THE IMPACT OF SMARTPHONES, BARCODE SCANNING, AND LOCATION-BASED SERVICES ON CONSUMERS’ SEARCH BEHAVIOR

Research-in-Progress

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Abstract

With their barcode scanning capabilities, positioning technologies and internet access smartphones converge online and offline world in consumers’ search. Combining context-specific information with consumer search data allows us to measure how consumers search on the mobile Internet. Our research objective is to investigate the drivers of consumer search on the mobile Internet. We use a novel and unique behavioral data set from a mobile location-based smartphone product information (i.e., barcode scanning) application. Our data comprises more than 200 million observations at the individual consumer level. Our preliminary results provide insights in consumer search behavior using smartphones. We show that information needs differ by the type of products that are scanned. We expect that our findings will give marketers a better understanding of consumers’ search behavior and thus help companies to proactively target them with marketing programs in order to acquire “search prone consumers” and to better retain existing consumers.

Keywords: Mobile commerce, Electronic commerce, Information search
Introduction

The increasing diffusion of smartphones and comparable mobile devices that provide Internet access anytime and anywhere facilitates consumer access to information. Examples of such information are prices and discounts in online and offline stores, detailed product information (e.g., from neutral third parties) and consumer reviews (i.e., user-generated content). In particular, during their search process and during their purchase decision phase, these new sources of information provide decision-making support to consumers. Technical features of modern smartphones such as barcode scanning or location-based services make the search process faster and more convenient as well as the resulting information more relevant to the consumers. This leads to reduced information asymmetries and therefore to a stronger bargaining power, all else being equal, on the side of the consumer. As a result of the mobile Internet and its search capabilities, companies will increasingly face a competitive environment where consumers are better informed in terms of product characteristics (e.g., product quality), independent reviews of the product (e.g., through consumer reviews), and alternative offers (e.g., retail prices in their vicinity).

Drawing upon previous literature on search theory (e.g., Branco et al. 2012, Stigler 1961), we aim to investigate the underlying drivers of mobile information search. Schmidt and Spreng (1996) propose that most of the effects of the antecedents of information search are mediated by four variables: ability, motivation, costs, and benefits. Smartphones and product information applications (“apps”) directly impact three of these variables: ability, costs, and benefits. Despite existing ranking effects due to the display size (Ghose et al. 2012), those smartphone apps potentially facilitate search and reduce the cost of search by providing relevant information (e.g. context-sensitive information) to consumers. But currently we have little understanding about how consumers use the unique opportunities provided by smartphones for their search for product-related information.

The goal of this exploratory study is to analyze and to explain consumers’ search behavior in a location-based mobile Internet context. More specifically, we aim to identify the drivers of mobile search. By using behavioral data from a major provider of mobile product information applications we are able to analyze location-based search behavior on an individual level. The data set on consumer search behavior contains: (1) search query data (n~77 million) and click data (n=140 million) by 9.5 million individual consumers. In doing so, we will answer the following research questions: (1) What drives consumer search behavior via location-based barcode scanning? (2) What types of information do consumers search for via location-based barcode scanning? and (3) How does individual search behavior using location-based barcode scanning change over time?

We aim to contribute to the literature in multiple ways. First, we analyze the consumer search process via location-based barcode scanning on smartphones. Second, we want to detail the factors that determine the attributes of the search for product related information using location-based barcode scanning apps. Finally, we want to use our modeling approach to document how consumers react to the search results and how individual search behavior using location-based barcode scanning changes over time. Our results are likely to provide marketers a better understanding of the process and implications of search via smartphones. By having an understanding of factors that affect information search, firms could potentially influence the extent of search and target specific offers to individual consumers (Branco et al. 2012). This will enable to proactively target these “search prone” consumers and to better retain existing consumers with tailored marketing programs.

