5-2-2012

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Abstract

The advent of smartphones enables more and more consumers to use the mobile internet. In addition, there is a continuing integration of location-based services (LBS). By means of Global Positioning Systems or WiFi-triangulation LBS provide context-aware information to consumers. This leads to a convergence of online and offline worlds. The usage of LBS delivers additional information to consumers (e.g., alternative offers or detailed product information). Particularly during the search process, information about prices or geographic distances, that are relevant for the purchase, are of importance. The goal of this study is to estimate search costs in a mobile internet context. We first illustrate the relevant literature on search theory (online/offline, mobile/desktop) and consumer behavior. Then we estimate search costs via a choice-based conjoint analysis for a large representative online sample. Our empirical results show that mobile search and LBS have a significant impact on consumer behavior. We quantify search costs in monetary units on an individual level by using geographic distance as a trade-off for price. We find that consumers trade off one extra minute of travel to another store with an average price reduction of 0.87 €.

Keywords: Search Theory, Location-Based Services, Mobile Marketing, Choice-Based Conjoint Analysis.

1 Introduction

Since the introduction of the iPhone by Apple Inc. in 2007 the mobile phone market has changed tremendously. Smartphones like the iPhone are increasingly important in this market. Today already 23.6 % of all devices sold are smartphones (Gartner, 2011). Smartphones are characterized by a set of features that are not available in traditional cell phones. Those features include (1) internet access through mobile networks, (2) location-based services (LBS), (3) a sophisticated operating system on the device that allows to install and to use third-party applications (apps), and (4) a large touch screen as a user interface.

In addition, most smartphones come with a built-in camera that allows users to take pictures or even to use it as an input device instead of the on-screen keyboard. One use case is to utilize the camera to scan a barcode on a product label in order to search for it in a database that provides further product information. For example, the app "RedLaser" by eBay provides – in addition to product related information – location-based price comparisons for the scanned products. By scanning a product the user can instantly see where else the product is offered nearby and at what price. Therefore, smartphones and LBS most likely have a strong impact on consumers' search behavior.

Although much work has been done in the area of information search and economic search theory, there is not much literature on the potential impact of these mobile services on consumer behavior. This is surprising given the fact that smartphones penetration is increasing and that they do offer features that are relevant in consumers' search processes and purchase decisions.

The goal of this paper is to (1) explore if mobile search has an impact on consumer behavior and (2) to quantify search costs in monetary units by using geographic distance as a trade-off for price. In our study we collect choice data in the context of smartphone usage. Therefore we conduct a choice-based conjoint analysis (CBC analysis) via an online survey. The study is representative for the online population of a large European country. The choice sets contain stimuli that reflect actual product offers with characteristics that include product attributes, price and distance to the offer. We analyze the CBC data using Hierarchical Bayes estimation to calculate the individual utility parameters on the individual level. This provides an estimation of actual search costs. Subsequently, we use psychometric constructs to explain consumers' relative attribute weights and thus their underlying choice behavior.

We make the following contributions: First, we show the impact of information technology on purchase decisions in a mobile context. Second, we calculate consumers' search costs in monetary units for this context based on a large representative online panel. Differences in search costs can partially be explained based on consumer characteristics. This article is organized as follows: We first review related literature and identify research gaps. Then, we outline our data and method. Next, we present the results of our empirical study. Finally, we discuss implications for practitioners as well as for researchers.

2 Related Literature

There are three research streams that are notably relevant for mobile search and its impact on consumers' search and purchase behavior. Those three streams are (1) information search theory, (2) the impact of information and communication technology on consumer search behavior and (3) the interplay between online and offline markets with respect to consumer behavior.

