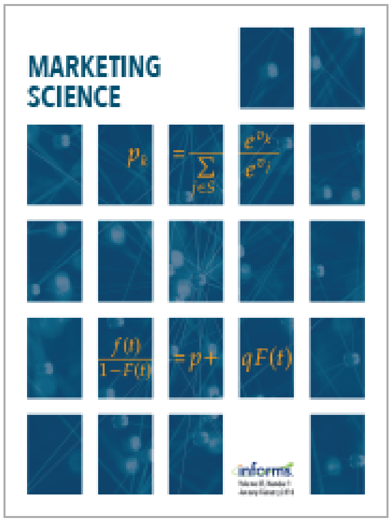

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The Path to Click: Are You on It?

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Abstract. The multibillion-dollar search engine marketing (SEM) industry's central objective is to gain visibility for businesses on search engine results pages (SERPs) to bring customers to a firm's website. This paper sheds light on a foundational element of SEM, namely, consumers' interactions with SERPs. Using eye-tracking equipment and a custom-built Google-like search engine, we conducted a laboratory experiment in which participants performed a series of online searches for a set of consumer goods while their eye movements and interactions with the results page (i.e., scrolling and clicks) were recorded. We provide model-free and model-based analyses of the inspection process, which encompasses a series of microdecisions, including what part of the page to look at, whether to scroll to bring additional results into view, what listings to explore and for how long, and ultimately which listing to click on. The results suggest that search goals (navigational, transactional, and informational), semantic context, spatial characteristics, viewing centrality, and prior inspection path are all predictive of both the flow of the inspection process and the ultimate listing choice. Managers should account for the significant variation in inspection scope across search tasks and SERP compositions when assessing a listing's performance and deciding on a desirable position on the SERP.

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1. Introduction

Search engine marketing (SEM) is one of the primary online customer acquisition tools in today's digital marketplace. Marketers use search engines to reach prospective customers through paid search advertising and organic search results (search engine optimization (SEO)). In paid search, marketers focus on keyword selection, bid optimization, landing page design, and ad creatives. Organic searches hinge on building inbound links and optimizing the website's performance and content. Ultimately, these efforts are aimed at gaining search visibility (i.e., the prominence of a firm's content on search engine results pages (SERPs)) to help attract visitors to a business's website.

From the consumer's perspective, interaction with a search engine begins with specifying a search query, proceeds with inspecting the search results, and concludes with making a listing selection ("click-out"). Typically taking only a few seconds, SERP inspection is a complex process in which customers make several interdependent decisions, including what part of the page to look at, what listings to explore, how much time to spend on each listing, whether to scroll the page to bring additional results into view, and, ultimately, which listing to click on.

For marketers, the flow of this process essentially determines if their listings are being noticed, considered, and selected. Our analysis shows that, on average, less than one-third of all listings on a SERP are visually inspected (i.e., noticed in a single search session) and only about 16% of these are viewed more than once; thus, there is good reason for SEM practitioners to be concerned about the on-page visibility of their content. Because marketers generally consider the positions at the top of SERPs more favorable in getting consumers' attention, the competition for top ranking is fierce and costly (either in terms of cost-per-click in paid search or investments in SEO). In this paper, we argue that although being at the top of the results certainly helps win attention, there is a significant variation in inspection processes across search tasks and screen compositions. Therefore, from a managerial standpoint, SEM strategy, with regard to a target listing's on-page position, should consider these variations and account for the factors that drive consumers' attention on SERPs. Consequently, this could help reduce advertising costs (e.g., a lower-ranked position could be equally effective in attracting attention compared with the higher and more costly one) or improve a listing's performance (e.g., by identifying the most prominent positions in the given SERP context).

Over the past decade, the topic of SEM has generated significant interest among marketing academics. Research spans from understanding consumers' decisions to click on search ads to factors affecting ad performance, to optimal ad design, to the role of competition, to bidding strategies in search auctions (e.g., Ghose and Yang 2009, Yao and Mela 2011, Berman and Katona 2013, Amaldoss et al. 2016, Lu and Yang 2017, Zia and Rao 2019). Considerably less is known about the SERP inspection process, which is arguably a precursor to or, in some cases, a driving force of the aforementioned marketing outcomes. The current paper sheds light on this foundational element of SEM, which has been largely overlooked in the extant literature.

An effective tool for studying the visual inspection process is eye tracking. Our study is based on an eye-tracking laboratory experiment in which participants perform a series of online searches for a set of consumer products under three search conditions: navigational, informational, and transactional (Broder 2002, Jansen et al. 2008). In the navigational search, the goal is to locate a particular website that the searcher believes to exist (e.g., Louvre Museum home page); in the informational search, the goal is to find the site that helps the user obtain certain information (e.g., check on Costco's product return policy); and in the transactional search, the goal is to locate a website to perform a certain transaction (e.g., buy noise-cancelling earbuds).

Using a custom-built Google-like search engine, we serve participants preset SERPs assembled from actual Google search results presented in a randomized order. This approach, adopted from Liu and Toubia (2018), allows us to better control for position effect, which, without randomization, could be confounded with listings' content and other contextual factors. After the participant clicks on a listing, the engine redirects the user to the actual destination site. All the interactions with the search engine, including eye movement, listing inspection duration, clicks, and scrolls, are recorded. We classify listings' content into six semantic categories: product attribute, quality, brand, price, promotion, and place (store) information. We then analyze the data using both a model-free approach and an originally developed descriptive model that captures the key element of the inspection process.

Because semantic information can be extracted only when the listing receives direct attentional spotlight (but not via peripheral vision), the path of the eye movement defines what the consumer learns about the SERP content. Our results indicate a strong correlation between the semantic content of the listings viewed and the flow of the inspection process. In other words, the content of listings viewed up to a certain inspection point affects what listings are more or less likely to be viewed next. Moreover, we show that semantic information extracted from individual listings and cumulative information gathered from particular sections of the page play different roles in driving inspection. Finally, the six previously noted semantic categories direct attention differently depending on the search task performed.

We find that spatial characteristics, such as relative position of a listing and subscreen, and screen boundaries play an important role in inspection. In addition, jointly with semantic information, spatial characteristics affect scroll decisions. In line with extant studies that report higher click-through rates for higher-ranked listings, we show an uneven distribution of visual attention favoring the upper parts of the SERP and listings located "above the fold." However, in contrast to extant studies that assess position performance in aggregate (i.e., number of times an ad is shown versus number of times it is clicked), our study offers a more nuanced perspective on the role of spatial factors and identifies novel dimensions, such as preference for the middle section of the screen (viewing centrality) and stickiness to the prior inspection areas, resulting in localized comparisons.

Finally, the inspection patterns observed in our experiments vary substantially across three search tasks, with consumers in the transactional task exhibiting the largest search scope and those in the navigational task showing a more limited range of exploration. In addition, the impact of semantic and nonsemantic factors (e.g., spatial characteristics, prior inspection path, viewing centrality) influence microinspection decisions in different ways across these search tasks.

Our contributions to the marketing field are fourfold. First, we are not aware of other studies across various academic disciplines, including marketing, information systems, and computer science, that explore a microlevel, dynamic visual inspection process on SERPs, linking the semantic elements of search listing composition to various consumer decisions that drive attention shifts on the SERP. In this respect, our work is pioneering in this research domain.

Second, to the best of our knowledge, our paper is the first to incorporate scrolling and subscreen selection decisions in the dynamic visual inspection process, thus making a unique contribution to the eye-tracking literature. We find that these two decisions are guided by the semantic context, prior inspection path, and spatial characteristics of a listing and a subscreen; furthermore, the weights of these factors vary by search tasks. This result might be of particular importance to SEM managers because it implies that the well-known benefits of staying above the fold (and thus paying more) are context specific and that the less attractive, below-the-fold listings might perform reasonably well depending on the SERP composition above the fold. With the recent prevalence of long-page design in the user interface domain (i.e., based on multipage scrolling on mobile devices), we believe that the original approach developed in this paper can spark further advancement in this field.

Third, in addition to original substantive findings uncovered in our analysis, this paper can help shape future SEM research by providing academics with an overview of the processes that are typically unobserved by researchers and thus require making assumptions. Using this paper as a reference could help improve the accuracy of these assumptions in future SEM studies.

Finally, our results hold important implications for practitioners. First, we demonstrate a significant variation in page inspection patterns across search tasks, pointing SEM practitioners to yet another dimension they should account for when deciding about desirable positions for their listings on the target SERP. For example, investing in rank improvement may result in a greater payoff in terms of incremental attention for informational and navigational searches compared with transactional searches. Second, we emphasize the importance of semantic and spatial context to the visibility of individual listings on SERPs. We find that for informational and navigational search tasks, certain types of semantic content may trigger local search behavior when users are more likely to stay within the same area of the search results. SEM managers can use this information to assess the attractiveness of a target placement position on a SERP. Third, we show how semantic composition of the target listing may affect the subsequent inspection process, including repeat inspections, scrolls, inspection duration, and ultimately click-through.

The paper proceeds as follows: We begin by briefly discussing the relevant literature on eye-tracking research, SEM, and consumer search to fit our work into the broader context of extant studies. We then articulate our conceptual framework, discuss our data collection procedure, and describe the experiment. We then present our descriptive model and report the results using both model-free analysis and model-based findings. Finally, we discuss the implications of our findings for SEM managers and suggest some directions for further research.

2. Relevant Literature

2.1. Search Engine Marketing

In the academic marketing literature, SEM has received substantial attention in recent years. Researchers have examined topics such as keyword performance evaluation and forecasting (e.g., Ghose and Yang 2009, Rutz and Bucklin 2011, Rutz et al. 2011, Amaldoss et al. 2016, Lu and Yang 2017); optimal bidding strategies and budget allocation (e.g., Katona and Sarvary 2010, Jerath et al. 2011, Yao and Mela 2011, Choi and Sayedi 2019, Zia and Rao 2019); the impact of SEO on competition in paid search (e.g., Berman and Katona 2013); the impact of search advertising on consumers search and purchase decisions (Edelman and Lai 2016, Ursu 2018); and consumer content preference inferences from online search queries (Liu and Toubia 2018). Most of these studies take either a firm's perspective on SEM, using data sets collected by advertisers (as an amalgamation of daily summary statistics on impressions, clicks, and the firm's own records of user transactions) or a search engine's perspective on SEM, using the data provided by a collaborating service provider. These studies typically offer relatively little insight into the consumer's perspective on SEM.

Our paper aims to fill this gap and, to the best of our knowledge, is the first study in the marketing literature to consider SEM (literally) through the eyes of consumers.

2.2. Visual Attention

Understanding the drivers behind visual inspection is crucial because it feeds into the fundamental component of the classic attention-interest-desire-and-action (AIDA) model: the ability to attract *attention* (Russell 1921). To paraphrase Teixeira (2014), for an ad to work, it must attract attention first. Chandon et al. (2009) share a similar view, pointing out that a critical measure for brand equity, in addition to the more conventional measures of brand recall and preference, is the brand's ability to attract attention. Meißner et al. (2016) also emphasize the important insights provided by eye-tracking data in understanding consumers' choice processes. Therefore, examining how consumers shift their attention among the various elements on a page is an indispensable component of assessing and understanding the effectiveness of search engine listings.

Visual inspection patterns are driven by both low-level stimuli, such as size, location, color, luminance, and edges of the design elements, which direct attention through a "fast, primitive mechanism," and high-level stimuli, such as search goals and textual information, which direct attention through "cognitive, volitional control" (Itti and Koch 2000, p. 1490; see also Nakayama and Mackeben 1989, Braun and Sagi 1990, Braun and Julesz 1998, Wolfe 1998, van der Lans et al. 2008). This is in line with stimulus-driven and goal-driven attention shifts discussed in Meißner et al. (2016). Most eye-tracking studies in information display optimization and the information search process focus primarily on low-level stimuli (e.g., Pieters et al. 2007, van der Lans et al. 2008, Teixeira et al. 2010). For example, in the SERP context, Sherman (2005) discusses the importance of the "golden triangle" (the upper-left corner of the page) on SERP; Guan and Cutrell (2007) investigate the impact of ranking and search tasks (informational or navigational) on consumers' search behavior; and Dumais et al. (2010) and Buscher et al. (2010) study how visual attention is distributed across different areas of the SERP, controlling for the type of search task, relevance of the listings, and order of presentation. However, the semantic composition of SERPs and its role in the visual inspection process have been generally overlooked.