Related Literature

Our study is related to previous literature on consumer search theory. The work of Stigler (1961) is the foundation of the economic search literature that is relevant for our paper. Stigler points out that the main purpose of search is the identification of sellers and the determination of prices for customers. Based on price knowledge and the expectation of the distribution of all prices in the market, customers make their purchase decisions. While a large portion of customers do not compare prices before making a purchase decision (Dickson and Sawyer 1990); prices are nevertheless an essential characteristic of offerings. The relevant search for price information is costly. Therefore market inefficiencies can be explained by search costs or transaction costs (Stiglitz 1989). Weitzman (1979) develops a model of the best search strategy for
product alternatives as well as an optimal stopping rule. Srinivasan and Ratchford (1991) describe the relationship between perceived risks and benefits when consumers decide if further search is reasonable or not. Most search models are based on the assumption of incomplete information (MacMinn 1980). In a recent study, Branco et al. (2012) present a tractable (continuous-time) model of gradual learning. In this model consumers perform search, which induces search costs, to collect further product information. As a result they continuously update their expectation of the product’s utility. There exist two bounds in the formal model: an upper bound which is called purchase threshold and a lower bound called exit threshold. If the expected valuation of the product exceeds the purchase threshold the consumer stops the search and buys. When the expected valuation falls below the exit threshold, the consumer cancels the search and refrains from a purchase. As long as the expected valuation is in between the two bounds, the consumer continues to search.

Like the Internet in general (Bakos 1997, Kuruzovich et al. 2008) also smartphones with their mobile Internet capabilities reduce search costs (Ghose et al. 2012). Nevertheless, a major impediment to online information search is the inability of search engines to incorporate semantics in the search process (Storey et al. 2008). In addition, the high volume and high complexity of information on the internet could lead to information overload effects as described by Malhotra et al. (1982). However, product information apps on smartphones provide context-awareness through location-based services and barcode scanning and therefore make search results more relevant to consumers.

The importance of location and the accessibility of offers have already been analyzed in an offline context. Consumers engage in cherry-picking by performing spatial or temporal price search and store switching (Fox et al. 2005, Gauri et al. 2008). In doing so consumers incur travel costs (i.e., fixed costs of shopping) which are influenced by their store choice decision (Bell et al. 1998). Therefore only geographically relevant alternatives are considered in consumers’ choice processes (Fotheringham 1988). In a mobile context, similar findings have been reported (Ghose et al. 2012, Liu et al. 2010). Geographic distance plays an important role in consumers’ decision processes. The mobile Internet, barcode scanning and location-based services increasingly blur the lines between online and offline worlds. For instance, it is technically possible to search for product-related information using a smartphone while being physically in a store. A recent study reveals that consumers would change purchase intentions when they get information on their smartphone about better alternative offers in their vicinity (Daurer et al. 2012). Previous literature also found geographic mobility to be a decisive factor in the usage of mobile Internet applications (Ghose and Han 2011). Furthermore, literature on the mobile Internet suggests that geographically near offers are more likely to be clicked on than more distant offers (Ghose et al. 2012, Molitor et al. 2012). However, these studies investigate the aspect of location in an advertising and social network setting (e.g., mobile coupons, sponsored twitter-like posts, and a mobile social network), whereas our study investigates consumers’ search for product and price information using the barcode scanning and location tracking functionalities of smartphones in a combined offline and online setting.

Winkler von Mohrenfels and Klapper (2012) find that relevant mobile product information can increase brand perception and at least for some product categories (e.g., organic foods) it can increase consumers’ willingness-to-pay. For companies this implies that the provision of product information to customers (especially to those using smartphones, since they can be targeted in the decision-making process at the point of sale) is an important differentiation criterion for their IS strategies (Pitt et al. 2011). To summarize, to the best of our knowledge, there is no previous study that combines context-specific information and consumer search data in order to measure how consumers search in the mobile Internet.

