinguish within-media synergies, such as between television and print advertising (e.g. Naik and Raman, 2003); cross-media synergies between offline and online channels (e.g. Naik and Peters, 2009); and cross-media synergies between different information sources, such as company-controlled and peer-driven media (e.g. Jayson *et al.*, 2018).

These contributions consistently rely on aggregate data about a company's media spending or peer-media traffic to assess media synergies, modelled as interaction effects among different media, on overall company sales. Compared with aggregated data, individual-level data pertaining to customer exposures to different media can provide richer insights, by capturing the information structure that individual customers receive. Assessing cross-media exposures along an individual customer journey also accounts for their changing information consumption, which is enabled by their more efficient access to a variety of media touchpoints. Interestingly, research that has capitalized on individual-level data focusses on the effectiveness of individual media touchpoints, not cross-media exposure and its potential media synergies (Baxendale *et al.*, 2015; Romaniuk and Hartnett, 2017). To address this shortcoming, we conceptualize a customer-centric metric of cross-media exposure.

Media entropy: a new metric to capture cross-media exposure with individual-level data

Our customer-centric cross-media exposure metric seeks to go beyond simple measures of overall media exposure and media frequency to account for the information structure entailed in a customer's individual customer journey. Measures of media frequencies and their interactions are not well suited for customer journey data, because more frequent media encounters do not necessarily mean better information or risk reduction that would lead to a purchase decision. During their customer journey, some customers might seek to reduce their purchase risk early, such that they do not encounter many touchpoints; others continue searching but never purchase, despite frequent interactions. We therefore use a structural measure of the information accessed during the customer journey, independent of the frequency of exposure to an information source.

To provide such a metric, we build on information and signalling theory. The structure in which information is provided influences customers' information processing and decision-making process (Lurie, 2004; Van Herpen and Pieters, 2002). According to information theory, assessing the structure of information is particularly important in rich information environments. To capture the structure of information, we operationalize cross-media exposure in individual-level customer journey data as the entropy of paid and earned media calculated over all previous media touchpoint encounters. Entropy is a common measure in information theory (Shannon, 1948) that also has been applied to customer decision-making in information-rich environments as an elaborate concept to assess the variability of an information structure (Lurie, 2004; Van Herpen and Pieters, 2002). Specifically, entropy is a variety measure of categorical data, such that it equals zero when only one information type is present and reaches its maximum when all information types are represented equally. In other words, higher levels of entropy indicate greater information variety. For a given customer, we calculate the cross-media exposure of media types in the customer journey for a given brand as

$$\text{MediaEntropy} = -\sum_{k=1}^{N} p_k \log p_k,$$

where p_k is the proportion of all media touchpoints categorized as the k^{th} media type.

Entropy also has two features that make it specifically applicable in our context. First, it provides an operationalization of the variation of categorical data, such that it can capture the heterogeneity of paid versus earned media touchpoints prior to the purchase decision. Second, it is independent of the total number of brand encounters in the customer journey. As such, it goes beyond simple measures of overall media exposure and media volume by capturing cross-media exposure. Low entropy of information sources describes a situation in which customers are mostly exposed to either paid or earned media touchpoints. In contrast, high entropy means that customers encounter media touchpoints from both paid and earned media categories. The cross-media exposure indicated by the entropy of information sources then provides a new layer of information, which can reveal better how information-rich environments affect consumer decision-making. Drawing on information economics and signalling theory, we develop specific hypotheses for the influence of this media entropy metric on customers' purchase decisions.

The effect of media entropy on brand purchase

To be relevant for customer journey analyses, media entropy, as an operationalization of cross-media exposure, must exert an effect on brand purchases. We rely on information economics to provide a justification for why our media entropy metric should influence brand purchases.

Customers lack full information about brands before purchase, so they search for brand-related information to reduce their purchase risk. In general, two key factors determine the value of a signal: clarity and credibility. Signal clarity depends largely on the consistency of brand-related information; it captures the extent to which a company's communication activities reflect the intended, overall message and provide unambiguous information. Signal credibility refers to the trustworthiness of the brand-related information, depending on the believability of the source. That is, clarity ensures information consistency across brand encounters, and credibility determines whether a source conveys information effectively (Erdem and Swait, 1998).

Signalling activities provided through paid media likely suffer from a lack of credibility but achieve greater clarity, due to the company's direct influence and desire to align communication activities. In contrast, signalling activities through peer-driven earned media tend to possess greater credibility but lack clarity, reflecting divergences in peer-to-peer interactions (Ho-Dac *et al.*, 2013). If customers encounter a brand through focussed media activities, based on either paid or earned media, they likely experience high levels of either clarity or credibility. These high levels of signal clarity and signal credibility remain mutually exclusive in cases of low media entropy, which could reduce customers' willingness to purchase the brand (Erdem *et al.*, 2006).

Conversely, purchase likelihood may increase if a media mix compensates for the weakness of obtaining either signal clarity or signal credibility through focussed media exposure. If customers encounter high levels of media entropy across paid and earned media, they might perceive high clarity and high credibility of the brand-related information concurrently. This notion is in line with the confirmation bias detected in consumer psychology, which leads people to ignore evidence that contradicts their existing beliefs, ideas or expectations (Nickerson, 1998). High media entropy should reinforce the effect of coherent company-controlled signals, because customers tend to focus more on favourable than unfavourable information conveyed by other customers. Similarly, positive peer-driven information about a brand (high levels of signal credibility) may be reinforced by company-orchestrated communication (high levels of signal clarity). The potential harmful effects of negative earned media coverage even might be alleviated by coherent paid media initiatives. Overall, we predict that greater cross-media exposure, as measured by the entropy of information sources in the customer journey, enhances purchase likelihood.

Compared with traditional, offline environments, digital channels typically are associated with greater uncertainty and lower perceptions of the clarity and credibility of paid and earned media (eMarketer, 2017; Nielsen, 2015). The incremental information gains caused by cross-media exposure thus should be more effective in digital (online) compared with traditional (offline) channels. That is, we propose that increases in media entropy are more effective in the online than in the offline channel. Thus,

H1. The increase of media entropy, measured as the extent of a customer's cross-media exposure in the customer journey, has a positive effect on customers' brand purchase likelihood.

H2. The effect of media entropy on customers' brand purchase likelihood is greater in digital (online) compared with traditional (offline) media environments.