2.3. Consumer Search

There is a long history in marketing of studying the information search process during decision making (e.g., Payne 1976, Bettman and Kakkar 1977, Payne et al. 1993). The information search process is commonly formalized as the sequential evaluation of a set of alternatives paired with a stopping rule. The focus of the search could be on a single product attribute (e.g., getting the best price) or on multiple attributes, with a potentially complex process of trading off between choosing the best option from already-researched alternatives and continuing to explore new alternatives with some probability of discovering a better option (Bronnenberg et al. 2016). Search models typically focus on how many alternatives are evaluated before the search ends and which alternative is selected. They also look at how attributes of each alternative contribute to these two decisions (i.e., stop-and-choose or continue exploration).

In this paper, we focus on a particular aspect of consumer search: visual inspection of search results produced by a search engine in response to a consumer query (or visual search within search results). The visual inspection process on SERPs has some common dimensions with a traditional consumer search (e.g., selection of alternatives to be evaluated and a stopping rule); however, it differs in several important respects.

First, attribute space on SERPs is not clearly bounded; as an extreme, each unique word can be counted as an individual attribute and each new set of search results can potentially introduce new, previously unseen attributes. Furthermore, attribute space exhibits high sparseness across alternatives (listings), making direct attribute-level comparisons difficult or even impossible.

Second, given that SERPs mainly consist of textual information, the semantic component (i.e., unstructured data representing each listing) plays a critical role in driving the inspection process. In addition to the semantic characteristics of a listing that do not change over the course of inspection, consumers' visual inspection may be affected by the cumulatively viewed semantic information, which is updated after each fixation.

Third, listings' spatial characteristics (e.g., section, rank, relative position on a screen) play a critical role in driving the inspection process. Furthermore, some of these factors may change as the inspection progresses. For example, the relative position of a listing on a screen will change as consumers scroll to a new subscreen. We note that spatial factors (e.g., adjacent product, their distance and direction correspondingly) have been considered in a few recent consumer search studies (e.g., Stüttgen et al. 2012, Yang et al. 2015); however, the context in these studies is a *static* display with directly comparable attribute sets, and the role of semantics is not examined.

3. Conceptual Framework

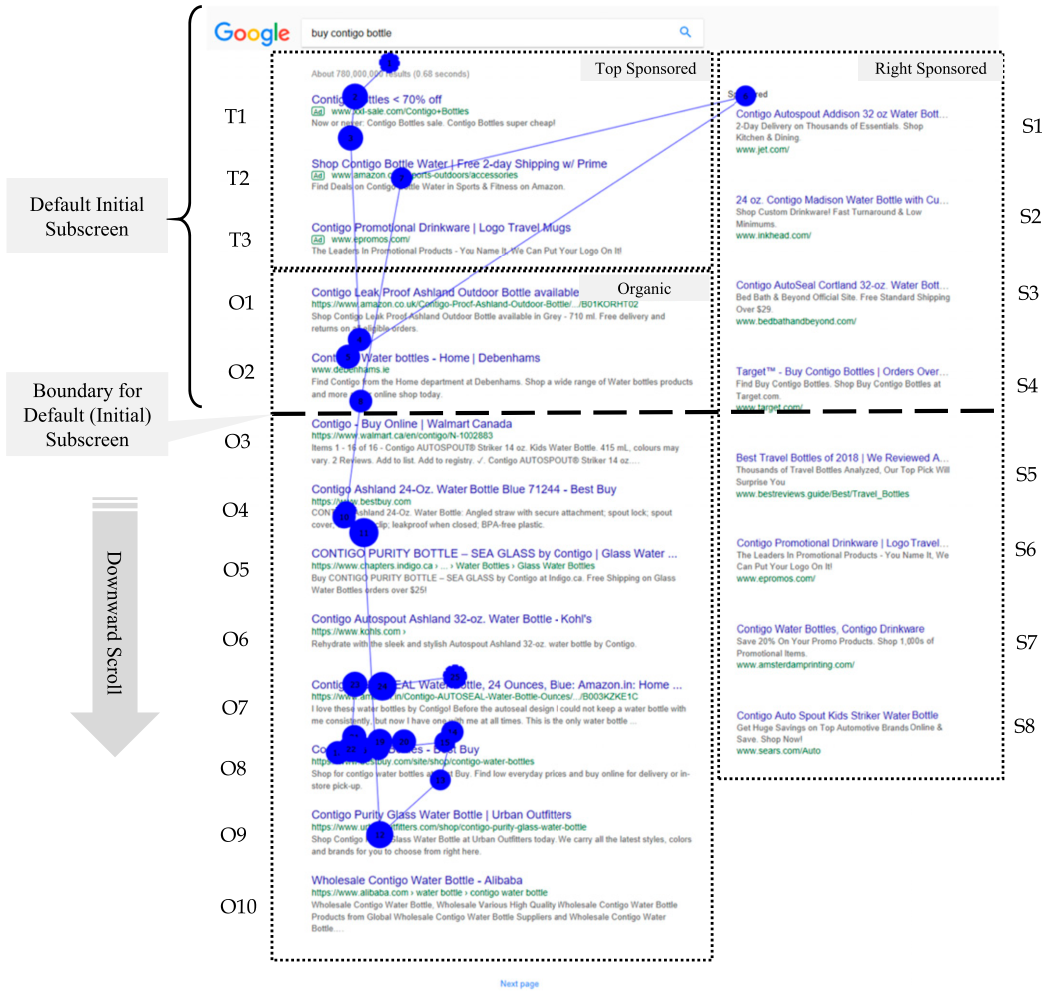
3.1. Motivational Example

Consider the example of the SERP inspection shown in Figure 1, in which a consumer is shopping for a Contigo water bottle.[1] The visual inspection is depicted as a sequence of eye fixations on various listings featured on the page. We denote the organic section as O, the top-sponsored section as T, and the right-sponsored section as S (e.g., O2 is the second listing in the organic section). The consumer started the inspection with the first listing in the T section (T1); "skipping" T2 and T3, the consumer then jumped directly to O2. Then, the consumer moved to the S section to quickly inspect S1 before regressing back to the T section to inspect T2. Afterward, the consumer jumped to O2, skipped O3, scrolled down to inspect O4, jumped to O9, moved upward to examine O8 and O7, and eventually clicked on O8.

This inspection path differs significantly from the top-to-bottom linear patterns observed in reading tasks, with a notable number of back-and-forth transitions across listings and screen sections. There is a nontrivial amount of skipping (i.e., jumping over adjacent listings) and scrolling, resulting in some areas of the screen between the inspected listings not being viewed. Some listings are inspected multiple times, and the listing eventually clicked is not the one that was discovered last. Furthermore, the consumer stopped inspection after viewing just a small share of listings featured on the SERP (i.e., 8 out of 21). Finally, the content of the inspected listings varies significantly in terms of the type of information provided. For example, listing O7 focuses on a customer review of the Contigo bottle; listing O4 notes key attributes of the bottle; and O1 features a promotion.

This example suggests a complex and perhaps even puzzling consumer decision process underlying the visual inspection of a SERP. We are not aware of any extant work that offers a comprehensive conceptual model describing this process. Although the goal of this paper is not to develop such a model either per se,

Figure 1. Sample Inspection Path on a SERP



Notes. Blue dots are eye fixations, and the blue lines are saccades. Because visual processing is suppressed during saccades, the main input to our analysis are fixations (blue dots) captured by the eye tracker.

in Table 1 we identify the set of factors—namely, low-level stimuli, semantic information, cognitive process, stopping rule, inspection strategy, and search goal—that might contribute to the observable outcomes of the inspection that we discuss next.

3.2. Nonlinearity of the Inspection Path (Attention Shifts and Skipping)

In their seminal work on information foraging theory, Pirolli and Card (1999) propose that, when choosing information sources, people maximize their rate of

Table 1. Factors Driving SERP Inspection Decisions

Factors	Description
Low-level stimuli (e.g., section belonging, rank)	Low-level stimuli that attract visual attention without knowledge of semantic content (i.e., no prior fixation on the listing or subscreen is needed)
Semantic information (a listing's content, semantic context)	Semantic information extracted from listings during the process of visual inspection (high-level stimuli); this information is encoded and used to make assessments of (a) a listing's and (b) a subscreen's relevance to the search goal.
Cognitive process	Cognitive process that makes (a) the assessment of listing's/SERP section's relevance to the search goal and (b) cross-listing/cross-section comparisons
Stopping rule	Triggers the user's decision to quit SERP inspection and follow the link from one of the listings for in-depth examination (i.e., the user clicks to visit the website)
Inspection strategy	The user's intrinsic inspection strategy (e.g., ignore ads, start from the top of the page, move eyes up and down versus scroll the page)
Search goal	Search goal that could be categorized as transactional, informational, or navigational

gaining relevant information and switch from one source (a "patch" in Pirolli and Card's notation, p. 645) to another when information gain from the patch falls beyond a certain level. Applying this concept to SERP inspection, we speculate that a similar mechanism may be at play: sections of the SERP (i.e., top sponsored, right sponsored, and organic) are perceived by consumers as three independent patches, which are sampled to assess the value (relevance) of the listings. A priori, adjacent listings are expected to be more similar; thus, jumping over listings (skipping) within the section is used to assess relevance of the entire patch. Other factors potentially contributing to nonlinearity in the inspection process are low-level stimuli, imprecise eye (re)fixation after screen shifts (scrolls), and listing reinspection due to forgetting or reconfirming.

3.3. Stopping Inspection and Clicking

In the extant consumer search literature, stopping is commonly depicted as an outcome of trading off the costs of acquiring additional information and the benefits of making a (potentially) better choice (for a recent overview, see Yang et al. 2015). We speculate that a similar mechanism is at play in the process of visual inspection of a SERP. However, stopping SERP inspections is not equivalent to stopping the search process in terms of reaching the search goal. Rather, it is an intermediary decision whether to commit extra time to collecting information from a particular source (website) by visiting it. After the site is visited, the search process may continue. Thus, what is being traded off in this case are the costs of acquiring additional information about the destination site referenced in the listing and the benefits of reduced uncertainty about the site's relevance to the search goal.

The expected value of additional information could also vary by search tasks. Consumers in a transactional task may gain more from expanding their exploration area on SERPs, given that their goal is to compare more alternatives and find the "best" web page for a transaction. The search scope might be narrower for an informational search because the amount of attribute or quality information consumers need to learn is limited; inspecting several relevant listings would be sufficient, and the marginal benefit of inspecting additional listings diminishes over time. Finally, in a navigational task, where the goal is to locate a link to a target website, the marginal benefit of exploring additional links is reduced to zero after the site is identified, resulting is the smallest inspection scope.

3.4. Relevance Assessment

It is worth noting that the major search engines are doing a reasonably good job of serving consumers with relevant search results when there is no ambiguity in the search query, so the user's search goal can be accurately inferred by the search engine. For example, the predicted probability of a user clicking on a given listing (i.e., as an indication of relevance) is one of the core inputs to Google's listing ranking algorithm. Nonetheless, consumers do not limit visual inspection to the top search result and often explore a nontrivial number of listings before the first click-out. This suggests some discrepancy between consumers' evaluation of relevance and that of the search engine. In addition, ranking of search results in ad sections, at least in part, is affected by advertisers' willingness to pay for a click, which may result in less relevant listings appearing above the more relevant ones.

