CONSUMER PRODUCT SEARCH AND THE DECISION BETWEEN INTERMEDIARY AND SUPPLIER ONLINE SHOPS

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Abstract

When shopping online, consumers have to decide between two vendor types – suppliers and intermediaries. The existing body of research on intermediation usually adopts a market-centric perspective, and subsequently neglects the consumer when making this focal decision. Therefore, using the example of digital music, we offer a consumer-centric view on this problem. We use experimental and simulation techniques to analyze how consumers decide between intermediaries and suppliers and what kind of search strategies they apply. Furthermore, we evaluate the efficiency of consumers’ decisions and find significant differences between strategies. Given that in practice, consumers usually possess less information on products and prices prior to search and that market structures are more complex, our study demonstrates that consumers may suffer from efficiency losses when having to make such decisions. This highlights the importance of consumer decision support systems that operate on a market-spanning basis and provides new insights for practical applications.

Keywords: Consumer behavior, intermediaries, electronic commerce, transaction costs, experimental economics.
Introduction

In recent years, the continuous growth of e-commerce has gone along with a significant increase in the variety of products available at online shops (Hinz and Eckert 2010). Since online shopping usually involves much lower search costs and less effort, consumers can choose between many different stores, which they can browse within seconds. Moreover, foreign online shops are now virtually equidistant to domestic online shops. When categorizing online shops based on their relation to the products they sell, one can distinguish between two types of vendors: suppliers and intermediaries.

Intermediaries have been known for centuries, for instance in the form of wholesalers and retailers. With their main function of matching supply and demand, these trade intermediaries also exist in e-commerce. As part of the e-commerce development, various large online intermediaries emerged, which aggregate and cover nearly all products from different suppliers in a given market. However, in comparison to the brick-and-mortar world, opening an online shop and accessing consumers directly also involves much lower costs to suppliers. In addition, since suppliers can save the margin the intermediary usually charges, they should have an interest in cutting the intermediaries from their value chains and selling products directly to consumers. Nevertheless, in many markets, intermediaries still seem to be powerful – maybe even more powerful than their counterparts in traditional retail. Good examples include the markets for travel, wholesale shopping, as well as various media markets, such as the markets for books or music, with the well-known market leaders Amazon respectively iTunes.

From a classical economical point of view, intermediaries exist because they may be capable of lowering the overall market's transaction costs (Baligh and Richartz 1964). In many cases, this is due to a larger product offering, which leads to a significant reduction in search costs for consumers. Although the main benefit of this seems to be on the consumers' side and it would be worth quantifying, research on intermediation usually takes on a market or supplier-centric perspective. In such research, consumers are modeled, if at all, as rational and decision-willing subjects, based on the homo economicus principles.

Adopting a different perspective, we maintain that intermediaries' existence is specifically due to consumers having a choice of vendors. We hold that, if consumer search and purchasing processes were better understood, all types of vendors could better align their product offer to consumer needs. Moreover, by including one of the main protagonists in the process, i.e. consumers, this study will contribute to closing an existing research gap.

In this study, we focus on digital music, also because it is a fast growing market that may overtake sales of its physical predecessor product (CDs) soon (Reuters 2011). Moreover, digital music profits from e-commerce as there is no need for physical stock and products can be reproduced and delivered to the consumer promptly. Therefore, classical stock keeping, which is presumably one of the primary functions of trade intermediaries, is obsolete in this case and indicates a decreasing need for intermediation. However, in practice, suppliers' offerings currently seem less successful than those of intermediary online shops. Therefore, digital music is a prime example of the market power of intermediaries (such as Apple's iTunes store). Suppliers (music labels) are trying to break this dominant market power with their own online shops but, at this stage, are failing to do so. Nowadays, even some artists, that formerly were only relevant for the production part of the value chain, use e-commerce technologies to open their own online shop to sell music directly. As a consequence, it seems essential to investigate how consumers decide between intermediary and supplier online shops. We deal with this issue by analyzing consumer behavior and by posing the following research questions:

(1) What strategies do consumers apply when deciding between intermediaries and supplier online shops?
(2) How efficient are consumers' decisions?

We address these research questions by running a laboratory experiment as well as a simulation since we believe that field data would not meet certain requirements. In particular, we doubt whether disturbing influence factors could be excluded appropriately, and whether the comparability of the participants' tasks

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1 Only 3 out of 160 participants from the current experiment had ever bought music from a music label's online shop, while 127 had bought some digital music from online intermediaries, such as the Apple iTunes Store.
could be ensured. Moreover, and needless to say, both intermediaries as well as suppliers are generally reluctant to disclose individual purchase data. Instead, the combination of a laboratory experiment and a simulation seems suitable, because it enables us to control for certain factors of influence and to establish a close relationship to theoretically grounded fundamentals. As part of this, we gave participants a task that was easy to understand but at the same time too complex to calculate optimal decision trees, which allowed us to record participants’ intuitive behavior.

