# The User-journey in Online Search
## *An Empirical Study of the Generic-to-Branded Spillover Effect based on User-level Data*

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Abstract: Traditional metrics in online advertising such as the click-through rate often take into account the users' search activities separately and do not consider any interactions between them. In understanding online search behavior, this fact may favor a certain group of search type and, therefore, may mislead managers in allocating their financial spending efficiently. We analyzed a large query log for the occurrence of user-specific interaction patterns within and across three different industries (clothing, healthcare, hotel) and were able to show that users' online search behavior is indeed a multi-stage process, whereas e.g. a product search for sneakers typically begins with general, often referred to as generic, keywords which becomes narrowed as it proceeds by including more specific, e.g. brand-related ("sneakers adidas"), keywords. Our method to analyze the development of users' search process within query logs helps managers to identify the role of specific activities within a respective industry and to allocate their financial spending in paid search advertising accordingly.

## 1 INTRODUCTION

Selling advertising linked to user-generated queries, the so-called sponsored search has become a critical component of companies marketing campaigns (Ghose and Yang, 2008). Although more than half of all search processes by individual users consist only of one query (Jansen and Mullen, 2008), consumers that have a transactional intention often do not reach their goals by conducting only a single search (Search Engine Watch, 2006). An aspect also confirmed by (Rutz and Bucklin, 2011). They demonstrate the so-called "spillover effect" from generic to brand-related searches for a company in the hospitality industry: the generic search ("hotel") and the corresponding advertisements by the hotel chain in question significantly contributed to the fact that users later turned to brand-related searches for this hotel chain (e.g. "hotel hilton") and finally to corresponding reservations. Their initial work clarifies how traditional metrics in online advertising such as the click-through rate (CTR) are alone no adequate tools to control for paid search advertising campaigns: they only take into account the users' search activities singularly and do not consider any interactions between them.

Our analysis is based on a complete query log published by AOL in 2006 (Pass et al., 2006) and explains users' search activities in more behavioral detail. Unlike (Rutz and Bucklin, 2011), who used keyword-level data aggregated on a daily basis of a paid search advertising campaign of a single company, we analyzed users' individual queries within and across entire industries in order to determine whether the resulting user-journey showed behavior indicating spillover effects. As evidence of such a spillover we regarded a user-journey that, for example, started with a generic and was followed by a brand-related search. We investigated and confirmed the spillover effect and its occurrence in users' online search behavior for several industries and, by doing so, highlighted the role of generic activities as gatekeepers for companies' online advertising. To the best of our knowledge, our work is the first to analyze a complete query log for the occurrence of the spillover effect and thus makes a contribution to research on consumers' online behavior. In addition, an improved understanding of the role of generic activities and of how consumers actually search for products and brands to satisfy their needs will help advertisers to allocate their budget on online advertising more efficiently.

The paper is structured as follows: first, we will review existing work on consumer online search behavior in general as well as in the specific context of

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paid search advertising. In the next chapters we will describe our method of analyzing spillover effects in query logs and introduce our dataset together with the filtering procedures applied. Next, we focus on the results of spillover effects across several industries. The last sections contain a discussion of our findings and will close this paper by mentioning the limitations of our study and by giving suggestions for further investigations.

## 2 RELATED WORK

The detailed records of users' Internet activities opened up the possibility of analyzing a variety of topics, such as consumers' online search behavior (see, for example, (Bucklin and Sismeiro, 2009) for a review and discussion of strengths and limitations of clickstream data for marketing research). General research classifies consumers' online searches into navigational, transactional, and informational purposes (Broder, 2002; Jansen and Spink, 2007). According to (Moe, 2003), searches heavily depend on the individual purchase intent such as involvement: while directed-buying sessions present very narrowly aimed shopping behavior, consumers with low purchase intention exhibit much broader search patterns for unspecific products. (Johnson et al., 2004) confirm that the depth of consumer search is generally low and shows no increase with a consumer's growing experience. This aspect is confirmed by analyses showing that the CTR on a search engine's (sponsored) link decreases with its position (Agarwal et al., 2011; Animesh et al., 2011; Ghose and Yang, 2009; Rutz et al., 2011). Despite the amount of literature focusing on users' search behavior no work has yet considered possible differences of this behavior across industries - an aspect considered and analyzed in more detail in the present paper.