**Research Questions**

We identify two gaps in the existing literature. First, there is not much prior research on actual consumer search behavior in a mobile Internet setting where consumers use smartphones for their location-based offline and online product search. We assume that the ubiquitous availability of the Internet search and the convenient product information apps do influence the consumer behavior during the purchase decision making process and during their search processes. Our first research question is:

**RQ1: What drives search behavior via location-based barcode scanning?**

In other words: What triggers the consumers’ decision to search using a product information app on a smartphone? Here we analyze the impact of various factors. We quantify the impact of the product
specific differences (e.g. product category) on the search intensity. Furthermore, we examine temporal aspects like time of the day, time of the week and time of the year. In addition, regional aspects like competitive environment in the area or number of stores in the near surroundings are to be investigated. Even more important is to know what type of information the consumers are actually looking for when they are in the search process. This leads to our second research question:

**RQ2: What types of information do consumers search for via location-based barcode scanning?**

While some studies on consumer search focus on price, there is evidence that many consumers do not check price information before the purchase (Dickson and Sawyer 1990). In this research we want to empirically assess the importance of prices for consumer search. In addition to the availability and the structure of price information (other stores in the vicinity; online stores; competitive environment in the area) other possible influencing factors on the consumer’s search behavior are: (1) The availability of product-related information. Different types of product information could be of interest in the search process (e.g.: manufacturer-provided product information, neutral product testing results, corporate social responsibility information about the manufacturer/retailer, nutrition facts, information about fair trade, animal welfare information). (2) Furthermore, third party opinions could be of interest during the search process (e.g. user-generated consumer reviews and product ratings). (3) Finally, the product category of the product in question might make a difference within the search process. For high involvement products there might be a more thorough search process than, e.g., for low involvement consumables.

Most search literature is based on the assumption of incomplete information and uncertainty (MacMinn 1980), however smartphones reduce this uncertainty. In addition, to the best of our knowledge no model embraces the experience of the consumers. While there is literature that points out the impact of previous knowledge on the consumers’ search behavior (e.g. Bettman and Park 1980, Brucks 1985, Cowley and Mitchell 2003), those findings are based on survey data. To the best of our knowledge so far there is no study that incorporates the actual search process of subjects (i.e., actual search behavior using smartphones and mobile internet). Therefore our third research question is:

**RQ3: How does individual search behavior using location-based barcode scanning change over time?**

Here we analyze the role of the individual previous search experience. Many search queries within a certain product category could indicate that the consumer accumulates more product knowledge in that field. The number of search queries, number of search sessions and days of app usage could be an indicator of experience and might explain further search activities.

**Empirical Data**

Our data set stems from one of Europe’s largest and leading mobile product guide providers. The provider offers product guides that are available as location-based smartphone apps as well as on a website. The app provides a search screen where product barcodes can be scanned via the build-in camera of a smartphone.¹ On the results screen, consumers are able to browse through available information (which varies between products). There is product information, price information (of offers in the vicinity) and user-generated consumer reviews provided in the app.

The data set contains all mobile consumer search data of the smartphone app over a period of 18 months (January 2011 – June 2012). The data set contains: (1) mobile consumer search queries and with corresponding search result types, and (2) mobile consumer click-behavior² within the app.

Our data set contains all search queries that were performed using the barcode scanning app and consumer behavior within the app during the 18 months from January 2011 to June 2012. The data contains about 77 million search queries. The search queries contain in most cases the European Article Number (EAN 13) that was scanned from the barcode on a product. In addition, manual text entry was possible and therefore some queries contain free text (product name, manufacturer name, brand name,

¹ Technically users can enter search queries also manually, but this is done only in very few instances.

² Some authors refer to a click performed on a touch screen of a mobile device as “tap”. For simplicity reasons, we use the term “click” throughout this document.
etc.). The search method of the query (scan, manual entry etc.) is available as well.

For each search query the types of the displayed search results are stored. Examples are: price information available, user reviews available, etc. Usually, the results screen for search query yields multiple different types of information. If a search query yields a result and the corresponding product is categorized (in 70.4% of all search queries) the product category is tracked. Examples for product categories are: chocolate, book, magazine, cosmetics, shampoo, juice, spices, etc. The behavior of the consumer on the search results screen is contained in the data as well. Examples for tracked behavior are: a click on the price tab to view alternative offers (incl. pricing) for that product in the vicinity, a click on a product guide, a click on user reviews, etc.

The geographic position\(^3\) of the user at the time of the search query is part of the data. Because the data was generated through smartphone apps it is possible to identify individual users. When a smartphone app is downloaded and installed, a unique anonymous user id is generated and transmitted with each search query. In order to identify search queries that belong to one search session there is a session id.