Being one of the core elements of the information retrieval field, relevance assessment of an information source to a search goal could be performed in numerous ways. Perhaps one of the most popular methods for establishing relevance is based on similarity between textual objects (e.g., words, sentences, documents). In our study, we use similarity between the search query and the listing content as a proxy for a listing's relevance.

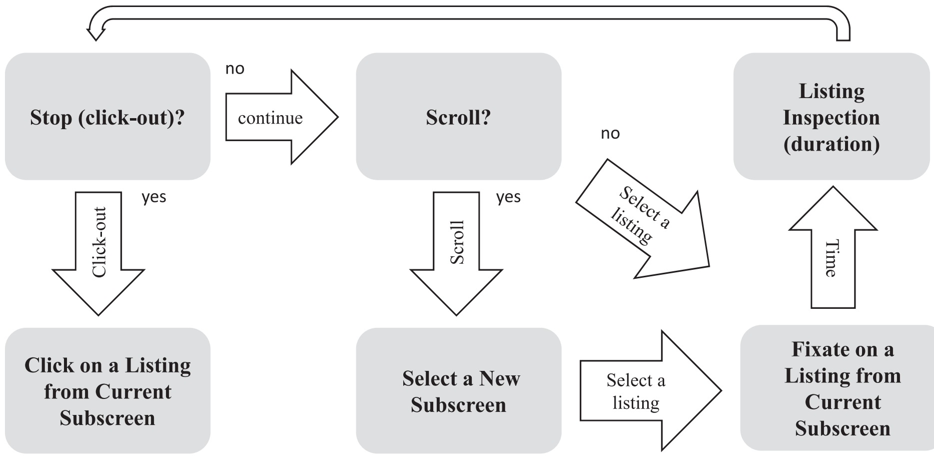
3.5. Scrolling

We believe that there are two major reasons for scrolling: (1) to get access to the information located outside the viewable screen area (e.g., below the fold) and (2) for viewing convenience, as some consumers might prefer to keep their eyes at the same level during the inspection process instead of looking up and down as they inspect the page.

3.6. Key Aspects of the Inspection Process

Building on the aforementioned ideas, we develop a model that decomposes the visual inspection process into a sequence of microdecisions (Figure 2). We define the start of the inspection process by the first recorded eye fixation on the newly served SERP and the end of the inspection, or "stop," by the first click-out from the result page.[2] At the top of the flowchart is the user's decision to continue visual inspection or stop the inspection by clicking on one of the listings. If the user chooses to continue the inspection, he or she may decide whether to scroll the page to bring currently hidden, outside-the-screen-boundary listings into view. If the user chooses not to scroll and stay with the current view (subscreen), he or she then decides which of the currently visible listings to focus (fixate) on and, consequently, how much time to spend on inspecting that listing. Alternatively, if the user chooses to scroll, the next microdecision is which subscreen to be brought into the view and subsequently which listing to fixate on and for how long. The goal of our empirical analysis is to identify the factors that help explain these microdecisions. We present the analyses in subsequent sections.

Figure 2. Decomposing the Visual Inspection Process into a Sequence of Micro Decisions



4. Experiment and Data Collection

We conducted a laboratory experiment in which participants—undergraduate students of a major mid-Atlantic public university—were tasked with finding information related to a set of specific products using a Google-like search engine (for details, see Online Appendix I).

4.1. Stimuli

We selected five products that we believed would be appealing to our participants: JanSport backpack, Nike Air Max shoes, Fitbit Charge 2, hotel in Manhattan, and Contigo water bottle. For each product, we specified three search goals reflecting navigational, informational, and transactional search tasks (Broder 2002, Jansen et al. 2008). For example, for the JanSport backpack, the navigational search instruction read as follows: "Please find the official page for JanSport's collaboration with Disney. Please use the following search query: [JanSport backpack Disney]"; the informational search instruction read as follows: "What are the benefits of JanSport backpack? Please use the following search query: [JanSport backpack benefit]"; and the transactional search instruction read as follows: "Please find a website that sells JanSport backpack. Please use the following search query: [buy JanSport backpack]." For each product search task, we created three variants of SERPs (i.e., a total of 45 distinct pages) by randomly selecting 10 organic and 11 sponsored listings from a pool of actual search results we collected from Google using the same search terms as in the experiment and placing them in corresponding sections of the SERP.

4.2. Data Collection Procedure

Each participant performed one type of search (informational, transactional, or navigational) for each of the five products. The order of the products and the type of search tasks were randomized across participants. For example, a participant could have been asked to perform a transactional search for products 1 and 4, an informational search for products 2 and 5, and a navigational search for product 3. The participants were instructed to start each new search using the provided search query and spend as much time as they needed. After each task, participants were asked a few questions related to the search. To motivate their search effort, participants were told that the quality of the information found would be evaluated and that they would have a chance to receive a monetary reward if they were selected as top performers (Liu and Toubia 2018). The web browser installed on the eye-tracker PCs was configured to use our custom-built Google-like search engine that would process the search query entered by the participant and match it to one of the 45 preset result pages, randomizing among three variants of a particular product/task combination. After participants inspected the page and clicked on one of the listings, the search engine redirected users to the actual destination site. Our search engine kept a log of the pages requested during each search session.

Participants' eye movement data were collected using binocular Tobii infrared corneal reflection eye-tracking equipment. Stimuli were presented on a 21-inch LCD monitor in full-color bitmaps with 1,280 × 768–pixel resolution. This eye-tracking equipment leaves participants free to move their heads and closely mimics real-life situations in which consumers interact with search engines. Eye movements consist of two main components: saccades and fixations. Saccades are rapid eye movements (20–40 milliseconds) that serve to redirect the line of sight to a new location or refixate on the current one. Fixations are brief moments (approximately 200–500 milliseconds) in which the eye is still and an area of a visual stimulus is projected onto the fovea for detailed visual processing (Rayner 1998). Because visual processing is suppressed during saccades, the main input to our analysis is a sequence of fixations captured by the eye tracker. To identify which listing is being inspected on a certain fixation, we match the screen coordinates of the fixation with the coordinates of listings presented on the SERP (for the screen layout, see Online Appendix II). Our matching procedure also accounts for scrolls, as the actual SERP is significantly "taller" than the viewable area of the screen (approximately 1,559 pixels versus 660 pixels, respectively). Finally, we record listing inspection durations and clicks.

To capture the scrolling process, we divide the SERP into several possibly overlapping subscreens based on the listing's height in pixels (see Online Appendix III). Specifically, starting from the default screen (the initial loading screen), we move down by one listing at a time to generate each subsequent subscreen, until we bring the bottom listing (O10) into view. For example, the initial loading screen would contain listings {T1, T2, T3, O1, O2, S1, . . ., S4} and the last subscreen would contain listings {O6, . . ., O10, S7, S8}.

To extract semantic information from listings, we follow the approach from Rutz et al. (2011) to categorize the words from the listings into two broad categories: descriptive information, which describes the product with attribute, quality, and brand information, and transactional information, which relates to the purchasing process and contains price, promotion, and place (store) information (Figure 3). First, we "seeded" each category with a reasonable number of words that strongly represent this category (e.g., the promotion category is seeded with words such as "discount," "sale," and "free"). Second, we used WordNet, a large lexical electronic database for the English language (Miller 1995), to identify synonyms and hyponyms for these words. This process resulted in a group of words that were meaningfully related within a category. Then, we reviewed the list of classified keywords, expanded the list of synonyms as needed, and repeated the first and second steps. Although this procedure does not classify every possible word that occurs in the listings, it allows us to focus on a subset of words that can be categorized into predetermined semantic constructs common to marketing applications. Equipped with this procedure, we parsed all listings and assigned individual words to appropriate semantic categories. We then normalized the semantic counts of each listing by the total descriptive and transactional word counts on the corresponding SERP.

5. Data Description

Our data set contains observations from 140 participants who viewed 503 SERPs (143 for the transactional task, 177 for the informational task, and 183 for the navigational task). The description of the semantic composition of SERPs on search task level appears in Online Appendix IV. Across the search tasks, the organic sections feature more descriptive words (attribute, quality, and brand) than transactional words (price, promotion, and place). This difference is the most prominent for the informational task (listings had an average of 5.667 more descriptive words than transactional words, $p < 0.000$). For sponsored sections, SERPs in the transactional task had significantly more transactional words than descriptive words (1.691, $p < 0.000$); in the other two search tasks, this pattern is reversed. In addition, for all three tasks, listings in the organic section had a significantly higher occurrence of query words than in the sponsored sections (average difference = 2.495, $p < 0.000$, for all three tasks).

The main descriptive statistics of the inspection patterns appear in Table 2. Consumers spent an average of approximately 13.93 seconds (standard deviation (SD) = 21.84) on a screen before clicking out and performed 13.11 nonconsecutive fixations (SD = 10.57),[3] with an average scan path of 2,047.69 pixels (SD = 1,943.51). For the listings that were inspected,

Figure 3. Semantic Hierarchy

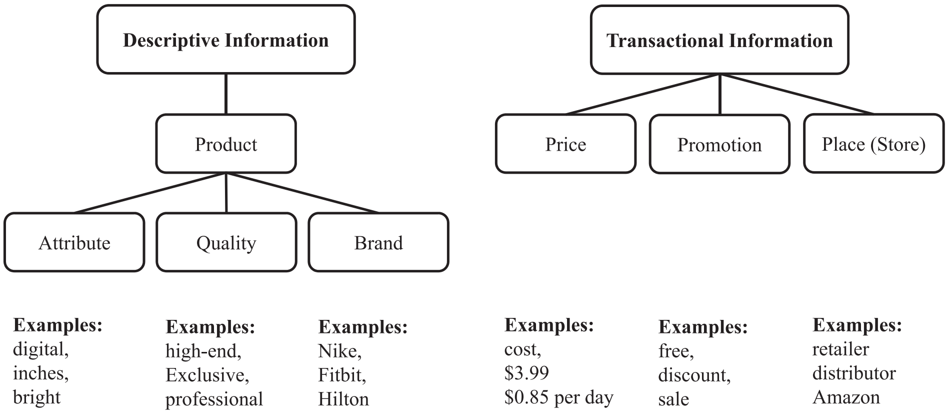


Table 2. Summary Statistics of Inspection Behavior on SERPs

Inspection behavior variables	All tasks (*SD*)	O Section	S Section	T Section	*p*-value	TRAN	INFO	NAVI	*p*-value
Browsing duration (in seconds)	13.93 (*21.84*)	**8.46***	**2.68**	**5.99**	0.000	12.71	15.59	13.29	0.445
Number of fixations	13.11 (*10.57*)	**8.87**	**2.23**	**4.79**	0.000	**14.34**	**13.42**	**11.85**	0.096
Number of fixations per (inspected) list	2.09 (*0.88*)	**2.32**	**1.12**	**1.92**	0.000	2.1	2.04	2.13	0.609
Total repeat inspection	7.31 (*8.12*)	**5.37**	**0.39**	**2.41**	0.000	7.87	7.51	6.68	0.390
Number of fixations per (inspected) subscreen	5.68 (*3.43*)	**3.47**	**1.49**	**3.39**	0.000	**5.32**	**5.52**	**6.12**	0.082
Number of listings receive at least one fixation	5.8 (*3.11*)	**3.51**	**1.84**	**2.39**	0.000	**6.48**	**5.91**	**5.17**	0.001
Number of listings receive at least two fixations	3.37 (*2.59*)	**2.34**	**0.28**	**1.22**	0.000	**3.76**	**3.38**	**3.04**	0.043
Distance between two listings with consecutive fix.	144.71 (*51.73*)	**157.69**	**487.55**	**123.57**	0.000	**149.7**	**150.08**	**135.62**	0.011
Distance between two subscreens with consecutive fix.	53.17 (*73.32*)	**70.34**	**39.77**	**42.22**	0.000	52.7	61.23	45.75	0.134
Total number of scrolls	3.84 (*5.13*)	**3.27**	**0.79**	**0.73**	0.000	**4.94**	**3.79**	**3.03**	0.004
Total scan distance (in pixels)	2,047.69 (*1,943.51*)	**1,375.9**	**906.26**	**662.22**	0.000	2,203.95	2,157	1,819.85	0.135
Percentage of subscreen inspected	29.16% (*23.06%*)	**0.29**	**0.16**	**0.16**	0.000	**35.28%**	**29.19%**	**24.35%**	0.000
Relative rank of clicked listing	1.93 (1.48)	1.99	4.00	1.79	0.003	**2.02**	**1.64**	**2.19**	0.006
Percentage of sessions follow complete	50.49%	41.43%	75.00%	38.69%		55.94%	51.41%	45.36%	
Percentage of sessions follow linear	28.03%	53.08%	1.99%	37.77%		25.87%	24.29%	33.33%	
Percentage of sessions follow strict linear	5.17%	4.37%	1.39%	9.34%		3.50%	6.21%	1.99%	

Note. Bold font indicates the difference among three sections (O, S, T) or three search tasks (transactional (TRAN), informational (INFO), navigational (NAVI) is statistically significant. SD, standard deviation.

each received approximately 2.09 fixations (SD = 0.88); for the subscreens that were inspected, each received approximately 5.68 fixations (SD = 3.43). As for scrolling, consumers scrolled an average of 3.84 times during inspection (SD = 5.13). Approximately 71.57% of search sessions included at least one scroll event, and 56.06% had two or more scrolls. The listings that received a click-through were typically at a higher rank than all listings inspected (relative rank = 1.93, SD = 1.48).