The empirical analysis of sponsored search has only recently begun to become the focus of the scientific community. (Ghose and Yang, 2009) examine the general impact of paid search advertising on measures such as the relationship between the type and length of keywords and different variables on consumers' click and conversion behavior. Although the authors uncover important differences in the click and purchasing intensity regarding a specific group of keywords, they miss to account for users' interactions between them. (Chan et al., 2011) build an integrated model of customer lifetime, transaction rate, and gross margin accounting for spillovers from sponsored search on customer acquisition and behavior in offline channels. Their results indicate that customers who were originally acquired through paid search advertising on Google have a significant higher lifetime value (about 20%) than customers acquired from other channels. In a recent study, (Rutz et al., 2011) criticize the common assumption that users respond homogeneously to keywords. The authors formulate a consumer-level approach to especially evaluate textual properties of paid search ads on consumers' responses and account in this way for heterogeneity. Besides several findings referring to the consumer-integrated focus, the authors confirm that keyword-specific factors, like the distinction between broad and narrow purposes, are important when linking searches to a CTR (see also (Ghose and Yang, 2009)). This stream of research typically uses aggregated-level data. Although the majority of papers discussed above claim a more behavioral focus on how users respond and act in the context of search engines, they only scratch the surface of an analysis of consumers' actual online search behavior (see (Abhishek et al., 2011) for discussion of aggregation bias in sponsored search data).

This paper is most closely related to (Rutz and Bucklin, 2011), who are able to demonstrate the spillover effect from generic to brand-related searches for a company in the hospitality industry. The generic search ("hotel") and the corresponding ads of the advertising hotel chain significantly contribute to the fact that users later turn to brand-related searches for this hotel chain (e.g. "hotel hilton") and finally to corresponding reservations. We will explore the differences between Rutz and Bucklin's method and our approach in the following chapter more closely.

## 3 DATA AND METHODOLOGY

Our analysis is based on a log published by AOL which consists of over 35 million queries from about 650,000 users over a three month period (March to May) (Pass et al., 2006).[1] Although this dataset dates back to 2006, it is still an unique and comprehensive query log containing extraordinary information about users' search and click behavior, which may be found in todays search engines like Google or Bing.[2]

In terms of analyzing user-journeys for specific behavioral aspects, such as the spillover effect from generic to brand-related searches, we, first, needed to define industries and, second, companies within

[1] Since the users who represent the queries are mostly located in the United States of America, our work is mainly based on the US region.

[2] We would like to thank an anonymous reviewer for pointing out this more clearly.

these. It was only then that we were able to categorize user queries into generic and brand-related types of searches respectively and to make a definite statement about both the existence and the extent of industry-specific interaction effects between generic and brand-related search activities.

We will explain this process in more detail in the following chapters. Please find all additional data and information such as the list of selected companies, keywords, or our final filtered query log on the author's website: *http://www.nottorf.org*.

## 3.1 The Initial Query Log

The log includes 36,389,567 records structured in five columns (see Table 1 for a short excerpt of the data):

- *AnonID:* A unique identification number of an anonymized user.
- *Query:* The user's query.
- *QueryTime:* The point of time at which the query was submitted for search.
- *ItemRank:* In case a user clicked on one of the result pages, the "ItemRank" shows the site's position in the result pages. If no page was selected, this field remained empty.
- *ClickURL:* Shows the URL of the clicked result (Pass et al., 2006).

We focused on three industries: the *hotel and hospitality industry* to make our findings comparable with those of (Rutz and Bucklin, 2011); the *clothing industry* as a representative of nondurable goods with the influence of brand strength being assumed to be strong; and the *healthcare industry* as a representative of the insurance sector. We further restricted our analysis to the top ten companies in 2006, their ranking being based on revenue and brand strength within a certain industry (Interbrand & Business Week, 2006). We did so on the assumption that these companies represented the major number of possible brand-related search activities within a specific industry. The consequences of this approach will be discussed later, for example of the fact that we did not consider the total number of brand-related or generic search activities recorded in the query log.

On the basis of the industries selected and each of the ten companies we filtered out generic and brand-related queries from the initial query log.

## 3.2 The Filtering Process for Queries

For each of the ten companies within each industry we defined **brand-related keywords** to analyze a specific query for their occurrence and, as the case may be, marked the query as a branded search. Because of the fact that many of the selected companies have subsidiaries, we had to define a set of keywords that were related to the parent-company.[3] We organized the brand names and keywords in hierarchical order as shown in Figure 1. Based on this structure we applied tools (e.g. the online toolset given by Google AdWords) to identify keywords that are often searched for in the context of the brand names mentioned.