### Econometric Model

We will estimate several discrete choice models to address our research questions. In order to answer RQ1, we will model the choice to perform a search query (i.e., the decision to search) as a function of the underlying product category, users' mobility (i.e., travel distance), time-specific effects (e.g. time of the day, time of the week, season, etc.) and location-specific effects (e.g. number of retail stores in the vicinity, distance to the next retailer depending on the product category, etc.) while controlling for individual-level fixed effects (Chamberlain 1980). Let the choice be represented by the binary choice variable \(y_{ijt} = 1\) (0), if a consumer \(i\) chooses to (not) perform a search \(j\) at time \(t\). A consumer's utility (i.e., resulting from the choice to perform a search query) can thus be written as:

\[
y_{ijt} = \begin{cases} 0 & \text{if } u_{ijt} \leq 0 \\ 1 & \text{if } u_{ijt} > 0 \end{cases}
\]

Hence, the latent utility \(u_{ijt}\) of consumer \(i\) to perform search \(j\) at time \(t\) is modeled as a function of the product category, mobility, time and location-specific effects:

\[
u_{ijt} = \alpha_i + \beta_1 \cdot \text{Category}_{ijt} + \beta_2 \cdot \text{Mobility}_{ijt} + \beta_3 \cdot \text{Time Specifics}_{ijt} + \beta_4 \cdot \text{Location Specifics}_{ijt} + \epsilon_{ijt}
\]

where \(\alpha_i\) is the individual-level fixed effect. We further assume that the error term \(\epsilon_{ijt}\) is i.i.d. and possesses a Type I extreme value distribution.

Regarding RQ2 we will use a multinomial logit (MNL) model to explain consumers' individual behavior (i.e., certain actions on the search results screen) based on their electronic trail. Consumers' choices reflected by discrete actions within the app (e.g., click on price information, on user-generated reviews, on product guides etc.) will be modeled as a function of the previous search history, the duration of the search session and the distance traveled during that session. Furthermore, we make use of product category, controlling for potential differences between products. We will also control for time-specific and location-specific effects. Hence consumer \(i\)'s utility choosing \(k\) (with \(k \in \{1, 2, 3, 4, 5, 6\}\)) at time \(t\) can be modeled as follows:

\[
u_{ijk} = \alpha_k + \beta_{1k} \cdot \text{Search History}_{ijt} + \beta_{2k} \cdot \text{Session Duration}_{ijt} + \beta_{3k} \cdot \text{Category}_{ijt} + \beta_{4k} \cdot \text{Mobility}_{ijt} + \beta_{5k} \cdot \text{Time Specifics}_{ijt} + \beta_{6k} \cdot \text{Location Specifics}_{ijt} + \epsilon_{ijk}
\]

where \(\alpha_k\) is the intercept that accounts for variation in the dependent variable. The six modeled choices \(j\) are the actions on the search results screen which are categorized in the following groups: click on (1) product information, (2) price information, (3) user reviews, (4) related social media content (5) advertisements and (6) others.

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\(^3\) Longitude and latitude; in some cases the position is not available because some users have deactivated location services on their smartphones or because a position could not be determined.
To answer RQ3, we expand model (2) by additional user and session related variables. We operationalize product knowledge using the previous search history within the product category of the user. Furthermore, we use the number of queries, number of sessions and duration of app usage as a proxy for search experience. Consumers i’s utility towards searching for product j at time t can now be modeled as follows:

\[
u_{ijt} = \alpha_i + \beta_1 \cdot \text{Category}_{ijt} + \beta_2 \cdot \text{Mobility}_{ijt} + \beta_3 \cdot \text{Time}\_\text{Specifics}_{ijt} + \beta_4 \cdot \text{Location}\_\text{Specifics}_{ijt} + \beta_5 \cdot \text{Search}\_\text{History}_{ijt} + \beta_6 \cdot \text{Search}\_\text{Experience}_{ijt} + \epsilon_{ijt}
\]

where \(\alpha_i\) is the individual-level fixed effect. We also assume that the error term \(\epsilon_{ijt}\) is i.i.d. and possesses a Type I extreme value distribution.