The primary research stream of search literature focuses on information search and the economic impact of search costs. First, Stigler (1961) emphasizes the importance of the identification of sellers and the determination of prices for consumers. The basis of all consumer decisions is their expectation about the distribution of prices in the market. Although not all consumers check prices before they make a purchase decision (Dickson and Sawyer, 1990), prices are an essential characteristic of offerings. The relevant search is costly and market inefficiencies can therefore be explained by search or transaction costs (Stigler, 1961, Stiglitz, 1989). Second, 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 more search is reasonable or not. Those models are all based on the assumption of incomplete information. At least there is uncertainty about actual prices in relevant stores. At the best there is knowledge about the distribution of prices in the market as a whole (MacMinn, 1980). Later studies expand those models by behavioral aspects of bounded rationality. For instance, Häubl et al. (2010) explain that consumers respond excessively to the attractiveness of a currently inspected product. In addition, consumers overreact to the difference in attraction between the current product and the one encountered just prior to it. Geographic distance and accessibility of offers have been analyzed in an offline context by Fotheringham (1988). He states that only geographically relevant alternatives are considered in the decision making process. On the supply side, Tellis (1986) identifies geographic pricing as a competitive pricing strategy. When consumers are able to buy on a remote market this entails transaction costs (e.g., transportation costs). Firms could react to that by introducing zone pricing, i.e., different prices according to the transaction costs of each zone (ibid.)

The second stream of research investigates the impact of information and communication technology on consumer search behavior. For instance, Johnson et al. (2004) analyze online search behavior before purchase decisions and actions. Jepsen (2007) finds that benefits of the internet, like the large amounts of information available, affect the use of the internet for information search positively. Online information sources are seen as a means to improve purchase processes (Kuruzovich et al., 2008). Bakos (1997) specifically quantifies the impact of information technology on markets and prices. The study shows that electronic markets reduce search costs for consumers and make it more difficult for sellers to earn monopolistic profits. It is reasonable to assume that the access to such platforms by using the mobile internet has an impact on offline consumer behavior as well. However, while the internet facilitates information search, users conduct pre-purchase price comparisons to a lesser extent than expected (Johnson et al., 2004). Furthermore, there are considerable price differences between electronic marketplaces, even for identical products (Brynjolfsson and Smith, 2000). In the light of the high information efficiency implied by price comparison sites and price search engines this finding is surprising. Those price differences can partially be explained by consumer specific search costs (Brynjolfsson et al., 2010). In particular, the high complexity of information on the internet can be a problem which could lead to information overload (Malhotra et al., 1982). Another important aspect is that search prone consumers engage in cherry-picking by spatial and temporal price search (Gauri et al., 2008). However, price search effectiveness is largely driven by geography and opportunity costs (ibid.); this indicates that location-based search services (through smartphones) are highly relevant for consumers. In the past, a major impediment to online information search was the inability of search engines to incorporate semantics in the search process (Storey et al., 2008). Nowadays with the availability of LBS, search results can be context-aware and therefore more relevant to consumers.

The third stream of research analyzes the interplay between online and offline markets. Forman et al. (2009) show that people switch from electronic markets to local stores if these stores open in near vicinity. This indicates that geographic distance plays an important role in consumer behavior. Because of the mobile internet and LBS, the lines between online and offline worlds become increasingly blurred. For instance, it is technically possible to research the internet using a smartphone while being physically in a store. A recent study which is based on a student sample 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). Furthermore, literature in the area of mobile commerce suggests that geographically near offers are more likely to be clicked on than more distant offers (Ghose et al., 2011, Liu et al., 2010). Other research on mobile commerce mainly analyzes the acceptance respectively adoption of mobile and location-based services (Lee et al., 2009, Kim, 2007) or technological aspects and privacy issues (Xu et al., 2009).

We identify two gaps in the previous literature. First, all search models are based on the assumption of incomplete information and uncertainty (MacMinn, 1980). Smartphones reduce this uncertainty because they allow mobile internet search and provide relevant information through LBS. There is not much prior research on the impact of mobile search on consumer behavior. This study analyzes the economic impact of location-based mobile internet search which is characterized by the interplay between online and offline worlds. We aim to contribute to this gap by answering our first research question: *Does mobile location-based information search have an impact on consumers' search and buying behavior?* The second gap reflects the fact that there is no commonly accepted method on how to measure search costs directly. There are varying concepts on the psychometric measurement of search costs. Usually, search costs are measured as the perceived value of time which is spent for search (Srinivasan and Ratchford, 1991). Sometimes – in addition to opportunity costs – search costs are measured in monetary units as actual spending such as travel expenses, communication costs or costs of magazine subscriptions (Bakos, 1997). While expenses are clearly measurable, opportunity costs are usually based on survey data. This leads to our second research question: *What are the search costs of mobile consumers?*

