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Sangman HAN
Sung Kyun Kwan University

Jin K. HAN
Singapore Management University, jkhan@smu.edu.sg

Il IM
Yonsei University

Sung In JUNG
Sung Kyun Kwan University

Jung Won LEE
Yonsei University

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Mapping consumer's cross-device usage for online search: Mobile- vs. PC-based search in the purchase decision process

HAN, Sangman[a]; HAN Jin K.[b]; IM, Il[c,1]; JUNG, Sung In[a]; LEE, Jung Won[c]

a SKK Business School, Sungkyunkwan University, Republic of Korea
b Lee Kong Chian School of Business, Singapore Management University, Singapore
c School of Business, Yonsei University, Republic of Korea
Corresponding author: jkhan@smu.edu.sg

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Abstract:

The ubiquity of both mobile devices and PC's has enabled the modern-day consumer to engage in cross-platform online searches as a new norm. The accumulated knowledge on cross-device search behavior to date, however, emanates largely from industry reports and at an aggregate level. To better understand the individual consumer's purchase decision process, we set out to investigate contingencies of *what* (subject of search), *how* (device of choice), and *when* (stage in the buying decision). To this end, we utilize a panel data consisting of clickstream from mobile and PC searches, coupled with entropy-based metric to chart the breadth and depth of browsing as well as topic modeling to glean insight into the nature and the themes of the search at different points *en route* to purchase. We find consumers generally preferring mobile device (PC) for breadth (depth) in search for the earlier (later) stages—lending support to the notion of two-stage decision-making even with cross-device usage. Other highlights include consumers exhibiting a pattern of extensively searching the purchased brand in the initial stages on mobile but not on PC. Moreover, a comparison of consumers with online conversion taking place exclusively via PC vs. across devices reveals a distinct preference for devices contingent upon the topics searched.

Keywords: Mobile search, Online conversion, Online search, Multichannel retailing, Topic modeling, Entropy

1. Introduction

With industry reports of smartphone ownership reaching saturation levels in recent years, coupled with over 75% of the retailers intending to boost mobile marketing spending in 2015 and beyond (Shankar et al., 2016), a key predictable outcome was a migration in the share of search activity from PC to mobile devices. Since Google's 2015 landmark announcement of mobile search overtaking PC-based search in their 10-country findings, Broadband Search (2020) reports mobile devices as incrementally gaining share of search over PC's—though still lagging in both engagement time (40.1% vs. 55.9%) and e-commerce conversion rate (1.53 vs. 4.14). While the firm-level or industry aggregate data may indicate the sheer volume of online queries to increasingly trend towards mobile, yet very little is known regarding the search behavior at the individual level. In other words, how does the modern-day consumer with access to Internet via both mobile and PC engage in search online? For instance, does the consumer utilize mobile online search to complement the PC-based query and vice-versa, or conversely, in the role of substitute for one another?

Much of the accumulated knowledge of online-search and shopping to date emanates from studies based on a single-modality usage – namely, the PC (e.g., Kim et al., 2011, Hu et al., 2014, Mallapragada et al., 2016, Moe, 2006, Rutz and Bucklin, 2011). Moreover, those studies that do examine mobile online behavior focus solely on the mobile-specific issues, i.e., advertising, coupons, or promotions designed exclusively for mobile devices (e.g., Bart et al., 2014, Danaher et al., 2015, Fong et al., 2015). Those studies that do address both mobile and PC online behavior have traditionally been comparisons in a non-search premised, microblogging context (e.g, Ghose, Goldfarb, & Han, 2013), search-based but comparisons made only at the aggregate level (e.g, Li, Huffman, & Tokuda 2009), or simply, anecdotal evidence from the industry (e.g., Lambrea, 2016). The two exceptions, however, are works by Xu et al., 2016, De Haan et al., 2018. The former uses natural experiment and latter clickstream data to investigate device switching on online conversion rates at the individual level, and the findings from both studies underscore the importance studying search behavior across

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the two modalities (mobile and PC) at the disaggregate level for a better understanding of the modern-day consumer. Specifically, Xu et al. (2016) find that cross-device browsing from small to large devices has positive effect on conversion rates, whereas, large to small leading to a lower likelihood of making purchases—attributing quality of browsing experience as key likely driver. Study by De Haan et al. (2018) device switching from more mobile device to less mobile one raises the conversion rate significantly, which is moderated by factors as perceived risk, price, and experience level. These studies demonstrate that, without considering the combination of device usage, the contribution to conversion rates would lead to under-/over-estimation for each device. However, as the predominant focus these studies are on the conversion rates, the granular details of how a consumer journeys through the purchase funnel in context of device-switching remains largely unaddressed to date.

The pursuit for a better understanding of a customer's purchase journey has been a perennial goal for marketing academics and scholars alike—as such knowledge would prove instrumental in designing effective marketing strategies. Dating back to the classical AIDA model of the pre-online era to today's multi-device and omni-channel shopping environment, the notions of purchase funnel and customer's purchase journey remain very much relevant to date—however, with added complexity (Kim, Song, Choi, Kim, & Hong, 2019; Lemon & Verhoef, 2016; Li & Ma, 2020). To this end, we set out to delineate consumers' online search and purchase behavior using a data set that captures both the mobile and PC online search history at a more detailed, individual level. Using an entropy-based metric employed for charting the breadth and depth of URLs that the consumers had browsed for each device, we depict the customer journey through distinct stages in the decision-making process. Moreover, we supplement this mapping with topic modeling to glean insight into the nature and the themes of the search at different points in time heading towards purchase. The robustness of this data set also allows for tracking of consumers' online search at both the sellers' and non-sellers' sites (e.g., review sites, blogs) from both devices.

We find that consumers who use both PC and mobile to search online show a very diverse pattern across the two modalities. Specifically, consumers tend to engage in pre-research with mobile early, and then followed by PC-based search closer to the purchase date. Our results also reveal consumers as searching their focal brand (which is their ultimately-selected brand/model) very extensively and early in the search process on mobile but not PC. In addition, consumer's breadth of brand/model search rises right before the purchase date with mobile but not via PC. Furthermore, we see stark differences among the single- vs. the multi-channel buyers in their device usage patterns as well as the contents searched across the modalities, and all signs point to the latter segment being more tech-savvy than the former. One similarity that we did observe between mobile and PC was in the information source: consumers found it more worthwhile to visit non-seller vs. seller sites, irrespective of the devices used in the search.

2. Background

2.1. Mobile- vs. PC-based search behavior

While similarities in browsing experience and search behavior across mobile and pc-based modalities exist, there are also definitive differences due to the distinct physical and contextual nature of the two modalities. Perhaps, the most evident is the mobile's relative small screen size compared to that of the PC/laptop. Along the same logic, Ghose et al. (2013) attribute mobile's small viewing area to "increase burden associated with information gathering." Whereas, PC screens offer consumers the ease of scrolling through the listing, the smaller screen of mobile device naturally suffers on this user-experience dimension. Not surprisingly, they find users who access Internet via mobile devices to click on the *better-ranked* posts (that is, those on top of the screen) significantly more than those accessing with PCs. Shankar et al. (2016) echo this point by noting that "mobile devices are not very conducive to extensive information search and processing that requires significant investment of time and effort." In fact, Choi, Im, and Yoo (2013) explain that mobile devices have intentionally been designed to minimize the user's attention in order to maintain mobility. This facet of mobile device is also related to the differences in the nature of browsing objectives. According to Lambrea (2016), consumers typically reach for a mobile device to perform quick, specific information searches, whereas, time-consuming activities are generally reserved for the comfort of the PCs. In addition, Lambrea (2016) reports the "top of funnel or even mid funnel users" of the *sales funnel* model as showing a heavy reliance on mobile devices for pre-purchase research activities.