The semantic information encountered along the inspection path (fixation sequence) varied. As a manifestation of repeat inspections, there is a decreasing trend in viewing brand information but an increasing trend in viewing attribute, price, and place information; users were also increasingly likely to return to the listings with more query words. In addition, a listing's viewing duration decreased as the inspection progressed, except for a pronounced spike around fixations 9–12, which coincides with the average length of an inspection session and, thus, a click-out event (see Online Appendix V).

5.1. Incompleteness and Nonlinearity in Inspection Patterns

Incomplete scanning of SERPs prevails. Consumers did not perform a full scan of SERPs; instead, as Table 2 shows, only approximately 5.80 (SD = 3.11) of 21 listings on the SERPs received at least one fixation and 3.37 (SD = 2.59) received at least two fixations. Such incompleteness also manifests in the subscreen inspection, with only 29.16% (SD = 23.06%) of the subscreens being examined. Despite the incompleteness, consumers in general scan SERPs in small steps. The average distance between two listings receiving consecutive fixations was slightly longer than the height of a listing (144.71, SD = 51.73), and so was the scroll distance between two subscreens receiving consecutive fixations (53.17, SD = 73.32). Furthermore, consumers rarely scrolled the entire viewable area but rather tended to move in small steps (only 7.5% of them scrolled more than five listings).

The attention paths on SERPs show a strong deviation from the top-to-bottom sequential pattern observed in natural reading, with a notable number of back-and-forth transitions across listings and sections. To illustrate, consumers switched sections approximately 30.27% (SD = 20.88%) of the time (i.e., they moved to a different section once per ~3.4 listing inspections), and they changed direction (i.e., they switched from going down to going up, or vice versa) 48.53% (SD = 17.13%) of the time, with only 46.02% (SD = 15.68%) of movements directed downward. Lorigo et al. (2006) proposes several formal measures for nonlinearity in inspection: a scan path preceding a click is *complete* if all the listings above the selected one are inspected (no skips); a scan path is *linear* if the minimal sequence of the user's scan path is monotonically increasing in steps of one (minimal scan path is the path obtained by removing repeat visits or regressions; e.g., for sequence 2-3-2-1, the minimal path is simply 2-3-1). A scan path is *strictly linear* if the corresponding sequence (without removing repeat visits or regression) is monotonically increasing in steps of one. Table 2 shows that approximately 50.49% of search sessions showed complete inspection (all listings were inspected above the clicked one), 28.03% of the sessions followed a linear inspection, and 5.17% of the sessions followed a strict linear inspection. These nonlinearity patterns in the inspection underscore the importance of probing the inspection patterns on SERPs.

Notably, consumers rarely click on the first inspection. Instead, approximately 80% of the chosen listings were clicked on after a returned inspection. After examining the (eventually) clicked-on listing, consumers performed approximately 8.99 more fixations (mean number of fixations = 13.11) and 3.21 more scrolls (mean number of scrolling = 3.84) before clicking out. These results suggest that a deliberate comparison and evaluation process takes place before click-through.

5.2. Measurement by Sections and Task Types

Section-wise, the inspection measurements differ. As we report in Table 2, consumers spent the most time in the O section (8.46 seconds), followed by the T (5.99 seconds) and S (2.68 seconds; $p < 0.000$) sections. The number of fixations and time spent per listing dropped as the rank decreased in the O and S sections; however, the amount of visual attention did not monotonically decline with rank in the T section, and T3 (being adjacent to the O section) received the largest share of attention. The observed pattern of inspecting top listings in the O and S sections is particularly interesting, given that the order of listings was randomized in our experiment and there were no apparent quality or relevance advantages for the listings in the top positions within the same section (see Online Appendix VI).

The path completeness was 41.42% for the O section, 75.00% for the S section, and 38.69% for the T section ($p = 0.312$). The S section showed the lowest linearity (1.99% versus 53.08% for the O section and 37.77% for the T section, $p < 0.000$) and strict linearity (1.39% versus 4.37% for the O section and 9.34% for the T section, $p < 0.000$), suggesting that consumers were more likely to skip or regress rather than move downward monotonically in steps of one in the S section.

The repeated inspection was more prevalent in the O section as well. The number of listings receiving at least one fixation was 46.93% higher than that in the T section and 90.36% higher than that in in the S section ($p < 0.000$); such a difference is more striking in the number of listings receiving at least two fixations; for example, the measurement in the O section was nearly twice that in the T section and more than eight times that in the S section ($p < 0.000$). Consumers seemed to scan a much longer distance between two consecutive fixations in the S section (487.55); yet they were more likely to take smaller steps when browsing in the other two sections (O: 157.69, T: 123.57; $p < 0.000$). In addition, most of the scrolling occurred while browsing listings in the O section (3.27 versus 0.79 in the S section and 9.73 in the T section, $p < 0.000$).

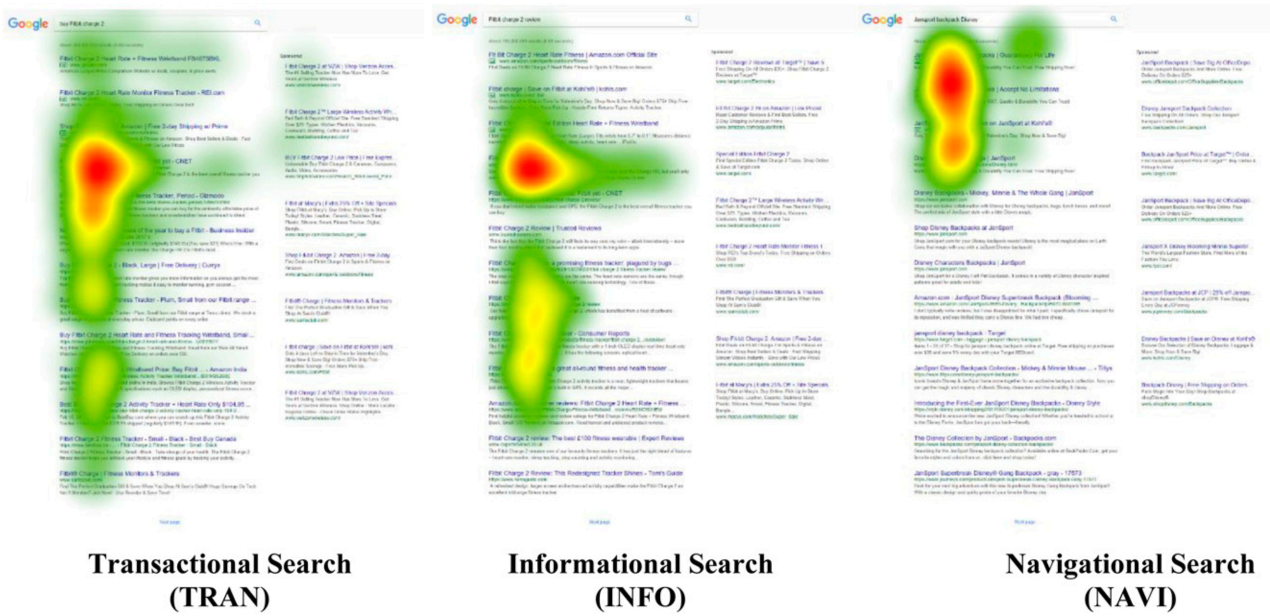
Task-wise, consumers varied in their inspection pattern. A general pattern is that consumers in the transactional task exhibited the largest search scope, whereas those in the navigational task were more restrictive. Figure 4 illustrates this search scope difference in the "JanSport backpack" search with heatmaps, in which the warmer color indicates higher visual concentration. When aggregating across individuals in the transactional task, the range of exploration is much larger than those in the navigational task. Specifically, Table 2 shows that consumers performing transactional tasks had a significantly larger number of fixations (14.34 versus 11.85 in the navigational task and 13.42 in the informational task, $p = 0.096$), a greater number of listings that received at least one fixation (6.48 out of 21 versus only 5.17 in the navigational task and 5.91 in the informational task, $p = 0.001$), and a greater number of listings that received at least two fixations (3.76 versus 3.38 in the informational task and 3.04 in the navigational task, $p = 0.043$). In addition, consumers performing transactional tasks examined a higher percentage of subscreens on the SERPs (35.28% versus 24.35% in the navigational task and 29.19% in the informational task, $p < 0.000$). Furthermore, consumers scrolled significantly more often (to explore SERPs) in the transactional task (4.94 times, which is 63% more than that in the navigational task and 30% more than the informational task; $p = 0.004$).

6. Empirical Analyses

Next, we develop an empirical model of multiple inspection decisions following the flowchart featured in Figure 2. We provide a list of main covariates and their operationalization in Table 3, grouping them by semantic factors, spatial characteristics (of subscreen and listing), viewing centrality, and prior inspection behavior (of subscreen, listing, and entire SERP). In all the models, we allow parameters $\Theta_{j,\cdot}$ ($j = 1, \ldots, 6$) to vary across individuals following a normal distribution ($\Theta_{j,\cdot} \sim N(\bar{\Theta}_{j,\cdot}, \delta^2_{j,\cdot})$).

First, we model consumers' *stop* or *continue* decision as a binary logit with full random coefficients.

Figure 4. Illustration of Visual Inspection Scopes Across Three Search Tasks



Note. Warmer color represents greater concentration of attention.

For consumer i, the probability of stopping the inspection of a SERP at fixation t is

$$P(Stop_{i,t} = 1) = \frac{\exp(\Theta_{1,i} \times X - Stop_{i,t})}{1 + \exp(\Theta_{1,i} \times X - Stop_{i,t})}. \qquad (1)$$

The explanatory factors used in $X - Stop_{i,t}$ include the (a) *prior inspection on the SERP* (i.e., cumulative number of repeated inspections, whether the last-viewed listing is a repeated view, cumulative browsing duration, cumulative number of scrolls, and the percentage of total sections viewed) and (b) *cumulatively viewed semantic information* on the SERP across six semantic categories (i.e., attribute, brand, quality, price, promotion, and place). The definitions of these variables appear in Table 3.