3 Data and Method

3.1 Survey of Online Access Panel

We gather data in a cross-sectional study through an online survey. We use a large sample from an online access panel which is representative for the online population of a large European country. The sample is representative based on the characteristics gender, age, education, household income, and household size. The panel consists of 46.4 % female and 53.6 % male participants. Target participants were of the age 14-29 years (29 %), 30-49 years (40.4 %) or above 50 years (30.6 %). The sample is geographically distributed over the whole country. The sample size n is 521.

In this study, we present a situation where participants are asked to make choices about a digital camera (see Appendix A for a detailed description of the setting). We conduct a choice-based conjoint analysis (CBC analysis) to estimate consumer preferences. Hereby, we use a trade-off between geographical distance (i.e., the spatial distance between the offer and the current location of a person) and price to measure search costs. As additional choice options, subjects are able to choose to buy online or to choose not to buy at all. The CBC analysis is explained in detail in the following section.

In addition to the CBC analysis, we gather data on consumer characteristics by using several latent constructs (see Appendix B). These constructs are utilized to explain the relative importance of the attributes of the CBC analysis and serve as a psychometric foundation of the study. All constructs are used as independent variables in a linear regression analysis. We employ these constructs since they cover individual traits concerning consumers' search and purchasing processes. All scales are coded in a way that higher scores mirror higher levels of the construct. They are measured using a 7-point Likert-type scale.

Consumers' perception of the price is measured by the price consciousness scale. Compared to Darden and Perreault (1976) we use three instead of four items since the forth item is not applicable to our study. The psychometric measurement of consumers' search effort is based on the search costs scale of Srinivasan and Ratchford (1991). This scale relates to the perception of search time that consumers have to invest before they actually purchase a product. Consumers' control over their shopping process is measured by Chandran and Morwitz's (2005) process control scale. The process control scale measures consumers' perception concerning their influence on the shopping process in terms of controlling the cost-benefit ratio of the focal product. The likelihood to compare products before the purchase was measured by the price comparison likelihood scale (Srivastava and Lurie, 2004). This scale measures consumers' attitudes towards the likelihood of comparing prices between different stores. Besides measuring these psychometric constructs we also control for participants' knowledge about the focal product. This knowledge is measured by two single item questions (see Appendix B).

3.2 Choice-based Conjoint Analysis

Conjoint analysis is a widespread method to measure preferences and the choice-based conjoint analysis is the most common variant of that method. As opposed to traditional conjoint analysis, the CBC analysis provides more realistic choice tasks for subjects (Haaijer et al., 2001). It is reasonable to assume that in the case of search processes and purchase decisions consumers do have heterogeneous preferences regarding product specific attributes. To account for that, individual part-worth utilities have to be estimated. This can be achieved by using Hierarchical Bayes-estimation (Allenby et al., 1995). In general, in a CBC analysis subjects receive the assignment to select one preferred offer from a set of alternative offers (Ben-Akiva and Lerman, 1994, McFadden, 1986). Participants are asked to put themselves in a described situation and get several choice tasks (also referred to as choice sets) in a row. It is assumed that participants pick the choice option that provides the highest utility for them.

In this study participants are required to evaluate alternative offers based on their attributes. We use two attributes in this study: (1) “Distance” is the geographic distance between the offer and the current location of the consumer. The attribute is used to measure search costs of subjects. Distance is measured in time (minutes) to be independent of the means of transportation. The level “buy online” is of a special kind: When buying online in an electronic store, perceived costs are induced through a delivery time of two days (instead of a travel distance). (2) The attribute “price” reflects the sales price that a consumer has to pay when buying the product. Given the highest price is the list price, the lower prices equal discounts of 10 %, 20 % and 30 %. Table 1 shows both the two attributes and their levels.