Two other key distinctions of mobile (vs. PC) manifest themselves in *temporal* and *spatial* dimensions. As the name implies, the very portable nature of mobile devices gives rise to the ubiquity of having them in an arm's length, arguably, *anytime* and *anywhere* for the modern-day consumer (Ghose et al., 2013; Shankar et al., 2016; Xu, Forman, Kim, & Van Ittersum, 2014). This element, in turn, makes mobile more conducive contextual information. Specifically, Choi et al. (2013) highlight that, on the temporal front, mobile-accessed search is more prone to timely, relevant information, and in turn, influencing the consumer's path in shopping journey more vis-a-vis PC-based search. Not surprisingly, marketers are starting to shift more resources to real-time mobile advertising and coupons to leverage upon the synchronous nature of the mobile interface (Bart et al., 2014; Danaher et al., 2015; Fong et al., 2015; Grewal, Bart, Spann, & Zubcsek, 2016).

On the spatial dimension, mobile-accessed information has been shown to be significantly more partial to the local proximity factor. Ghose et al. (2013) report that stores or brands located geographically closer to the user's home have a higher likelihood of being clicked on mobile vs. PC. In addition, people have been shown to be more open to location sharing on mobile than PC (Lambrea, 2016). The reason being that, with most PCs located either in home or office, heightened concerns on cyber security and privacy threats become more salient with PCs than with mobile devices.

Accordingly, the accumulated knowledge on mobile- vs. pc-accessed online behavior, though sparse and still evolving, is highly indicative of different search path(s) across the two modalities. Therefore, a compelling argument can be made for the need to explore and chart the mobile/pc cross-modal online search behavior.

2.2. Online search to choice: Two-staged vs. one-staged process?

The goal of uncovering consumer decision/choice process has invariably been a high-priority research agenda in the marketing discipline (e.g., Bettman, Johnson, & Payne, 1990; Gensche, 1987; Moe, 2006; Shocker, Ben-Akiva, Boccara, & Nedungadi, 1991). Among the many theories forwarded in the extant literature, the prevailing paradigm in the field emanates as a two-stage process model. Starting from a relatively large number of alternatives in the consumer's knowledge base or even a larger *universal set*, the individual is believed to initially construct a goal-driven set with alternatives satisfying the goal prerequisites – with the resultant collection often referred to as the *consideration set*. In forming such a filtered set, Ratneshwar and Shocker (1991) posit that consumers typically apply a relatively less effortful decision rule – simply due to the sheer number of evaluation required at this stage. In the subsequent stage, however, the consumer is thought to narrow down the alternatives further to a smaller set of final few options, which is termed the *choice set*, or sometimes also referred to as the *final consideration set* (Shocker et al., 1991). To arrive at this stage, the consumer is considered to engage in more costly, effortful processing of the alternatives – as the benefit of accurately identifying the best choice tends to dominate the cognitive costs when faced with a reduced number of alternatives (Bettman et al., 1990).

Nevertheless, researchers in the decision-making domain note one of the biggest limitations in studying consideration and choice sets is that these constructs were "not directly observable" (Shocker et al., 1991) – that is, until recently. The availability of clickstream data had, for the first time, provided a direct glimpse into the consideration set – or at least its proxy – based on consumer's online search logs (Moe, 2006). As to whether the online search process mirrors the two-staged search theories with origins in the offline context remains, however, inconclusive to date. For instance, the work by Moe (2006) supports a two-staged choice model, whereas, Bronnenberg, Kim, and Mela (2016) suggest a single-stage choice model – of which both studies are premised on PC-based clickstream data. Due to the discordant findings on the generalizability of the offline theories onto the online context, coupled with the added unknown of the mobile/PC cross-modality search dynamics, we do not assume *a priori* a stage-specified decision model or distribution for the online search process in our study. Instead, we proceed with an exploratory mapping of the cross-modal search using a non-parametric method of capturing the search dynamics using an *entropy* measure, which we next elaborate in detail.

2.3. Entropy

In marketing, Hauser (1986) first introduced the notion of entropy in the context of information search and choice. Using entropy as a measure of *uncertainty* in search, Hauser (1986) notes that, when entropy is high (low), consumers have very little (good) information about the choice outcome. The underlying rationale traces back to Shannon's seminal *information theory* (Shannon, 1948). According to Shannon, *entropy* is the average amount of information contained in each 'message' received. A *message* here can be an event, a sample, or a character drawn from a distribution or data stream. In Fig. 1, higher entropy represents a higher level of disorder, and lower entropy represents a lower level of disorder.

In the context of information search, entropy pertains to the extent to which diverse information is considered in the search. This notion of entropy is closely related to 'uncertainty' or 'unpredictability' because higher entropy means higher uncertainty or lower predictability, respectively. While having originated in the natural science discipline, entropy also has been used widely in business research, e.g., to measure consumers' information search patterns (Kim, Im, Han 2016), dispersion of word-of-mouth across multiple newsgroups (Godes & Mayzlin, 2004), decision task complexity (Swait & Adamowicz, 2001).

When applied to consumers' purchase decision-making processes, Shannon's information theory implies that the level of entropy varies across different phases of the purchase process. From decision-making research and studies based on information theory, consumers' information search patterns – in particular, the diversity of information searched – can be measured by entropy (Kim, Im, & Han, 2016). Adapting this notion, we transform the data collected from clickstreams as a measure of entropy and use it for finding patterns in online behavior. The essence of the studies in consumer behaviors is that consumers explore broad and diverse products at the earlier stage of purchase and then, narrow down to a small number of choice alternatives at the later stage. Therefore, it is reasonable to expect higher entropy in the information search activities at the earlier stage of purchase than that at the later stage of purchase.

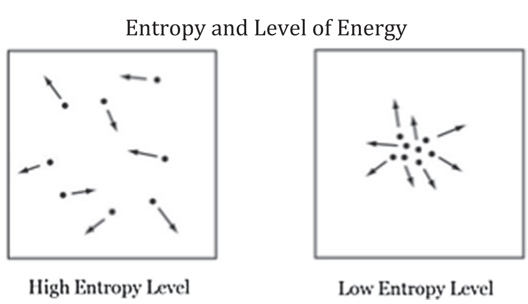

Fig. 1. Entropy at High & Low Levels of Energy.

$$E(p) = -\sum_{i=1}^{n} P_i log_2 P_i \quad (1)$$

where

n: the number of unique URLs that the current user visited
P_i: the probability that the i^{th} URL will be visited = (the number of visits to the i^{th} URL / the number of visits to all URLs)

Formula (1) shows the entropy of each user in the context of online behavior. The formula stipulates that entropy will increase if users visit more diverse URLs or visit all URLs equally frequently, which is consistent with Hauser (1986)'s interpretation that entropy is "maximized when choice objects are equally likely to be chosen." Conversely, entropy will decrease if they visit fewer URLs or visit some URLs more than other URLs. In the formula, URLs can be replaced with domain names, which shifts the entropy to domain level.

3. Data

3.1. Data sources

In this section, we provide an overview of data sources and collection approach. The data set for this study comes from a major advertisement agency in Asia, which agreed to collaborate on this research on the condition of anonymity. The firm's consumer panel consisted of 5000 volunteers, and the entire clickstreams from the panel members' PCs and smartphones (or other mobile devices such as tablets) were collected by pre-installed agent software. The data collection covers the period from April 1 to June 30, 2014, and the information collected include URL-level browsing histories with exact visit time-stamp of both PC and mobile. This data allows us to infer the panels' online search behaviors over time (see Table 1).

3.2. Data collection

Transaction data. Since online tracking of financial transactions (e.g., credit card payments) is prohibited by the country's regulation, the actual purchase data were collected through a supplemental survey administered in July 2014. In the survey, panel members were asked to answer questions about their online information searching and buying behavior. The panel members had to recall and indicate when they made the purchase. Potentially, customers may refer to the purchase and delivery information which would have likely been sent to their mobile devices by the retailer and the courier. Due to the high incidences of unsanctioned credit card abuses in the past, it has become a standard

Table 1
Sample of the URL Data Set.

