MONETIZING SEARCH MARKETING:
ONLINE RETAIL KEYWORD CHARACTERISTICS AND DECISIONS

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April 2012

A Research Paper Submitted to Communications of the Association for Information Systems
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Abstract

To make judicious resource allocation decisions in search marketing, it is essential to understand the motives behind online shoppers’ searching and purchasing behavior. Taking the approach of understanding consumers’ desires to reduce cognitive load in online shopping, we construct a goal-related keyword characterization framework. Most search keywords reflect a combination of the following characteristics - retailer specific, brand specific, product specific, feature related, and shopping intention. We analyze search ad visibility (including result rankings and dual-appearances), click-through, and revenue data associated with visitor-disclosed search keywords from a leading Web-only retailer over one year. We also investigate whether the relationships vary for head and tail keywords. Our findings show a variety of interesting impacts of keyword characteristics and dual-appearances of ads on search marketing performance. In addition, the impacts of search ad visibility on click-through are enhanced when searchers use head keywords. The contributions of the research include a comprehensive search keyword characterization framework, and the analysis of the relationships among keyword characteristics, search ad visibility, and search performance that have strong implications for search marketing monetization decisions.

Keywords: search keywords, keyword characteristics, search ad visibility, paid and organic search engine rankings, head and tail keywords, search marketing revenue, click-throughs, regression models
Introduction

According to a recent study by Compete (2010), 61% of consumers use Internet search engines to gather information for shopping. Due to the potential of reaching an increasingly large number of online consumers via search engines, search marketing that promotes a website in the paid and organic search result listings has become the most popular type of online marketing. Paid or sponsored search listings are advertising creatives displayed in a pre-specified region of a result page for a search keyword. A search engine charges a placement fee, measured by cost-per-click (CPC), when a search engine user clicks on a paid ad to visit an advertiser’s website (i.e., a click-through). The placement fee is primarily determined by the auction of a keyword’s position (e.g., rank position 1 or 2) on the paid listing (Xing and Lin 2006). Free of charge, organic search result listings rank order websites that a search engine discovers using its native keyword matching and ranking algorithm based on websites’ relevancy to a search keyword.

The search marketing performance of an e-tailer depends on the effectiveness of reaching and attracting search engine users who are likely to visit and conduct transactions at its website. To reach search engine users, the e-tailer’s website needs to be “visible” in search result listings by effectively selecting keywords for either paid search keyword auctions, or landing page optimization to increase search visibility. Search keywords can reveal a broad variety of user goals in only a few words (Chau et al. 2005; Mehta et al. 2007) and website visibility based on search result positions also greatly influence search marketing performance (Sen 2005) by inducing more visits to the website. Hence, the analysis of search keywords and website visibility in search result pages are considered instrumental to support and improve search keyword decisions.
This study focuses on analyzing online shoppers’ search behavior and decision making activities in a problem-solving process that require shoppers’ cognitive processing (Kamis et al. 2008). An individual enters search keywords in a search engine to find information related to a shopping decision, and uses the “cues” on search result listings to help choose useful information from the numerous results. Most search keywords exhibit one or more of the following characteristics - retailer specific, brand specific, product specific, feature related, and shopping intention. Premised in the cognitive load theory in problem solving, we focus on the different gaps in achieving online shopping goals that these keyword characteristics reflect, and how search ad visibility leads visitors to an e-tailer’s website by reducing their cognitive loads. Search visibility and search marketing performance of keywords by various characteristics have strong implications for monetizing keyword selections. Specifically, we are interested in the following questions related to search marketing decisions:

1. What are the relationships among keyword characteristics, search visibility (i.e., result rankings and dual-appearances of search ads on result pages), and search marketing performance?

2. Do users respond differently toward paid ads and organic listings?

To address these questions, we build our research framework on the cognitive load theory in problem solving (Sweller 1988). The proposed hypotheses are then tested using the performance data associated with paid and organic search keywords from an e-tailer. Compared to past studies focusing mainly on paid advertisement only, a unique focus of this study is to analyze the keyword characteristics by consumers’ information needs reflected in the keywords they enter (i.e., user-disclosed keywords), together with organic and sponsored advertisement visibility on search result pages.
Over a one-year period, paid and organic search ranking data were extracted from Google on a daily basis for 4,000 user-disclosed keywords relevant to a leading, Web-only, e-tailer. This data set was then combined with keyword-based weekly click-through and purchase information. To evaluate the impacts of keyword characteristics and search result visibilities, we used regression models to evaluate their relationships to search marketing outcomes. To the best of our knowledge, our study is the first to cover a longitudinal time span and a large keyword set with detailed keyword characteristics and fine-grain paid and organic search-ranking data. Both the keyword characteristic framework and the empirical models can provide foundations for continuing studies on search keywords, marketing performance analysis and keyword selection decisions.

**Related Research and Gap**

In this section, we summarize the findings of prior studies on analyzing the relationships between search keywords and search marketing performance to make clear the gap this study intends to address.

**Related Research**

By codifying consumer queries into five categories, including intent to buy, product-specific, location-specific, company, and general information, Jansen (2007) found that a large number of search queries fell into the product-specific category (48.34%). However, Jansen’s (2007) study did not examine the impact of product and other keyword characteristics on search marketing outcomes. Further studies are necessary to examine the relationships of these types of keyword characteristics to search marketing performance. Ghose and Yang (2008; 2009) analyze the impact of retailer-specific keywords and brand-specific keywords on paid search marketing performance. They found
that these two types of keywords show different influences on click-through rates, conversion rates, cost-per-click, search result ranking, order values and profits. However, their studies focus on two types of keywords and analyze paid keywords only.

Website visibility based on search result positions also greatly influence search marketing performance (Sen 2005) by inducing more visits to the website. Several studies are interested in the effect of search result rankings on search marketing performance (e.g., Agarwal et al. 2011; Animesh et al. 2007; Ghose and Yang 2009; Yang and Ghose 2010). Animesh et al. (2007) found that result rankings of paid ads are positively associated with website visits, customer ratings and website inlinks; in addition, the relationships are more salient for vendors of search goods (i.e., low quality uncertainty goods), compared to those for experience and credence goods (i.e., high quality uncertainty goods). Agarwal et al. (2011) also provide empirical evidence that while click-through rates of keywords decrease with keywords’ paid search rankings, their conversion rates first increase and then decrease with paid search rankings. Ghose and Yang (2009) find that paid keywords on the top of search result pages are associated with high click-through rates and conversion rates. However, most of prior studies only focus on the rankings and performance of paid keywords selected and managed by experts, and the rankings of organic search results are rarely examined.

Many advertisers invest in optimizing both paid and organic search result rankings. Marketing literature has shown that multiple exposures to an advertisement can enhance impression and increase conversion (McDonald 1996; Von Gonten and Donius 1997). If an e-tailer’s website appears in both paid and organic result listings on the same page, it provides multiple exposures to a website, and is considered to have similar marketing effects as traditional advertisement. However, this conjecture has not yet been investigated and remains unclear to practitioners and researchers.
A recent survey conducted by the Internet Retailer Association (Siwicki 2009) of the top 211 Web-only retailers, chain retailers, catalog sellers and consumer brand manufacturers indicates that 55.3% intend to increase spending on search engine optimization (SEO) for organic searches. To obtain insights into optimizing organic search keyword performance, it is important to further examine the characteristics, rankings and performance of keywords in organic search listings. Some studies (Jansen et al. 2007; Xing and Lin 2006) have indicated that search engine users prefer organic results because they are considered more objective and unbiased than sponsored results. On the other hand, some empirical evidence has shown that the conversion rates, order values and profits from paid search marketing are higher than those from organic natural search optimization (Ghose and Yang 2008). The results of performance comparisons between paid and organic search keywords may be highly website-dependent, and worth further investigation.

Yang and Ghose (2010) also model and estimate the inter-relationship between paid search advertisements and organic search listings. Their findings conclude that the respective probabilities to click on the advertiser’s paid and organic listings in the same search result page are positively interdependent, and the positive interdependence leads to an increase in expected profits for the e-tailer. However, past results did not address the impact of dual-appearances of search ads on click-throughs and purchases via paid searches or organic searches.