The participants receive choice tasks which are combinations of four choice options. Three of those options are combinations of offer attributes (also known as concepts) and one is a “No-Choice-Option”. The No-Choice-Option is included to make the choice situation more realistic (Haaijer et al., 2001). In the survey it is shown as “Do not purchase (I would choose none of the presented options.)” It could be interpreted in different ways: First, it could be that the subject is not interested at all in the presented product. Second, it could be the case that the prices for all available options are above the subject’s willingness-to-pay. Third, the distance could be too large for all the presented options.

Attribute	Levels
(1) Distance	Buy on-site Buy at another store (5 min. from here) Buy at another store (10 min. from here) Buy at another store (15 min. from here) Buy online (Delivery time 2 days)
(2) Price	199.99 € 179.99 € 159.99 € 139.99 €

Table 1: Attributes and Levels in the Choice-based Conjoint Analysis

The choice tasks are created with the software package Sawtooth Software SSI Web. We use the Balanced Overlap Method to ensure some level overlap within the tasks (Sawtooth Software, 2011). Duplicate concepts are not permitted within the same task. We created 300 versions of questionnaires to maximize the possible concept combinations that are presented to subjects and to control for order effects (Sawtooth Software, 2011). The versions were randomly assigned to participants. Each questionnaire contains 12 random choice tasks that are generated through the software (random choice sets). This adds up to 3,600 different choice tasks. In addition, three choice tasks were created manually (i.e., hold-out tasks). Those were held constant over all questionnaire versions. Those hold-out tasks contain different attribute level combinations. It is important that hold-out tasks do not contain concepts that are dominant, i.e., are preferable over others on all dimensions. Hold-out tasks are not used for the estimation. They are used to assess the quality of the responses and the estimation.

With the first hold-out task we measure the hit-rate of the estimation. The other two hold-out tasks contain the same concepts but in another order. If the choices of both tasks are identical then this indicates consistent response behavior of individuals and thus test-retest validity.

4 Empirical Results

4.1 Reliability and Validity

The usage of the Hierarchical Bayes model in our CBC analysis enables us to estimate individual part-worth utilities. This approach leads to better estimation results – given our underlying research problem – compared to other estimation methods such as the latent-class model (Andrews et al., 2002).

Before presenting and discussing the results of the estimation, we analyze the goodness of fit of our data. The reliability of the latent constructs was assessed by calculating Cronbach's Alpha. The results appear in Appendix B. All latent constructs have been used in other studies before and have a high reliability (Nunnally, 1978, Peterson, 1994). The reliability of the price comparison likelihood measure, which is below 0.7, can be explained by the fact that it only consists of three items (Peterson, 1994). Similarly, Churchill and Peter (1984) found a positive correlation between the number of items and the size of the coefficient alpha.

Next, we evaluate the reliability, predictive validity and internal validity of the CBC analysis. Participants' choices are potentially influenced by several factors (e.g., negligence, lack of interest). Those sources of irritation may lead to a biased estimation that should be prevented. To control for potential biases, two identical hold-out tasks were integrated in the survey. The result of the test-retest statistic shows that 87.1 % of all participants chose the same products in both hold-out tasks. Compared to other studies this test-retest validity is high (Huber et al., 1993).

To assess the predictive validity of the CBC analysis, we also make use of the hold-out tasks. The predictive validity refers to the ability to predict participants' choices by using the estimated utility parameters (Akaah and Korgaonkar, 1983). The corresponding validity measure is the hit-rate. The observed choices were compared to the estimated choices. Here, the hit-rate is 96.4 %. Such a hit-rate is considered to be high (Lenk et al., 1996). The hit-rate which depicts the number of correctly estimated choices can also be used to test the internal validity. Here, we predict subjects' responses to the choice tasks used for estimation. The subsequent hit-rate of 87.5 % signifies that a large degree of participants' choices is predicted correctly. The internal validity can thus be considered as high (Moore, 2004).