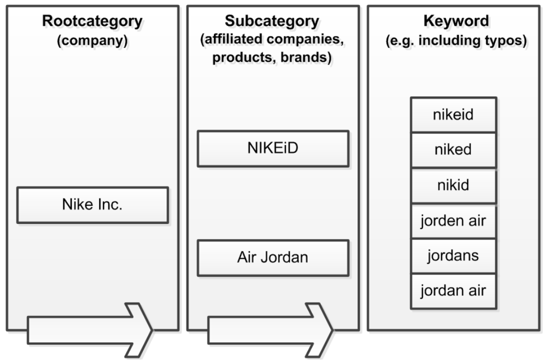


Figure 1: Structure of the filtering process of brand-related keywords.

We started with the company names (e.g. "Nike Inc."), which were placed in the root section of this structure. Next to it we put brand and product names which we derived from the company's information itself (e.g. "NIKEDiD" or "Air Jordan") and from the help of the keyword tools mentioned above. On the basis of these subcategories was defined the final set of keywords (e.g. "nikeid", "nikid", or "jordans") for our analysis (see the right column of Figure 1). In this section were also taken into account variant names and typing errors. However, we defined 120 brand-related keywords for the healthcare, 228 for the hotel, and 720 for the clothing industry.

Defining the set of **generic keywords** required us to limit which queries could directly be related to the mentioned industries. Therefore, we may have had to consider those queries that had no direct relationship to a specific industry and its companies or products, but still were able to generate clicks on links to these companies. For example, the analysis of the hotel industry raised the question whether the search for a country or a flight could have already be seen as a generic query or not. It is possible that a selection of a final dataset that is too comprehensive may also cover users who do not have the intention to purchase something at all. This is a problem every paid search advertising campaign has to face to some extent, since advertisers want to become displayed and ranked when

[3]The Harrah's Entertainment Inc., for example, had about 21 hotels and hotel chains in 2006.

Table 1: Extract from the AOL dataset.

| AnonID | Query | QueryTime | ItemRank | ClickURL |
|---|---|---|---|---|
| 1927 | does bcbs cover ci | 03.05.2006 00:24 | | |
| 1927 | does bcbs fl cover ci | 03.05.2006 00:25 | | |
| 7117 | www.anthem.com | 09.05.2006 09:33 | 3 | http://www.maine.nea.org |
| 7117 | www.anthem.com | 09.05.2006 09:33 | 4 | http://hr.nd.edu |
| 7117 | www.anthem.com | 10.04.2006 06:57 | 1 | http://www.myuhc.com |

a possible consumer searches for products or services that the respective company offers. The consequences of a potentially incorrect or incomplete selection will be discussed later.

We proceeded from the advertiser's point of view and defined generic keywords that reflected the intention to gather information about the product or to purchase it. Hence, we restricted our set of generic keywords to directly product-related terms, their synonyms and variations. To achieve this, we also made use of the keyword tools referred to above but mostly we derived the keywords manually by gathering general information from the companies' websites. Thus, we defined 196 generic keywords for the healthcare (e.g. "health care", "dental insurance", "medicare"), 335 for the hotel (e.g. "hotel", "motel", "suites"), and 197 for the clothing industry (e.g. "shoes", "shorts", "underwear").

On the basis of our brand-related and generic keywords we **filtered and categorized** the query log records (see Figure 2). First, all log records whose "Query"-columns contained brand-related keywords were moved into an industry-specific table and were marked as brand-related queries. This ensured that a record with both brand-related and generic keywords appearing in the same query was not duplicated. The second step was to filter the reduced dataset (without brand-related queries) on the basis of generic keywords, which were moved to the three industry-specific tables with only generic queries. Ideally, the remaining dataset should no longer have contained any relevant queries. It is important to mention that our procedure also filtered out log records that were not related to the industries selected. This was due to the fact that some queries occur also within an irrelevant context. We handled this problem by manually scanning the filtered data and by deleting records giving information about an irrelevant context (e.g. queries in a pornographic context).

The records not only contain information about a user's query itself but also the URL of a **clicked result**. We distinguished between URLs on pages that were related to the ten companies defined above and between URLs that were not, such as websites of retailers (e.g. "www.ebay.com" or "www.amazon.com"). Thus, we were able to separate relevant clicks (from the perspective of the ten companies) from irrelevant ones and were in a position to make more precise statements about the effects of generic and/or brand-related searches. To determine those (relevant) clicks we analyzed the information contained in the "ClickURL"-column of our final dataset and manually checked whether the clicked pages were related to the companies examined. Following this procedure, we identified 244 websites for the clothing, 298 for the healthcare, and 838 for the hotel industry.