**Research Gap**

Prior studies focus on only one or two keyword characteristics, and therefore lack empirical examination of the relationship between diverse keyword characteristics and marketing performance. Many advertisers note diverse characteristics of search keywords, and are interested in optimizing
their paid and organic search marketing performance by using a wide range of keyword characteristics. Nevertheless, past findings have not expanded the potential to monetize keywords with more characteristics.

Although the importance of search ad visibility has been well-received, most of prior studies only focus on the rankings of sponsored search ads which may not sufficiently represent keywords disclosed in user queries. Furthermore, the multiple exposure effect of dual-appearance of paid and organic result listings has been mostly ignored in empirical investigations. To make informed decisions on how to invest in paid and organic search marketing of the same keyword, it is important for e-tailers to discover the impact of dual-appearances of sponsored and organic search ads on search marketing performance.

Past studies use datasets that spanned up to 3 months to analyze search keyword performance (e.g., Ghose and Yang 2009; Yang and Ghose 2010). Since marketing campaigns of an e-tailer can vary greatly for seasonal events, and online customers change their search goals according to holidays or other time-sensitive needs, it is valuable to track the keyword performance over a one-year period and control for time effects in analyzing search marketing performance. In addition, past studies primarily focus on websites that transact via both off-line and on-line channels. Their findings need further validations in order to be applicable to Web-only retailers. Since Web-only e-tailers are a fast growing segment of Internet Retailers (Siwicki 2009), research based on data from Web-only e-tailers would have a profound impact on future research and practices of search marketing analysis.

More importantly, prior studies mostly analyze the search ad performance from the perspective of maximizing advertisers’ profit, and focus on sponsored search ads. The findings thus are limited in
explaining consumers’ behavior in online search and purchase. In order to better understand the underlying process in consumers’ online searching and purchasing decisions, a solid theoretical foundation is needed in analyzing users’ search and shopping behavior. We focus on the goals behind consumer actions in order to better predict their behavior. Specifically, we aim at understanding Internet shoppers’ use of search engines to gather information, reach a retailer website, and finally make purchase decisions. This approach can help advertisers systematically examine consumers’ search, visit and purchase behavior.

The Research Framework and Conceptual Model

*Online search and shopping as a problem-solving process*

Consumers’ online shopping behavior can be considered as a problem-solving process that consists of a series of decision making activities (Kamis et al. 2008). In order to solve a problem, an individual must attend to differences between a current problem state and the goal state, and search for information or solutions that can help to close the gap between the current state and the goal state (Sweller 1988). In the context of online shopping, the goal state is to make a purchase decision, and the differences between the current state and goal state may be the lack of retailer, product, brand or other shopping related information. To reach the goal state, an online shopper composes queries for search engines based on his/her information needs, and find efficient ways to retrieve useful information from the vast amount of search results.

This process can be explained by the cognitive load theory in problem solving (Sweller 1988). According to Sweller (1988), two mechanisms may be particularly important in a problem-solving process: selective attention and limited cognitive processing capacity. Selective attention describes
that a problem solver selectively pays attention to critical information causing the differences between a current problem state and the goal state. For online shoppers using search engines to collect information, they first identify/select/prioritize the information needed to reach a purchase decision, and compose their search queries accordingly. In this sense, the search queries consumers submit to search engines reflect their selective shopping focus and preference; since the online shopper selectively pays attention to problem-solving related information, unrelated keywords would not be included in the search queries. Thus, we can analyze search queries to better understand online shoppers’ search goals. The uses and gratifications theory (Katz et al. 1974) in mass communication also suggests that Internet research which targets the understanding of user behavior should take users’ needs/motivations/goals into consideration, so that users’ interactions with Internet functions (e.g., search engines or search advertisement) can be better explained. Thus, a comprehensive search-goal oriented framework for keyword characteristics is valuable to search marketing performance analysis and decisions.

In addition, solving problems imposes cognitive loads on a problem solver, and the means-ends strategy is a burden on a problem solvers’ limited cognitive-processing capacity (Sweller 1988). A problem solver must simultaneously consider the current problem state, the goal state, the relation between the current problem state and the goal state, and the possible solutions. The cognitive-processing capacity needs to handle a vast amount of information. In the context of online shopping, when utilizing search engines, online shoppers need to use their limited cognitive-processing capacity wisely, and identify useful information from numerous search results. In this stage, users tend to use external cues to reduce their cognitive load in an information seeking task (Paas and van Merrienboer 1994). In search marketing, both paid and organic search result rankings can be used as external cues to reduce users’ cognitive loads. While the top ranked search ads are perceived as more
relevant results by those searchers, the multiple exposures to an advertisement can enhance the impression of these results (McDonald 1996; Von Gonten and Donius 1997). Furthermore, search ads with high visibility (e.g., rank on the top of the result pages, multiple exposures) can easily be seen and recalled by search engine users (Dou et al. 2010) and require less cognitive load if users choose them. Thus, search ad visibility can greatly influence search marketing performance (Sen 2005).

In order to address the research gaps in analyzing the factors influencing search marketing performance, we propose a conceptual model based on the cognitive load theory in problem solving, including the two critical aspects of search marketing (as shown in Figure 1): (1) keyword characteristics of search user queries that reveal target consumers’ information needs and online search goals, and (2) ad visibility that includes website rankings and dual-appearances in paid and organic listings on the same result page.

Figure 1. Conceptual Model
Keyword Characterization

Search queries represent consumers’ information needs in the shopping process. We therefore focus on these information needs in characterizing search keywords entered by online visitors and shoppers. The information processing perspective of consumer behavior (Bettman 1979) suggests that consumers initiate a search process to acquire relevant information in order to reduce purchase uncertainty. The purchase uncertainty also represents the gap between users’ current problem state and goal state that needs to be addressed by attaining relevant information. The risk or uncertainty in online shopping comes from various sources such as product quality and seller quality (Pavlou et al. 2007) that can be mitigated by trust, website informativeness, product diagnosticity, and social presence (Pavlou et al. 2007). Along this line, the search keywords that online shoppers choose to help gather information can be characterized by the type of uncertainty they seek to reduce.

Thus, search keywords entered by consumers to gather information can be characterized by the aspects of product and seller uncertainty. Product uncertainty can come from product availability, product quality and detailed specifications; seller uncertainty relates to information about a certain seller, some specifics of buying from a seller (e.g., price, shipping costs, discounts, time of estimated delivery, etc.), and product availability. A consumer initiates search behavior to acquire relevant information in order to reduce purchase uncertainty, and to cope with the perceived risk (Murray 1991).

Users’ shopping and search behavior can then be analyzed as a series of decision making activities where various product and seller uncertainties need to be addressed. From the perspective of shopping stages, shoppers’ decision activities include problem recognition, alternative evaluation, and finally purchasing decision (Nicosia 1966). A consumer starts the process once he/she
recognizes a problem (i.e., in the problem recognition stage), and searches for information on products and services that can solve his/her problem. While the product uncertainty is high at this stage, the consumer may rely on sellers or brands he/she is already familiar with as a starting point to limit the scope of the search and reduce his/her cognitive load, since a shopper has limited cognitive processing capabilities and can only selectively pay attention to the most critical information he/she needs. In this context, retailer names or branded words are used to help the shopper identify products that fulfill his/her shopping goals at a higher level.

The information which makes an impression on the consumer during the initial stage involves brands, price range and features. The consumer then moves to the alternative evaluation stage. The major purpose of this stage is to compare brands and detailed product features that are within their consideration. The consumer tends to use branded and feature words to locate certain information for the alternatives under consideration. In this context, the product uncertainty is high, and branded words and feature-related words would be used together with product words to find price and detailed product specifications.

Once the alternatives have been evaluated, the consumer proceeds to the purchase decision process. The decision to be made within this stage entails choosing a seller. When the seller uncertainty is high, retailer name and keywords related to transaction details (e.g., buy, shipping cost, discount, etc.) would be used together with product words to gather price information or product availability from various sellers. In this stage, sellers should provide information which encourages the consumer to act on their purchasing intention. Information like credit or payment terms, or a sales promotion may provide an incentive to buy now rather than waiting or continuing to search.
The discussion of purchase uncertainty, shopping stage and the search strategies are summarized in Table 1.