Based on the subsequent results, the contribution of this research is twofold. First, this study contributes to consumer behavior research by extending the current knowledge to a different, but very essential environment that, due to its importance, deserves to be analyzed separately. We highlight the importance of assistance to consumers, even in comparably small environments with a fairly low complexity. Second, the research provides practical insights for all vendor types (both intermediaries as well as suppliers) on how to better adapt to consumer desires by focusing on their applied strategies and the key determinants underlying their decisions.

The remainder of this paper is structured as follows. The next section develops the underlying theoretical basis of this work by drawing on literature in the areas of consumer product search, consumer decisions in e-commerce and intermediation. We then describe the basic foundation of our research model, the laboratory experiment as well as the simulation environment, and present the results. In the concluding section, we discuss the results’ implications for research and practice, point out the paper’s limitations, and suggest areas for future research.

Related Literature

This project builds on existing work and insights from research on consumer product search and decision processes as well as on intermediation in e-commerce. Consumer search and decision processes have long been subject to considerable research, particularly in the fields of marketing and psychology. Intermediation, on the other hand, has mostly been discussed in economics and organizational theory. However, all of these have gained major research interest in the IS community after the rise of e-commerce (Brousseau 2002; Darley et al. 2010).

Consumer Product Search

Consumer product search usually involves a buyer choosing one or several products from a larger selection of products. The potential benefits of search are defined as outcomes that increase the consumer’s utility or provide value by facilitating the achievement of higher-level goals or value (Gutman 1982). After a purchase has been made, consumers may be more or less satisfied with their choices (Kim et al. 2010; Kohli et al. 2004).

Research on consumer product search differentiates between classical normative models of search and behavioral models of search, whereas normative models are mostly based on Stigler’s seminal work (Stigler 1961). However, the current literature provides conflicting findings on whether normative models are good approximations of actual consumer search behavior or whether behavioral accounts provide additional value (Brannon and Gorman 2002; Houser and Winter 2004; Moon and Martin 1996; Phipps and Meyer 1985; Shu 2008). Some approaches integrate normative principles and behavioral influences into one hybrid model (Häubl et al. 2010; Zwick et al. 2003).

There is also a fundamental difference between sequential and non-sequential search. Under sequential search, consumers evaluate one alternative after the other, i.e. after having seen the first product, they explicitly decide whether or not to continue searching for another product, whereas each additional search step usually implies costs (Ratchford 1982; Stigler 1961). Regarding sequential search, consumers face a tradeoff between the potential benefit of an additional search step (e.g. in the form of a lower price or a more fitting product) and the additional costs associated with this search. Therefore, consumers should only perform an additional search step if the expected revenue due to this search step is greater than the costs that it involves (Goldman and Johansson 1978; Weitzman 1979). In non-sequential search, consumers make only one decision, taking different alternatives into consideration at the same time. In contrast to sequential search, in non-sequential search, consumers’ decision to continue searching does not depend on the outcome of previous searches.
Consumers’ motives for pursuing their search are also taken into account when differentiating between different types of search models. In the case of consumer information search, consumers need to find more information on a specific product. In consumer product search however, the nature of a particular product is unknown to the consumer prior to its inspection (Häubl et al. 2010). Consumer price search describes the case of consumers that aim to find the lowest price for a given product (Grewal and Marmorstein 1994). Ratchford provides an overview of different models of search and discusses the effects of individual search behavior on markets (Ratchford 2008).

**Consumer Search Behavior and E-Commerce**

Using e-commerce for shopping is different to shopping in brick-and-mortar markets. Therefore, findings from the offline world are not always applicable to online environments. There are various factors that have an influence on whether consumers shop online or use a traditional channel for their purchases (Chiang and Dholakia 2003; Monsuwé et al. 2004; Zhou et al. 2007). For instance, in a physical space, consumers take into account the physical appearance of a shop as well as the physical distance to the shop, whereas, on the Internet, all sellers are equidistant from the consumer and consumers cannot derive quality perceptions of the seller based on its physical appearance (Balasubramanian 1998). The latter also has a major impact on the consumer’s trust of the seller, as a nice looking physical shop may serve as a symbol of the supplier’s trustworthiness (Kim et al. 2009; Pavlou and Fygenson 2006; Pavlou and Gefen 2004). In line with this, since consumers cannot touch and try out products prior to the purchase, it is more difficult for them to evaluate the quality of the product prior to the purchase. As a consequence, consumers may be more likely subject to deception or fraud than in physical environments (Xiao and Benbasat 2011).