The total number of unique users, of impressions, and of (relevant) clicks in our final dataset for each industry following our filtering procedure are shown in Table 2. The resulting **descriptive statistics** confirm strong differences in efficiency between generic and brand-related keywords. Although we filtered out far more generic than brand-related queries from the initial query log, the number of clicks in response to branded searches was much higher. This fact results in quite different CTRs as already shown by e.g. (Ghose and Yang, 2009; Ghose and Yang, 2010), (Rutz and Bucklin, 2011), and (Yang and Ghose, 2010). Companies focusing only on these statistics might conclude that the concentration on brand-related keywords and the neglect of generic terms would increase profitability since the metrics for key-

Table 2: Descriptive statistics on the final dataset.

| **Hotel** | Users | Imp. | Clicks | CTR |
|---|---|---|---|---|
| Generic | 71,405 | 327,563 | 3,801 | 1.16% |
| Branded | 32,039 | 97,070 | 21,154 | 21.79% |
| Total | 84,408 | 424,633 | 24,955 | 5.88% |
| **Clothing** | Users | Imp. | Clicks | CTR |
| Generic | 51,105 | 293,645 | 350 | 0.12% |
| Branded | 14,225 | 46,586 | 5,695 | 12.22% |
| Total | 58,166 | 340,231 | 6,045 | 1.78% |
| **Healthcare** | Users | Imp. | Clicks | CTR |
| Generic | 10,876 | 33,115 | 719 | 2.17% |
| Branded | 9,304 | 20,516 | 7,896 | 38.49% |
| Total | 18,255 | 53,631 | 8,615 | 16.01% |

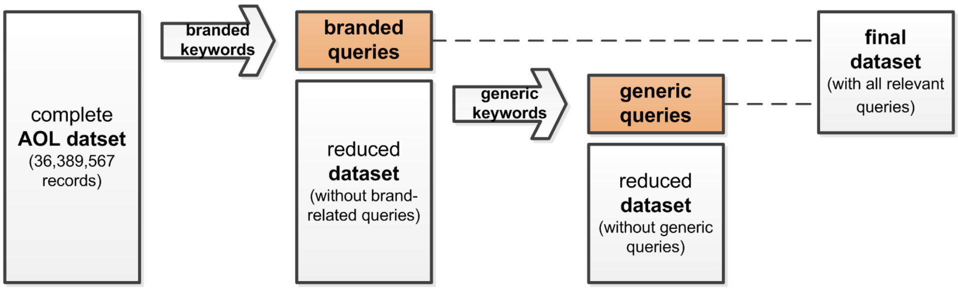


Figure 2: Schematic illustration of the filtering procedure for a given industry.

words containing brand-specific information seem to be more effective than for those keywords describing generic purposes. The major problem of these types of keyword-based analyses is, however, that they only link users' actions to a specific keyword one at a time and do not consider any interactions between several searches and clicks. We, on the other hand, aimed at a processual analysis of the data and considered the development of users' search activities over time.

### 3.3 Indicating Spillover Behavior in Query Logs

The development of the search process from generic to brand-related searches may be attributed to the fact that individual brands gain the users' attention during the search process. We defined two levels of the spillover effect in user-journeys:

**Spillover Behavior Level 1.** *A user-journey shows a generic-to-branded spillover effect, when a user first searches for generic and next, at any further time, for brand-related terms.*

**Spillover Behavior Level 2.** *A user-journey shows a generic-to-branded spillover effect, when a user first searches for a generic term and her last search that leads to a (relevant) click is a brand-related one.*

For each of the two definitions we assigned all considered user-journeys to the four fields in a 2x2 matrix (generic→branded, generic→generic, branded→branded, branded→generic). For the level 2 spillover effect we obviously had less user-journeys than for level 1, since we required those users to had at least one (relevant) click in their journeys.

Our analysis is different from the one of (Rutz and Bucklin, 2011) as we utilize user-level instead of keyword-level data. Rutz and Bucklin use the daily number of generic searches and clicks as independent variables modeling a latent construct of awareness which in turn affects the number of brand-related searches. In addition, they use data from a paid search advertising campaign of one company thus having a clear boundary of the study.