### Table 1: Information needs in various shopping stages

<table>
<thead>
<tr>
<th>Shopping Stage</th>
<th>Possible Purchase Uncertainty</th>
<th>Possible Search Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem recognition</td>
<td>Product uncertainty</td>
<td>Using seller names or branded words help identify products that fulfill shopping goals</td>
</tr>
<tr>
<td>Alternative evaluation</td>
<td>Product uncertainty</td>
<td>Branded and feature words are used to locate certain information for the alternatives under consideration.</td>
</tr>
<tr>
<td>Purchase decision</td>
<td>Seller uncertainty</td>
<td>Retailer names and transaction related keywords are used to gather price information or product availability from various sellers</td>
</tr>
</tbody>
</table>

Based on Table 1, we construct a goal-related framework of search keyword classification. Most search keywords\(^1\) submitted by users exhibit more than one characteristic. For example, the search keyword - “buy unlocked cell phones” contains product and feature related information, and the word – “buy” indicates shopping intention. Therefore, it would be more useful to codify search keywords with different characteristics rather than to categorize them into disjunctive categories. We include the following characteristics in this framework based on past literature and common search marketing practitioners’ considerations:

- Retailer specific: Keywords referencing the name of an online retailer, for example, “RetailerName”, Retailer Name, RetailerName.com (Ghose and Yang 2009) are often submitted by searchers who are familiar with, loyal to or interested in the retailer. Shoppers may have an impression of a certain retailer based on prior experiences. Direct use of a

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\(^1\) A keyword may not be a single word; instead, most of the keywords are combinations of multiple words. Search keywords are referenced interchangeably with search terms, search queries and search phrases in literature and practice.
retailer’s name in the search query may help shoppers easily locate a retailer’s website or locate specific information regarding buying from this retailer.

• Brand specific: Keywords containing a brand or trade name (Ghose and Yang 2009; Rutz and Bucklin 2011), e.g., Nike or Wii. Brand names become more important online than in the traditional market (Degeratu et al. 2000), serving as quality or style cues for products. Brand names are often used by shoppers to reduce cognitive loads or eliminate product uncertainty since they may be familiar with a certain brand. Brand specific words are used by shoppers to find products that fulfill their needs, and/or to compare alternatives.

• Product specific: Keywords containing specific product terms (Jansen 2007), e.g., clothing or bed, indicating searchers’ product-related information needs. Product specific keywords are most widely used and also directly indicate shoppers’ goals in making a purchase.

• Feature specific: Keywords used to specify certain attributes of products, including material, version, color, shape, size, style or the context; some examples are red, limited, and Halloween. In online consumer searches, such desired features of the products are also used as a way to narrow down choice sets and search results, and to locate certain product specifications. Feature specific keywords are also used to reduce product uncertainty, and are mostly used together with product specific keywords.

• Shopping intention: Keywords related to purchase behaviors (Jansen 2007), e.g., buying, order or purchase; or related to promotions and discounts, e.g., coupon, sale, 20% off, or free shipping. Searchers using such search keywords may have strong shopping intentions. Shopping intention keywords help users lower overall shopping costs, either by finding the best price, or by identifying the best seller in order to reduce seller uncertainty. Shopping intention keywords are also often used with product specific keywords.
This framework fully covers our data set and can be used in the keyword analysis for general online retailing websites. An advertiser can target consumers based on the characteristics of the search keywords they enter in search engines by designing search advertisements related to consumers’ specific search goals.

In addition, common practices in keyword selection contrast head keywords with tail keywords. A head keyword is more general for example about a product (e.g., TV) or brand (e.g., Sony). A tail keyword (e.g., discount Sony 1080p TV) is more detailed or is specific about a retailer (e.g., amazon.com). Head keywords are popular to shoppers; since they do not suggest preferences for a specific retailer, they are also subject to steep competition with other retailers for visibility on search result pages. Used by limited number of searchers, tail keywords may indicate keen information needs and shopping interests. To monetize head keywords, it is important to understand the respective returns on investment in head and tail keywords.

**Advertisement visibility**

To investigate the impact of the visibility of an e-tailer in search result listings, we measure search visibility based on its position on the paid and organic listings for a given keyword, as well as the dual-appearance when the e-tailer’s advertisements appear in both paid and organic listings of the keyword. We assume that the search results which appear at or near the top of the page, up to the first 30 search results in this study, attract more consumer attention. In addition, dual-appearances of an e-tailer’s paid and organic ads in the same search result page are considered a critical factor in search ad visibility. As both advertisement and organic results space is limited, simultaneous exposures in both areas allow an e-tailer to substantially increase its prominence on a result page.
**Consumer responses**

Advertisers strategize their advertising campaigns based on consumers’ actions – patronage, purchase and the advertising media they choose (Peterson and Merino 2003). In the context of online search and shopping, marketers focus on consumer behavior such as by what means do customers reach an advertiser’s website through their search queries, and whether customers purchase at the website once there. Thus in this study, we focus on click-throughs (i.e., visits) and revenue that reveal “user reactions” or “behaviors that could impact a website’s bottom-line” to evaluate the performance of search marketing.

Click-through is a quantity of interest to search engine marketers as a metric for evaluating advertising effectiveness (Regelson and Fain 2006). Click-throughs from paid ads also have a direct impact on the cost of sponsored ads. Some researchers use profitability to assess the performance of different search engine marketing strategies (e.g., Sen 2005). However, the cost of paid and organic search ads is not directly comparable and even may not be precisely measurable. Hence, we use revenue, which is product sales without shipping and handling fees generated from the visits associated with the keywords, as another search marketing metric. Some of the past studies (Agarwal et al. 2011; Ghose and Yang 2008; 2009; Yang and Ghose 2010) measured search marketing performance by click-through rates and conversion rates. “Click-through rate” is the percent of searches using a keyword that actually lead to click-throughs, whereas “conversion rate” is the percent of click-throughs via a keyword actually resulting in purchases. As an e-tailer does not know the actual number of organic search results in which its website has appeared, organic click-through rates tend to be estimated based on keyword search volumes made available by search engines. As the accuracy of click-through rate estimates is unknown, this study adopts click-throughs instead.
Conversion rates of visits can be directly measured in our data set. However, the focal e-tailer sells a variety of products with a wide range of prices. Hence, this study adopts revenue to measure purchase outcomes. As keyword popularity and order value affect keyword performance, hypothesis testing for our model should control on these factors.

**Hypotheses**

Based on the cognitive load theory in problem solving, we have developed hypotheses regarding the relationships among keyword characteristics, website visibility in search results, and search marketing performance. We also draw relevant arguments from theories regarding customer loyalty, advertisement competition, and consumer attention to better support our hypotheses. The hypotheses to be tested are summarized in Figure 2. We will test each of the hypotheses for paid and organic search keywords respectively.

![Figure 2: Summary of hypotheses](image-url)

*Figure 2: Summary of hypotheses*
Retailer keywords can be used at different shopping stages, as we discuss in the keyword characterization framework. Nevertheless, a searcher who includes an e-tailer’s name in search keywords needs to know the retailer before starting the information search process. Since the shopper selectively pays attention to this retailer and include its name in the search, he/she may tend to be a loyal customer of the e-tailer, or be familiar with the e-tailer.

However for online shoppers, the focuses of their searches are products that can fulfill their needs; in most cases, e-tailers’ names are used to help collect information, limit scope, and shorten the search process. Compared to the whole population of consumers submitting a vast amount of queries about diverse products, consumers using an e-tailer’s name only generate a relatively small amount of searches for the e-tailer. Although some searchers may use only the e-tailer keywords to directly reach a specific website (i.e., use the search engine as though it was the Yellow Pages), the population using search engines in this manner is small (Jansen 2007). Hence, the click-throughs via retailer-specific search keywords are relatively low compared to keywords with other characteristics.