Moderating effects of brand strength and brand ownership

When assessing media entropy as a metric, we also account for contextual factors that might influence the effectiveness of customers' cross-media exposure. In particular, the strength of the positive link between cross-media exposure and brand purchase might depend on factors that determine how customers interpret available information (Lurie, 2004). One prominent context factor that might influence the effectiveness of exposure to different type of media on purchase decision is rooted in prior brand knowledge (Pauwels *et al.*, 2016). Customers' previous brand ownership and perception of brand strength thus might represent important contextual variables, because they reflect customers' cumulative prior exposures to a brand's communication efforts and peer-to-peer interactions (Basuroy *et al.*, 2006; Erdem *et al.*, 2006). Previous brand ownership and strong brands both provide valuable sources of information for customers seeking to reduce their purchase risk. Conversely, previously non-owned brands or those perceived as weaker by customers lack pre-existing signalling strength that could decrease their purchase risk. That is, customers who do not currently own the brand and weaker brands should benefit relatively more from incremental information gains caused by media entropy. Thus:

H3. The effect of media entropy on customers' brand purchase likelihood is greater for customers who do not own the brand, compared with current brand owners.

H4. The effect of media entropy on customers' brand purchase likelihood is greater for brands that are perceived as weak, compared with brands perceived as strong.

Data

Data collection

We seek to provide and test a metric of the effect of media entropy on an individual customer level. Because we need data on individual customer journeys, we employed an experience tracking approach. Instead of collecting data retrospectively, this approach asks respondents to report all their encounters with competing brands directly after the encounter (Baxendale *et al.*, 2015), through their smartphone devices. It thus can collect data on individual brand encounters across media types (i.e. paid and earned) and channels (i.e. offline and online). It also reduces the cognitive burden associated with recalling brand encounters and the memory decay that can arise with retrospective surveys (Danaher and Dagger, 2013). For an overview of this data collection method, see Baxendale *et al.* (2015) or Lovett and Peres (2018).

To report on their brand encounters, respondents answered three questions through a smartphone app: Which brand is encountered? Which type of media touchpoint is encountered? How is the media touchpoint perceived (i.e. attractive vs not attractive)? This experience tracking method differentiates 23 media touchpoints and ten competing brands. The list of media touchpoints was generated for the focal product category, in cooperation with a marketing agency, on the basis of qualitative studies with customers and industry experts (see Appendix 1). Through a pre-survey, we also collected data on individual respondent characteristics, including current brand ownership and pre-existing perceptions of brand strength. We collected data over a six-week period, which resulted in 26,285 reported paid and earned media touchpoints.

Sample

We recruited respondents in five countries (i.e. China, France, Germany, United Kingdom and United States) who were at that time considering a search for and purchase of a certain consumer electronics product. Although consumer electronics do not represent a service category, their purchase process features notable similarities with typical service purchases. First, consumer electronics and services both are dominated by experience and credence qualities, so customers need additional information (sources), beyond the offering itself, to predict quality levels. Second, because of this need for an in-depth information search, purchase decisions in both categories typically involve a customer journey that encompasses multiple touchpoints. This feature is a central requirement for our empirical data. Participants had previously indicated their interest in buying the consumer electronics product, so they already had developed a consideration set. Accordingly, we can assess their ensuing customer journey and resulting purchase decision. From the initial respondents, we excluded those who did not participate in the pre-survey, did not report any brand encounters or did not participate in biweekly reviews (see Baxendale *et al.*, 2015). During the six-week period, we obtained 1,831 (79.2%) useable responses from our initial sample. Appendix 2 contains an overview of the initial respondents, the percentage of useable responses per country and distinct customer characteristics.

Robustness check

To gauge the validity of the data collection method, we compare self-reported data with aggregated data sources from media research companies (for similar approach, see Danaher and Dagger, 2013). Due to the data availability offered by the media companies, we rely on our US sample ($n = 419$) for this comparison. We first compare respondents' self-reported purchases (i.e. purchase share) with established market share data obtained from the multinational market research institute GfK. Next, we compare US respondents' self-reported paid media exposure across brands with media spending data obtained from Kantar Media's AdSpender tool during the time of the survey. We correlate aggregated media spending across different paid media types with actual advertising exposure to the media type, as captured by experience tracking. Finally, we validate the earned media data by correlating self-reports of such exposure across brands with historical social media mentions of the brand during the time of the survey. Specifically, we use Facebook's "people talked about this" (PTAT) metric, obtained from the Quintly database. The PTAT measure summarizes peer-to-peer interactions with a brand through various Facebook actions (e.g. likes, mentions, comments). For all three comparisons, the correlations between self-reported experience tracking data and aggregated data from industry sources exceed 0.70, with print advertising (0.71) having the lowest and television advertising the highest correlation (0.88). These results support the robustness of data collection through experience tracking (see Table 1).

Variables

Media touchpoints and media entropy. We identify whether each media touchpoint represents one of four possible categories: offline paid, offline earned, online paid or online earned. As outlined, we operationalize cross-media exposure as the entropy of paid and earned media types calculated over all previous media touchpoints in the customer journey.

Current brand ownership, pre-existing brand strength and brand purchase. Respondents reported their existing brand ownership and perception of brand strength in an online survey before the experience tracking phase. Building on Kirmani's (1990, p. 160) operationalization of brand strength as the "overall quality as well as the perceptions of physical or abstract quality-related product attributes, such as the comfort, style, or durability", our measure of brand strength spans three dimensions: brand quality, design and innovation (e.g. "[Brand name] has a more attractive design and style than other [category of consumer electronic product] brands"). We measure responses on a six-point scale ranging from "strongly disagree" to "strongly agree". Respondents report their brand purchases directly on the smartphone app, along with the purchase price.