4.2 Estimation and Results

In Table 2 we present the estimated parameters (i.e., part-worth utilities). The mean values of the estimated part-worth utilities for the attribute distance range from -1.86 to 2.88. The estimated part-worth utilities for the attribute price range from -11.79 to 12.54. All signs and thus the direction of influence of these part-worth utilities are plausible. These results indicate face validity. As expected, higher prices and higher distances decrease consumers' utilities, lower prices and distances are more preferred. Table 2 also shows that the online purchase provides the lowest utility to consumers compared to the other physical distance attributes. This might be explained by the fact that the online purchase delays the actual purchase (i.e., the receipt) of the focal product. Additionally, consumers might prefer the haptic experience which is not possible in a pure online purchase.

The interpretation of the different attributes (i.e., distance and price) is not feasible in a direct manner (Train, 2003). Therefore the measurement of the relative attribute importance is used. The relative importance measures the relevancy of one attribute utility compared to the sum of all attribute utility ranges. To calculate the relative attribute importance, the part-worth utility ranges of each attribute are used. These part-worth utility ranges are the difference between the highest and the lowest part-worth utility parameter of each attribute. The relative attribute importance of the attribute distance is calculated by the utility range of the distance divided by the sum of all attribute utility ranges. The same applies to the relative importance of the attribute price. The results show that the attribute price has a higher relative importance to the participants compared to the attribute distance. The mean of relative importance of the attribute price is 83 %. The corresponding mean of relative importance of the attribute distance is 17 % and thus less important than the attribute price. Please note that we only consider the offline distance utility ranges here.

Attribute	Level	Mean	Median	SD
Distance	On-site	2.88	3.14	1.13
	5 minutes	1.00	1.20	0.80
	10 minutes	-0.32	-0.36	0.69
	15 minutes	-1.71	-1.83	0.92
	Online	-1.86	-2.06	1.97
Price	199.99 €	-11.79	-12.83	4.84
	179.99 €	-4.00	-4.26	1.73
	159.99 €	3.26	3.70	2.01
	139.99 €	12.54	13.44	4.73

Table 2: Parameter estimates

A further means to interpret the estimated part-worth utility parameters is the possibility to normalize these by the price.[1] Table 3 shows the additional willingness-to-pay for the different attribute levels of the attribute distance of our focal product. Comparability between the additional willingness to pay is hence possible. Table 3 shows that participants would pay 11.97 € more on average at the point of sale compared to a store that is 15 minutes away. The other results also have to be interpreted in relation to the attribute level “15 minutes away”.

Distance	Additional willingness-to-pay
Online	-0.63 €
15 minutes	0.00 €
10 minutes	3.71 €
5 minutes	6.62 €
On-site	11.97 €

Table 3: Average difference in willingness-to-pay for the attribute distance

The estimation of individual part-worth utilities by using the Hierarchical Bayes model also allows the calculation of individual search costs. Thereby, the ratio of the absolute range of the attribute price and the relative utility range of the attribute price is multiplied by the relative utility range of the attribute distance divided by the number of minutes (i.e., maximum distance). This formula results in search costs of 0.87 € per minute (SD=0.74). Please note that the maximum travel distance is 15 minutes and we only consider offline distances.

Subsequently, we analyze the relative attribute importance of the CBC analysis as a function of the psychometric constructs price consciousness, search costs, control of the shopping process, price comparison likelihood and the product knowledge. The relative attribute importance provides insights on consumers’ attitude towards the price and the distance of our focal product. The psychometric constructs measure individual traits concerning consumers’ search and purchasing processes. We use a multiple linear regression to explain the relative attribute importance by several psychometric

[1] The utility ranges between each level of the attribute distance (difference between each level and largest distance of 15 minutes) are divided by the quotient of the utility ranges of the attribute price (highest-lowest utility) and the range of the monetary differences (highest-lowest price = 60 €). The result is a utility per monetary unit which can be interpreted as difference in willingness-to-pay.