On the other hand, a consumer using an e-tailer’s name to reach its website has less uncertainty regarding the e-tailer and has lower cognitive load due to familiarity with the e-tailer. This familiarity can help the consumer to subjectively reduce uncertainty, simplify interactions, build trust in the e-tailer, and then decide to buy (Gefen 2000, Ghose and Yang 2009). Therefore, we speculate retailer-specific keywords are correlated to high revenue for the e-tailer. We hence test the following hypothesis:

\textit{H1: Retailer-specific search keywords generate (a) fewer click-throughs but (b) higher revenue than non-retailer-specific keywords.}
Branded keywords are used in early shopping stages to reduce product uncertainty. Prior research suggests that searches on specific brand names are analogous to consumers going to the Yellow Pages—shoppers know they need a product or service, but do not yet know where to buy it (Ghose and Yang 2009). The goal of search engine users who submit such queries tends to collect product information by brand that can be sold by a number of different e-tailers. Although searches related to brand names are likely to come from brand-loyal consumers who are driven by brand awareness (Ghose and Yang 2009), branded keywords do not suggest searchers’ preferences for a specific retailer. While the shoppers’ focuses are reducing product uncertainty, e-tailers providing relevant information are equally attractive to searchers at this stage.

Branded keywords are subject to steep competition with other retailers for search visibility (Green 2003; Jansen 2007). Consumers using brand-specific keywords may need to deal with a large number of search results that increase consumers’ cognitive load. In addition, because of the low search and switching cost on the Internet, branded keywords may not be correlated to high click-throughs for any one e-tailer. Therefore we expect the click-through via branded keywords to an e-tailer would be low, compared to situations when other types of keywords are used.

In addition, since searchers use branded keywords primarily during the early shopping stages, they need to further obtain information to reduce seller uncertainty in order to reach an optimal purchase decision. Therefore, even when consumers visit an e-tailer via branded keywords, they are less likely to transact with the e-tailer than other keyword characteristics. Thus, we test the following hypothesis:

*H2: Brand-specific search keywords generate (a) fewer click-throughs and (b) lower revenue than non-brand-specific keywords.*
A consumer often uses product keywords (e.g., TV, bedding, etc.) to reflect explicit needs for product information. In fact, queries containing product-related keywords are the most popular types of queries submitted to search engines, accounting for more than 45% of the queries (Jansen 2007). However, advertisements for product related keywords are also subject to fierce competition; not only e-tailers but also the manufacturers are competing for the visibility in search result pages. In this context, a consumer’s cognitive load in finding relevant information from the numerous search results is greatly increased, and the decisions whether to visit an e-tailer are difficult to make. Thus, product keywords are not expected to generate high click-throughs for a certain e-tailer.

On the other hand, consumers who use product related keywords may have their target products in mind, and are close to the end of the shopping process. With the selective attention on product information, searchers in any shopping stage would be easily affected by information that can reduce their product and seller uncertainty. Once a searcher reaches an e-tailer’s website using a product-related search query, the e-tailer may have a better chance to meet the searcher’s shopping needs or induce impulsive shopping for products that the searcher targets. We hence test the following hypothesis:

\[ H3: \text{Product-specific search keywords generate (a) fewer click-throughs but (b) higher revenue than non-product-specific keywords.} \]

According to the cognitive load theory (Sweller 1988), the number of search results a searcher may read is restricted to a finite amount. On search result pages, searchers first pay attention to search results that are easily seen among numerous search results. According to eye tracking studies (e.g., Hotchkiss 2005), searchers tend to pay more attention at the top left portion of a search result page,
and therefore results appearing in this area have higher click-throughs. This normal eye-movement behavior aspect supports the limited-cognitive processing capacity arguments.

Search results rankings are also perceived as a reflection of the relevancy of the websites to searchers’ queries. Consumers tend to use search result rankings as an important hint of the quality/relevance/importance of websites (Dou et al. 2010). Therefore, results which appear first or are nearer to the top of the results page are more likely to be clicked on by searchers in order to reduce their cognitive processing. Prior studies on search marketing have also highlighted the effect of rankings on search performance (Agarwal et al. 2011; Ghose and Yang 2009; Yang and Ghose 2010). However, most of prior studies only examine the rankings and performance of sponsored keywords. We would like to further conjecture that the same relationship would also exist in organic search results, and be even more salient than that in the paid search listings. Hence, we test the following hypothesis:

\textit{H4: Top search result ranking of an e-tailer’s website for a search keyword increases (a) the click-throughs and (b) the revenue generated by the keyword.}

Advertising literature suggests that multiple ad exposures can lead to better results (McDonald 1996; Von Gonten and Donius 1997), as repeated exposures can enhance an advertised message and an e-tailer’s image. On a search result page, paid and organic listings are shown side-by-side. When an e-tailer’s ads appear in the paid listings as well as the organic results, searchers’ impression of the e-tailer is deepened. Jansen and Spink (2007) have suggested that searchers are more likely to recall the name of a company from a search listing if it appears multiple times in search listings on the same page. When the advertisement message is easily recalled, it saves consumers’ cognitive processing and therefore increased the consumers’ likelihood to visit the website.
Furthermore, the creative content of an e-tailer’s paid ad may also provide additional information that is not shown in the organic counterpart. Complementary messages from an e-tailer can help reduce seller uncertainty during the purchase decision making process. Thus, it induces click-throughs via the organic result to the e-tailer. On the other hand, when an e-tailer’s URL and ad content are shown among the top positions in the organic listings, it may make the e-tailer’s paid ads appear non-biased and objective (Xing and Lin 2006), and improve visitors’ likelihood to purchase at the paid advertiser’s website. Thus, we hypothesize that the dual-appearance of an e-tailer’s search advertisement in both paid and organic listings on the same search result page of a keyword can increase click-throughs as well as revenue.

H5: Dual-appearances of an e-tailer’s search ads in both paid and organic search result listings on the same search result page of a keyword increase its (a) click-throughs and (b) revenue.

Head keywords typically include brand (e.g., Nike) or product (e.g., bedding) only words. Searchers combine one of these words with, retailer name, product feature or shopping intention words to produce tail keywords (e.g., coach soft large leather; discount bedding accessories). Head keywords are more popular and competitive, affording them a wealth of search results and options. Due to the limited cognitive capabilities, searchers rely on other hints on the result page, namely relevancy of top-ranked advertisements and the rich information and ease in recall of advertisements with multiple exposures. Therefore, the effects of top result rankings and dual-appearances on head keywords’ performance would be enhanced over that of tail keywords. Hence, we test the following hypotheses:

H6: Head keywords further enhance the increase in (a) click-throughs and (b) revenue of search advertisements induced by top result rankings of these keywords.
H7: Head keywords further enhance the increase in (a) click-throughs and (b) revenue of search advertisements induced by dual-appearances of e-tailer’s ads.

Data

Similar to past studies on search marketing (e.g., Agarwal et al. 2011; Ghose and Yang 2008; 2009; Yang and Ghose 2010), we test the hypotheses on data collected from a single site. Our focal company is a full-service Web-only e-tailer that has been ranked among the top 20 e-tailers for many consecutive years according to the surveys by Internet Retailer (Siwicki 2010). A sponsored or organic referral keyword is the search query entered by a user who clicked on the landing page link in the e-tailer’s search ad. These keywords disclose website visitors’ goals and preferences. Our visitor-disclosed keywords consist of 2,000 randomly sampled sponsored referral keywords and 2,000 randomly sampled organic referral keywords during the month prior to the start of the 52-week data collection period. The size of each keyword set is slightly less than 1% of the total keywords from the same source.

We manually codified the characteristics of the search keywords. Two trained codifiers reviewed the keywords, and labeled their keyword characteristics according to a given guideline that described the characterization framework and definition of each characteristic.

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2 A search referral is a user visit originated by sponsored or organic search results.
3 The two codifiers are master students in IS or business. Both codifiers have sufficient knowledge regarding search keywords, e-tailer context, and the definition of the keyword characteristics used in this study. Apart from codifying keywords for this particular study, these codifiers have also had parallel responsibilities to codify keywords in other projects. The authors developed codification procedure specific to this study, and then trained the codifiers on several hundred keywords. The codification results were reviewed by the authors to confirm their validity and to correct any inconsistent characterizations.
An e-tailer can track search rankings of keywords in the paid listings in Google Analytics (http://google.com/analytics/) or by a paid advertising agency. The majority of Web analytics typically do not track or report organic search engine rankings because of the complexity of tracking such data at large scales. Using our own Web mining software\(^4\), we submitted the 4,000 search keywords to gather the rankings they received from Google\(^5\) in the organic and the paid search listings daily over the 52-week period. We retrieved the top 30 paid and organic search results respectively. If the actual search rankings were greater than 30, or some unknown search engine server changes or network issues occurred, our software returned null values for the daily search rankings. Properly handling null values and the derivation of the weekly rankings are critical to our empirical analysis. If a keyword on average had been ranked among the top 25 and then suddenly dropped out of the top 30 search results for only one or two days, we assume a server change or network issue caused the drop. We replace the missing (null-value) ranking with a sliding window (five days) average. If a keyword ranked between positions 26 and 30 prior to the day when its ranking became null, the missing-value replacement is the five-day average plus 3 times of the five-day variance\(^6\), as we assume the e-tailer just slightly fell out of the top 30 listing for this keyword. If the ranking of a keyword is missing for five days in a row, no replacement value will be applied.