Model development

Our unit of analysis is at the individual touchpoint level. Because customers encounter many media touchpoints throughout their customer journey for each brand, we decompose the customer journey into a series of periods. Each period consists of a particular interaction with a touchpoint and a decision to purchase. To test our hypotheses, we use a probit model that incorporates unobserved individual-level heterogeneity. Let $y_{ijn} = 1$ if individual i purchases brand j during the interaction with the nth media touchpoint and 0 if we do not observe any purchase activity. We specify i's latent purchase utility as:

$$\begin{aligned} U^{*}_{ijn} = {} & \beta_{i0} + \beta_1 \,\text{MediaEntropy}_{ijn} + \beta_2 \,\text{OfflineEarned}_{ijn} + \beta_3 \,\text{OnlinePaid}_{ijn} \\ & + \beta_4 \,\text{OnlineEarned}_{ijn} + \beta_5 \,\text{NumTP}_{ijn} + \beta_6 \,\text{Price}_{ij} + \beta_7 \,\text{BrandOwnership}_{ij} + \epsilon_{ijn} \end{aligned} \tag{1}$$

The focal variable is $\text{MediaEntropy}_{ijn}$, which measures the extent of cross-media exposure entropy across the type of media touchpoints previously encountered over touchpoints 1, 2, . . ., n. That is, our measure for cross-media exposure is updated for each individual i and each brand j up to the n^{th} period. In addition, β_{i0} is an individual-level fixed effect that captures unobserved heterogeneity. Then $\text{OfflineEarned}_{ijn}$, OnlinePaid_{ijn} and $\text{OnlineEarned}_{ijn}$ are dummy variables that indicate the type of media touchpoint individual i encounters during the n^{th} period. Offline paid media serves as the baseline. We also control for other observable factors: (1) the total number of previous media touchpoints NumTP_{ijn}, (2) the purchase price $Price_{ij}$ of brand j that individual i paid and (3) whether individual i currently owns the brand using the indicator variable $\text{BrandOwnership}_{ij}$, which equals 1 if individual i owns brand j.

Table 1.
Correlation between experience tracking data and established industry sources

	Market share[a]	Paid media[b] Television advertising	Print advertising	Display advertising	Earned media[c] WOM
Experience tracking	0.79*	0.88**	0.71*	0.78*	0.86*

[a] Correlation of self-reported purchases through experience tracking with market share data from GfK market research institute across brands; [b] Correlation of self-reported paid media exposure across brands with media spending obtained from Kantar's AdSpender market research tool; [c] Correlation of self-reported earned media exposure across brands with Facebook's PTAT key metric from Quintly database; $^{**}p < 0.01$, $^{*}p < 0.05$

We are also interested in the moderating effect of brand ownership and brand strength. To assess the interaction between media entropy and brand ownership, we apply the following model:

$$U^*_{ijn} = \beta_{i0} + \beta_1 \,\mathrm{MediaEntropy}_{ijn} + \beta_2 \,\mathrm{OfflineEarned}_{ijn} + \beta_3 \,\mathrm{OnlinePaid}_{ijn} + \beta_4 \,\mathrm{OnlineEarned}_{ijn} + \beta_5 \,\mathrm{NumTP}_{ijn} + \beta_6 \,\mathrm{Price}_{ij} + \beta_7 \,\mathrm{BrandOwnership}_{\mathrm{ij}} + \beta_8 \,\mathrm{BrandOwnership}_{ij} x \mathrm{MediaEntropy}_{ijn} + \epsilon_{in} \quad (2)$$

For the interaction between media entropy and brand strength, we average the three items that measure perceptions of brand strength, obtained from the pre-survey before the experience tracking period, to create $\mathrm{BrandStrength}_{ij}$. Because it was measured in the pre-survey, it only varies across individuals for a specific brand. We assess both its main effect and interaction with media entropy in follow-up models. In particular, we specify:

$$U^*_{ijn} = \beta_{i0} + \beta_1 \,\mathrm{MediaEntropy}_{ijn} + \beta_2 \,\mathrm{OfflineEarned}_{ijn} + \beta_3 \,\mathrm{OnlinePaid}_{ijn} + \beta_4 \,\mathrm{OnlineEarned}_{ijn} + \beta_5 \,\mathrm{NumTP}_{ijn} + \beta_6 \,\mathrm{Price}_{ij} + \beta_7 \,\mathrm{BrandOwnership}_{ij} + \beta_8 \,\mathrm{BrandStrength}_{ij} + \beta_9 \,\mathrm{BrandStrength}_{ij} x \mathrm{MediaEntropy}_{ijn} + \epsilon_{in}. \quad (3)$$

Identification

The primary goal in our model specification is to identify the impact of our focal media entropy variable on purchase activity. Therefore, we also must control for factors that may confound our results. First, the media touchpoint interactions are self-reported by users in our sample, which could lead to systematic over- or under-reporting. Although we cannot observe whether customers do or do not have a reporting bias, we use data robustness checks, as outlined previously, as well as model controls, as specified subsequently, to address this concern. Second, unobserved, time-invariant differences across customers could bias our results. For example, some customers may shop frequently and consume different types of media, in which case they would be more likely to purchase and be exposed to more media touchpoints. This individual-level unobservable variable might correlate with both the media entropy variable and latent purchase utility (through the error term), which would bias our results. To control for such unobserved individual-level heterogeneity, we follow Soysal and Krishnamurthi (2016) and include individual-level fixed effects. By capturing user *i*'s baseline media consumption habits through the fixed effects, our model controls for the portion of the error term that is correlated with both media entropy and latent purchase utility. The identifying assumption is that unobservable variables, such as touchpoint reporting behaviour and media consumption habits, should remain fixed over the six-week observation period. We also control for observed heterogeneity across brands and countries, using brand- and country-specific fixed effects. Third, correlated unobservable variables are another concern. For example, some customers could have higher interest in the particular consumer electronic product. We control for this and other time-invariant correlated unobservable variables using individual-level fixed effects. For time-varying unobservable variables, we use latent instrumental variables (LIVs) to address endogeneity concerns.

Latent instrument variables

Considering the potential unobservable variables and self-selection concerns that could confound our results, it may be difficult to identify a strong instrument to adopt for the instrumental variables approach to resolve endogeneity concerns. To address potential sources of endogeneity, we use LIV to estimate our model. This method does not rely on the validity of specific instruments. Since being introduced by Ebbes *et al.* (2005), LIV has been applied in multiple contexts (e.g. Rutz *et al.*, 2012; Zhang *et al.*, 2009), and it offers an appropriate approach for our empirical context. Specifically, we follow Ebbes *et al.* (2005) and Rutz *et al.* (2012) and decompose the endogenous variables into one component that is correlated and another that is uncorrelated with the error term (e.g. ϵ_{ijn} in Equation 1). Considering $\text{MediaEntropy}_{ijn}$ as our endogenous variable, we specify:

$$\text{MediaEntropy}_{ijn} = \theta \cdot D_{ijn} + \psi_{ijn}, \tag{4}$$

where D_{ijn} is a latent categorical variable that we estimate with the Gibbs sampler, and θ is a vector of category means for the latent variable. Similar to Ebbes *et al.* (2005) and Rutz *et al.* (2012), we set the number of categories to two. Then D_{ijn} follows a binomial distribution with probabilities π_1 and π_2 (π_h is the probability that latent instrument h equals 1, or $\sum \pi_h = 1$). We assume that the error terms $[\epsilon_{ijn}, \psi_{ijn}]$ follow a multivariate normal distribution with mean 0 and the variance–covariance matrix:

$$\Omega = \begin{bmatrix} \sigma_{\epsilon\epsilon} & \sigma_{\epsilon\psi} \\ \sigma_{\epsilon\psi} & \sigma_{\psi\psi} \end{bmatrix},$$

where $\sigma_{\epsilon\psi}$ captures the correlation between the endogenous variable and the error term in Equation (1).