The fact that we built our analysis on a complete query log further enabled us to consider user-specific behavior within a whole industry instead of analyzing keyword-level data aggregated on a daily basis for just one company. We captured all search activities for three different industries and determined the number of users who searched for either generic or brand-related terms only, alternatively, performed spillovers from generic to brand-related searches and vice versa. In addition, we were able to establish the point of time when a user performed an action and analyzed the exact time span in which possible spillover effects might occur.

## 4 RESULTS

### 4.1 Spillover Results

The results of the spillover analysis for each industry following the **level 1 spillover definition** are shown in Table 3. It shows the proportion of all unique users in relation to each group of user-journeys, resulting in a 2x2 matrix for each industry.

The results indicate that the interaction effects between generic and brand-related searches differ across industries. Take, for instance, the healthcare industry. Here, 41.1% of all users conducted only brand-related and 48.3% only generic searches. Note that these homogeneous groups also contain user-journeys with only a single search. The remaining 10.6% of all users who switched either from generic to branded or from branded to generic searches during their user-journeys divide nearly equally into the two hybrid groups. There is no clear sign of users' favoring one specific interaction direction within the healthcare industry.

The results for the clothing industry, on the other hand, indicate at least a small spillover behavior from generic to brand-related search activities. We found

Table 3: Proportions of first search activities within user-journeys per industry (spillover behavior level 1).

| **Hotel** | to generic | | to branded | |
|---|---|---|---|---|
| from branded | 8.6% | (7,258) | 20.8% | (17,523) |
| from generic | 56.7% | (47,849) | 13.9% | (11,778) |
| **Clothing** | to generic | | to branded | |
| from branded | 4.7% | (2,720) | 15.0% | (8,784) |
| from generic | 72.6% | (42,218) | 7.7% | (4,444) |
| **Healthcare** | to generic | | to branded | |
| from branded | 4.9% | (897) | 41.1% | (7,509) |
| from generic | 48.3% | (8,821) | 5.7% | (1,028) |

Note: Both the percentage and the total number (in brackets) of all unique users within one of the journey-groups are represented for each industry.

Table 4: Percentages of first search activity and last search activity before a click within user-journeys per industry (Spillover behavior level 2).

| **Hotel** | to generic | | to branded | |
|---|---|---|---|---|
| from branded | 2.7% | (338) | 50.9% | (6,428) |
| from generic | 12.7% | (1,602) | 33.7% | (4,206) |
| **Clothing** | to generic | | to branded | |
| from branded | 0.9% | (36) | 63.9% | (2,532) |
| from generic | 6.2% | (244) | 29.0% | (1,150) |
| **Healthcare** | to generic | | to branded | |
| from branded | 1.0% | (58) | 80.0% | (4,206) |
| from generic | 9.0% | (471) | 10.0% | (523) |

Note: Both the percentages and the total number (in brackets) of all unique users within one of the journey-groups are represented for each industry.

a large number of users searching only for generic terms (72.6%) while a much smaller group searched only for brand-related ones (15.0%). Although there were no more than 12.4% of users in total conducting hybrid searches, there were 3.0% more user-journeys starting with a generic search that was followed by a brand-related one (7.7%) than in the opposite group (4.7%). Users looking for articles in the clothing industry, such as shirts, shoes, or underwear, seemed to switch more likely their type of search from generic to brand-related terms than from brand-related to generic ones.

An obvious sign of spillover behavior was shown by the results for the hotel industry. Here, nearly 14% of all users switched to brand-related searches after they initially searched for generic terms. Although the opposite group, starting with branded and switching to generic terms, was also relatively large (8.6%), it significantly differed from the actual spillover group. This can be seen as evidence for the fact that users' search behavior within the hotel industry initially started with broad and general search terms (e.g. "hotel", "bed and breakfast", "suite") which became more (brand-)specific as the search proceeded (e.g. "harrah", "sheraton", "hyatt").

Table 4 shows the results for the **level 2 spillover effect**. The focus in this spillover definition on users' clicks on (relevant) links led to a shift in favor of brand-related keywords. This is not surprising since the brand-related queries received far more clicks compared to generic ones (see Table 2). But, similar to the differentiation into an exploratory and a goal-directed searching mode (e.g. (Janiszewski, 1998) and (Moe, 2003)), this alternative spillover analysis has the ability to differentiate between users intending to purchase something (which results in a click) and users behaving in a less goal-directed manner (resulting in no click on a company's website). We acknowledge that there might be a purchase intention even if a user did not click on a link to a company's website (e.g., that a user clicks on a third party's link, such as Amazon or Ebay).