Second, conditional on continuing inspection, we model the *scrolling* decision for consumer i at fixation t as a binary logit:

$$P(Scroll_{i,t} = 1 | Stop_{i,t} = 0) = \frac{\exp(\Theta_{2,i} \times X - Scroll_{i,t})}{1 + \exp(\Theta_{2,i} \times X - Scroll_{i,t})}. \qquad (2)$$

The scrolling decision can be affected by (a) *semantic factors*, including the semantic information of a recently viewed listing and the cumulatively viewed semantic information on the current subscreen; (b) *prior inspection on the current subscreen* (e.g., percentage of listings viewed); and (c) *viewing centrality*, which captures whether a listing viewed previously is in the top or middle section of the subscreen, reflecting the impact of viewing comfort on scrolling decisions. We also control for cumulative browsing duration on the SERP.

Third, conditional on scrolling, the consumer will choose a *subscreen* to inspect (otherwise, the consumer will stay at the current subscreen and fixate on a listing, following Equation (4)). We model the subscreen choice with a mixed multinomial logit model. Assume that the SERP is partitioned into K subscreen ($S_1, \ldots, S_k$), the probability of consumer i choosing subscreen S_k at fixation t is

$$\begin{aligned} P(Subscreen_{i,t} = S_k | Scroll_{i,t} = 1, Stop_{i,t} = 0) \\ = \frac{\exp(\Theta_{3,i} \times X - Subscreen_{S_k,i,t})}{\sum_{q=1}^{K} \exp(\Theta_{3,i} \times X - Subscreen_{S_k,i,t})}. \end{aligned} \qquad (3)$$

The explanatory variables $(X - Subscreen_{S_k,i,t})$ contain (a) *semantic factors* (i.e., the cumulatively viewed semantic information on subscreen S_k); (b) *spatial characteristics of subscreen S_k*, including the rank of the subscreen, the distance to the subscreen from the current position, and whether an upward scroll or a same-direction scroll is needed to reach the subscreen; and (c) *prior inspection of subscreen S_k*, including whether this subscreen was viewed before, cumulative browsing duration of the subscreen, and percentage of listings viewed on the subscreen.

Fourth, given the current subscreen that the consumer is on, he or she will *fixate* on a listing for inspection. The utility predictors for listing l in subscreen S_k for consumer i at time t $(X - List_{l,i,t})$ consist of (a) *semantic factors*, including the semantic characteristics of listing l, if listing l had been viewed before. Once the listing has

Table 3. Model Variables

Category	Covariates (for consumer i at fixation t)	Description
Semantic factors	*Info. in the listing*$_{i,l,t}$	Semantic information of listing l, if listing l had been viewed before (six semantic categories: attribute, brand, quality, price, promotion, and place)
	Info. in the listing viewed recently$_{i,t}$	Semantic information of the listings viewed at $t-1$ (six categories)
	Cumu. info. viewed on SERP$_{i,t}$	Cumulatively viewed semantic information on the SERP
	Cumu/info. viewed on subscreen $_{S_k,i,t}$	Cumulatively viewed semantic information on the subscreen S_k
	Tran. perc. of listing $_l$	Share (%) of the combined transactional information in a listing, if this listing had been viewed before
	Similarity btw. listing & cumu text $_{i,l,t}$	Cosine similarity between the share of six semantic categories for the listing l and the share of cumulatively viewed six semantic categories on the SERP
	Num. query words $_l$	Number of query-match words in listing l
	Num. words in listing $_l$	Number of words in listing l
Spatial characteristics of subscreen S_k	*Distance to previous subscreen* $_{S_k,i,t}$	The scroll distance to the subscreen S_k center based on the current position
	Scroll up to subscreen $_{S_k,i,t}$	If an upward scroll is needed to reach the subscreen S_k from the current position, it is coded as 1, and 0 otherwise.
	Same scroll to subscreen $_{S_k,i,t}$	To get to subscreen S_k from the current position, if the scroll will be in the same direction as the previous scroll, it is coded as 1, and 0 otherwise.
	Subscreen rank $_{S_k,i}$	Rank of the subscreen S_k
Prior inspection on subscreen S_k up to fixation $t-1$	*Perc. list viewed on subscreen* $_{S_k,i,t}$	Percentage of listings viewed on subscreen S_k up to fixation $t-1$
	Time spent on subscreen $_{S_k,i,t}$	Cumulative browsing duration on subscreen S_k up to fixation $t-1$
	Subscreen repeat dummy $_{S_k,i,t}$	If subscreen S_k has been viewed before, it is coded as 1, and 0 otherwise.
Spatial characteristics of listing l	*Rank of listing* $_l$	The rank of the listing l in a section
	Section_O $_l$; *section_T* $_l$	Dummy variables capture whether listing l is in the organic or top-sponsored section (right-sponsored section as baseline).
	Different section $_{i,l,t}$	Whether the listing l requires user to move to a different section
	Require moving downward $_{i,l,t}$	If listing l is located below the previous fixation in terms of screen coordinates, it is coded as 1, and 0 otherwise.
	Distance to previous listing $_{i,l,t}$	Scan distance (in pixels) to listing l from the previous fixation location
Prior inspection on listing l up to fixation $t-1$	*Recency if is repeat* $_{i,l,t}$	The recency (in number of fixations between) of listing l's inspection if the listing has been inspected before
	Repeat list $_{i,l,t}$	If the listing l has been inspected before, it is coded as 1, and 0 otherwise.
	Cumu. dura. on the listing $_{i,l,t}$	Cumulative inspection duration of listing l up to fixation $t-1$
	Last inspection repeat dummy $_{i,l,t}$	Captures whether the recent inspection of the listing is a repeated inspection
Viewing centrality	*Listing at top/mid* $_{i,l,t}$	If listing l is at top or middle section of the subscreen at fixation t, it is coded as 1, and 0 otherwise.
	Last listing at top/mid $_{i,t}$;	If the listing viewed at fixation $t-1$ is at top or middle section of the subscreen at fixation $t-1$, it is coded as 1, and 0 otherwise.
Prior inspection on the SERP up to fixation $t-1$	*Cumulative dura. on SERP* $_{i,t}$	Cumulative browsing duration on the entire screen up to fixation $t-1$
	Cumulative num. scrolls $_{i,t}$	Cumulative number of scrolls up to fixation $t-1$
	Cumulative repeat inspection $_{i,t}$	Total number of repeated listing views up to fixation $t-1$
	Perc. total sections viewed $_{i,t}$	Percentage of the sections viewed up to fixation $t-1$

been inspected, its textual content will be "remembered" for subsequent comparison and evaluation. This setup allows the content of a listing to be relevant to the decision to revisit this listing but not the decision to visit it for the first time. Furthermore, we account for the carryover effect of the cumulatively viewed semantic information across the SERP by including a cosine similarity measure between the vector of the share of six semantic categories for listing l and the share of cumulatively viewed six semantic categories across the SERP. The $X-List_{l,i,t}$ also include (b) *spatial characteristics of listing* l, including the rank of the listing l in a section, the interaction effect between the rank and the semantic composition[4] of the listing l, section-specific effect, the scan distance to listing l, and whether listing l requires moving downward or to a different section; (c) *prior inspection of listing* l, including whether it was inspected before, the recency of the recent inspection, and cumulative browsing duration of this listing; and (d) *viewing centrality of listing* l on the current subscreen. Last, we control for the number of words and the number of query-matching words in listing l, if this listing was viewed before. The probability of consumer i fixating on listing l on the current subscreen S_k at fixation t is a mixed multinomial logit setup:

$$P(List_{i,t}=l|Subscreen=S_k,Stop_{i,t}=0) = \frac{\exp(\Theta_{4,i}\times X-List_{l,i,t})}{\sum_{j\in S_k}\exp(\Theta_{4,i}\times X-List_{j,i,t})}. \quad (4)$$

Conditional on listing l being chosen, we then model the *browsing duration of listing* l with a log-linear model. We use the same set of variables in $X\text{-}List_{l,i,t}$ described in the listing choice model in this duration model, and we control for the number of words and cumulative viewing duration. Specifically,

$$P\left(Dura_{i,t}|List_{i,t}=l,Subscreen_{i,t}=S_k,Stop_{i,t}=0\right) \sim LogNormal(\mu_i,\sigma_i^2) \text{ in which } \mu_i=\Theta_{5,i}\times(X-List_{l,i,t},NumWords_l, CumuDururation_l). \quad (5)$$

Last, we model the click-through decision with a mixed multinomial logit model. We write the probability of consumers i clicking on listing l on the SERP as follows:

$$P(Click_i=l|Stop_{i,t}=1)=\frac{\exp(\Theta_{6,i}\times X-Click_{i,l})}{\sum_{l\in S_k}\exp(\Theta_{6,i}\times X-Click_{i,l})}. \quad (6)$$

The explanatory variable $X\text{-}Click_{i,l}$ is a combination of (a) *semantic factors*, including the semantic characteristics of listing l, if listing l had been viewed before, and (b) *spatial characteristics of listing* l, including the section belonging of listing l and its ranking in a section. We also control for the number of query words in l, if this listing had been viewed before.

The likelihood of observing all six decisions for consumer i is

$$\begin{aligned}
&L\Big(Stop_{i,t=1\ldots N_t},Scroll_{i,t=1\ldots N_t},Subscreen_{i,t=1\ldots N_t},\\
&List_{i,t=1\ldots N_t},Dura_{i,t=1\ldots N_t},Click_i|\Theta_{i,\cdot}\Big)=\\
&\prod_{t=1}^{N_t}\left\{\begin{array}{l}P\left(Stop_{i,t}=0\right)^{I\left(Stop_{i,t}=0\right)}\times\\
\left(\left[\begin{array}{l}P\left(Scroll_{i,t}=0|Stop_{i,t}=0\right)^{I\left(Scroll_{i,t}=0\right)}\\
\times P\left(List_{i,t}=l|Subscreen=S_k,Stop_{i,t}=0\right)^{I\left(List_{i,t}=l\right)}\\
\times P\left(Dura_{i,t}|List_{i,t}=l,Subscreen_{i,t}=S_k,Stop_{i,t}=0\right)\end{array}\right]\times\right.\\
\left.\left[\begin{array}{l}P\left(Scroll_{i,t}=1|Stop_{i,t}=0\right)^{I\left(Scroll_{i,t}=1\right)}\\
\times P\left(Subscreen_{i,t}=S_k|Scroll_{i,t}=1,Stop_{i,t}=0\right)^{I(Subscreen=S_k)}\\
\times P\left(List_{i,t}=l|Subscreen=S_k,Stop_{i,t}=0\right)^{I\left(List_{i,t}=l\right)}\\
\times P\left(Dura_{i,t}|List_{i,t}=l,Subscreen_{i,t}=S_k,Stop_{i,t}=0\right)\end{array}\right]\right)\end{array}\right\}\\
&\times P\left(Stop_{i,t}=1\right)^{I\left(Stop_{i,t}=1\right)}\\
&\times P\left(Click_i=l|Stop_{i,t}=1\right)^{I\left(Click_i=l\&Stop_{i,t}=1\right)}
\end{aligned} \quad (7)$$

We estimate the random-coefficient model using a simulated maximum likelihood approach for each search task.

7. Model Results

In this section, we highlight the key findings of our empirical model of multiple inspection decisions (Figure 2). To help navigate the results, we tie the inspection patterns to the factors presented in Table 1 (i.e., low-level stimuli, semantic information, cognitive process, stopping rule, inspection strategy, and search goal).