To estimate the model (Equations 1 and 4), we use Bayesian estimation and specify the following priors: $[\beta] \sim N(\bar{\beta}, \sigma^2)$. We ran 20,000 iterations (first 10,000 as burn-in). The iterations converge to a stable posterior, according to a visual examination of the posterior iterations and Geweke's (1992) diagnostic. To use the Gibbs sampler to estimate the model, we first relax the assumption in the probit model that $\sigma_{\epsilon\epsilon} = 1$, which provides a more stable estimation of Ω. We then identify the posterior estimates through post-processing of the posterior draws (Edwards and Allenby, 2003). After running the Gibbs sampler, we rescale the estimates by first setting each iteration of $\sigma_{\epsilon\epsilon}$ to 1, then rescale all other parameters accordingly.

Results

The effect of media entropy on brand purchase

Table 2 contains the main results pertaining to how media exposure across paid and earned media, as measured by media entropy, affects customers' purchase likelihood. In Model 1, we calculate media entropy across media types. In Model 2, we separately calculate the effect of the media entropy metric in offline and online channels, to assess the effect of media entropy in digital (online) and traditional (offline) media environments. The parameter estimates for the media entropy variable are consistent with our theory; media entropy appears to have a positive effect on customers' brand purchase likelihood. Specifically, we find that customers who encounter more diversity in media types are also more likely to purchase the brand (*media entropy* = 0.367), in support of H_1.

We find varying effectiveness of media entropy across offline and online channels. Specifically, the coefficient of media entropy within the online channel is greater than that within the offline channel (media entropy (offline) = 0.089, media entropy (online) = 0.585). Enhancing media entropy in the online channel likely increases purchase likelihood more than enhancing in media entropy in the offline channel, as we predicted in H_2.

The control variables also provide interesting results. The main effect of a particular media channel on the likelihood of purchase, compared with the baseline condition of offline

Latent IV results	Main effect (Model1)	Media entropy in online/offline channel (Model 2)
Constant	−2.340^ [–4.694, 0.068]	−2.324^ [–4.692, 0.086]
Media entropy	0.367* [0.362, 0.372]	
Media entropy in offline channel		0.089* [0.087, 0.092]
Media entropy in online channel		0.585* [0.578, 0.591]
Control variables		
Offline earned	0.086* [0.084, 0.084]	0.087* [0.085, 0.085]
Online paid	0.007* [0.005, 0.009]	0.006* [0.005, 0.008]
Online earned	0.024* [0.022, 0.025]	0.023* [0.021, 0.025]
Price	−0.0001** [–0.0001, −0.0001]	−0.0001** [–0.0001, −0.0001]
Brand ownership	0.095* [0.093, 0.097]	0.096* [0.094, 0.097]
Number of touchpoints	−0.001** [–0.001, −0.001]	−0.001** [–0.001, −0.001]
N	26,285	26,285
Individual fixed effects	YES	YES
Brand fixed effects	YES	YES
Country fixed effects	YES	YES

Note(s): The baseline condition is offline paid. The 95% Bayesian credible intervals are reported in brackets, $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\wedge}p < 0.1$

Table 2. Effect of media entropy on brand purchase

paid media, indicates that that offline earned, online paid and online earned media have greater value in driving purchase incidence. We also find a negative price coefficient as expected – because higher prices generally are associated with lower purchase incidence. In addition, we find a brand ownership effect; customers who currently own the brand are more likely to repurchase the same brand than are non-owners.

Moderating effects of brand strength and brand ownership

Media entropy is positively related to purchase likelihood. However, different context factors, such as brand ownership and brand strength, could moderate our results. Table 3 reports both the main effects of brand ownership and its interaction with media entropy. For comparison, we present the main effects of brand ownership from Model 1 and include the interaction component in a new Model 3. The parameter estimates for the media entropy variable (media entropy = 0.367 and 0.558 for Models 1 and 3, respectively) and brand ownership (brand ownership = 0.095 and 0.108) are consistent with our previous results. Also consistent with our predictions, we find a negative interaction between media entropy and brand ownership (−0.437). This suggests that the positive impact of media entropy is stronger for customers who currently do not own the brand than for current brand owners, in support of H_3.

In Table 4 we report both the main effects of brand strength (Model 4) and its interaction with media entropy (Model 5). Not all respondents provided data on brand strength for each brand, so we rely on 19,893 reported paid and earned touchpoints in Models 4 and 5. The parameter estimates for the media entropy variable are consistent with our previous results (media entropy = 0.364 and 2.236 for Models 5 and 6, respectively). In addition, Models 4 and 5 indicate positive effects of brand strength (brand strength = 0.014 and 0.022 for Models 4 and 5, respectively). That is, stronger brands are associated with higher purchase incidence. We also find a negative interaction between media entropy and brand strength (−0.370),

Latent IV results	Main effect (Model 1)	Interaction effect (Model 3)
Constant	−2.340^ [–4.694, 0.068]	−2.339^ [–4.698, 0.075]
Media entropy and brand ownership		
Media entropy	0.367* [0.362, 0.372]	0.558* [0.551, 0.565]
Brand ownership	0.095* [0.0933, 0.097]	0.108* [0.106, 0.110]
Media entropy *x* brand ownership		−0.437** [–0.444, −0.429]
Control variables		
Offline earned	0.086* [0.084, 0.084]	0.086* [0.084, 0.084]
Online paid	0.007* [0.005, 0.009]	0.007* [0.005, 0.008]
Online earned	0.024* [0.022, 0.025]	0.024* [0.022, 0.026]
Price	−0.0001** [–0.0001, −0.0001]	−0.0001** [–0.0001, −0.0001]
Number of touchpoints	−0.001** [–0.001, −0.001]	−0.001** [–0.001, −0.001]
N	26,285	26,285
Individual fixed effects	YES	YES
Brand fixed effects	YES	YES
Country fixed effects	YES	YES

Note(s): The baseline condition is offline paid. The 95% Bayesian credible intervals are reported in brackets; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\wedge}p < 0.1$

Table 3.
Moderating effect of brand ownership

which suggests that the positive impact of media entropy is greater for weak brands than for strong brands, in support of H_4.