This analysis shows very strong evidence for spillover behavior. See, for example, the results for the hotel industry. Here, 33.7% of all users that clicked on a company's link started their user-journeys with a generic search and switched to a brand-related one. This means that more than one third of these users first looked for generic terms before they specified their searches using brand-related keywords and finally clicked and ended their search-to-click-processes. The magnitude of the effect for the hotel industry becomes even more pronounced, since the reverse-spillover effect (users that first searched for brand-related keywords before they conducted a generic search and clicked on a company's link) was the smallest of all four groups by far.

Similar findings to the hotel industry can be found for the clothing sector. Here, about 29% of all users that clicked on a company's link looked for brand-related terms after they conducted generic searches. The reverse-spillover is insignificantly small, since less than 1% of the users first searched for brand-related and afterwards for generic terms before they clicked.

Focusing on the healthcare industry, the findings of the level 1 spillover analysis can be partly confirmed. Again, a large number of users seemed to search only for brand-related or generic terms before clicking on a respective link. Nearly 90% of all users who clicked on a company's link did not switch their type of search, that is they searched only for either brand-related or generic terms. This fact had an immediate influence on the strength of the

Table 5: Time spans for each industry in which the Spillovers occurred.

| | Quantiles of time difference in days | | | | |
|---|---|---|---|---|---|
| Industries | 10% | 25% | 50% | 75% | 90% |
| **Hotel** | | | | | |
| Level 1 | 0.01 | 0.10 | 8.95 | 30.13 | 55.47 |
| Level 2 | 0.03 | 4.85 | 22.87 | 51.17 | 70.15 |
| **Clothing** | | | | | |
| Level 1 | 0.01 | 1.73 | 14.91 | 37.54 | 59.07 |
| Level 2 | 0.04 | 6.86 | 23.12 | 47.86 | 66.70 |
| **Healthcare** | | | | | |
| Level 1 | 0.00 | 0.02 | 4.95 | 22.01 | 49.91 |
| Level 2 | 0.01 | 0.72 | 12.07 | 37.26 | 60.90 |

Note: "Level 1" denotes the time differences in "Spillover Behavior Level 1". "Level 2" denotes the time differences in "Spillover Behavior Level 2" accordingly.

spillover effect from generic to brand-related search: only a relatively small number of users' (nearly 10%) first searched for generic terms and next conducted a brand-related one before they clicked on a corresponding link.

We are not able to fully explain this relatively small number of interactions between generic and branded terms, especially when compared to our findings for the hotel and clothing industry. Still, there are some differences in the data of the three industries (see Table 2) that may at least give a clue to this relative lack of interactions. For example, the total number of impressions within the healthcare industry is considerably smaller than in the two others. In particular, there are about ten times fewer generic impressions. Also, the CTR of the brand-related keywords is by far the highest. This can already be seen as an indicator for a relatively small interaction-rate between generic and brand-related searches, since these two metrics indicate that searches of a single type alone seem to be able to lead to a possible solution for the user.

## 4.2 Time Differences between Actions

Table 5 shows the time spans and the quantiles for each industry within which the generic-to-branded spillover effects occurred. "Level 1" denotes the time differences of spillover behavior from (first) generic to (first) brand-related searches (see the above definition of "Spillover Behavior Level 1"). The time that elapsed between the users' first generic search and last brand-related one that resulted in a click on a company's link is denoted by "Level 2" ("Spillover Behavior Level 2").

Let us first focus on the hotel industry. The results of the analysis of the time differences for the first spillover definition suggest that 25% of all users switched from generic to brand-related searches within only 2.4 hours. These users changed their search behavior very quickly when compared with the average time span of about 9 days (8.95) in which the generic-to-branded spillover occurred. As expected, the "Level 2"-results indicate a longer time difference since we focused on users' last brand-related search that led to a click on a company's link. Overall, our findings are consistent with the results of (Rutz and Bucklin, 2011) who find that the search process for lodging seems to be short and to occur mainly in between a couple of days to two weeks. We confirm an even shorter time difference on the basis of our results since we found many users who switched their type of search in between only a few hours and up to one day. That rest of the users spread their search process over the further investigation period, see Figure 3, seems likely to be a coincidence.