User ID	Date & Time	Device	URL
201207271D58790EEC78	01APR14:00:06:12	Mobile	http://m.cafe.naver.com/artcollection/172039
201207271D58790EEC78	01APR14:00:06:44	PC	http://m.blog.naver.com/gkfl82/150177131749
20130429267E39786BB3	02APR14:09:50:20	PC	http://analytics.ad.daum.net/act?ask = kZHnJQyGaEBbG
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practice for credit card companies in this country to immediately send SMS of any charges to the credit card holder. Moreover, it has become a standard practice of delivery companies to text the impending time and date of the product's arrival at the destination address. A total of 1066 panel members answered the survey, and the clickstreams of the people who completed the survey were used in the analysis. After removing duplications (that is, same URLs from the same user with exactly same time stamp), the total number of URLs generated by the survey respondents were 61,206,370 from PC and 3,376,649 from mobile.

Although there is a plethora of online shopping sites (2,251,016 sites in July 2014) for the country, top-3 ranked sites have over 90% of the market share in 2014 according to an industry report (MezzoMedia 2015). Hence, we created data sets of domains that are ranked in top-10 of online shopping sites' traffic in 2014 to identify user's online shopping sites.

Text data. Although URL data set contains user's historical web visit records, this kind of data has common limitation in that the data cannot show us exact information that the user actually processed during their decision-making process. To address this limitation, we used web-crawling tools (Jsoup package) to collect every user's text data from the records of visited URL by PC and mobile. Some pages in the click-stream were not available for crawling because they were temporary pages, required to login, or contains robot exclusion codes. Excluding these pages, texts were crawled from all available URLs, and the percentage of successfully crawled URLs was 71.9%. After removing stop-words (e.g., HTML markups, or meaningless words like particle), we extracted noun words that have unique meaning from the text data. R codes using extractNoun function in KoNLP package was utilized for this purpose. The text data allows us to analyze the contents of the web (both PC and mobile) that each user actively searched during their purchase processes in online shopping circumstances.

3.3. The final data set

Among the survey respondents, 410 people answered that they purchased a product in the electronics category in June. Respondents who answered that they purchased in more than one product category among the other categories collected by the agency at the same time

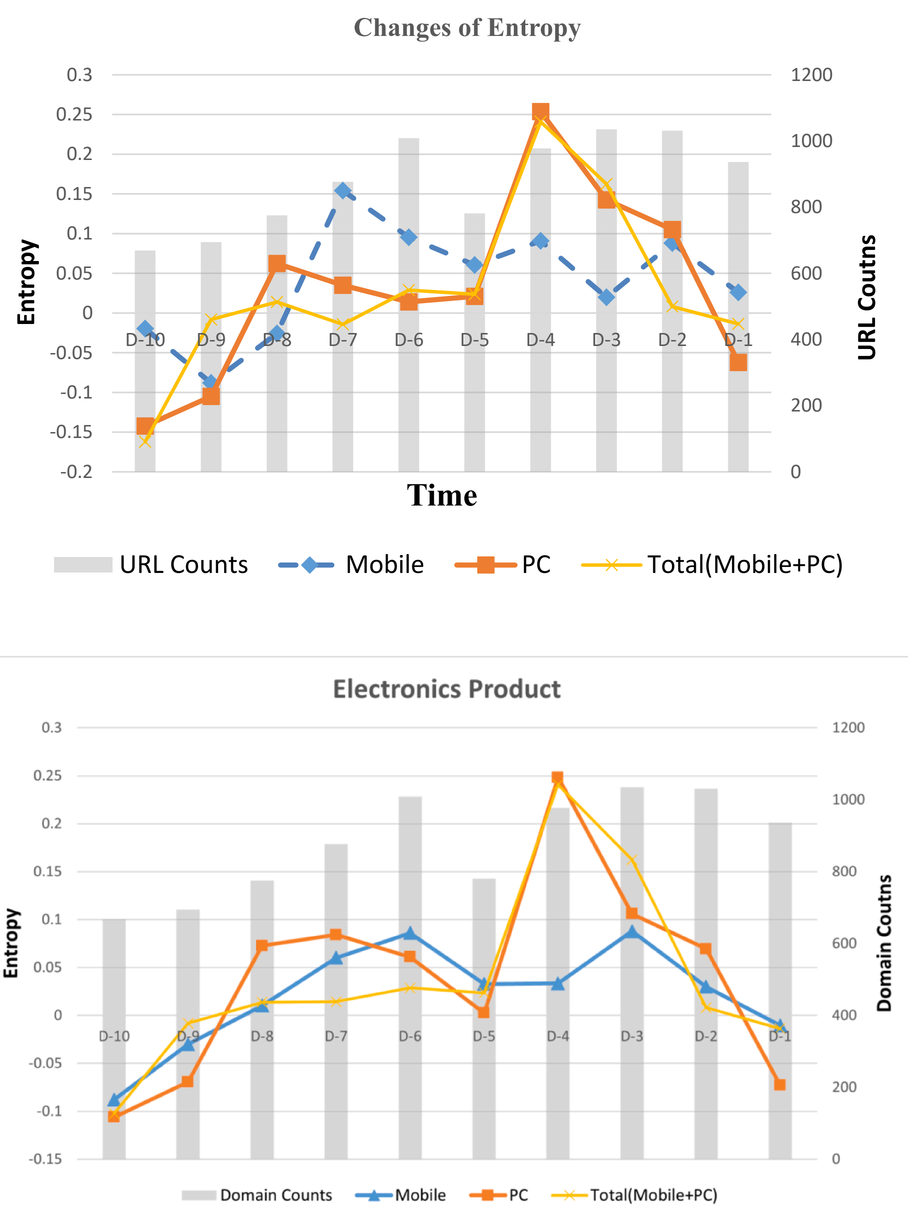


Fig. 2. Change of Entropy in URL & Domain Counts.

period were excluded from the analysis to prevent any potentially confounding effects. Also, people who generated extremely too many or too few URLs (out of $\pm 3\sigma$) were also excluded to minimize biases. After excluding the above, a total of 169 electronics product purchasers were included in the final data analysis. For the electronics buyer group, URLs were aligned by individual purchase date. For example, people who answered that they purchased an electronics product in the period of 1–10 June, June 5th was set as D-0 and June 4 as D-1, June 3 as D-2 and so forth. A total of 2,166,679 URLs (2,011,013 from PC and 155,666 from mobile device) for electronics buyers were included in the final data analysis.

3.4. Standardization of data

There is an issue when diversity is measured at URL level. Different URLs may represent different information (product description page and delivery option page, for example) about a same product in a same shopping mall. Also, different URLs from different shopping malls or domains may represent a same product. In both cases, however, different URLs still indicate different aspects of the product and therefore, shows higher uncertainty or diversity. For further test, URLs and domain names were analyzed in this study, and the results from the two methods showed similar patterns as in Fig. 2. URLs were considered more appropriate for this study, because URLs (webpages) represent information diversity better than domain names in consumer information search. For example, for an online shopping mall containing information pertaining to diverse products, the limitation of domain-level entropy lies in not being able to capture the diversity of product pages within the domain that a consumer visited. Therefore, the entropy measures based on URLs are used in the rest of analysis in this study.

The raw data (URLs) needed processing before the main data analyses in order to minimize potential noises and biases. First, if there were a newsworthy event, such as a terror attack or an important sports competition such as Olympics, people will likely engage in increased levels of online searching and browsing. In order to eliminate these effects, relative entropies, instead of raw ones, were calculated and used for analysis. To calculate the relative entropies, the average of everyone (1066 who answered survey) for each day were calculated, and then deviations of each user's entropies from the corresponding date were calculated. With this method, sudden fluctuations due to certain incidents are eliminated.

Secondly, users have different browsing patterns across days of week. For example, some users do more browsing during weekends while others use Internet more during weekdays. Also, some users carry out heavy browsing on a certain day of the week. In order to remove this 'day-of-the-week effect,' another pre-processing had to be performed. For each user, in addition to the pre-processing depicted above, averages of weekdays were calculated. Two-week data (14 days) was used, and therefore, the average of each day of the week is the average of two days (entropies from same day of first and second weeks). Afterwards, the deviations of entropies from the averages for the days of the week were calculated as the final entropies. This pre-processing enables elimination of biases due to different information browsing patterns of users, hence, standardized entropies are utilized in the main analyses to follow.

4. Results

We present entropy-based mapping of mobile/PC cross-modal online search for those individuals who have purchased a product in the electronics category, which is then followed by a set of analyses probing in more detail with the contents of the search.