In addition, we are planning to employ various instrumental variables to address potential issues related to endogeneity concerning all our models above. We assume that there are regional differences in the search behavior and thus in the app usage behavior. The following variables might be appropriate instruments: purchasing power of each region (operationalized by the nominal GDP per citizen per county and the discretionary income per citizen), indicators on the importance of retail in an area (operationalized by the gross value added of the trade industry per county), and indicators on price dispersion in an area (operationalized by the average price of building land as a proxy for price levels in the region and regional fuel prices and prices of selected goods from a national retail chain with local pricing). We will also control for external effects caused by weather conditions (temperature, precipitation, etc.)

### Preliminary Results and Discussion

As the research is in progress the econometric analyses are ongoing. However, there are interesting descriptive statistics and preliminary results. In a first step, the data has been analyzed in an exploratory way to understand the data and basic search patterns of consumers. As illustrated in Table 1 the data subset contains 77 million search queries from 37 million sessions by 9 million users.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N (number of observations)</td>
<td>217,259,965</td>
</tr>
<tr>
<td># of search queries</td>
<td>77,432,559</td>
</tr>
<tr>
<td># of clicks on the search results screen</td>
<td>139,827,406</td>
</tr>
<tr>
<td># of unique users</td>
<td>9,551,731</td>
</tr>
<tr>
<td># of sessions</td>
<td>37,542,207</td>
</tr>
<tr>
<td>avg. no. of search queries / user</td>
<td>8.11</td>
</tr>
<tr>
<td>sessions with only 1 query</td>
<td>62.2 %</td>
</tr>
<tr>
<td>avg. (median) distance / session a)</td>
<td>279 m</td>
</tr>
<tr>
<td>avg. (median) duration / session b)</td>
<td>122 s</td>
</tr>
<tr>
<td>zero distance sessions</td>
<td>74.0 %</td>
</tr>
<tr>
<td>avg. no. of search queries / session c)</td>
<td>2.07</td>
</tr>
<tr>
<td>avg. no. of product categories / session d)</td>
<td>1.76</td>
</tr>
<tr>
<td>avg. actions on the results screen / user</td>
<td>17.04</td>
</tr>
<tr>
<td>avg. actions on the results screen / session</td>
<td>3.46</td>
</tr>
</tbody>
</table>

Notes: a) only non-zero distance multi-query-sessions  
       c) for multi-query-sessions: 3.81  
       b) only non-zero duration multi-query-sessions  
       d) for multi-query-sessions: 3.01
A search session lasts on average 122 seconds (median). The median of the travel distance is 279 meters. The data shows that consumers are travelling during their search process and it is likely that the visiting of different stores is the reason for the travel. A search session consists of 2.07 search queries on average (standard deviation: 7.50). However, a large number of sessions consist of only one query. If only the multi-query sessions are considered, then the average number of queries per session is 3.81 (median=3; SD=11.97). Within the search sessions products out of on average 1.76 different product categories are scanned (SD=4.07). For multi-query sessions, the average number of different product categories per session is 3.01 (median=2; SD=6.42). If considering only the multi-product-category search sessions, then there are search queries over on average 3.44 different product categories performed (median=2; SD=6.99).

During their search process all consumers performed in total almost 140 million actions that were tracked in our data set. The arithmetic mean of tracked actions per user is 17.04. However, this includes many one-time users of the app. In an average search session 3.46 different user actions are tracked. For our econometric analysis we will categorize those actions into six groups: click on (1) product information, (2) price information, (3) user reviews, (4) related social media content (5) advertisements and (6) others.

As a first result the proportion of different scanned product categories is depicted in Figure 1. Food and beverages with together almost 40 % are the top categories. They are followed by media (8.43 %), drugstore articles (7.27 %), non-food products like do-it-yourself equipment and tobacco (6.26 %) and electronics (4.43 %).