Robustness checks

We conducted an additional analysis to check the robustness of the results. First, whether customers perceive a touchpoint as more or less attractive might influence their purchase decision. Thus, we obtained results from a model in which we included information about touchpoint valence, collected via experience tracking. The results for media entropy and the

Latent IV results	Main effect (Model 4)	Interaction effect (Model 5)
Constant	−2.367^ [–4.750, 0.017]	−2.425* [–4.798, −0.030]
Media entropy and brand strength		
Media entropy	0.364* [0.359, 0.369]	2.236* [2.207, 2.266]
Brand strength	0.014* [0.013, 0.015]	0.022* [0.021, 0.023]
Media Entropy *x* Brand Strength		−0.370** [–0.380, −0.365]
Control variables		
Offline earned	0.087* [0.084, 0.084]	0.0871* [0.085, 0.085]
Online paid	0.007* [0.005, 0.008]	0.006* [0.005, 0.008]
Online earned	0.024* [0.022, 0.026]	0.023* [0.021, 0.025]
Price	−0.0001** [–0.0001, −0.0001]	−0.0001** [–0.0001, −0.0001]
Brand ownership	0.092* [0.090, 0.094]	0.092* [0.050, 0.053]
Number of touchpoints	−0.001** [–0.001, −0.001]	−0.001** [0.021, 0.023]
N	19,893	19,893
Individual fixed effects	YES	YES
Brand fixed effects	YES	YES
Country fixed effects	YES	YES

Note(s): The baseline condition is offline paid. The 95% Bayesian credible intervals are reported in brackets; $^{**}p < 0.01$; $^{*}p < 0.05$; $p < 0.1$

Table 4.
Moderating effect of brand strength

moderating effects are consistent with our preceding model. Second, instead of using a LIV approach, we obtained results from a logit model using maximum likelihood estimation. The results of both models are consistent for the main model (see Appendix 3) and for the moderating effects (see Appendix 3).

Discussion

Theoretical implications

In the age of digital media, customer journeys are characterized by increasingly fragmented information sources that reside within and outside the company's direct control. In this complex media landscape, the analysis and management of customer journeys have become vital for managerial practice and particularly for managers in service industries. Although customers' exposure to information from different media has increased, decision-makers lack a metric to track the ramifications of this trend. Therefore, this article introduces a new metric, media entropy, to capture cross-media exposure on the individual customer level and illustrates its effect on customers' purchase decisions. The media entropy metric contributes to service research that seeks to improve the management of communication and information search efforts in the pre-purchase or pre–core service encounter stage (Voorhees *et al.*, 2017). In contrast to the core service delivery, and despite its importance for the ultimate purchase decision, this initial part of the customer journey has received little attention so far. Our empirical results highlight that neglecting the effect of cross-media exposure in the pre-purchase stage will result in missed opportunities to provide a better service experience and exert a bottom-line impact on customers' purchase decisions.

By providing a novel media metric for customer journey analyses, we investigate patterns of interactions that may alter customer experiences before a purchase. We thereby address calls to develop new metrics to measure customer experiences during the customer journey (Bolton *et al.*, 2018; Lemon and Verhoef, 2016; McColl-Kennedy *et al.*, 2015). Importantly, our metric addresses the need for service firms to obtain a more complete view of customer interactions across media and channels (McColl-Kennedy *et al.*, 2015). Finally, this study emphasizes the need to track and manage customer experiences carefully in the service context (Bolton *et al.*, 2014).

Empirically, the results reveal that customers' exposures across paid and earned media increase brand purchase likelihood, beyond what can be achieved by focussed exposure to paid or earned media alone. The amplifying effect across paid and earned media implies media synergies and, as such, offers insights for the cost-effectiveness of media allocations. Diversifying a media budget across paid and earned media should lead to greater brand purchase likelihood.

We specifically assess the effect of media entropy in digital (online) environments and find that media entropy is more effective in driving purchase likelihood in digital (online) than traditional (offline) environments. This effect is due to the information gains caused by cross-media exposure in digital channels, which typically are associated with higher uncertainty and perceived as less clear and credible than traditional media (eMarketer, 2017; Nielsen, 2015). Our findings thus shed new light on the effects of new media on purchase decisions (Hennig-Thurau *et al.*, 2010; Lamberton and Stephen, 2016).

Our study also provides a methodological contribution to customer journey analyses in service research (e.g. Halvorsrud *et al.*, 2016; Tax *et al.*, 2013; Zomerdijk and Voss, 2010) and for considerations of media synergies in general (e.g. Naik and Raman, 2003; Pauwels *et al.*, 2016; Srinivasan *et al.*, 2016). By moving from an aggregate to an individual-level metric, our measure offers a customer-centric perspective on media synergies that capitalizes on the information structure of individual customers. Such knowledge about customers' information structure may assist service firms in steering their communication activities and ultimately reducing customer perceived purchase risk.

Beyond the main effect, we investigate the effectiveness of media entropy in light of heterogeneous customer characteristics. We reveal the effects of pre-existing brand strength and current brand ownership on media entropy and thus extend recognition of the influence of customer characteristics on media-type effectiveness (Ho-Dac *et al.*, 2013; Leeflang *et al.*, 2014). The findings show that media entropy is less effective for current brand owners than for non-owners. Previous research on brand ownership similarly acknowledges that current brand owners have first-hand access to brand information, based on their own experience (Kirmani *et al.*, 1999). For existing research on media synergies that investigates the effectiveness of exposure across media and channels for different brand-related conditions (e.g. Pauwels *et al.*, 2016), our findings also suggest that companies can leverage media entropy to enhance brand-switching behaviour among customers who currently do not own the brand. Moreover, weak brands can gain more from media entropy than strong brands. This result underlines the importance of incorporating brand measures into customer journey models and the need to investigate the effects of media synergies in different conditions.