4.1. Mapping of entropies in cross-modal online search

We follow the entropy level from 10-days before purchase (D-10) to the one-day prior (D-1) to the purchase for electronic products. In Fig. 2, the line with the triangle legend represents entropies of search on mobile devices, and the line with square legend represents entropies of PC-based search. The bars show the average number of URLs visited by the panel members on each day. We also carried out same analysis with domain level data for comparison. As shown in the two diagrams in Fig. 2, analyses with URL level data and domain level data show similar patterns of entropy.

One general observation is that there are two peaks in entropies across mobile and PC until D-1. The first peak occurring at D-7 is on mobile and the second peak at D-4 on PC, which means that consumers search for diverse information for purchase on the mobile devices in the earlier period, and then another extensive search takes place on the PC as they approach purchase. These entropy results generally corroborate the anecdotal observations from the industry, which posit a heavy reliance on mobile devices for "pre-purchase research," and later followed-up with PC-based search (Lambrea, 2016). Moreover, the second peak belonging to PC is of higher amplitude than the first one from mobile search. This difference is also consistent with the device-inherent distinctions (Shankar et al., 2016), which gives the PC an edge over mobile (e.g., screen size, keyboard typing, etc.) in engaging in more extensive searches.

In order to test whether there are statistically significant differences in daily entropy, Wilcoxon matched pairs signed-ranks test (Wilcoxon test, hereafter) and Mann-Kendall test (Kendall test, hereafter) were performed. Wilcoxon test and Kendall test are common nonparametric methods to test differences in matched pairs that severely violate the assumption of normal distribution (MacFarland & Yates, 2016). The test results are shown in Appendix A. We tested whether the change in entropy in each two-day combination. For example, the first column indicates the change of entropy between D-9 and D-10. All Wilcoxon test results for Fig. 2 were significant at the alpha = 0.1 level, and all Kendall tests were significant at the alpha = 0.1 level, except between D-7 and D-6 (shown in Appendix A). Therefore, it can be concluded that the changes in entropy across days before purchase are, with few exceptions, statistically significant.

4.2. Entropy search patterns by information sources

In practice, consumers typically acquire information from diverse sources throughout their search/purchase process. Information source is very important in understanding consumers' behavior because information sources reveal their information search goals. A common information source for purchases are online-seller sites, such as Amazon.com, where consumers can get product information from manufacturers as well as other buyers' reviews. Consumers also look to non-seller sites, which include online community sites such as blogs, cafés, news sites, among others. To explore the behavioral patterns of mobile/PC usage in context of information sources, we set out to chart changes of entropies in seller sites compared to those in other (non-seller) sites.

We identified top-10 online sellers in the country and isolated URLs from those sites. The percentage of URLs from these seller sites was 39.8% in our data set. Since these online sellers' market share collectively exceeds 90%, a vast majority of consumers' search in seller sites can be captured by covering these sites. The domain names of non-seller sites were also analyzed. Among the URLs from non-seller sites, portal sites are 55.9%, online community sites such as blogs and cafés are 25.1%, news sites are 9.8%, and others are 9.8%. Fig. 3 compares entropies for the seller sites against those of the non-seller sites by mobile and PC, respectively.

There is a common pattern being observed from the mapping in Fig. 3. Entropies in seller sites are relatively stable while entropies in non-seller sites exhibit bigger changes. Considering that the non-seller sites are mostly online communities, reviews, or news sites, it seems that consumers explore diverse reviews and information sources outside the seller sites when they decide to purchase a product. On the other hand, although consumers slightly increase diversity of information

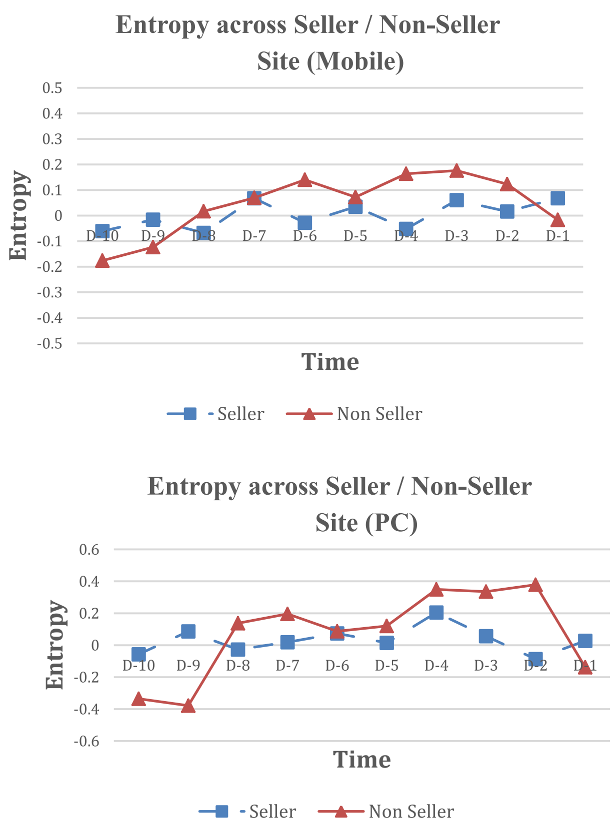


Fig. 3. Entropy across Seller/Non-seller Site for Moblie & PC.

search in seller sites, the increase is not as dramatic as in non-seller sites. Hence, interestingly, while we previously found contrasting patterns of the general entropies across mobile and PC searches, the principal basis of variation does not appear to be the *source* (seller vs. non-seller) of information. Wilcoxon and Kendall tests for Fig. 3 were also conducted. All Wilcoxon tests and Kendall test results were significant at alpha = 0.1 level (shown in Appendix B). The entropy measure, while diagnostic of the diversity in the URLs visited, does not address the *content* of the search *per se*. We, thus, proceed with analyses on the contents of the consumers' search for additional insights.

4.3. Diversity of brand/model names in the visited pages

To further ascertain how brand search would differ or be similar across the mobile/PC modalities, we proceed with an investigation into the diversity of brand/model names in the pages the consumers visited. In this study, the panel members were asked to provide the brand or model name that they purchased, and then we calculated the ratios of the number of pages containing the brand or model name purchased to the total number of pages visited. The averages of these ratios are in Fig. 4.

We observe diametrically different patterns in the ratios charted across the two modalities. Specifically, the ratio for PC-based search is a relatively low and stable throughout the observed period (D-10 to D-1), which signifies that consumers search information for diverse brands without particularly focusing on the ultimately-purchased brand or model. In contrast, the ratio for mobile devices fluctuates dramatically, with a sharp spike in the early stage (D-9) and followed by relatively smaller fluctuations heading towards purchase. The mobile ratio pattern implies that consumers search information on the ultimately-selected brand or model quite early on this device, and they subsequently use both mobile and PC to search information on diverse brands or models. The overarching implication is that the brand/model searched early on the mobile device is highly diagnostic of the final choice – irrespective of whether consumers are implicitly or explicitly aware themselves. All in all, PC-based only search mapping would be amiss of the mobile-based dynamics. All Wilcoxon tests and Kendall tests for Fig. 4 were significant at alpha = 0.01 level (shown in Appendix C).