7.1. Stopping Decision

We start with the model results for the stop decision (Table 4). Cumulative inspection duration on a SERP is predictive of the stopping decision in transactional and informational search tasks but not in the navigational task. Featuring the least deliberate exploration of the SERP (Table 2), the navigational search could end shortly after the target URL has been identified because fewer comparisons are needed to reassure the user that the selected listing fits the search objective. Accordingly, depending on the visual inspection path, the user can "stumble upon" the target listing sooner or later during the session, making session duration not a strong predictor for stopping. In turn, a higher degree of scrolling activity may signal

Table 4. Results of Stop Decision Across Search Tasks

	TRAN			INFO			NAVI		
Stop decision (stop = 1)	Parameter	p-value	SD	Parameter	p-value	SD	Parameter	p-value	SD
(Intercept)	**−8.958*****	0.000	0.011	**−5.685*****	0.000	3.6E-05	**−3.653*****	0.000	0.118
Cumulative repeat inspections	0.072	0.740	1.0E-06	0.102	0.546	7.0E-05	**0.703*****	0.000	2.3E-06
Last inspection repeat dummy	**1.139*****	0.000	0.261	**0.967*****	0.000	0.020	**0.916*****	0.000	0.030
Cumulative duration SERP	**6.790*****	0.000	1.1E-04	**3.317*****	0.002	0.507	0.334	0.799	1.2E-04
Cumulative number of scrolls	−0.263	0.109	0.138	**−0.292***	0.071	0.004	**−0.362****	0.013	1.9E-04
Percentage of total sections viewed	−0.439	0.468	0.002	−0.202	0.680	0.425	0.500	0.286	0.009
Cumulative attribute viewed on SERP	−0.769	0.472	4.6E-04	−0.728	0.153	0.002	**−1.214***	0.060	0.004
Cumulative quality viewed on SERP	**−6.516***	0.051	0.062	−0.780	0.776	0.333	−2.421	0.756	0.357
Cumulative brand viewed on SERP	−0.999	0.554	2.306	−1.069	0.535	0.101	0.212	0.926	0.004
Cumulative price viewed on SERP	11.724	0.223	0.006	−2.739	0.727	0.819	**38.102****	0.042	27.905
Cumulative place viewed on SERP	0.076	0.983	0.074	−1.698	0.572	1.806	**−4.778****	0.033	0.001
Cumulative promotion viewed on SERP	4.081	0.327	0.008	**4.598***	0.075	0.440	−0.441	0.765	0.774

Notes. In this result table and the following ones (Tables 5, 6, 7, 8, and 9c), we use the "SD" column to report the standard deviation of parameter estimates across the participants. Bold font indicates significant p-values.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

a more elaborate approach to SERP inspection, pushing the session's end further out.

Interestingly, it is more likely for the user to inspect additional listings after the eventually clicked listing has been discovered than to stop the inspection right after the first encounter. The *Last Inspection Repeat Dummy* variable is a consistent predictor across all three search tasks, suggesting users tend to stop inspection when they return to a previously inspected listing. In addition, in the navigational search, stickiness to a smaller set of listings (cumulative repeat inspections) is predictive of the session culmination.

In terms of cumulative semantic information, across all three search tasks, we observe that the amount of attribute and quality information discovered is associated with the decision to continue visual inspection, whereas cumulative transactional information (i.e., promotion in informational searches and price in navigational searches) leads to quicker session termination. We offer two possible explanations for these patterns. First, the discovery of descriptive information may put a higher cognitive load on the user triggering the need for deeper exploration and analysis of the SERP (e.g., as new dimensions for alternative comparisons are discovered or more difficult trade-offs need to be made across not-directly-comparable attribute sets). Second, in contrast to transactional information, which could be easier to incorporate into decision making, descriptive information may be perceived as less relevant, thus raising the need for additional search (for informational and navigational search tasks).

7.2. Scroll Decision

The parameter estimates from the scrolling model (Table 5) indicate that the current gaze location (captured by Last listing at top and at middle) is a consistent predictor for the scroll decision across all three tasks. This is likely due to the typical multiscreen viewing behavior when the user scrolls down when getting closer to the bottom edge of the viewable area to maintain viewing comfort and to bring additional content into the view.

For consumers in informational and navigational tasks, scrolling occurred when they examined a greater number of listings on the current subscreen (Perc. list viewed on subscreen); together with overall less frequent scrolling in these two search tasks (Table 2), this result suggests that the visual search is more localized in these two tasks.

The scrolling decision could also be linked to the semantic information viewed in the informational and navigational tasks. Specifically, consumers are less likely to scroll out of the current subscreen if they have viewed more attribute or quality information on the current subscreen. In turn, cumulative exposure to the place information (e.g., name of the online store) on a subscreen is more likely to trigger scroll out. To some extent, this pattern is in line with the information foraging theory (Pirolli and Card 1999), which proposes that people stay within the same informational patch (i.e., conducting localized search) while their information gain from the patch is sufficiently high. This scenario is more likely to occur with descriptive information, where content variation across listings is higher; thus, it may take longer to reach a satiation point. Interestingly, the cumulative information viewed on a subscreen does not influence the scrolling decision for consumers in the transactional task. Instead, the scrolling decision is influenced more by instantaneous factors, namely, the content viewed in the last fixation (variables labeled as "viewed recently" postfix; see Table 5). For example, users are more likely to stay on the same screen if they just encountered price information, which provides valuable information to judge

Table 5. Results of Scrolling Model Across Search Tasks

	TRAN			INFO			NAVI		
Scroll (scroll = 1)	Parameter	p-value	SD	Parameter	p-value	SD	Parameter	p-value	SD
(Intercept)	**−4.589*****	0.000	3.3E-05	**−3.499*****	0.000	0.288	**−5.246*****	0.000	0.475
Cumulative duration on SERP	**4.815*****	0.000	1.1E-04	**3.115*****	0.000	0.069	**4.693*****	0.000	0.008
Perc. list viewed on subscreen	0.591	0.138	1.047	**1.058*****	0.003	0.130	**1.362*****	0.001	0.704
Last listing at top	**−0.377*****	0.003	0.370	**−0.634*****	0.000	1.5E-06	**−0.475*****	0.001	0.217
Last listing at middle	**−0.322*****	0.006	0.012	**−0.521*****	0.000	0.161	**−0.591*****	0.000	1.1E-06
Cumulative attribute viewed on subscreen	−0.181	0.135	1.0E-04	**−0.194****	0.013	0.000	**−0.273*****	0.004	5.6E-05
Quality viewed on subscreen	−0.309	0.216	2.9E-05	**−0.475***	0.060	0.397	−0.394	0.279	1.2E-05
Cumulative brand viewed on subscreen	−0.133	0.753	0.420	−0.458	0.174	6.0E-05	−0.768	0.287	1.6E-05
Price viewed on subscreen	−0.203	0.499	0.291	−0.125	0.729	0.004	−0.179	0.362	1.0E-06
Cumulative place viewed on subscreen	−0.599	0.171	4.2E-05	**0.916****	0.020	5.4E-06	−0.014	0.958	0.085
Cumulative promotion viewed on subscreen	0.067	0.949	3.796	−1.829	0.175	1.0E-05	−2.749	0.214	1.4E-04
Attribute in the listing viewed recently	−0.351	0.542	0.001	**−0.656***	0.095	1.5E-05	0.706	0.101	1.5E-04
Quality in the listing viewed recently	**2.701***	0.067	0.004	0.738	0.581	2.3E-05	**10.140*****	0.000	9.854
Brand in the listing viewed recently	0.278	0.815	0.007	**2.079****	0.022	1.6E-04	−0.134	0.915	1.7E-04
Price in the listing viewed recently	**−4.346****	0.039	0.001	1.465	0.650	14.510	−1.305	0.810	3.5E-04
Place in the listing viewed recently	**2.908****	0.040	8.9E-05	1.123	0.443	4.4E-06	0.768	0.382	1.5E-04
Promotion in the listing viewed recently	0.308	0.725	4.768	**−2.465****	0.015	2.414	0.119	0.890	4.830

Note. Bold font indicates significant p-values.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

the aptness of the target site for transaction, whereas quality information prompts scrolling.

7.3. Subscreen Choice Decision

We present the results of the subscreen choice model in Table 6. As for spatial characteristics, not surprisingly, consumers prefer higher-ranked subscreens, reflecting both the typical top-to-bottom inspection strategy and a prior belief in higher relevance of top-ranked listings served by the search engine. In addition, consumers are more likely to choose a subscreen that is closer to the current view and change scrolling direction than to move in the same direction. As for prior inspection on subscreens, consumers prefer a subscreen with a higher number of listings inspected previously.

The impact of semantic context on subscreen choice can be attributed to semantic relevance assessment. For the search goal of locating a specific website on a SERP (navigational), viewing more attribute, price, or place information on a subscreen discourages (re) inspection of that subscreen because the subscreen is less likely to serve the search purpose. Similarly, if the search goal is to locate an informational source about a service or product, place- or brand-related words might be less relevant than product-specific information. Consistent with the scroll model results, we did not observe a significant impact from semantic context on subscreen choice for the transactional task.

7.4. Listing Inspection Choice

The listing inspection choice model results appear in Table 7. As for the spatial characteristics, three tasks exhibit consistent patterns. A listing is more likely to be inspected when it is located in the O or T sections, ranked higher in a section, requires going down, and is closer to the previous fixations; these results suggest the influence exerted by low-level stimuli (see Table 1). Consumers also exhibited strong viewing centrality preference in informational and navigational tasks, as parameter estimates (Listing at mid) show that a listing in the middle section of the current subscreen is more likely to draw attention than other listings. Prior inspection of the listing also plays a role; we observe some stickiness effect, as users are more likely to examine a listing that has been viewed before or more recently (informational task) and less likely to switch sections (transactional task).

The impact of the semantic content of a listing influences inspection decisions. We should reiterate that semantic content plays a role exclusively in reinspection decisions, as semantic information is unknown to the user until the listing has been inspected for the first time. Thus, the effects of semantics on viewing should be analyzed only from a reinspection decision point of view. We speculate that this decision can be triggered by different factors, including forgetting, reaffirmation of previously extracted information, need for additional detail, and so forth. For example, we find that featuring place information in the listing is associated with reinspection in the transactional task but discourages comebacks in the navigational search. In the informational search task, price-related words trigger repeat viewing, whereas a listing with more descriptive information is less likely to be reinspected. Furthermore, we show that semantic information in a listing moderates the impact of ranking. Although attention devoted to a listing declines as the listing

Table 6. Results of Subscreen Choice Model Across Search Tasks

	TRAN			INFO			NAVI		
Subscreen choice	Parameter	*p*-value	SD	Parameter	*p*-value	SD	Parameter	*p*-value	SD
Subscreen rank	**–1.421*****	0.000	0.002	**–1.534*****	0.000	0.404	**–1.254*****	0.000	0.148
Distance to previous subscreen	**–1.277*****	0.000	0.288	**–1.454*****	0.000	0.029	**–1.354*****	0.000	0.114
Scroll up to subscreen	**0.509****	0.014	0.001	**0.587****	0.011	0.001	0.306	0.212	3.4E-12
Same scroll to subscreen	**–1.213*****	0.000	0.371	**–1.124*****	0.000	0.001	**–0.565*****	0.003	9.5E-06
Percentage of list viewed on subscreen	**5.056*****	0.000	0.500	**6.769*****	0.000	0.016	**6.840*****	0.000	0.005
Subscreen repeat dummy	**–0.982*****	0.000	0.004	**–1.042*****	0.000	4.7E-04	**–0.790*****	0.000	4.0E-04
Time spent on subscreen	–0.135	0.217	3.0E-04	0.042	0.306	0.005	0.057	0.377	0.002
Cumulative attribute viewed on subscreen	–0.430	0.828	0.002	0.399	0.748	0.008	**–4.133*****	0.007	1.409
Cumulative quality viewed on subscreen	11.426	0.100	0.029	0.415	0.941	5.222	–14.055	0.257	10.668
Cumulative brand viewed on subscreen	–5.047	0.192	3.554	**–11.569*****	0.001	0.082	7.474	0.117	0.001
Cumulative price viewed on subscreen	–5.557	0.198	20.609	8.697	0.153	0.045	3.745	0.229	9.1E-05
Cumulative place viewed on subscreen	–5.224	0.413	0.057	**–18.101*****	0.004	0.121	**–12.158*****	0.002	1.0E-04
Cumulative promotion viewed on subscreen	–1.448	0.921	1.032	26.021	0.172	0.528	**–74.057***	0.056	2.320

Notes. We employ a control function approach (Ebbes et al. 2016, Petrin and Train 2010) to correct for endogeneity bias in "Perc. list viewed on subscreen" variable across three search tasks. Bold font indicates significant *p*-values.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

ranks lower in a section, having more transactional information (i.e., price, promotion, and place) in the listing moderates this negative trend in the informational and transactional tasks.