constructs. All independent variables are depicted in Appendix B. As already mentioned, the relative attribute importance of the attribute price is 83 %, whereas the attribute price has a relative attribute importance of 17 %. We estimate the following linear model:

$$\textit{Relative attribute importance}_{ij} = \beta_{0j} + \beta_{1j} * \textit{price consciousness}_i + \beta_{2j} * \textit{search costs}_i + \beta_{3j} * \textit{process control}_i + \beta_{4j} * \textit{price comparison likelihood}_i + \beta_{5j} * \textit{product\_knowledge\_1}_i + \beta_{6j} * \textit{product\_knowledge\_2}_i + \varepsilon_{ij}$$

where the dependent variable stands for the relative attribute importance of the attribute price or the attribute distance and the betas are the estimators of the independent variables of participant *i*. Index *j* reflects the attribute (price or distance).

First, we test for violations of the assumptions of the linear regression model. To test if our model has a proper functional form, we use the Ramsey test. The results indicate that our model is specified properly.[2] To test for heteroskedasticity, we use the Breusch-Pagan/Cook-Weisberg test. This test indicates that heteroskedasticity is indeed a problem.[3] We therefore use a robust model (White, 1980) for testing the effects of the psychometric measures on the relative attribute importance (see Table 4). A test for the normality of residuals indicates that the residuals of our models are normally distributed.

Independent variables	**(Robust) relative attribute importance distance**	**(Robust) relative attribute importance price**
Price consciousness	-0.005**	0.005**
	(0.002)	(0.002)
Search costs	0.001	-0.001
	(0.001)	(0.001)
Process control	-0.009***	0.009***
	(0.003)	(0.003)
Price comparison likelihood	-0.002	0.002
	(0.002)	(0.002)
Product knowledge_1	0.005**	-0.005**
	(0.002)	(0.002)
Product knowledge_2	-0.002	0.002
	(0.002)	(0.002)
Intercept	0.242***	0.758***
	(0.023)	(0.023)
Observations	521	521
R-squared	0.058	0.058
F-test	3.87***	3.87***

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Linear regression results

Table 4 shows that the estimated coefficients in column two reflect those in column three with reverse signs except for the intercept. This is explained by the fact that the dependent variables (i.e., the relative attribute importance of the participants) sum up to one on the individual level. The independent variables thus explain two sides of the same coin.

The F-test in Table 4 indicates the overall significance of our model (F-test = 3.87; p<0.01). The *process control* coefficient is highly significant (+/-0.009 (0.003)). This has a negative impact on the relative attribute importance of the attribute distance and a positive impact on the relative attribute importance of the attribute price. Consumers with a high tendency to be in control of the shopping process are more inclined to overcome larger distances and thus have lower search costs. The *price consciousness* coefficient is also significant (+/-0.005 (0.002)). Therefore, price consciousness has a

[2] Ramsey test is the same for both models (distance & price): F-test=2.14 prob>F=0.00 H_0: model has no omitted variables
[3] Breusch-Pagan/Cook-Weinsberg for both models (distance & price): chi^2=168.11 prob>chi^2=0.00 H_0: constant variance

positive impact on the relative attribute importance of the attribute price and a negative impact on the size of the relative attribute importance of the attribute distance. Similar to consumers with a tendency to be in control of the shopping process, price conscious consumers also rather "go an extra mile" than buy at a higher price. Finally, the *product knowledge* coefficient one is significant (+/-0.005 ((0.002)). For consumers that possess good product knowledge the relative importance of the attribute distance is higher and the effect of the relative importance of the attribute price is lower. Increased product knowledge thus indicates higher sensitivity to distance and higher search costs. This might be explained by the fact that highly involved consumers also spend more time in the purchase decision process of their focal product compared to less involved and thus less knowledgeable consumers.

5 Conclusion

In this paper we analyze the impact of mobile search on consumer behavior and show how mobile search costs can be measured using a CBC analysis. On average, consumers' search costs are 0.87 € per minute. Consumers are hence indifferent between paying 0.87 € more and travelling for one minute to another store. Further, the parameter estimates of the linear regression indicate that the amount of product knowledge has a positive impact on the importance of search. However, increased knowledge about the price and the tendency to be in control of the shopping process has a negative impact on the importance of search. The results indicate that location-based information on prices and distances have a substantial influence on consumers' purchase decisions. From a methodological perspective we outline an approach to measure individual search costs in a mobile context.