4.4. An aggregate-level summary on text-mining of the pages visited

For an overview of the general patterns of the topics searched over the10-day period prior to purchase (D-10 to D-1), we conducted text-mining analyses of the visited pages on an aggregate level. By analyzing these texts, our aim was to identify and better understand the consumers' topics of interest during the decision-making period. The texts from the webpages visited by 169 buyers of electronics category comprehensively represented the information they had searched and

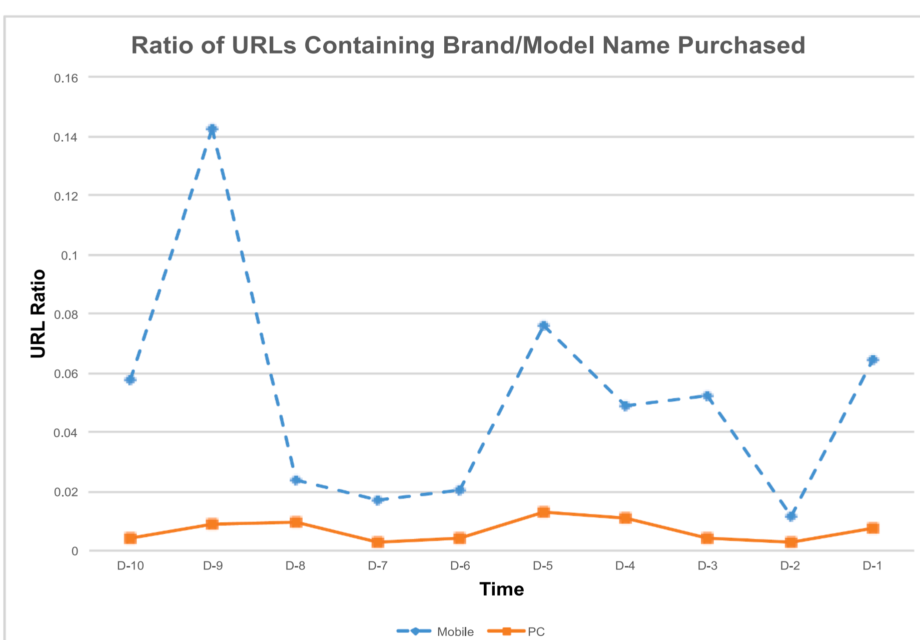


Fig. 4. Ratios of Number of URLs Containing Brand/Model Purchased to Total URLs Visited.

acquired online.

'Topic modeling' method was employed to extract topics of the texts of the page buyers visited. Topic modeling is a statistical probabilistic modeling to infer hidden subjects in a volume of texts, which typically are distributed in a large number of documents. Topic modeling is a new technique that can represent meanings of documents better than traditional topic representation techniques such as pLSI (Griffiths & Steyvers, 2004). The most common algorithm for topic modeling is LDA (Latent Dirichlet Allocation), which is an algorithm that discovers hidden topics and their structures from observed variables in texts such as words and documents, with the assumption that words in documents are not independent. Through its generative process, LDA finds statistically optimal values of important parameters such as probability of each topic to be included in a document and probability of each word to be selected for a topic. As the result, LDA can identify a set of important topics from a set of documents, portion of topics in each document, and probability each word to be included in a topic (Blei, 2012). In sum, LDA is a statistical algorithm that extracts from a set of documents a certain number of most important topics, each of which contains a few closely related keywords. In this study, topic modeling was conducted using the LDA function of 'topicmodels' package in R. As the result, a set of topics (5–12, depending on the volume and structure of the texts) were extracted for each day.

The results show that the texts from pages visited via PC can be best summarized with 12 topics for each day and the texts from pages visited by mobile device can be best summarized with 9 topics for each day. Therefore, a total of 210 keyword clusters – 12 topics $\times$ 10 days (PC) + 9 topics $\times$ 10 days (mobile) – were extracted. Each word cluster contains 2–5 keywords that represent the topic. For comparability, 9 topics in Table 2 were used for both PC and mobile and the topics extracted from PC and mobile were re-coded. Two researchers coded the topics using the coding scheme as shown in Table 2. The nine categories in the table were identified based on extant studies (e.g., Bronnenberg et al., 2016).

After the first training and information sessions, each coder coded the extracted topics independently in the first round. Afterwards, their coding results of one randomly-selected day were compared, and any discrepancies were resolved through discussions. In the second round, the coders re-coded the whole topics independently. Inter-coder reliability measures (ratios of topics that both coders coded as same) after the second round were 0.705 for PC texts and 0.727 for mobile texts, respectively. Coded topics were counted by categories for each day, and the numbers from the two coders were summed. The results are in Table 3 and Fig. 6.

Correlation analysis should reveal any trade-offs between among the topics, and there are three pairs of topics that show significant negative correlations as in Table 4. Since the observations were topics by day, a negative correlation between two topics means that these topics tend not to appear together on a same day.

The results suggest that consumers tend to search product, brand, and model name separately, which indirectly shows consumers' tendency to sequentially search for information on product, brand, and model names, respectively. Another result worth noting is that there is a strong negative correlation between attribute and delivery, signifying that consumers rarely search information on delivery when searching for product attribute information, and vice versa. It is probably because consumers search for attribute information typically in the early stage of the purchase process while delivery information usually is sought in the later stage of purchase. Fig. 6 also shows similar patterns – the number of topics related to attribute is high in the early and middle stages of the purchase decision, and the number of topics on delivery increases in the later stage of the purchase process.

Table 2
Coding scheme for the topic modeling.

Category	Description	Examples
1	Product	refrigerator, TV
2	Brand	Samsung, LG, Galaxy
3	Model Name	NT900, Galaxy6S, G3
4	Attributes	size, resolution, efficiency rating
5	Price	low price, sale, price comparison
6	Delivery/Retailer	department store, specialty store, delivery, installation
7	Reviews/ Opinions	review, blog, popular, recommendation
8	Mix	mix of above
9	Etc	others

4.5. Relationship between entropy and topics of interest

Based on the data extracted from topic modeling, we investigated how changes in topics are related to entropy. Specifically, we wanted to find out if and which topics searched will lead to changes in entropy, that is, the diversity of information explored. For example, when consumers seek certain types of information, they might explore more diverse sources compared to when searching for other types of information. With entropy as the dependent variable, we ran a regression analysis using the 'frequency' of topics as independent variables. The PC and the mobile data were merged, which yielded a total of 20 observations – 10 days $\times$ 2 devices (PC and mobile). VIF (variable inflation factor) values of all variables were less than 6, which indicate that multicollinearity was not a serious problem in our data. Adjusted R^2 was 0.318. Among the 9 topics, two topics exhibited significant relationship with entropy as shown in Table 5.

The results imply that consumers are more explorative when they search for information on price and review. The large coefficient and t-value of price suggest that consumers explore most different sources when they search for price information. This result concurs with the previous study on sponsored-link advertisement (Im, Jun, Oh, & Jeong, 2016), which shows that consumers visit most number of pages when their search keyword is related to price.

4.6. Single-channel vs. multi-channel buyers

Although the usage of mobile has become quite prevalent for online search, this phenomenon actually bears a relatively short history. In other words, while much of the search activities may have shifted towards mobile, the actual act of ordering on this device may not have followed suit for a segment of buyers – whether it be due to interface issues, security concerns, or simply, out of an old habit. As work by Kushwaha and Shankar (2013) has shown distinct differences between single-channel vs. multi-channel buyers to exist, we extend this rationale to the context of PC-only vs. mobile/PC purchasers to observe for differences in search behavior – that is, if any.

In the survey, the panel members had to indicate the device(s) that they generally utilize to place the actual order for online purchases: (1) exclusively on PC; (2) exclusively on mobile; or (3) both on PC and mobile devices. Out of 169 panel member, 54 had indicated "exclusively on PC" and 115 had responded "both on PC and mobile devices," while no one had checked the "exclusively on mobile" category. Based on this segmentation scheme, we proceed with two types of analyses comparing single- vs. multi-channel buyers: (1) *by entropy* – that is, mapping diversity of online search across the two modalities, and (2) *by content* – that is, using 'topic modeling' to detect differences in the search content across the two modalities.

By entropy. For the single-channel buyers, the entropies of mobile- vs. PC-based searches are shown to move in the direction opposite of one another. That is, when mobile-based entropy hits a peak, PC-based entropy hits a valley, and vice versa. One interpretation is that single-channel buyers are utilizing mobile and PC as *substitutes* in the role of online search. Possibly, these consumers are more tradition-bound and opting for intensive usage of simply one-device at a time any particular day. On the other hand, the multi-channel buyers may well be more

Table 3
Counts of topics.