7.5. Listing Inspection Duration

In Table 8, we present the results from the listing inspection duration model. The parameter estimates of the spatial characteristics reveal a significantly longer inspection duration for the listings featured in the right-hand-side sponsored section (used as a base case in the model) compared with organic and top-sponsored listings. We speculate that being a relatively "unpopular" results section, conditional on inspection, listings featured here are subject to more in-depth scrutiny by users.

Furthermore, we find that a listing will be inspected longer if users "arrive" at it when moving in a common inspection sequence from the top versus from the bottom of the page. Consumers in the informational

Table 7. Results of Listing Inspection Choice Model Across Search Tasks

	TRAN			INFO			NAVI		
Listing inspection choice	Parameter	*p*-value	SD	Parameter	*p*-value	SD	Parameter	*p*-value	SD
Section_O	**3.257*****	0.000	0.138	**3.039*****	0.000	0.152	**2.739*****	0.000	1.56E-04
Section_T	**4.092*****	0.000	3.71E-05	**3.967*****	0.000	0.114	**3.467*****	0.000	0.001
Rank of listing	**–0.799*****	0.000	0.001	**–0.953*****	0.000	2.08E-06	**–0.794*****	0.000	1.86E-04
Require moving downward	**1.240*****	0.000	0.133	**1.333*****	0.000	0.377	**1.340*****	0.000	1.98E-04
Distance to previous listing	**–1.661*****	0.000	0.004	**–1.604*****	0.000	1.894	**–1.638*****	0.000	0.018
Listing at top	–0.110	0.615	0.238	–0.259	0.186	0.332	0.075	0.728	0.002
Listing at middle	0.192	0.109	6.12E-05	**0.245****	0.022	2.42E-06	**0.516*****	0.000	0.002
Different section	**–0.142***	0.071	2.46E-06	0.091	0.210	0.113	–0.014	0.853	0.131
Repeat list	0.802	0.206	2.42E-07	**1.153****	0.034	0.150	–0.478	0.349	4.35E-05
Recency if is repeat	–0.077	0.234	0.286	**–0.102****	0.047	0.002	–0.079	0.147	9.00E-06
Attribute in the listing	0.235	0.595	9.15E-05	–0.328	0.378	6.65E-07	0.050	0.897	0.002
Quality in the listing	–1.313	0.306	0.001	**–2.411****	0.019	4.17E-05	–0.603	0.753	0.033
Brand in the listing	0.864	0.453	0.003	**–2.004****	0.039	2.57E-06	0.354	0.760	0.002
Price in the listing	–2.690	0.171	3.111	**6.153****	0.028	3.45E-04	3.838	0.388	0.025
Promotion in the listing	1.358	0.101	0.057	0.073	0.934	1.095	–0.042	0.961	0.924
Place in the listing	**2.948****	0.012	0.001	0.204	0.872	7.69E-05	**–1.969****	0.026	3.198
Transactional Percentage in the listing × rank	**0.842*****	0.008	2.66E-04	**1.042*****	0.009	2.88E-04	0.117	0.743	0.004
Similarity between listing and cumulative text	–1.043	0.108	0.210	–0.881	0.108	4.05E-07	0.552	0.286	5.07E-05
Number of query words	**–1.626****	0.044	1.35E-04	0.152	0.826	0.841	1.059	0.122	0.167

Notes. Bold font indicates significant *p*-values.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 8. Results of Listing Inspection Duration Model

	TRAN			INFO			NAVI		
List inspection duration	Parameter	*p*-value	SD	Parameter	*p*-value	SD	Parameter	*p*-value	SD
Intercept	**6.523*****	0.000	0.003	**6.700*****	0.000	2.6E-05	**6.102*****	0.000	0.040
Section_O	**−0.436*****	0.003	0.008	**−0.431*****	0.001	2.8E-04	**−0.298****	0.031	7.9E-06
Section_T	**−0.400*****	0.003	0.491	**−0.539*****	0.000	1.3E-05	**−0.304****	0.017	8.0E-05
Rank of listing	−0.044	0.457	0.026	−0.020	0.725	0.012	0.065	0.309	0.040
Require moving downward	**0.112***	0.081	0.303	**0.142****	0.021	1.5E-04	0.002	0.980	0.068
Distance to previous listing	−0.045	0.456	0.058	−0.072	0.276	0.077	−0.086	0.249	0.001
Listing at top	−0.043	0.666	0.007	0.116	0.211	0.263	0.102	0.307	0.153
Listing at middle	0.070	0.361	0.009	**0.256*****	0.000	0.104	**0.334*****	0.000	0.005
Different section	0.023	0.752	0.002	**0.134****	0.048	0.093	−0.044	0.519	0.100
Repeat list	**0.866***	0.097	0.096	−0.462	0.368	0.191	−0.130	0.763	2.9E-04
Recency if is repeat	**−0.139*****	0.005	0.008	**−0.071***	0.073	0.120	**−0.156*****	0.000	0.007
Attribute in the listing	−1.742	0.151	0.024	0.672	0.301	3.6E-06	−2.565	0.541	1.7E-04
Quality in the listing	−0.213	0.885	0.025	1.292	0.160	0.003	−2.956	0.476	4.315
Brand in the listing	**−2.469***	0.064	0.019	1.004	0.247	3.2E-04	−1.315	0.758	0.549
Price in the listing	−1.760	0.300	0.313	−0.935	0.628	4.238	−3.751	0.438	0.045
Promotion in the listing	−1.215	0.352	0.014	1.093	0.196	1.7E-04	−1.642	0.693	4.4E-04
Place in the listing	**−2.912****	0.050	0.011	0.795	0.433	0.801	−2.742	0.509	0.910
Transactional percentage in the listing × rank	0.020	0.916	0.133	−0.203	0.388	1.029	−0.002	0.992	0.003
Similarity between listing and cumulative text	**−1.071*****	0.052	0.008	0.397	0.450	0.162	0.114	0.796	1.8E-05
Number of query words	0.503	0.316	0.549	**−0.974****	0.045	0.001	0.000	1.000	0.002
Cumulative duration on the listing	0.146	0.296	0.012	0.046	0.718	0.239	−0.023	0.861	0.001
Number of words in listing	1.557	0.195	0.060	**−1.307****	0.040	0.181	2.807	0.502	5.4E-05

Notes. Bold font indicates significant *p*-values.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

task are more likely to prolong their gaze duration when inspecting listings that are in a new section; across all three tasks, inspection is abbreviated if the listing was recently examined. Viewing centrality plays a significant role in informational and navigational tasks. Listings in the middle part of the screen receive longer gaze times than those in the top or bottom areas. Thus, inspection comfort may prelude detailed assessment.

Semantic-wise, consumers shorten their inspection of a listing if it has a similar composition to the cumulatively viewed semantic information in the transactional task, yet they will not do so in the other two tasks. This pattern may reflect a stronger desire to explore different listings and expand the search scope when searching for the best websites to conduct a transaction. In addition, more place- and brand-related information in a listing tends to shorten inspection length; because these information categories are more structured and might be easier to process, there may be no need to dwell. We also find that when more words matched the search query, this decreased inspection time in the informational task, perhaps because merely repeating the search query is not useful for the product-learning goal.

7.6. Click Decision

Table 9a shows the distribution of clicks across listings in the three search tasks. Although most of the clicks fall on the listings above the fold (e.g., the rank effect is the strongest in navigational searches, with the share of clicks close to 86%); in transactional searches, below-the-fold listings still enjoy approximately 33% of clicks. Comparing click-through rates for each result section across search tasks, we find that although there is no significant difference in the share of clicks falling on organic results (approximately 83%), the top-sponsored section in transactional and informational searches (approximately 16% and 13%, respectively) get significantly more attention from users than in navigational searches (approximately 6%, $p = 0.012$).

Semantic-wise (Table 9b), clicked listings feature an average of 23.50% more attribute information than

Table 9a. Distribution of Clicks Across Listings

Clicks	All Tasks		TRAN		INFO		NAVI	
	T and O	S	T and O	S	T and O	S	T and O	S
T1	25		8		8		9	
T2	20	0	5	0	13	0	2	0
T3	12	1	10	0	2	1	0	0
O1	233	7	58	0	74	0	101	7
O2	88	7	15	1	35	0	38	6
O3	46	8	26	2	16	6	4	0
O4	17	0	6	0	6	0	5	0
O5	9	0	3	0	4	0	2	0
O6	11	3	3	0	6	0	2	3
O7	12		4		5		3	
O8	2		1		1		0	
O9	1		1		0		0	
O10	1		0		0		1	
Above the fold/Total			67.13%		75.14%		85.79%	

Notes. To facilitate comparison, we color-coded each task separately (except for the Above the fold/total line). In line with the SERP layout, the left panel in each box represents listings from T1–O10; the right panel in each box represents listings from S1–S8. The section above the dashed line represents the above-the-fold subscreen on SERPs.

nonclicked listings ($p < 0.000$). More brand information also leads to a higher click likelihood for informational and navigational tasks. However, consumers in these two tasks were less likely to click on the listings that were heavy on promotion information. For the transactional task, the clicked listings featured significantly more place information (13.92%, $p = 0.001$) than its counterparts. Last, having the search query words in the listing seems to encourage click-through in all three search tasks.

Similar patterns emerge in click model results (Table 9c). As for spatial characteristics, listings in the O section are more likely to be clicked across all three tasks, whereas the T section is the least preferred in the navigational search. Interestingly, conditional on visual inspection, a listing's rank does not help explain the click decision. This suggests that the main benefit of being placed in top positions is a higher probability of being noticed. Prior inspection behavior on the listings also matters. For informational and navigational tasks, listings that have been inspected for a longer time are more likely to be selected for click-through; however, prior gaze duration on a listing does not help predict click decisions in a transactional task.

Semantic-wise, more promotion- and store-related (place) words encourage click-through in transactional tasks, whereas this content deters clicking in informational tasks; instead, having more brand information seems to elicit clicks in informational tasks. Last, we find that the listings clicked in the navigational task feature more attribute information.

8. Discussion

In display advertising, ad "viewability" is a core performance metric that distinguishes between the ad being served (i.e., loaded in a web browser or an app) and the ad being viewed (i.e., appearing on the screen for X+ milliseconds). Clearly, from a marketer's perspective, only the ads that are viewed can have an impact on consumer behavior and thus are of greater value to the advertiser. Therefore, minimizing losses from served but not viewed ads is a key concern to practitioners involved in display advertising. In the SEM domain, the measure of viewability is not that common. Although most advertisers recognize the importance of top-ranked positions in attracting consumers' attention to their listings, they do not use viewability as a standalone metric in their standard set of key performance indicators, which customarily include a listing's position, number of impressions, and clicks. In addition, the pay-per-click payment model used in SEM makes the ads that are served but not viewed somewhat of a lesser pain point compared with display ads charged on a cost-per-impression basis.