Most researchers and agents use programs to crawl through search result pages once per week, and apply the one-day ranking snapshot as the weekly rankings for the search keywords. This method is considered to be reasonable in estimating keyword rankings because rankings do not vary much

\(^4\) The web mining software used in this study is Search Impact (http://searchimpact.aculus.com/searchimpact), which is a commercial web mining service. The service was available to the authors pro bono.

\(^5\) According to the data collected by the Web analytics software used by the focal e-tailer, the click-throughs coming from Google account for 77.85% of the click-throughs from search engines, and the revenue generated from visits via Google accounts for 73.97% of the revenue from visits via search engines. Therefore, we use the rankings on Google result pages to represent the visibility of the e-tailer’s website on the search result page.

\(^6\) We found that average plus 3 times standard deviation covers 95% of the data without missing rankings, and therefore considered 3 times standard deviation a good augmentation of the abnormally missed rankings.
within a week (Yang and Ghose 2010); however, it can be biased when the ranking variations within a week are significant, for example, when keywords are in high competition. We derive weekly average rankings from our detailed daily ranking data to account for potential day-to-day variations for our empirical analysis.

With normal web browser settings, the first five search results can be read in a single glance without scrolling and are deemed to be highly relevant to users’ search interests. We discretize result positions at intervals of 5 to rank classes to streamline the analysis and decisions of search rankings. Hence, the top 5 positions are rescaled to rank class 1, the next 5 rank positions to rank class 2, and so on. The missing rank class is scaled as 10. By taking the mode (the value that occurs the most frequently) of the rank class for each week to generate the weekly rank class, we obtained weekly rankings for each keyword.

Table 2 shows the distribution of the search keyword characteristics. Only 7% of paid search keywords are related to retailer information. Similar but slightly lower distributions are observed in organic search keywords as well. It is interesting to note that 31% of organic keywords include brand related information, which is higher than the percent of branded paid search keywords by 5%. 84.55% of the paid search keywords contain product related information, followed by 51.90% of paid keywords with feature related information. Most of the search keywords are of multiple characteristics. Only 24.60% of the paid search keywords and 23.36% of organic search phrases are of single characteristic keywords. This pattern is similar to the distribution reported in Jenson’s (2007) study, and echoes the need to further examine these characteristics to understand the intent of searchers (Jansen 2007).
Table 2. Keyword statistics by characteristics

<table>
<thead>
<tr>
<th></th>
<th>Paid Search Keywords</th>
<th>Organic Search Keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># of keywords (%)</td>
<td># of keywords (%)</td>
</tr>
<tr>
<td>Retailer Specific</td>
<td>140 (7.00)</td>
<td>116 (5.80)</td>
</tr>
<tr>
<td>Brand Specific</td>
<td>520 (26.00)</td>
<td>620 (31.00)</td>
</tr>
<tr>
<td>Product Specific</td>
<td>1,691 (84.55)</td>
<td>1,612 (80.64)</td>
</tr>
<tr>
<td>Feature Specific</td>
<td>1,038 (51.90)</td>
<td>1,016 (50.80)</td>
</tr>
<tr>
<td>Shopping Intention</td>
<td>296 (14.80)</td>
<td>259 (12.95)</td>
</tr>
<tr>
<td>Single Characteristic</td>
<td>492 (24.60)</td>
<td>467 (23.36)</td>
</tr>
</tbody>
</table>

Table 3 summaries the distribution of the search results over 52 weeks by visibility. About 67% of the organic keywords’ search results are ranked among the top 30 organic listings, which is about 7% more than that of paid keywords ranked among the top 30 paid ads. Furthermore, results for organic keywords are more likely to be ranked in the top half of the first listing page than paid keywords. 26.34% of the organic keywords’ search results appear both in paid ads and organic listings; 28.09% of the paid keywords’ search results appear both in paid ads and organic listings.

Table 3. Search result visibility statistics over 52 weeks

<table>
<thead>
<tr>
<th>Rank Class</th>
<th>Paid Keywords in Listings</th>
<th>Organic Keywords in Listings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># of keyword-weeks (%)</td>
<td># of keyword-weeks (%)</td>
</tr>
<tr>
<td>1</td>
<td>23,034 (22.18)</td>
<td>37,159 (35.78)</td>
</tr>
<tr>
<td>2</td>
<td>24,160 (23.27)</td>
<td>14,805 (14.26)</td>
</tr>
<tr>
<td>3</td>
<td>14,905 (14.35)</td>
<td>7,263 (6.99)</td>
</tr>
<tr>
<td>4</td>
<td>226 (0.22)</td>
<td>4,990 (4.81)</td>
</tr>
<tr>
<td>5</td>
<td>6 (0.01)</td>
<td>3,572 (3.44)</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>2,179 (2.10)</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>134 (0.13)</td>
</tr>
<tr>
<td>10</td>
<td>41,253 (39.73)</td>
<td>33,741 (32.49)</td>
</tr>
<tr>
<td>Dual-appearance</td>
<td>29,217 (28.09)</td>
<td>27,275 (26.23)</td>
</tr>
</tbody>
</table>

We obtained weekly aggregates of click-throughs and revenue from the Web analytics software used by our focal e-tailer. Table 4 summarizes the paid and organic search performance of the 4,000
keywords over 52 weeks. The data indicates that our study’s focal e-tailer has been more successful with search engine optimization to improve marketing performance of organic keywords than with paid keyword to generate customer responses. It is worth noting that this performance trend is different from that reported in some of the prior studies (e.g., Ghose and Yang 2008) of a retailer which sells both on- and off-line. Specifically, their keywords’ paid listings outperformed the organic listings. Analyzing and strategizing organic and paid search marketing for different types of online retailers needs to be aware of this contrast.

<table>
<thead>
<tr>
<th>Table 4. Performance of visitor-disclosed keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image_url" alt="Table Image" /></td>
</tr>
</tbody>
</table>

**Regression Models and Results**

**Main Effects of Keyword Characteristics**

We use regression models to examine the effects of search keyword characteristics, search advertisement visibility, and performance metrics. We use six dummy variables to represent (1) the five keyword characteristics in the conceptual model, and (2) whether an e-tailer’s search advertisement appear both in paid and organic listings on the same result page of a keyword. The rank class is included in the model as an ordinal variable. We also include three additional control variables - average revenue per order, the length of search queries entered by users, and the cost-per-click (CPC) of the keywords in paid placement. The CPC of a keyword represents the competition in paid ads auction, and is also considered a proxy of the competition and popularity for keyword
visibility in organic searches. To account for the effect of product price on revenue, we include the average revenue per order as another control variable in our models. Prior studies (Agarwal 2011; Ghose and Yang 2008; 2009; Yang and Ghose 2010) have included the length of paid ads as an independent variable. However, we focus on user-specified keywords, rather than paid ads. The length of search keywords may represent the specificity of the consumer’s information needs. Therefore, we also include the length of search keywords as a control variable. The time variable representing the week number is also included in our models. Because of the high variance in click-throughs and revenue among keywords, we adopt log-transformations of the performance metrics for dependent variables as exemplified in past related studies (Agarwal et al. 2011; Chau et al. 2005; Ghose and Yang 2009; Regelson and Fain 2006). Ordinary least square (OLS) regression models with time fixed effect (i.e., include the week numbers –week 1 or 2 in the model as a fixed effect controlling for the seasonal fluctuation) were constructed to evaluate the relationships between keyword characteristics and performance. Equations (1) and (2) show the expressions of the regression models:

Log (click-throughs) = \( \beta_0 + \beta_1 \text{Retailer} + \beta_2 \text{Brand} + \beta_3 \text{Product} + \beta_4 \text{Feature} + \)

\[ + \beta_5 \text{Shopping} + \beta_6 \text{Rank} + \beta_7 \text{Dual-appearance} + \beta_8 \text{Cost-per-click} + \]

\[ + \beta_9 \text{Revenue-per-order} + \beta_{10} \text{Length} + \beta_{11i} \text{Week}_i \] (1)

Log (revenue) = \( \alpha_0 + \alpha_1 \log (\text{click-throughs}) + \alpha_2 \text{Retailer} + \alpha_3 \text{Brand} + \alpha_4 \text{Product} + \)

\[ + \alpha_5 \text{Feature} + \alpha_6 \text{Shopping} + \alpha_7 \text{Rank} + \alpha_8 \text{Dual-appearance} + \]

\[ + \alpha_9 \text{Cost-per-click} + \alpha_{10} \text{Revenue-per-order} + \alpha_{11} \text{Length} + \alpha_{12i} \text{Week}_i \] (2)

Table 5 shows the results from the regression models.
Table 5. Log-transformation regression on click-throughs and revenue

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Paid log(click-throughs)</th>
<th>Organic log(click-throughs)</th>
<th>Paid log(revenue)</th>
<th>Organic log(revenue)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>R²</td>
<td>0.494</td>
<td>0.345</td>
<td>0.611</td>
<td>0.575</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.494</td>
<td>0.345</td>
<td>0.611</td>
<td>0.575</td>
</tr>
<tr>
<td>log(click-throughs)</td>
<td></td>
<td>0.221 **</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Retailer</td>
<td>-0.083 **</td>
<td>-0.300 **</td>
<td>0.180 **</td>
<td>0.180 **</td>
</tr>
<tr>
<td>Brand</td>
<td>-0.585 **</td>
<td>-0.524 **</td>
<td>-0.027 **</td>
<td>-0.051 **</td>
</tr>
<tr>
<td>Product</td>
<td>-0.698 **</td>
<td>-0.400 **</td>
<td>0.059 **</td>
<td>0.185 **</td>
</tr>
<tr>
<td>Feature</td>
<td>-0.374 **</td>
<td>-0.404 **</td>
<td>0.014</td>
<td>-0.041 **</td>
</tr>
<tr>
<td>Shopping</td>
<td>-0.144 **</td>
<td>-0.193 **</td>
<td>-0.044 **</td>
<td>-0.052 **</td>
</tr>
<tr>
<td>Rank</td>
<td>-0.072 **</td>
<td>-0.060 **</td>
<td>0.002</td>
<td>-0.022 **</td>
</tr>
<tr>
<td>Dual-appearance</td>
<td>0.259 **</td>
<td>-0.048 **</td>
<td>0.043 **</td>
<td>0.032 **</td>
</tr>
<tr>
<td>Cost-per-click</td>
<td>0.523 **</td>
<td>0.626 **</td>
<td>0.117 **</td>
<td>0.136 **</td>
</tr>
<tr>
<td>Revenue-per-order</td>
<td>0.011 **</td>
<td>0.008 **</td>
<td>0.018 **</td>
<td>0.012 **</td>
</tr>
<tr>
<td>Length</td>
<td>-0.241 **</td>
<td>-0.268 **</td>
<td>0.015 **</td>
<td>0.003</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.310 **</td>
<td>-0.362 **</td>
<td>-2.504 **</td>
<td>-2.157 **</td>
</tr>
</tbody>
</table>

**p < 0.01; *p < 0.05.

**Model 1 and Model 2.** We first report the relationships between keyword characteristics and click-throughs revealed in the results. The log-transformed regression model for click-throughs generated by all of the paid listings explains a substantial amount of the variances (49.4%) in the click-throughs, and predicts better than the organic counterpart (34.5%). Retailer-specific, branded, and product related keywords separately have significant negative relationships with click-throughs via paid and organic listings. The result supports **H1a, H2a** and **H3a**.

In terms of search visibility, our results show that keywords for which the e-tailer is ranked near or at the top of paid and organic search listings can generate more click-throughs than keywords for which the e-tailer is less visible; **H4a** is thus supported. This confirms the conventional wisdom about the importance of investing in both keyword auction and search engine optimization to improve search rankings. The coefficient for dual-appearance is significant and positive for paid results only, but it is significantly negative for organic listings (**H5a** is only partially supported). It
implies when an advertiser’s paid creative and its organic search snippet appear simultaneously, consumers tend to click on the paid search result.

**Model 3 and Model 4.** Retailer-specific keywords have significant positive relationships with revenue from both paid and organic listings. Branded keywords have significant, negative relationships with revenue from paid and organic listings, while product-specific keywords have significant positive relationships with revenue from paid and organic listings. The result supports **H1b, H2b and H3b.**

The effect of result ranking on revenue via organic listings is significant; however the effect of result ranking is not significant on revenue via paid listings (**H4b** is only partially supported). The result indicates that consumers who visit the e-tailer via organic search results in top positions would be more likely to make purchases; however, the paid search results in top positions do not have the same desirable effect for the e-tailers. This result underscores the importance of optimizing Web pages to improve the e-tailer’s visibility in organic result listings. The effect of advertisement dual-appearance is significant on revenue from both paid and organic listings; **H5b** is thus supported. The multiple exposures of search results not only attract consumers to click on the result links, but also induce the consumer to conduct transactions on the website. This result is consistent with the advertising literature that repeated exposures enhance the advertised messages and lead to high probability of purchase (McDonald 1996; Von Gonten and Donius 1997).

**Effects of Advertisement Visibility for Head versus Tail Keywords**

In order to test H6 and H7, we obtain two sub-samples of keywords with branded words and keywords with product related information. We obtained sub-samples of 518 paid keywords and 619 organic keywords containing branded words, and subsamples of 1,788 paid keywords and 1,804
organic keywords containing product-specific words. Within each subsample, less than 30% are head keywords, as shown in Table 6.

### Table 6. Summary of sub-samples with brand-specific or product-specific characteristic

<table>
<thead>
<tr>
<th>Keywords with Brand-specific characteristic</th>
<th>Keywords with Product-specific Characteristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paid Keywords in Listings</td>
<td>Organic Keywords in Listings</td>
</tr>
<tr>
<td># of keywords</td>
<td>%</td>
</tr>
<tr>
<td>Head Keywords</td>
<td>103 19.88</td>
</tr>
<tr>
<td>Tail Keywords</td>
<td>415 80.12</td>
</tr>
</tbody>
</table>

We use a dummy variable (Head) to represent the branded only and product only keywords as head keywords. By doing so, we can test the moderating effect of head keywords on the relationships between search visibility and search marketing performance. Equations (3) and (4) show the expressions of the regression models:

\[
\text{Log (click-throughs)} = \delta_0 + \delta_1 \text{Head} + \delta_2 \text{Rank} + \delta_3 \text{Dual-appearance} + \delta_4 \text{Head} \times \text{Rank} + \\
\delta_5 \text{Head} \times \text{Dual-appearance} + \delta_6 \text{Cost-per-click} + \delta_7 \text{Revenue-per-order} + \\
\delta_8 \text{Length} + \delta_{9i} \text{Week}_i \tag{3}
\]

\[
\text{Log (revenue)} = \gamma_0 + \gamma_1 \text{Log (click-throughs)} + \gamma_2 \text{Head} + \gamma_3 \text{Rank} + \gamma_4 \text{Dual-appearance} + \\
\gamma_5 \text{Head} \times \text{Rank} + \gamma_6 \text{Head} \times \text{Dual-appearance} + \gamma_7 \text{Cost-per-click} + \\
\gamma_8 \text{Revenue-per-order} + \gamma_9 \text{Length} + \gamma_{10i} \text{Week}_i \tag{4}
\]

Table 7 and Table 8 show the results of the regression analysis using sub-samples.
Table 7. Log-transformation regression on click-throughs and revenue (Sub-sample of keywords with brand-specific characteristic)