		D-10	D-9	D-8	D-7	D-6	D-5	D-4	D-3	D-2	D-1
PC	Product	4	10	5	5	5	1	2	5	5	1
	Brand	4	2	5	5	5	2	2	4	3	4
	Model Name	3	0	0	2	0	4	3	1	0	3
	Attributes	2	6	2	3	7	12	6	8	5	8
	Price	0	1	0	2	1	0	1	2	0	0
	Delivery/Retailer	5	4	8	2	0	0	2	0	6	0
	Reviews/Opinions	2	1	2	4	4	3	7	2	4	1
	Mix	1	0	2	0	1	1	1	0	1	2
	Etc	3	0	0	1	1	1	0	2	0	5
Mobile	Product	2	4	3	4	3	3	2	2	2	3
	Brand	5	3	2	2	3	3	0	2	5	1
	Model Name	2	1	0	2	3	0	4	1	0	3
	Attributes	4	8	7	9	4	9	6	8	4	0
	Price	0	0	0	0	2	1	2	0	2	2
	Delivery/Retailer	2	0	0	0	2	1	2	0	2	7
	Reviews/Opinions	0	2	6	0	0	0	2	3	2	0
	Mix	2	0	0	1	1	1	0	1	1	1
	Etc	1	0	0	0	0	0	0	1	0	1

technologically savvy consumers, who employ the two devices interchangeably, or as *complements*, not only in ordering but also in search tasks as well. Accordingly, the mapping of entropies for the multi-channel buyers shows the mobile- and PC-based entropies to be more-or-less moving in tandem.

Wilcoxon and Kendall tests were conducted for the results in Fig. 5. The tests showed mixed results. Wilcoxon test results were not significant at $\alpha = 0.1$ level, while Kendall tests were significant at $\alpha = 0.1$ level. In the case of multi-channel, Wilcoxon tests showed no difference at $\alpha = 0.1$ level, while Kendall tests were significant at $\alpha = 0.1$ level (shown in Appendix D). It seems that the differences of entropy between mobile and PC are marginally significant for both single and multi-channel buyers.

By content. The texts from these two groups were separately analyzed using 'topic modeling' method, using the same tools and coding schemes explained in the previous section. Each group generated two sets of data – one from PC and the other from mobile. With the topic modeling analysis method, it was determined that 8 word clusters each day were optimal for the texts from PC and 5 word clusters were optimal for mobile. Each extracted cluster was examined and coded by two independent coders. The final inter-coder reliabilities for these four datasets ranged from 0.745 to 0.875, which shows that there is a high level of agreement between the two coders. After coding the topics and summing the results from the two coders, the ratios of topics were calculated for each day. The averages of ratios by topics are shown in Table 6.

In terms of the topics searched, the single-channel buyers show no significant differences in the contents searched by modality. On the other hand, the multi-channel buyers engage in search for *attributes* more on PC while they use mobile significantly more to search for *price*. This type of multi-channel buyer is highly characteristic of the archetypal modern-day consumer, whose tech-savvy skills allow the individual to take advantage of the key benefits of each device (e.g., the portability and time-sensitive contextual facet of the mobile is suited for frequently checking prices, whereas PC's interface is more suited for rigorous search tasks). Moreover, no differences across modalities in the topics searched for the single-channel buyers also go to reinforce our intuition from the entropy results (not to mention from their insistence in being single-channel buyers) that this segment may be a tradition-bound, less tech-savvy group. In other words, not showing any specialization in the topic search by device may perhaps be due to a lack of full grasp in modality-specific benefits.

5. General discussion

The goal of this study was to better understand the cross-modal (mobile and PC) online search behavior of the modern-day consumer. In this discovery process, we corroborated some anecdotal evidence from the industry, accrued several novel insights, as well as observed similarities and also stark differences across mobile- and PC-based search behavior. We highlight and discuss our key findings in the following.

First, the mapping of the entropies, as the construct for the diversity of information search, charted twin-peaks – the first peak belonging to mobile-based search and the second, higher peak to the PC. In the context of the decision-making literature, the twin-peaks we observed are consistent with the two-stage process (e.g, Gensche, 1987; Shocker et al., 1991). To elaborate, in the first stage, the extant literature posits consumers to engage in a less effortful processing to narrow down the large number of options to a *consideration set* – and what we found was that consumers tend to explore more with mobile device, indeed, suiting such a task of that nature. In the second stage, consumers are believed to engage in a more costly, effortful processing to narrow down further to a *choice set* (Bettman et al., 1990) – which is consistent with the later, higher peak belonging to PC. Altogether, the general entropy patterns suggest that different devices (mobile and PC) assume key roles in the first and second stages, respectively – and yet, in support of the two-stage decision-making paradigm.

The similarities we observed between the mobile- and PC-based search patterns emerged in the information sources. Overall, the seller sites were associated with relatively more stable entropy patterns, whereas, the non-seller sites demonstrated generally higher, more diverse entropy patterns. As non-seller sites typically represent online communities, reviews and news sites, consumers evidently exhibited higher marginal utility in search for diverse information outside of the sellers' sites. It is very likely, due to the source-credibility differences amongst seller vs. non-seller sites, consumers found it more worthwhile to further explore in the latter category.

In the plotting of ratios of the purchased brand/model to the webpages visited, aside from the key finding of consumers searching extensively for the ultimately-chosen brand early in the stage on mobile, we noticed another interesting phenomenon. The notable pattern close to purchase date is that the ratio on the mobile dips to an all-time low at D-2, but recovers at D-1. In the customer purchase journey in the online shopping context, Jacobs, Holland, and Prinz (2018) observe a similar pattern with flight ticket search. Once consumers reach the flight configuration page where "a chosen flight is displayed without the possibility of further search refinements" before purchase, there is a "high rebound" of 19% among the consumers tracking back to the flight selection webpage. Jacobs et al. (2018) attribute this behavior to cognitive dissonance and elaborate in the following: "A consumer, continuing to search, might just want to persuade himself that his temporarily chosen option is the best one he can choose." Hence, one