Managerial implications

Due to the development of digital media, managers need to address the challenges of customer journey analyses by relying on either internal departments or external service providers, such as marketing agencies, consultancies and SaaS platforms. To help these internal and external service providers meet these managerial needs, we provide a new metric that captures cross-media exposure and its effect on purchases. With this media entropy metric, managers can monitor the information structure of an individual customer's journey, allocate marketing investments to different types of media to balance media investments in accordance with their bottom-line effects on sales and target individual customers on the basis of their prior experience (i.e. prior ownership and brand perception). These implications are especially relevant for customer journey analyses in services settings, because firms must offer effective communication measures to lower customers' perceived purchase risk caused by traditional high share of experience and credence qualities. Applying our metric to digital services, such as marketing dashboards, can help companies manage their customer journeys more effectively and identify the impact of their communication efforts on bottom-line purchases. We encourage managers and professional marketing service providers to use this metric to track individual-level data and closely monitor media entropy in customer journey analyses, as well as communicate these effects to clients. Although brand perception tracking (e.g. YouGov's BrandIndex) and social media tracking (e.g. Facebook analytics) provide profound insights on the aggregate level, insights about customers' information structure provide further valuable information on the individual level.

On a more general level, this study focusses on customers' information search and information obtained from company-controlled and peer-driven sources in traditional and digital media channels. Thus, companies can adopt the proposed media entropy metric to understand and more effectively manage customer journeys in pre-purchase stages.

Our findings also address a question that has plagued executives deciding how to allocate limited media budgets: Should they diversify their investments in both paid and earned media or instead focus media efforts in a particular channel? We show that companies can increase brand purchases by diversifying their fixed budget across more media types. In other words, instead of seeking repeated paid media exposure, they should attempt to increase media entropy. Thus, we call for proactive management of customers' cross-media exposures in their journeys, including the proactive creation of peer-to-peer interactions beyond organic WOM. Managers of brands that are perceived as weaker by customers can especially benefit from these media synergies. Moreover, managers of brands that are currently not owned by the customer might target potential customers with media synergies to increase purchase probabilities. In doing so, companies can reach currently untapped customer groups that might be reluctant to purchase the brand because they already own a competing brand or have a weak perception of it.

Limitations and avenues for further research

We capture cross-media exposure using entropy (i.e. variation) of media within a customer journey to provide a metric that is easy implementable in managerial practice. Extending this metric to include more complex features of customer journeys provides an interesting avenue for further research. For example, it might include time-related aspects of the customer journey, such as the sequence of brand encounters or decay effects. Additional investigations might consider how media entropy affects the dynamics of customers' information search from competing brands. While the current metric is well suited for applications in research and managerial practice, advancing it to address other features of the customer journey could contribute further to research that relies on attribution modelling with individual-level data (e.g. Baxendale *et al.*, 2015; Danaher and Dagger, 2013).

By capturing the effects of cross-media exposure between company-controlled and peer-driven media, we illustrate that the information structure in the customer journey influences customers' purchase decisions. As the fragmentation of media increases at the touchpoint level, other interesting effects might emerge, beyond the overall media level. Due to the vast heterogeneity of customers' exposures to individual touchpoints, we could not assess these effects with our data set. However, investigations of the effects of media entropy on the individual touchpoint level would offer an interesting opportunity to generalize our results from a media to a touchpoint level.

The benefits of experience tracking as a data collection method enabled us to assess the effects of our metric on brand purchases overall, as well as in the digital and traditional channels, but there are also limitations of this method. We illustrated its robustness by comparing self-reported data with aggregated data obtained from media research companies (see also Lovett and Peres (2018)). However, because it relies on self-reporting, our data collection method cannot detect brand encounters below perceptual thresholds. We encourage replication research that uses clickstream data to test the effect of our metric on customers' brand purchases in digital channels.

Finally, our study underlines the novel challenges for managing customer journeys that result from the increasing usage of peer-driven media in the digital age. To address these evolving challenges, we recommend continued research across media and channels at the individual customer journey level, particularly in service settings (Voorhees *et al.*, 2017). Specifically, companies that actively seek to shape the customer journey need tools to track customers, as well as actionable metrics that can be implemented easily. The development of metrics that address cross-media, cross-channel and cross-service provider exposures offers great promise and high value for managerial practice.

References

Bain and Company (2018), "Customer experience tools: experience dashboards", available at: https://www.bain.com/insights/customer-experience-tools-experience-dashboards/ (accessed 1 September 2019).

Basuroy, S., Desai, K.K. and Talukdar, D. (2006), "An empirical investigation of signaling in the motion picture industry", *Journal of Marketing Research,* Vol. 43 No. 2, pp. 287-295.

Baxendale, S., Macdonald, E.K. and Wilson, H.N. (2015), "The impact of different touchpoints on brand consideration", *Journal of Retailing,* Vol. 91 No. 2, pp. 235-253.

Bolton, R.N., Gustafsson, A., McColl-Kennedy, J., Sirianni, N.J. and Tse, D.K. (2014), "Small details that make big differences: a radical approach to consumption experience as a firm's differentiating strategy", *Journal of Service Management,* Vol. 25 No. 2, pp. 253-274.

Bolton, R.N., McColl-Kennedy, J.R., Cheung, L., Gallan, A., Orsingher, C. and Witell, L., *et al.* (2018), "Customer experience challenges: bringing together digital, physical and social realms", *Journal of Service Management,* Vol. 29 No. 5, pp. 776-808.

Court, D., Elzinga, D., Mulder, S. and Vetvik, O.Jr. (2009), "The consumer decision journey", *McKinsey Quarterly*, No. 3, pp. 96-107.

Danaher, P.J. and Dagger, T.S. (2013), "Comparing the relative effectiveness of advertising channels: a case study of a multimedia blitz campaign", *Journal of Marketing Research,* Vol. 50 No. 4, pp. 517-534.

Ebbes, P., Wedel, M., Böckenholt, U. and Steerneman, T. (2005), "Solving and testing for regressor-error (in)dependence when no instrumental variables are available: with new evidence for the effect of education on income", *Quantitative Marketing and Economics,* Vol. 3 No. 4, pp. 365-392.

Edelman, D.C. and Singer, M. (2015), "Competing on customer journeys", *Harvard Business Review,* Vol. 93 No. 11, pp. 88-7.

Edwards, Y.D. and Allenby, G.M. (2003), "Multivariate analysis of multiple response data", *Journal of Marketing Research,* Vol. 40 No. 3, pp. 321-334.

eMarketer (2017), "Consumer trust is evolving in the digital age", available at: https://www.emarketer.com/Article/Consumer-Trust-Evolving-Digital-Age/1014959 (accessed 1 October 2018).

Erdem, T. and Swait, J. (1998), "Brand equity as a signaling phenomenon", *Journal of Consumer Psychology,* Vol. 7 No. 2, pp. 131-157.