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Paid</th>
<th>Organic</th>
<th>Paid</th>
<th>Organic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>R²</td>
<td>0.234</td>
<td>0.233</td>
<td>0.597</td>
<td>0.582</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.234</td>
<td>0.233</td>
<td>0.597</td>
<td>0.582</td>
</tr>
<tr>
<td>log(click-throughs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head (dummy)</td>
<td>0.317 **</td>
<td>0.264 **</td>
<td>-0.085 **</td>
<td>-0.010 **</td>
</tr>
<tr>
<td>Rank</td>
<td>-0.026 **</td>
<td>-0.019 **</td>
<td>-0.001</td>
<td>0.000</td>
</tr>
<tr>
<td>Dual-appearance</td>
<td>0.030</td>
<td>-0.050 *</td>
<td>-0.002</td>
<td>-0.008</td>
</tr>
<tr>
<td>Head * Rank</td>
<td>-0.021 **</td>
<td>-0.013 **</td>
<td>0.006 **</td>
<td>-0.005 **</td>
</tr>
<tr>
<td>Head * Dual-appearance</td>
<td>0.179 **</td>
<td>0.118 **</td>
<td>0.046 *</td>
<td>-0.027</td>
</tr>
<tr>
<td>Cost-per-click</td>
<td>0.517 **</td>
<td>1.327 **</td>
<td>0.005</td>
<td>0.420 **</td>
</tr>
<tr>
<td>Revenue-per-order</td>
<td>0.016 **</td>
<td>0.016 **</td>
<td>0.020 **</td>
<td>0.023 **</td>
</tr>
<tr>
<td>Length</td>
<td>-0.154 **</td>
<td>-0.181 **</td>
<td>0.000</td>
<td>0.007 **</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.962 **</td>
<td>-1.850 **</td>
<td>-2.553 **</td>
<td>-2.573 **</td>
</tr>
</tbody>
</table>

**: p < 0.01; *: p < 0.05.

Model 5 to Model 8. According to the negatively significant coefficients of Head*Rank for paid and organic keywords in model 5 and 6, effects of result ranking on branded head keywords’ click-throughs are greater in magnitude than those of branded tail keywords’. In other words, consumers using branded head keywords are more likely to visit an e-tailer’s website via search result in higher positions than those using branded tail keywords. Therefore the analysis of branded keyword subset supports H6a. The significant, positive coefficients of Head*Dual-appearance in model 5 and 6 indicate that dual-appearance induces more click-throughs via paid and organic branded head keywords than via tail keywords. Hence, H7a is supported by the branded keyword subset. The results support our hypotheses that users rely more on search ad visibility to select a certain website to visit when the head keywords are more popular and has more corresponding results. The results have strong implications for investment decisions of branded head versus tail keywords.

According to the coefficients of Head*Rank in model 7 and 8, the result rankings improve the revenue of branded head keywords in organic listings, but reduce the revenue of branded head
keywords in paid listings. Consumers using branded head keywords are more likely to transact on an e-tailer’s website via organic search results in higher positions than those using branded tail keywords. The analysis of the branded keyword subset partially supports \( H6b \). The coefficients of \( \text{Head} \times \text{Dual-appearance} \) in model 7 shows that dual-appearance induces higher revenue via paid branded head keywords than via tail keywords. However, this effect on organic branded keywords (model 8) is not significant. \( H7b \) is therefore partially supported.

Table 8. Log-transformation regression on click-throughs and revenue (Sub-sample of keywords with product information)

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Paid</th>
<th>Organic</th>
<th>Paid</th>
<th>Organic</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(click-throughs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 9</td>
<td>0.348</td>
<td>0.371</td>
<td>0.611</td>
<td>0.582</td>
</tr>
<tr>
<td>Model 10</td>
<td>0.371</td>
<td>0.611</td>
<td>0.582</td>
<td></td>
</tr>
<tr>
<td>Model 11</td>
<td>0.348</td>
<td>0.371</td>
<td>0.611</td>
<td>0.582</td>
</tr>
<tr>
<td>Model 12</td>
<td>0.211</td>
<td>0.340</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(revenue)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head (dummy)</td>
<td>0.650 **</td>
<td>1.085 **</td>
<td>0.057</td>
<td>0.298 **</td>
</tr>
<tr>
<td>Rank</td>
<td>-0.044 **</td>
<td>-0.049 **</td>
<td>0.010</td>
<td>-0.006</td>
</tr>
<tr>
<td>Dual-appearance</td>
<td>0.233 **</td>
<td>-0.041 **</td>
<td>0.023 **</td>
<td>0.018 *</td>
</tr>
<tr>
<td>Head * Rank</td>
<td>-0.048 *</td>
<td>-0.028 *</td>
<td>-0.024</td>
<td>-0.079 **</td>
</tr>
<tr>
<td>Head * Dual-appearance</td>
<td>0.202 **</td>
<td>-0.250 **</td>
<td>0.100 **</td>
<td>0.099 **</td>
</tr>
<tr>
<td>Cost-per-click</td>
<td>0.565 **</td>
<td>0.760 **</td>
<td>0.147 **</td>
<td>0.222 **</td>
</tr>
<tr>
<td>Revenue-per-order</td>
<td>0.011 **</td>
<td>0.007 **</td>
<td>0.017 **</td>
<td>0.011 **</td>
</tr>
<tr>
<td>Length</td>
<td>-0.245 **</td>
<td>-0.248 **</td>
<td>0.015 **</td>
<td>0.007 *</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.519 **</td>
<td>-1.401 **</td>
<td>-2.500 **</td>
<td>-2.077 **</td>
</tr>
</tbody>
</table>

** : p < 0.01; * : p < 0.05.

**Model 9 to Model 12.** The effects of result ranking on the click-throughs via paid and organic listings are significantly enhanced in product head keywords (i.e., more negative). \( H6a \) is supported by product related keywords. The effect of dual-appearance of search ads on the click-throughs via paid listings is significantly enhanced (i.e., more positive) in product-related head keywords. The dual-appearance of search ads further decreases click-throughs generated by organic product head
keywords compared to product tail keywords. \textit{H7a} is partially supported by the product related keyword subset.

The effect of result ranking on revenue is only significant via organic product head keywords, partially supporting \textit{H6b}. The effects of dual-appearance of search ads on revenue via paid and organic are both significantly enhanced (i.e., more positive) in product head keywords, supporting \textit{H7b}. The results indicate that the dual-appearance of search advertisement would improve the revenue generated by product related head keywords more than tail keywords. Table 9 summarizes the hypotheses testing results.

\begin{table}[h]
\centering
\caption{Summary of hypothesis testing results}
\begin{tabular}{|l|p{16cm}|c|c|}
\hline
 & Hypotheses & Paid Keywords & Organic Keywords \\
\hline
H1 & Retailer-specific search keywords generate (a) fewer click-throughs but (b) higher revenue than non-retailer-specific keywords. & Supported & Supported \\
\hline
H2 & Brand-specific search keywords generate (a) fewer click-throughs and (b) lower revenue than non-brand-specific keywords. & Supported & Supported \\
\hline
H3 & Product-specific search keywords generate (a) fewer click-throughs but (b) higher revenue than non-product-specific keywords. & Supported & Supported \\
\hline
H4a & Top search result ranking of an e-tailer’s website for a search keyword increases the click-throughs generated by the keyword. & Supported & Supported \\
\hline
H4b & Top search result ranking of an e-tailer’s website for a search keyword increases the revenue generated by the keyword. & Not Supported & Supported \\
\hline
H5a & Dual-appearances of an e-tailer’s search ads in both paid and organic search result listings on the same search result page of a keyword increase its click-throughs & Supported & Not Supported \\
\hline
H5b & Dual-appearances of an e-tailer’s search ads in both paid and organic result listings on the same search result page of a keyword increase its revenue. & Supported & Supported \\
\hline
H6a & Head keywords further enhance the increase in click-throughs of search advertisements induced by top result rankings of these keywords. & Supported & Supported \\
\hline
\end{tabular}
\end{table}
<table>
<thead>
<tr>
<th></th>
<th>Head keywords further enhance the increase in revenue of search advertisements induced by top result rankings of these keywords.</th>
<th>Partially Supported</th>
<th>Supported</th>
</tr>
</thead>
<tbody>
<tr>
<td>H6b</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H7a</td>
<td>Head keywords further enhance the increase in click-throughs of search advertisements induced by dual-appearances of e-tailer’s ads.</td>
<td>Supported</td>
<td>Partially Supported</td>
</tr>
<tr>
<td>H7b</td>
<td>Head keywords further enhance the increase in revenue of search advertisements induced by dual-appearances of e-tailer’s ads.</td>
<td>Supported</td>
<td>Partially Supported</td>
</tr>
</tbody>
</table>

**Discussion**

According to the testing results, the proposed relationships between keyword characteristics and search marketing performance are supported. That is, a consumer’s selective attention is reflected in the characteristics of search keywords and directly related to his/her reaction to the search advertisement. For practitioners, the results imply that consumers can be targeted by the varying characteristics of search keywords to generate click-throughs and revenue.