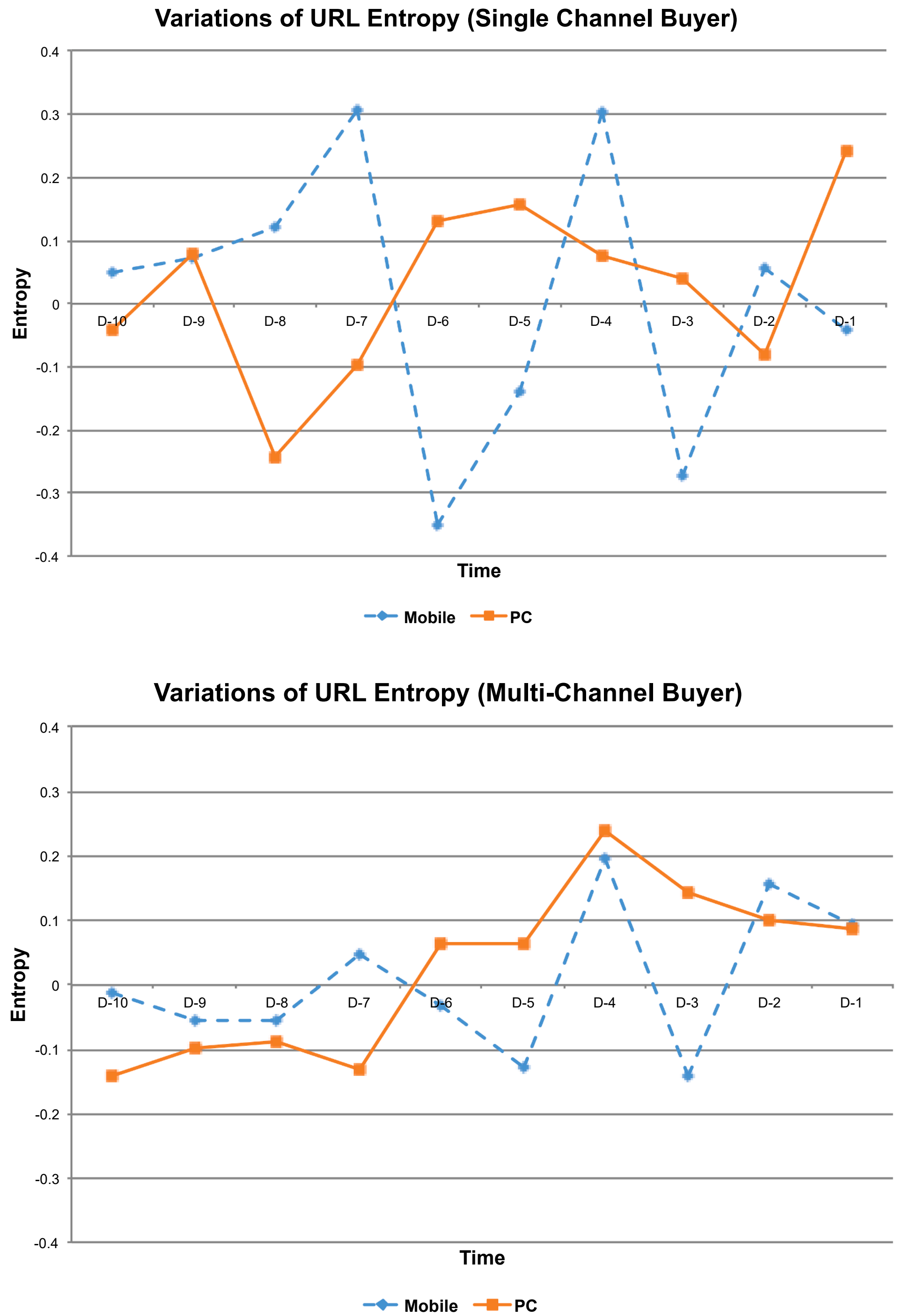
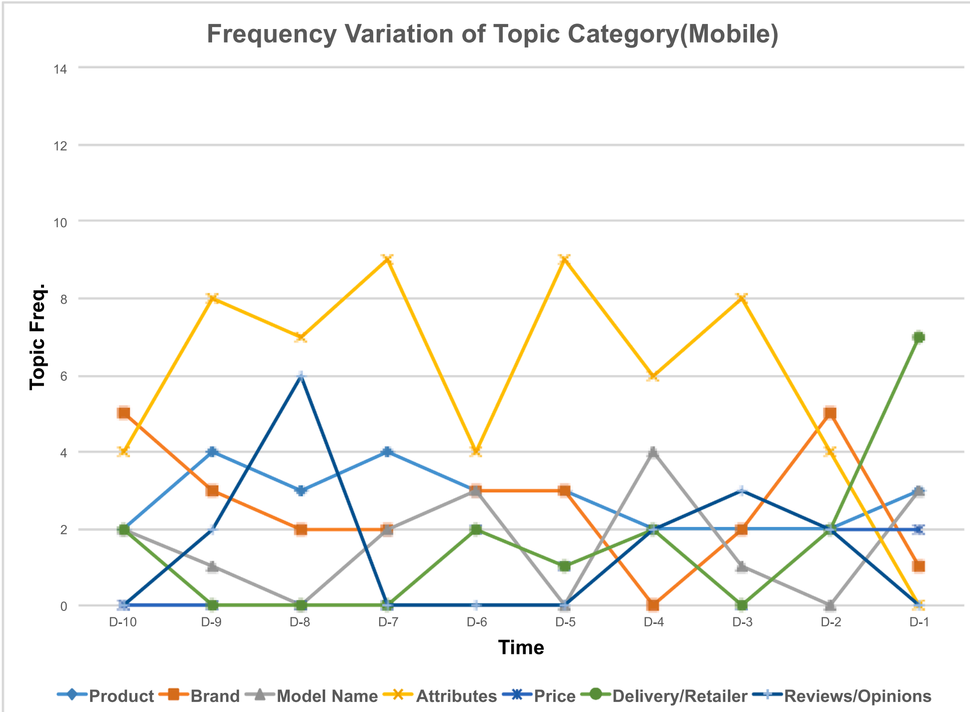


Fig. 5. Variations of URL Entropy for Single & Multi-Channel Buyers.

potential explanation for the observed pattern may be cognitive dissonance or anticipated buyer's regret that consumers are believed to undergo – especially, for infrequently-purchased, high-involvement product categories (Tsiros & Mitta, 2000). That is, as most choices involve some type of compromise or trade-off between the selected and the foregone options, consumer are believed to devote additional effort in counterfactual thinking to minimize regret or optimize choice. Perhaps, high incidences of shoppers abandoning item(s) placed in their shopping carts (85.49% for consumer electronics in March 2020 Statistica Report) may be attributable to irresolution of "second thoughts" or "cognitive dissonance" occurring at the very late stages of the purchase funnel.

We also set out to test whether single- and multi-channel buyers utilize PC and mobile devices differently in their purchase decision process. Indeed, we find the multi-channel buyers as engaging in PC and mobile devices in a rather versatile manner – designating certain topics to a certain device. Specifically, multi-channel buyers rely heavily on mobile devices for price related topics – most likely to find a good deal or monitor price changes. However, they resort to PC heavily for their search on attributes – which would require more of an extensive search suited more for PC than mobile. On the other hand, the single-channel buyers use both devices similarly in topics searched – as they may be less tech-savvy than the multi-channel buyers. Altogether, the differential results across the single- vs. multi-channel buyers underscore the



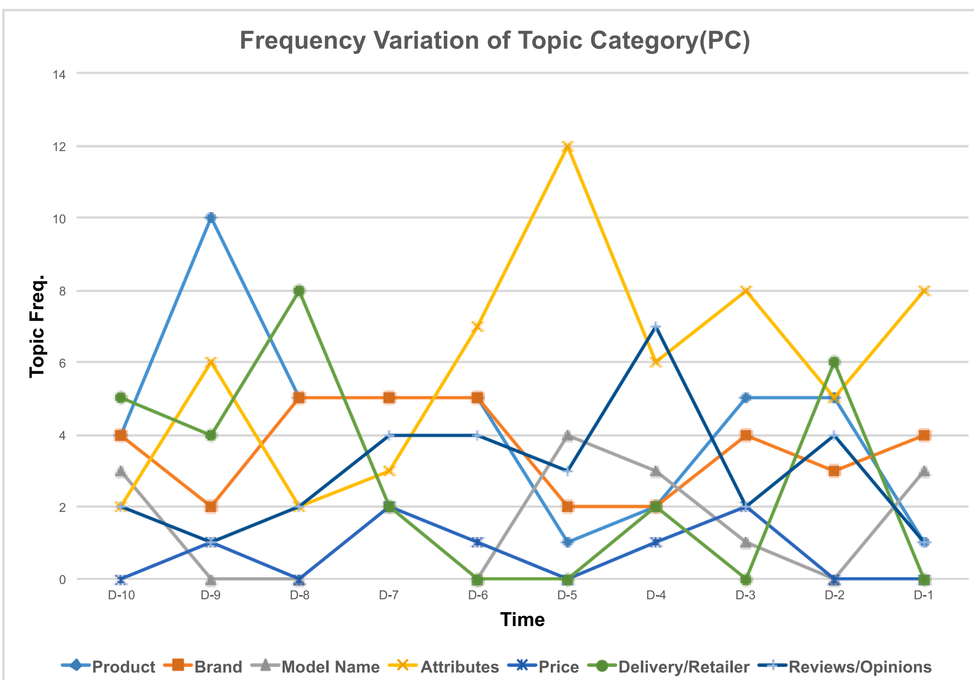


Fig. 6. Frequency Variation of Topic Category for Moblie & PC.

Table 4
Correlations between Topics.

Topic Pairs	Correlation Coefficient	p-value
Product – Model Name	−0.522	0.018
Brand – Model Name	−0.392	0.087
Attribute – Delivery	−0.786	0.000

patronized channels as an important discriminant factor, which was initially highlighted by Kushwaha and Shankar (2013) in the offline vs. online context.

6. Managerial implications

As the new behavioral norm of consumers using both mobile and PC to search online is starting to take root, our study offers several implications for the practitioners in this regard. First, mobile-accessed interface and PC-accessed interface for the company's websites need

Table 5
Regression analysis of topics on entropy.