We argue that having a listing's viewability information (i.e., knowing if the listing that generated an impression was looked at by the searcher who chose to click somewhere else) could open various performance optimization opportunities to SEM practitioners. For example, this information could be helpful in diagnosing problems in a rank-bidding strategy. When the paid-search practitioner raises a bid amount, he or she expects an increase in click volume resulting from improved ad rank. The expected magnitude of the increase, however, is typically left to experimentation, where the relationship between ad rank and click-through rate is established empirically (e.g., Skiera and Abou Nabout 2013). The downside of this approach is that it does not take into consideration other factors that also affect ad performance, such as ad copy design. Knowing ad viewability in the target position would help predict the expected traffic increase resulting from an improvement in ad rank. A significant discrepancy between predicted and observed click volume may point to a problem with the ad copy. In other words, the ad might already be getting a fair share of consumer attention but underperforms in terms of stimulating clicks because of design issues. Thus, instead of focusing on more aggressive bidding (i.e., getting a presumably "better" position by paying more), the advertiser may want to work on the ad copy.

Assuming that listing viewability can be assessed for multiple positions on the SERP, SEM practitioners could identify the set of key "visual" competitors. By identifying listings that receive the most visual

Table 9b. Model-Free Evidence: Click vs. Nonclick (Inspected) Listings

Semantic variables	All tasks	*p*-value	TRAN	*p*-value	INFO	*p*-value	NAVI	*p*-value
Attribute	**23.50%**[a]	0.000	**19.82%**	0.000	**16.28%**	0.001	**34.98%**	0.000
Quality	–6.82%	0.431	–3.86%	0.798	–3.79%	0.794	–14.20%	0.151
Brand	**14.38%**	0.000	9.24%	0.133	**20.85%**	0.001	**12.50%**	0.001
Price	**–47.31%**	0.000	**–51.55%**	0.004	–28.62%	0.231	**–75.32%**	0.007
Promotion	**–35.97%**	0.000	–6.45%	0.508	**–74.28%**	0.000	**–36.60%**	0.000
Place	**9.31%**	0.062	**13.92%**	0.001	–6.97%	0.296	**17.58%**	0.098
Number of query words	**23.94%**	0.000	**13.74%**	0.004	**23.97%**	0.000	**29.93%**	0.000

[a]Calculated as (the measurement of clicked – the measurement of nonclicked listings)/the measurement of nonclicked listings.

Table 9c. Results for the Click Model

	TRAN			INFO			NAVI		
Click decision	Parameter	p-value	SD	Parameter	p-value	SD	Parameter	p-value	SD
Section_O	**2.609*****	0.000	4.6E-04	**1.921*****	0.000	0.547	**1.197*****	0.003	1.0E-18
Section_T	1.019	0.149	0.870	0.752	0.146	0.677	**−1.202****	0.012	6.3E-19
Rank of listing	0.166	0.628	1.170	0.515	0.105	0.585	0.143	0.687	8.4E-18
Number of repeated views	**0.912*****	0.001	0.404	**0.864*****	0.001	0.007	**0.656****	0.014	1.320
Total browsing duration of listing	0.849	0.280	3.3E-04	**2.180*****	0.000	0.258	**1.680*****	0.009	2.6E-16
Attribute in the listing	**2.249****	0.033	3.1E-04	−0.367	0.646	0.769	**2.948*****	0.001	1.306
Quality in the listing	**7.040***	0.071	6.107	−1.606	0.581	0.007	5.514	0.388	4.8E-09
Brand in the listing	**−6.989***	0.051	7.556	**5.014***	0.061	3.899	−2.978	0.270	6.660
Price in the listing	−8.988	0.253	0.003	−0.857	0.922	0.023	−286.322	0.914	15.822
Promotion in the listing	**4.058***	0.052	0.001	**−10.939*****	0.003	0.004	0.460	0.818	0.003
Place in the listing	**8.402****	0.007	16.116	−1.878	0.528	2.951	2.756	0.108	1.5E-17
Number of query words	2.622	0.226	0.001	**4.176****	0.014	0.003	1.774	0.274	9.590

Note. We employ a control function approach (Petrin and Train 2010, Ebbes et al. 2016) to correct for endogeneity bias in the "Total browsing dura of listing" variable across three search tasks.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

attention on a given page, SEM managers would have a better understanding of effective ad design (in search engine advertising) or page titles and meta descriptions of webpages (in SEO). For example, they could tailor their promotional message relative to competitors' offerings (e.g., Animesh et al. 2011) that receive the most attention on a given SERP. Instead of competing with everything that appears on the same page, marketers can focus on a few selected listings that consumers are more likely to compare against their own listing.

Although the value of listings' viewability information is easily recognizable, the data are not available to SEM practitioners. First, collecting such data by search engine (e.g., using webcams or mouse movement tracking that is shown to correlate with gaze location; Chen et al. 2001) would certainly raise consumer privacy issues. Second, assuming the data are collected, it will not necessarily be in the search engine's interests to share the data with advertisers. Although the analysis of economic implications of data sharing is beyond the scope of this research, we note that historically very little detail about consumers' interactions with a search engine is revealed to advertisers.

Thus, because a direct solution for getting a listing's viewability data to the SEM community is probably not feasible at this point, this paper provides some insights that may help practitioners start incorporating viewability consideration into their decision making. The results of our model-free and model-based analyses support the notion that the listing's content, the semantic context it is placed in on the page, and consumers' search intent all affect how the visual inspection process of SERP unfolds and, accordingly, how much of consumers' attention the listing may get. Although, not surprisingly, we find strong evidence that the top listings in the organic section are the most attractive placements for getting consumers' attention, given the significant costs associated with obtaining these premium positions, it might be worthwhile to broaden the placement strategy by identifying alternative locations on the given SERP that could still produce reasonable results. In Table 10, we summarize some of our empirical findings that could assist practitioners in this endeavor.

First and foremost, we want to emphasize the importance of the searcher's intent (i.e., the search task) in shaping the inspection process. The differences in search patterns across search tasks are prominent in the number of listings and subscreens inspected, scroll frequency and timing, and clicking preference. Specifically, navigational searches focus mainly on the top part of the page, with sponsored listings getting the least amount of attention across the three search tasks. Thus, if navigational keywords are the target for the firm, a greater emphasis should be placed on SEO efforts. Transactional searches manifest the broadest scope of inspection, with a significant amount of visual attention falling below the fold and the top-sponsored section being the most effective compared with the other two tasks. In other words, not making it all way to the top of a SERP is less of a problem in transactional searches and lower listings still have a good chance of being viewed. Paired with our finding that relative rank does not have a significant effect on the click decision conditional on visual inspection (Table 9c), we consider this good news for practitioners targeting transactional search terms because they still attract traffic to their websites from less premium positions. However, it is also important to keep in mind that the number of visual competitors can be higher for transactional tasks than the other two tasks, as the scope of inspection is the largest. Thus, particular

Table 10. Summary of Key Results and Implications for Practitioners

<table>
<tr><th></th><th></th><th colspan="3">Impact of search task[a]</th></tr>
<tr><th></th><th></th><th>Transactional</th><th>Informational</th><th>Navigational</th></tr>
<tr><td>General inspection patterns</td><td></td><td>• Highest number of listings and subscreens inspected
• Highest number of scrolls and highest likelihood of going below the fold
• Shortest attention span per listing</td><td>• Longest average inspection time per listing</td><td>• Lowest number of listings and subscreens inspected
• Lowest number scrolls and lowest likelihood of going below the fold</td></tr>
<tr><td>Impact of semantic</td><td>Listing's semantic composition[a]</td><td>• Listings with more transactional words get more attention in terms of repeat inspections and are more likely to be clicked.</td><td colspan="2">• Listings with more descriptive words receives more clicks.
• Listings heavier on transactional content are less likely to be repeatedly inspected or clicked.</td></tr>
<tr><td></td><td>Semantic context</td><td>• Cumulative semantic information is not a strong predictor for subsequent inspection decisions regarding scrolling and subscreen choice.
• Most recently inspected content is predictive for scrolling.
• The inspection duration is shorter for a listing of similar semantic composition with cumulatively viewed semantic information.</td><td colspan="2">• Cumulative semantic information is predictive of subsequent inspection decisions regarding scrolling and subscreen choice.</td></tr>
<tr><td>Impact of location</td><td>Listings rank and section[a]</td><td colspan="3">• Higher ranked listings are more likely to be noticed (inspected).
• Organic section gets approximately 83% of all clicks.</td></tr>
<tr><td></td><td></td><td>• Listings above the fold receive 67.13% of clicks.
• Top-sponsored section gets highest (~16%) share of clicks.</td><td>• Listings above the fold receive 75.41% of clicks.</td><td>• Listings above the fold receive 85.79% of clicks.
• Top-sponsored section gets the least share (~6%) of clicks.</td></tr>
</table>

[a]Denotes variables that can be influenced by SEM managers.

attention should be dedicated to the listing's content because it is likely to be compared with multiple alternatives featured on the SERP.

Our second takeaway pertains to the role of the semantic context in which the listing is placed. Across our various microdecision models and model-free analysis, we consistently find a connection between semantics and the inspection course. In addition, the role of semantics changes across the tasks. Using our proposed text categorization approach, we find that users in informational and navigational tasks show some degree of localized search behavior such that they stay within the same part of the page when exposed to more attribute or quality information. In turn, exposure to some other types of content (e.g., name of the online store) is more likely to trigger a move to other parts of the page (Table 6). Interestingly, a localized search is not observed in transactional tasks, where the motivator for staying in or moving out of an area is the content of the most recently inspected listing (e.g., encountering price information encourages further exploration, whereas place information leads to scroll). From the practitioner perspective, these results suggest that having their listing placed in the "neighborhoods" of listings that feature attribute or quality information in informational and navigational tasks or price information in transactional tasks may increase the chances of the target listing being inspected.

A final takeaway relates to the listing's composition. Specifically, semantic congruency with search goals is essential in directing attention. Our model results consistently suggest that transactional information (e.g., price, promotion, place) encourages attention and click-through for consumers in transactional tasks, whereas this information backfires in informational and navigational tasks. Instead, descriptive information (e.g., brand, attribute, quality) promotes attention and click likelihood when the goal is to learn more about a product or to locate the official website. Moreover, if the marketer's goal is to prolong the inspection duration of the target listing, making the listing's content stand out in transactional searches may help achieve this outcome.

9. Limitation and Future Research

Our study has several limitations that also present opportunities for further research. First, the focus of this paper is on the visual inspection of SERPs, which is only one element in a complex consumer purchase process that involves numerous activities, including visitation to various websites, product comparisons, and ultimately a purchase decision. A next logical step in developing this stream of research would be to incorporate these downstream decisions. Second, some consumers return to the SERP after clicking on one of the listings to continue page inspection. Our current analysis does not consider such inspections, so this could be another worthwhile extension. Third, the participants used in the current studies are mainly undergraduate students; future studies should try to analyze the behavior of a more diverse group of consumers. Questions such as the information overload problem on SERPs and the optimal allocation of sponsored and organic search spaces are also promising areas for further exploration. Finally, in terms of the modeling approach, a more flexible model with time-varying effects (e.g., based on a hidden Markov model) might be considered to potentially provide insights into the studied phenomenon.

To conclude, we believe that our work makes an important contribution to the marketing literature by shedding light on the largely unexplored process of visual inspection of SERPs and the role of the semantic environment in driving consumers' attention. Using eye-tracking tools, we are able to offer novel insights into the microlevel decision-making processes consumers are engaged in while interacting with search engines. It is of both academic and managerial interest to further our understanding in this leading area of digital marketing.

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Endnotes

[1] Although the SERP layout may vary across major search engines (i.e. Google, Bing, Baidu, Yandex), all of them feature a combination of organic and sponsored results, with sponsored sections being clearly marked.

[2] We choose not to include the inspections that may occur if the user returns to the *same* result page after the first click-out because interactions with other pages and websites beyond the search engine introduce confounding factors that are technically difficult to control for when consolidating with the preclick inspection analysis.

[3] We combine consecutive fixations on the same listing into a single inspection event.

[4] To mitigate the multicollinearity problem, we used the percentage of transactional information (i.e., price, promotion, and place) in a listing to measure the semantic composition.

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