The increase in click-throughs by high search result rankings and the enhancement of this lift for head keywords are in general supported, showing that users’ cognitive load in screening the search results plays a critical role in the process. However, dual-appearances of search ads do not increase click-throughs via organic listings. This may reflect the effectiveness of paid creative copies, and the higher cognitive load to read organic search snippets and to scroll through a larger number of organic listings than paid listings. In this line of inquiry, consumers choose a “short-cut” of visiting via paid ads rather than the corresponding organic results when they observe a dual-appearance of search ads to reduce their cognitive loads.

The findings suggest that advertisers cannot rely on top ranking of paid advertisements to increase revenue. Even head keywords cannot break this trend. Consumers can be attracted by top-positioned
paid advertisements, but once they visit the e-tailer’s Web site, other factors would become more important than ranking on the search result pages. One of the possible explanations for this is that compared to organic result listings, only a few paid advertisements appear on a result page. The favorable effects of top-ad-position therefore may not be strong enough to influence consumers’ purchase decisions that involve many other considerations. The results can also be justified by the selective attention according to the cognitive load theory in problem solving. Consumers utilize explicit information and solid cues to make purchase decision that demands cognitive loads; and hence ignore relatively weak hints. In the final purchasing decisions; top search ad rankings along can be a weak cue to consumers, and therefore may be ignored when consumers selectively pay attention to other critical information. Since head keywords can be costly for high visibility in paid listings, advertisers should be cautious about the return on investment in bidding for top positions of paid search ads for head keywords. However, when both sponsored and organic ads appear in top result positions, the cue to customers becomes strong enough to induce revenue. Advertisers need to properly balance their investments in improving paid as well as organic search visibility to obtain desirable returns.

**Conclusion**

Data driven research on search marketing strategies is an emerging research area. Motivated by the research gaps identified, we take the approach of focusing on consumers’ cognitive processing and propose a research framework that considers both search-goal-oriented keyword characteristics and search ad visibility. This framework can be used to explain the complex relationships among keyword characteristics, ad visibility and search marketing performance. Because multi-channel and Web-only e-tailers have different online marketing strategies and Web-only e-tailers are among the fastest growing categories of Internet retailers, we perform hypotheses testing using data gathered on
a top Web-only full-service e-tailer. Our major findings include: (1) Keywords with retailer or product information reduces click-throughs but increases revenue of paid ads and organic listings; (2) Branded keywords hurt performance (both click-throughs and revenue) of paid ads and organic listings; (3) In general, search results shown on the top of the result page increase click-throughs and revenue, but this effect is not consistent with the revenue of paid ads; (4) In general, when the e-tailer appears in both paid ads and organic listings on the same page, the search keyword performs better, except click-throughs of organic listings; and (5) The performance-lifting impacts of search result visibility on click-through might be enhanced when branded or product head keywords are used by searchers.

In turn, this study makes several research contributions. First, by utilizing the cognitive load theory in problem solving, we recognize the importance of analyzing user queries that reflect users’ uncertainty reduction goals and selective attention, and include search visibility that reduces users’ cognitive load. The theories are applied in a new context, and have the potency to provide new insights into these theories. By connecting cognitive load theory to problem-based online shopping, the underlying processes of users’ search and shopping behavior on the Internet can be better explained and understood. Second, whereas most previous search marketing research concentrates on advertiser specified keywords in paid search advertising, we target visitor-disclosed keywords to advance our understanding of the users’ actual information needs, and how search engine advertisements capitalize on various types of users’ information needs. The use of visitor-disclosed keywords also makes the resulting implementations sustainable.

Third, we leverage the problem-solving perspective to highlight the needs to characterize search keywords by users’ information needs in different shopping stages. A comprehensive search
keyword characterization framework is then proposed. This framework sufficiently covers all the search keywords entered by online shoppers and can be generalized for various types of websites. We also analyze the relationships between keyword characteristics and search performance; the results enable the advertisers to comprehensively monetize search keywords.

Fourth, the visibility metrics proposed in this study (i.e., considering both rankings and dual-appearance of paid and organic listings on the same result page) provide further insights into the need for advertisers to invest in both paid and organic search marketing. A larger variety of keyword characteristics and the visibility metrics of search advertisement also afford us the opportunities to analyze the increasingly complex relationships keywords have with search performance. We also examine the performance-lifting effects of search ad visibility on head versus tail keywords. The results extend our understanding on the characteristics, visibility and performance of keywords.

Fifth, this study responds to the need for the analysis and comparison of search marketing performance, for both paid and organic search results. We analyze and track the performance of organic search results and compare it with paid ads. The results provide empirical support for investigating both types of search marketing mechanisms.

Based on longitudinal keyword performance data, our findings have strong implications for future research and practices. We focus on the search goals disclosed in the visitors’ keywords from both the organic and sponsored search listings. As such, the analysis can provide broader insights into their characteristics and effects on search marketing performance. For advertisers who want to maximize returns on investments in search marketing, this study provides an approach that is easy to implement, with easily interpretable results that facilitate marketing decision making in keyword
selection. The proposed approach of keyword selection is particularly useful in the cold-start situation where a set of new keywords, for example for a newly introduced product category or brand, need to be selected without historical performance data specific to the new keywords. In this context, the advertiser can apply our approach to analyze the performance of keywords for existing product categories to build models, and use the estimates to predict the performance of candidate keywords for the new product category. Based on the prediction result, the advertiser can make informed decisions on new keyword selections for search engine marketing.

In addition, prior research has indicated that the optimal advertisement strategies for offline and online stores are not the same (Zhang and Wedel 2009), and the marketing strategies for multichannel retailers have a different effect when compared with conventional single-channel retailing (Zhang 2009). Accordingly, the online advertisement strategies for mix-play retailers may have to also align with the offline advertising campaign, while the offline promotion and sales may also impact the performance of search engine advertisements. The insights from prior research using offline or multichannel advertiser data may not be as applicable to Web-only e-tailers. Web-only e-tailers are the fastest growing category compared to their retail chain, catalogs sellers, and direct manufacturer counterparts generating almost $37 billion Web sales according to a recent survey by the Internet Retailer Association (Brohan 2009). The insights from analyzing the relationships between keyword characteristics and performance for a top Web-only of full-service e-tailer can be timely important.

Our study is limited in several ways. First, we primarily focused on the predictive abilities of keyword characteristics on keyword performance in this study. Ghose and Yang’s (2009) study shows that the landing page quality also has an impact on the search result performance. The
The purpose of this study is to first understand the impact and the explanation powers of the search keyword characteristics without the landing page factors. In future studies, the landing page factors as well as the listing factors (e.g., the title, URL, and summary of each result links) on the search result page can be included to understand the effects and the potential interactions with the search keyword characteristics. Second, click-through rate is widely used in the research in the online advertisement area. The panel data we used in this study does not include the number of impressions of each search phrase, and therefore we could not include the click-through rate as one of the performance metrics in our models. Third, we use the rankings on Google search result pages as a proxy of an e-tailer’s visibility in search results. Future efforts in consolidating rankings on different search engine result pages are needed to provide a precise visibility metric. Fourth, the data did not include sessions linked by customer ids to analyze search keywords of all the sessions from one customer. It limits us from examining search strategies over multiple sessions. Future examination can be done if the session data is available. In addition, our findings are based on the single dataset used in this study. The rankings of keywords can be influenced by the e-tailer’s strategy of SEO and paid search keyword auctions, which may lead to problems of endogeneity. Consequently, our results should be carefully interpreted before they are generalized. Designing field experiments using A/B testing is recommendable for future research and real world applications. Further testing and validation using data from websites in other categories with various search marketing strategies can help to generalize the findings of this study.

References