Topic	Standardized Coefficient	t-value
Product	0.011	0.03
Brand	−0.075	−0.24
Model Name	0.108	0.37
Attributes	0.496	1.21
Price	0.754	2.87**
Delivery/Retailer	0.119	0.27
Reviews/Opinions	0.431	1.93*
Mix	0.683	1.81
Etc	−0.444	−1.80

*: significant at $\alpha = 0.1$ level, **: significant at $\alpha = 0.05$ level (PC vs. mobile). $R^2 = 0.801$, adj. $R^2 = 0.318$.

Table 6
Average ratios of topics (single- vs. multi-channel buyers).

Topics	Single-Channel		Multi-Channel	
	PC	Mobile	PC	Mobile
Product	0.119	0.082	0.159	0.118
Brand	0.176	0.182	0.170	0.155
Model Name	0.011	0.018	0.006	0.027
Attributes	0.307	0.182	0.403***	0.173***
Price	0.102	0.055	0.006**	0.245**
Delivery/Retailer	0.114	0.127	0.085	0.109
Reviews/Opinions	0.119	0.173	0.114	0.055
Mix	0.023	0.027	0.011	0.009
Etc	0.028	0.155	0.045	0.109

: significant at $\alpha = 0.05$ level, *: significant at $\alpha = 0.01$ level (PC vs. mobile).

to be designed to take advantage of the device's characteristics and browsing patterns of the consumers. The former should be suitably designed for easy, shallow searches and the latter for rigorous, deep searches. In particular, the multi-channel buyers show a high preference for a certain content/device (e.g., price/mobile and attribute/PC) configuration, hence, marketers should take note in the designing and communicating the message with the device in mind.

In practice, many online retailers promote and even reward customers who order through their mobile apps instead of their websites of either PC or mobile versions. As single-channel customers may not be as easy as multi-channel customers to be persuaded in the move, such promotions perhaps should be specifically targeted at the multi-channel customers only so as not risk alienating single-channel customers with offers that seemingly only reward behavior averse to this segment.

Marketers planning to shift more resources to mobile marketing appears to be a very timely decision. Our findings indicate that consumers search for the ultimately-purchased brand/model early only on mobile, and that they engage in cognitive-dissonance reducing search late, again, only on mobile. Hence, allocating resources to mobile marketing is warranted for the sponsor firm – with the aim of designing programs to facilitate the aforementioned activities to their advantage. Nonetheless, marketers still need to maintain budget for programs on both modalities. As we found consumers to find higher marginal utility in exploring non-seller vs. seller sites for both mobile- and PC-based searches, firms need to allocate substantive budget across the two modalities to manage positive WOM on online communities, support PR activities to be featured in news sites, and/or engage in long-term relations with influential bloggers.

By design, some company websites do not display or feature price information of their market offerings (e.g., instructing visitors to enquire with their representatives, asking the enquirers to visit the nearest dealer or retailer, or sign-up as a member to access information). Our results show that the price information acts as a powerful catalyst for consumers to engage in extensive searches, which signifies that commercial websites should feature some element of the price information (e.g., MSRP or price ranges) to further encourage consumer search and engagement.

Moreover, since our results show that consumers—in particular, for multi-channel buyers—prefer to search/browse certain type of information on mobile (e.g., price) vs. PC (e.g., product attribute), the retailers/marketers should tailor the content of the adverting specific to the devices to help this category of consumers in their search and evaluation process.

7. Limitations and directions for future research

Our data on purchase information comes from the supplementary survey data, hence, may be subject to recall error or biases. Moreover, as this study covered one durable product category, the study's generalizability to other product categories (e.g., frequently-purchased consumables, hedonic products, or low-involvement categories) may be somewhat limited. Future studies should map the cross-modal dynamics across different product categories.

A future application of topic modeling may be considered for brand loyalty measures. We can collect all the webpages containing competing brand names and apply topic modeling separately to different brands, which in turn, should yield specific key words related to different brand names. Another venue for future study is exploring how different keyword searches lead to different search patterns. In this study, keyword search was not included in the analysis of the search behaviors, therefore, it would be very interesting if we can identify how a specific keyword search eventually leads to the final choice. Capturing semantics of texts using deep learning techniques could help us better understand the relationship between text information searched and behavioral patterns.

CRediT authorship contribution statement

Sangman Han: Conceptualization, Data curation, Project administration. **Jin K. Han:** Conceptualiztion, Writing - original draft, Writing - review & editng. **Il Im:** Conceptualization, Funding acquisition, Methodology. **Sung in Jung:** Formal analysis, Validation. **Jung Won Lee:** Formal analysis, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Nonparametric test results for Fig. 2 (changes in entropy)

		D-10 D-9	D-9 D-8	D-8 D-7	D-7 D-6	D-6 D-5	D-5 D-4	D-4 D-3	D-3 D-2	D-2 D-1
Mobile	Wilcoxon	0.012**	0.060*	0.008***	0.053*	0.088*	0.088*	0.041**	0.012**	0.060*
	Kendall	0.000***	0.000***	0.003***	0.018**	0.000***	0.000***	0.000***	0.000***	0.000***
PC	Wilcoxon	0.024**	0.083*	0.086*	0.074*	0.076*	0.081*	0.038**	0.083*	0.086*

(*continued on next page*)

(*continued*)

		D-10 D-9	D-9 D-8	D-8 D-7	D-7 D-6	D-6 D-5	D-5 D-4	D-4 D-3	D-3 D-2	D-2 D-1
	Kendall	0.000***	0.000***	0.021**	0.366	0.022**	0.000***	0.000***	0.000***	0.000***
Total (Mobile + PC)	Wilcoxon	0.041**	0.029**	0.054*	0.082*	0.031**	0.000***	0.072*	0.081*	0.018**
	Kendall	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

Significance level: * < 0.1, ** < 0.05, *** < 0.01.
Wilcoxon: Wilcoxon Matched Pairs Signed-Ranks Test.
Kendall: Mann-Kendall test.

Appendix B. Nonparametric test for Mobile/PC entropy for Seller/Non-Seller site

Seller vs.	Mobile	Wilcoxon	0.026**
		Kendall	0.020**
Non-seller	PC	Wilcoxon	0.054*
		Kendall	0.020**
	Total (Mobile + PC)	Wilcoxon	0.083*
		Kendall	0.024**

The approximate significance level is displayed. p* < 0.1, p** < 0.05, p*** < 0.01.
Wilcoxon: Wilcoxon Matched Pairs Signed-Ranks Test.
Kendall: Mann-Kendall test.

Appendix C. Nonparametric test results for Fig. 4 (ratio of URLs containing brand)

Mobile	Wilcoxon	0.005***
vs. PC	Kendall	0.002***

Significance level: * < 0.1, ** < 0.05, *** < 0.01.
Wilcoxon: Wilcoxon Matched Pairs Signed-Ranks Test.
Kendall: Mann-Kendall test.

Appendix D. Nonparametric test results for Fig. 5 (single and multi-channel)

Single-channel	|Mobile| vs. |PC|	Wilcoxon	1.000
		Kendall	0.038**
Multi-channel	Mobile vs. PC	Wilcoxon	0.959
		Kendall	0.052*

Significance level: * < 0.1, ** < 0.05, *** < 0.01.
Wilcoxon: Wilcoxon Matched Pairs Signed-Ranks Test.
Kendall: Mann-Kendall test.
The meaning of '| |' is an absolute value, and it is a test of whether or not it is a substitute.

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Jin K. Han is Professor of Marketing & Area Coordinator at LKCSB School of Business, Singapore Management University (SMU). He received A.B. in Applied Mathematics/Economics from Brown University and M.Phil & Ph.D. in Marketing from Columbia University. Prof. Han's expertise spans across the areas of innovation, strategy, and branding—topics on which he has published in leading marketing and management journals. He has served as V.P. of Asia for American Marketing Association's Strategy SIG and the international advisory for the Korean Marketing Association, where he current sits in their governing board. Leveraging on his areas of expertise, he has consulted and/or conducted custom programs around the world for IBM, Samsung Electronics, LVMH, Johnson & Johnson, Standard Chartered Bank, OCBC, HP Printing Group, Amore Pacific, among others. Prior to joining SMU, he has held positions at the Hong Kong University of Science & Technology, KDI School of Public Policy & Management (Seoul), and the International Security Council (Washington, DC).