The results for the clothing industry show some deviations from those for the hotel industry. Although we expected a search process for garments to change in a shorter period of time from generic to brand-related terms, as it does in searches for the right hotel, this was not borne out by the findings for this industry. Indeed, the mean time span of the spillover behavior was about 2 to 3 weeks. This can be explained by the possibility of users being confronted with far more possibilities of choice compared to the hotel industry since competition in the clothing industry is not restricted to a certain location. In other words, a user searching for a hotel in a specific location (e.g. "hotel barcelona") might not have as many choice alternatives when searching for an appropriate room as a user looking for a specific garment (e.g. "hoodie jacket"). This circumstance could reduce the time users needed to spend on finding the right hotel. Another explanation of the relatively long time differences compared to the hotel industry is that searching for the garments might not be that selectively intensive and target-oriented as looking for the right hotel.

In the healthcare industry, the time spans in which the spillover occurred were the shortest by far. Focusing on the "Level 1"-results, 25% of all users whose journey showed spillover behavior switched the type of search within half an hour (0.02). The results of "Level 2" confirm this short interaction period since more than one out of four of all spillovers did not take more than one day even though considering the clicks. Following our previous chain of reasoning, this short period between switching from one search to the other appears reasonable: the (health) insurance sector is easily the least fragmented in comparison with the other two. This is demonstrated, for instance, by the

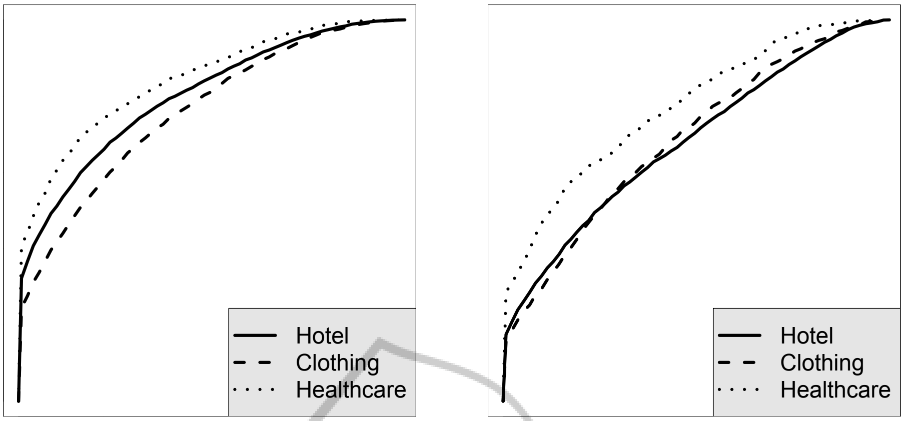


Figure 3: Time spans within which "Spillover Behavior Level 1" (Left) and "Spillover Behavior Level 2" (right) occurred.

total number of brand-related keywords that we defined for this industry (120) as opposed to the hotel (190) and clothing industry (720) industries. This limited number of keywords increases the probability of users switching to a brand-related search in a shorter period of time. Either they found the "right" company more easily or simply were in a more goal-directed mode compared to users searching within the clothing industry.

All results are additionally illustrated in Figure 3, which displays the respective number of user-journeys for each industry that showed a very short time span in which the spillover effects occurred (see the cumulative density at point "0 Days"). Further, it can be seen that each time span slowly approximates the total investigation period of 90 days. The analysis of the time difference provides evidence for both a substantial percentage of users that switched from generic to brand-related searches in a very short period of time (less than one day or several hours) and the average percentage of users that changed their type of search over several days or weeks.

## 5 DISCUSSION

Our results emphasize the role of generic search activity in the users' search and decision process since it is crucially important for companies and individual brands to gain the users' attention during the search process and thus probably to be considered a potential solution.

By investigating online search behavior we were able to show that traditional research vindicates and can be applied in the online setting. Following this literature, consumers' decision processes can be divided into at least two stages: the first is a set of products or brands a consumer is aware of at any given point of time. This is referred to as the "awareness set". In the second, the so-called "evoked set", a consumer is likely to reduce his or her set of products that the final decision is based upon (Howard and Sheth, 1968). Therefore, the chance of a brand being considered for purchase does not exist if that brand is not part of a consumer's awareness set (Narayana and Markin, 1975). When a consumer does not know which brand may satisfy his or her initial need (e.g., has no distinctive evoked or awareness set), a search-process will more likely begin with general searches and show a narrowing by becoming (brand-)specific as it proceeds. We can confirm this assumption within the setting of online search, since it is indeed crucial for companies to gain the users' attention during the early stage of their search and decision processes.