Erdem, T., Swait, J. and Valenzuela, A. (2006), "Brands as signals: a cross-country validation study", *Journal of Marketing,* Vol. 70 No. 1, pp. 34-49.

Geweke, J. (1992), "Evaluating the accuracy of sampling-based approaches to calculating posterior moments", in Bernardo, J.M., Berger, J., Dawid, A.P. and Smith, J.F.M. (Eds.), *Bayesian Statistics 4,* Oxford University Press, Oxford, pp. 169-193.

Halvorsrud, R., Kvale, K. and Følstad, A. (2016), "Improving service quality through customer journey analysis", *Journal of Service Theory and Practice,* Vol. 26 No. 6, pp. 840-867.

Hennig-Thurau, T., Malthouse, E.C., Friege, C., Gensler, S., Lobschat, L. and Rangaswamy, A., *et al.* (2010), "The impact of new media on customer relationships", *Journal of Service Research,* Vol. 13 No. 3, pp. 311-330.

Ho-Dac, N., N., Carson, S.J. and Moore, W.L. (2013), "The effects of positive and negative online customer reviews: do brand strength and category maturity matter?", *Journal of Marketing,* Vol. 77 No. 6, pp. 37-53.

Homburg, C., Jozić, D. and Kuehnl, C. (2017), "Customer experience management: toward implementing an evolving marketing concept", *Journal of the Academy of Marketing Science,* Vol. 45 No. 3, pp. 377-401.

Jahn, B. and Kunz, W. (2012), "How to transform consumers into fans of your brand", *Journal of Service Management,* Vol. 23 No. 3, pp. 344-361.

Jayson, R.O.B., Block, M.P. and Chen, Y. (2018), "How synergy effects of paid and digital owned media influence brand sales: considerations for marketers when balancing media spend", *Journal of Advertising Research,* Vol. 58 No. 1, pp. 77-89.

Kirmani, A., Sood, S. and Bridges, S. (1999), "The ownership effect in consumer responses to brand line stretches", *Journal of Marketing,* Vol. 63 No. 1, pp. 88-101.

Kirmani, A. (1990), "The effect of perceived advertising costs on brand perceptions", *Journal of Consumer Research,* Vol. 17 No. 2, pp. 160-171.

Lamberton, C. and Stephen, A.T. (2016), "A thematic exploration of digital, social media, and mobile marketing: research evolution from 2000 to 2015 and an agenda for future inquiry", *Journal of Marketing,* Vol. 80 No. 6, pp. 146-172.

Leeflang, P.S.H., Verhoef, P.C., Dahlström, P. and Freundt, T. (2014), "Challenges and solutions for marketing in a digital era", *European Management Journal,* Vol. 32 No. 1, pp. 1-12.

Lemon, K.N. and Verhoef, P.C. (2016), "Understanding customer experience throughout the customer journey", *Journal of Marketing,* Vol. 80 No. 6, pp. 69-96.

Lovett, M.J. and Peres, R. (2018), "Mobile diaries – benchmark against metered measurements: an empirical investigation", *International Journal of Research in Marketing,* Vol. 35 No. 2, pp. 224-241.

Lurie, N.H. (2004), "Decision making in information-rich environments: the role of information structure", *Journal of Consumer Research,* Vol. 30 No. 4, pp. 473-486.

McColl-Kennedy, J.R., Gustafsson, A., Jaakkola, E., Klaus, P., Radnor, Z.J. and Perks, H., *et al.* (2015), "Fresh perspectives on customer experience", *Journal of Services Marketing,* Vol. 29 Nos. 6/7, pp. 430-435.

McKinsey and Company (2019), "From touchpoints to journeys: seeing the world as customers do", available at: https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/from-touchpoints-to-journeys-seeing-the-world-as-customers-do (accessed 1 September 2019).

Naik, P.A. and Peters, K. (2009), "A hierarchical marketing communications model of online and offline media synergies", *Journal of Interactive Marketing,* Vol. 23 No. 4, pp. 288-299.

Naik, P.A. and Raman, K. (2003), "Understanding the impact of synergy in multimedia communications", *Journal of Marketing Research,* Vol. 40 No. 4, pp. 375-388.

Nickerson, R.S. (1998), "Confirmation bias: a ubiquitous phenomenon in many guises", *Review of General Psychology,* Vol. 2 No. 2, pp. 175-220.

Nielsen (2015), *Global Trust in Advertising - Winning Strategies for an Evolving Media Landscape*, available at: https://www.nielsen.com/us/en/insights/report/2015/global-trust-in-advertising-2015/ (accessed 1 September 2019.

Pauwels, K., Demirci, C., Yildirim, G. and Srinivasan, S. (2016), "The impact of brand familiarity on online and offline media synergy", *International Journal of Research in Marketing,* Vol. 33 No. 4, pp. 739-753.

Romaniuk, J. and Hartnett, N. (2017), "The relative influence of advertising and word-of-mouth on viewing new season television programmes", *European Journal of Marketing,* Vol. 51 No. 1, pp. 65-81.

Rutz, O.J., Bucklin, R.E. and Sonnier, G.P. (2012), "A latent instrumental variables approach to modeling keyword conversion in paid search advertising", *Journal of Marketing Research,* Vol. 49 No. 3, pp. 306-319.

Shannon, C.E. (1948), "A mathematical theory of communication", *The Bell System Technical Journal,* Vol. 27 Nos. 3-4, pp. 379-423, 623-656.

Soysal, G. and Krishnamurthi, L. (2016), "How does adoption of the outlet channel impact customers' spending in the retail stores: conflict or synergy?", *Management Science,* Vol. 62 No. 9, pp. 2692-2704.

Srinivasan, S., Rutz, O. and Pauwels, K. (2016), "Paths to and off purchase: quantifying the impact of traditional marketing and online consumer activity", *Journal of the Academy of Marketing Science,* Vol. 44 No. 4, pp. 440-453.

Stephen, A.T. and Galak, J. (2012), "The effects of traditional and social earned media on sales: a study of a microlending marketplace", *Journal of Marketing Research,* Vol. 49 No. 5, pp. 624-639.

Tax, S.S., McCutcheon, D. and Wilkinson, I.F. (2013), "The service delivery network (sdn): a customer-centric perspective of the customer journey", *Journal of Service Research,* Vol. 16 No. 4, pp. 454-470.

Van Herpen, E. and Pieters, R. (2002), "The variety of an assortment: an extension to the attribute-based approach", *Marketing Science,* Vol. 21 No. 3, pp. 331-341.