Consumers are increasingly better able to conduct mobile price comparisons and are thus better informed about products and prices. This leads to reduced information asymmetries between sellers and buyers. Businesses with B2C business models could proactively benefit from that effect by using mobile information services and mobile marketing to their advantage for both customer retention and new customer acquisition. Users with high search intensity could be targeted with special mobile advertising. They are not only more likely to find a better alternative offer but they are also more likely to react to the advertising (Goh et al., 2009). Companies' (mobile) campaigns could include mobile websites, mobile apps and the provision of LBS. The contribution of our findings is that they help companies to understand the impact of distance on mobile consumer behavior. They are able to consider these findings in their marketing activities and geographic pricing strategy. In addition, mining mobile consumer data, especially involving geographical information such as GPS data, provides further insights regarding the impact of distance on consumers' search and purchase behavior. This could be monetized for instance by targeted advertising.

This study also has some limitations. For example, to estimate differences in the willingness-to-pay between the attribute levels, a linear relationship has to be assumed. In addition, we collect the data using a survey. Such stated preferences are not consequential for consumers but standard practice in empirical research. These limitations provide avenues for future research. The results of this survey-based study could be validated in a field experiment. Search costs could be measured via smartphones in controlled real life situations. Furthermore, it would be interesting to analyze if the effects are different for other products or different countries. Especially the product category could make a difference for the quantified search costs. Additionally, it would be interesting to test various economic search models in a mobile setting. It can be assumed that the diffusion of smartphones will further accelerate and consumers' mobile search costs can thus be reduced on a large scale. Furthermore, companies could react to that development and target mobile consumers proactively.

Appendix A: Description of Situation (CBC-Analysis)

You are in a store and you are interested in buying a digital camera. Previously you have not conducted any search about this. You pick a specific model (e. g., the Sony DSC-HX7VW with 16 mega pixels and 10x optical zoom) and you decide to buy it.

Since you have got your smartphone with you, you are able to check the prices at other stores via the internet. Maybe the product is on offer somewhere else at a better price. In this case you may have to travel to another store for a couple of minutes. Alternatively it is possible to buy the product online.

Each of the following choice tasks reflects a situation where you have got four options. Which of the options would you pick? Please make a new decision in each situation, independent from any previous decisions. If none of the options is attractive for you, it is possible to select "Do not purchase (I would choose none of the presented options.)"

Appendix B: Scales

Construct (all measured on a 7-point Likert-type scale)	**α**	**Reference**
Price Consciousness (strongly disagree / strongly agree): • I will shop at more than one store to take advantage of low prices. • I usually purchase items on sale only. • I usually purchase the cheapest item.	0.70	(Darden and Perreault, 1976, Kopalle and Lindsey-Mullikin, 2003)
Cost of Search (strongly disagree / strongly agree): • I seem to be busier than most people I know. • Usually there is so much to do that I wish I had more time. • I usually find myself pressed for time.	0.82	(Srinivasan and Ratchford, 1991)
Control over Shopping Process (strongly disagree / strongly agree): • There is a lot that I, as a consumer, can do to get the best value for my dollar. • With enough effort I can get very good value for money spent. • By taking an active part in the shopping process, I can have considerable influence as a consumer. • In the long run, I as a consumer am responsible for getting the best value for my money.	0.88	(Chandran and Morwitz, 2005)
Price Comparison Likelihood: • Most consumers of *digital cameras* would be willing to shop around. (strongly disagree / strongly agree) • How likely is it that most consumers will compare *digital cameras'* prices to other stores? (very unlikely / very likely) • How difficult or easy is it to compare the prices of *digital cameras* with other stores? (very difficult / very easy)	0.68	(Srivastava and Lurie, 2004)

Single Items
Product Knowledge: • How do you assess your knowledge regarding digital cameras? (very low / very high) • How relevant are digital cameras for you? (not relevant at all / very relevant)

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