With respect to understanding users' search behavior in general and with respect to paid search advertising in specific, we agree with the work of (Rutz and Bucklin, 2011), since we found the generic search activities of primary importance for the users' search and decision process: although generic searches receive far less clicks as brand-related ones, they are indeed indispensable in managing online advertising campaigns. Since there are also strong differences in the extent of the spillover effects (e.g. hotel vs. healthcare industry), it is recommended for each company to identify the degree of this interaction effect between generic and brand-related activities and adjust their spending accordingly.

The differences of the extent of the spillover behavior across industries might not only result from different market and competition set-ups, but might also be due to different factors influencing users' search behavior, such as involvement.

Searching for the right hotel room or for the best health insurance may be more functionally driven than choosing the right sneakers or underwear. A further differentiation into users with a goal-directed searching mode and those with a low purchase intention may reveal some more insights into the extent of the spillover effect. We focused on that circumstance by considering clicks on companies' websites (definition Spillover Behavior Level 2) and have found a much stronger spillover behavior in the first group compared to users that search only. Further research should investigate this differentiation in more detail.

The opportunity of investigating users' search behavior upon a very large query log suffers from a variety of drawbacks. Turning to our filtering and categorization procedures, there may be several sources that could skew our findings. Although we have been very detailed on the keyword-creation-process, we still might not have captured all of the generic and brand-related search activities. For instance, we may have defined too few brand-related keywords, which would result in too few brand-related queries being filtered out of the initial query log. If, on the other hand, we had filtered out more brand-related queries, this would have, under constant conditions and chargeable to the generic homogeneous group, increased both the hybrid and the homogeneous ("from branded - to branded") search groups proportionally. We also could have picked out more (unknown) companies instead of focusing on the top ten for each industry. Unknown brands might not receive as many homogeneous searches as the top ten industries. Additionally, users would be more likely to become aware of these unknown brands through generic searches, which probably would have increased the spillover effect from generic to branded searches. Restricting our study to the top companies therefore can be seen as resulting in conservative figures since it more likely leads to an underestimation than an overestimation of the spillover effect.

# 6 CONCLUSIONS

To better understand the search behavior of users we analyzed the query log published by AOL in 2006 (Pass et al., 2006) for the occurrence of the spillover effect first described by (Rutz and Bucklin, 2011). Our results confirm the occurrence of spillover effects in online search behavior, but also show that these effects differ between industries.

Starting from the initial AOL query log we (1) filtered out every brand-related log record that could refer to one of the selected companies or their products, and (2) filtered out log records of the remaining queries that contained generic terms for a specific industry. Within our analysis we found more user-journeys starting with generic and switching to brand-related searches than the other way round. Among the three industries selected, the effect is most noticeable in the hotel, closely followed by the clothing industry. The weakest degree of a spillover was detected in the healthcare industry.

We could prove the key role of generic activities and the early anchoring of companies and brands within user-journeys. Both our understanding of users' search activity as a process and our findings of the spillover effect within user-journeys allowed us to transfer the theoretical concepts of the evoked and (un-)awareness set of (Howard and Sheth, 1968) and (Narayana and Markin, 1975) to the user's search and decision process in the context of search engines: the development of the search process from generic to brand-related searches may at least partially be attributed to the fact that individual brands gain the users' attention during the search process, who thus "become aware" of these companies or brands. The focus on generic activities becomes indispensable since they seem to play the role of gatekeeper for companies in online advertising.

This paper has several limitations. Although we have been very detailed on the data filtering process there might be effects that blurred our results, since the manually selected and revisited generic keywords for each industry as well as the brand-related ones for each company might not capture all users and his or her search intentions. Another limitation is the missing information on conversions which would have enabled us to formulate a more specific occurrence of the spillover effect. Our approach, therefore, neglects the fact that one user might have made several purchases during the investigation period within one industry. An alternate dataset might overcome these limitations in a further investigation.

Although we analyzed several industries in this paper, we neither considered possible interactions between them nor between companies within these (e.g. spillovers from company A to company B). Since, for example, (Ghose and Yang, 2010) found that there are cross-category purchases within one company for several keywords in sponsored search, a complete query log to some extent contains information for such a further analysis. Our work can be seen as a first step in directing attention more to the behavioral aspects of users' online search activities.

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