Verhoef, P.C., Neslin, S.A. and Vroomen, B. (2007), "Multichannel customer management: understanding the research-shopper phenomenon", *International Journal of Research in Marketing,* Vol. 24 No. 2, pp. 129-148.

Verhoef, P.C., Kannan, P.K. and Inman, J.J. (2015), "From multi-channel retailing to omni-channel retailing introduction to the special issue on multi-channel retailing", *Journal of Retailing,* Vol. 91 No. 2, pp. 174-181.

Voorhees, C.M., Fombelle, P.W., Gregoire, Y., Bone, S., Gustafsson, A. and Sousa, R., *et al.* (2017), "Service encounters, experiences and the customer journey: defining the field and a call to expand our lens", *Journal of Business Research,* Vol. 79, pp. 269-280.

Zeithaml, V. (1981), "How consumer evaluation processes differ between goods and service", in Donnelly, J.H. and George, W.R. (Eds.), *Marketing of Services*, American Marketing Association, Chicago.

Zhang, J., Wedel, M. and Pieters, R. (2009), "Sales effects of attention to feature advertisements: a bayesian mediation analysis", *Journal of Marketing Research,* Vol. 46 No. 5, pp. 669-681.

Zomerdijk, L.G. and Voss, C.A. (2010), "Service design for experience-centric services", *Journal of Service Research,* Vol. 13 No. 1, pp. 67-82.

Appendix 1

Media	Source	Channel	Touchpoint
Paid	Company-controlled media touchpoints	Traditional (offline)	- Television advertising - Newspaper/magazine advertising - Radio advertising - Advertising leaflet - Advertising on billboards or in train/taxi/bus - Sponsoring (e.g. sports, music)
		Digital (online)	- Display advertising - Banner advertising - Search engine advertising - Online mailing or newsletter - Advertising in social media
Earned	Peer-driven media touchpoints	Traditional (offline)	- WOM from friends or family - Peer observation (i.e. seeing people using the brand) - Celebrity observation - Test reports in newspaper/magazine - Publicity/press mentions - Tested product from friends or family
		Digital (online)	- Online reviews from experts - Online consumer reviews/consumer ratings - Online price comparison/online test - Posts in social media from friends, family - Posts in social media from celebrities - Post in forum or blog - Test reports on television

Table A1.
List of touchpoints in the experience tracking study

Appendix 2

Variable	Levels	Percentage of initial sample (n = 2,311)	Percentage of useable sample (n = 1,831)
Country	China	21.8	22.5
	Germany	19.8	19.8
	France	16.0	15.1
	United Kingdom	19.8	19.6
	United States	22.7	22.9
Gender	Male	52.3	52.6
	Female	47.7	48.4
Age	16–25 years	15.9	15.3
	26–35 years	37.0	38.7
	36–45 years	27.2	28.4
	>46 years	19.9	17.6
Professional status	Employee	74.4	75.1
	Entrepreneur	6.8	6.7
	Student	7.4	7.6
	Homemaker	5.5	5.2
	Other	5.9	5.4

Table A2. Overview of sample by country and customer characteristic

Appendix 3

Results obtained from a logit model using maximum likelihood estimation

To address potential sources of endogeneity, we use a latent instrumental variables (LIV) approach to estimate our model. Here, we provide the results from a logit model using maximal likelihood (ML) estimation.

ML results	Main effect (Model 1)	Media entropy in online/offline channel (Model 2)
Constant	−3.054** (0.080)	−3.041** (0.080)
Media entropy		
Media entropy	1.872** (0.371)	
Media entropy in offline channel		1.603** (0.516)
Media entropy in online channel		2.028** (0.467)
Control variables		
Offline earned	0.340** (0.091)	0.340** (0.092)
Online paid	0.025 (0.082)	0.025 (0.082)
Online earned	0.120 (0.092)	0.117 (0.092)
Price	−0.001** (0.000)	−0.001** (0.000)
Brand ownership	0.465** (0.067)	0.456** (0.067)
Number of touchpoints	−0.012** (0.002)	−0.021** (0.002)
N	26,285	26,285
Individual fixed effects	YES	YES
Brand fixed effects	YES	YES
Country fixed effects	YES	YES

Note(s): The baseline condition is offline paid. The standard errors are reported in the parentheses; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\wedge}p < 0.1$

Table A3. Effect of media entropy on brand purchase (ML results)

Table A4. Moderating effect of brand ownership (ML results)

ML results	Main effect (Model 1)	Interaction effect (Model 3)
Constant	−3.054** (0.080)	−3.078** (0.080)
Media entropy and brand ownership		
Media entropy	1.872** (0.371)	3.075** (0.482)
Brand ownership	0.465** (0.067)	0.554** (0.071)
Media entropy *x* brand ownership		−2.513** (0.733)
Control variables		
Offline earned	0.340** (0.091)	0.342** (0.091)
Online paid	0.025 (0.082)	0.023 (0.082)
Online earned	0.120 (0.092)	0.123 (0.092)
Price	−0.001** (0.000)	−0.001** (0.000)
Number of touchpoints	−0.020** (0.002)	−0.020** (0.002)
N	26,285	26,285
Individual fixed effects	YES	YES
Brand fixed effects	YES	YES
Country fixed effects	YES	YES

Note(s): The baseline condition is offline paid. The standard errors are reported in the parentheses. $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\wedge}p < 0.1$

Table A5. Moderating effect of brand strength (ML results)

ML results	Main effect (Model 4)	Interaction effect (Model 5)
Constant	−3.407** (0.253)	−3.610** (0.271)
Media entropy and brand strength		
Media entropy	1.829** (0.399)	8.247** (2.743)
Brand strength	0.0841^ (0.050)	0.124* (0.054)
Media entropy *x* brand strength		−1.279* (0.547)
Control variables		
Offline earned	0.368** (0.101)	0.370** (0.101)
Online paid	0.017 (0.091)	0.016 (0.091)
Online earned	0.103 (0.102)	0.101 (0.103)
Price	−0.001** (0.000)	−0.001** (0.000)
Brand ownership	0.395** (0.074)	0.394** (0.074)
Number of touchpoints	−0.019** (0.002)	−0.019** (0.002)
N	19,893	19,893
Individual fixed effects	YES	YES
Brand fixed effects	YES	YES
Country fixed effects	YES	YES

Note(s): The baseline condition is offline paid. The standard are errors reported in the parentheses. $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\wedge}p < 0.1$

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