![Figure 1: Proportion of search queries per product category (total 77 million queries)](image)

The category fashion has a very low share of all scanned products (0.4 %). Compared to the sales revenues of retail, the category fashion and clothing should represent a larger fraction. In (offline) retail the revenue share is almost 14 % in the country of our study (bte 2008). This represents the third largest retail category in terms of sales – after foodstuffs, drinks and tobacco (38.4 %) and drugstore articles (15.7 %). In online retail fashion and clothing is even the largest category in the country of our study (bvh 2013). There are two possible explanations for this finding: First, price comparisons might be difficult when there is no barcode on items to identify them. Second, for clothing there might be less relevant
information that could be provided by an app since sizes, fabric type and care instructions are usually on the label. It will be interesting to investigate this further, since production information and fair-trade information is increasingly of interest for consumers also for clothing.

Further, we analyze the relationship between consumers’ search behavior and the type of the product being scanned. Preliminary results based on scanning behavior from one month are illustrated in Table 2. After a search query (i.e., barcode scan), the resulting information about a product is grouped in three different choice alternatives (i.e., tabs) in the app. These are information about product characteristics, price information and user-reviews related for the scanned product. We find significant differences in the specific information retrieval ($\chi^2$-tests) depending on the product category of the scanned product.

<table>
<thead>
<tr>
<th>Type of information retrieval (click on tab)</th>
<th>Durables</th>
<th>Consumables</th>
<th>Hedonic</th>
<th>Utilitarian</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product characteristics</td>
<td>12.3%</td>
<td>11.6%</td>
<td>11.8%</td>
<td>11.8%</td>
<td></td>
</tr>
<tr>
<td>Price information</td>
<td>66.7%</td>
<td>52.6%</td>
<td>55.1%</td>
<td>55.1%</td>
<td></td>
</tr>
<tr>
<td>User-reviews</td>
<td>21.0%</td>
<td>35.7%</td>
<td>33.2%</td>
<td>33.2%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>17.4%</td>
<td>82.6%</td>
<td>100.0%</td>
<td>35.6%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Type of information retrieval (click on tab)</th>
<th>Search</th>
<th>Experience</th>
<th>Credence</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hedonic</td>
<td>12.9%</td>
<td>11.6%</td>
<td>11.9%</td>
<td>11.8%</td>
</tr>
<tr>
<td>Utilitarian</td>
<td>67.1%</td>
<td>53.2%</td>
<td>54.8%</td>
<td>55.1%</td>
</tr>
<tr>
<td>Total</td>
<td>19.6%</td>
<td>35.2%</td>
<td>33.2%</td>
<td>33.2%</td>
</tr>
</tbody>
</table>

$\chi^2 = 1.2e+04; p < 0.001$  
$\chi^2 = 469.285; p < 0.001$  
$\chi^2 = 1.0e+04; p < 0.001$

Note: The percentages of a column sum up to 100%. The total of a column is the percentage of the product category. The product characteristics tab is displayed by default in the app. These clicks represent returns to the tab.

For instance, price information seems to be more relevant for consumers searching for durables compared to consumables. On the other hand, user-reviews are more requested for consumables. User-reviews are also more retrieved in search queries concerning utilitarian goods, while the price seems to be more important for hedonic goods. Looking at search goods, information on product characteristics are slightly more demanded as opposed to experience or credence goods. However, user reviews appear more relevant for the latter two categories.

### Conclusion and Next Stage of Research

Preliminary results of this research show that product information apps are used in a mobile context. Consumers seem to use such apps on their mobile devices while they go shopping and on average they cover travel distances of 279 m. We show that consumers seem to use location-based barcode scanning purposeful (focused in terms of product category) during their shopping. The importance and retrieval of information on product characteristics, price information and user-reviews differs significantly between product categories.

The further analysis of our research questions determines factors that drive search behavior of consumers using location-based product information apps in a mobile context. In addition we will empirically analyze what types of information consumers actually search for via location-based barcode scanning and which ones are most interesting for them. Finally, using our large data set of scanning behavior, we will analyze how individual search behavior using location-based barcode scanning does change over time.

After a rather explorative analysis of scanning behavior on a product category level and on a search session level, the next stage of research will be to explain consumer behavior on an individual level. With
our data we will be able to conduct an analysis of individual search paths. Here we will analyze factors like location, different types of product information (e.g., product characteristics, price information, user-reviews) and time-specific effects (e.g., day of the week, time of the day). Furthermore, individual analyses allow us to account for consumer-specific effects like experience (search intensity).

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