When shopping online, consumers’ actions can be divided into certain stages, processes, and contexts, for instance into the field of online auctions (Ariely and Simonson 2003). Overall, and for each of the different stages of the search and purchase process, a myriad of factors may influence and explain consumers’ shopping decisions. Exemplary influence factors range from product type, task complexity, and user experience to website quality and motives of search (Huang et al. 2009; Kumar et al. 2005; Parboteeah et al. 2009; Wells et al. 2011; Zhou et al. 2007). There are also several factors that can interrupt the purchase process (Xia and Sudharshan 2002). Moreover, users’ interactions during the shopping process have received recent attention in the research as well as vendor strategies for supplying information during the shopping process (Granados et al. 2010; Huang and Chen 2006; Zhu et al. 2010).

Shopping online also implies changes in consumers’ search behavior, as searching offline usually follows sequential patterns, whereas online technological tools have enabled new opportunities for non-sequential search (Sen et al. 2006). In turn, consumer search depth and search intensity can be related to whether consumers conduct a purchase and, if so, what they purchase (Awad et al. 2006). In offline markets, the time consumers spend on searching is a major element of cost. Opportunity cost is commonly associated with the search activity (Ratchford and Srinivasan 1993; Srinivasan and Ratchford 1991; Stigler 1961). However, search efforts may also have positive effects that are able to compensate or even exceed the incurred costs (Aggarwal and Mazumdar 2008).

In comparison to brick-and-mortar environments, the advent of e-commerce technologies has led to significantly lower search costs, since it is much easier to compare various shops and prices online. The reduction of search costs can be seen as one of the key competitive advantages of electronic markets (Bakos 1997; Grewal et al. 2003). Although Internet technologies help reduce search costs, Internet shopping still requires significant consumer time and effort (Brynjolfsson et al. 2010a; Hinz and Eckert 2010; Kohli et al. 2004). In turn, search costs can have a significant impact on whether or not consumers decide to buy online or offline and heavily affect consumer welfare (Chintagunta et al. 2012; Su 2008; Wu et al. 2004).

From a technological point of view, search engines have a significant impact on consumer search (Kamis 2006). In addition, many shops nowadays employ personalization and recommender systems to assist consumers in handling the growing amount of products in their shops (Xiao and Benbasat 2007). Among others, the acceptance of recommendations depends on the type of recommender system applied and the algorithm it uses, the time spent during the shopping process when a recommendation is issued, as well as on the user’s experience (Ho et al. 2011). However, there is conflicting evidence on whether recommender systems lead consumers to purchase more similar or more diverse products (Brynjolfsson
et al. 2010b; Fleder and Hosanagar 2009).

**Intermediation in Online Environments**

Intermediation has been a research subject long before e-commerce (Biglaiser 1993; Rubinstein and Wolinsky 1987; Spulber 1996). From most economic perspectives, search cost reduction is considered one of the major functions of intermediaries through which they additional value for consumers is created. However, some more recent approaches discuss the possibility that intermediaries may have an interest in doing the opposite by intentionally increasing search costs for consumers (Ellison and Ellison 2009; Hagiu and Jullien 2011).

The development of Internet and e-commerce technologies has also created new research perspectives and opportunities in the field of intermediation. A main driver is the digitalization of trade relations, which has important implications for intermediaries. For instance, it is now possible for consumers to easily compare a large number of products and different shops, and, if necessary, switch suppliers quickly. Furthermore, delivery times are negligible when digital products are traded, since there is almost no shortage of products and delivery takes place instantly over the Internet. Reduced transaction costs and matching supply and demand, indicate that, while intermediaries are valuable in physical markets, they could lose their impact in electronic markets. Due to additional costs that intermediaries may add to the value chain some earlier research questioned whether there will be a need for intermediaries in the future (Benjamin and Wigand 1995; Malone et al. 1987). As intermediaries usually charge a margin for their services, they assumed that suppliers would put more effort into selling their products directly to consumers and thus save on this margin. This question is closely related to research on price dispersion in electronic markets (Clemons et al. 2002; Hinz et al. 2011; Walter et al. 2006).

However, intermediaries still seem to be very powerful in many markets; in some of them (such as Amazon in the case of books, for instance) maybe even more than comparable intermediaries in the brick-and-mortar world. Newer research has also pointed out the necessity for intermediation in electronic markets (Datta 2005) and discusses new aspects, such as two-sided-platforms (Bakos and Katsamakas 2008; Evans 2003). In addition, other traditional intermediary functions, such as providing trust, may play a more important role in online shopping, as the product in question cannot be touched beforehand since there is a physical distance to the supplier. Studies in this area usually apply analytical models and motivate intermediation’s potential benefits from a market perspective. They assume that consumers make optimal purchase decisions. However, to make such optimal decisions, consumers require comprehensive information on the product and on the market, which is seldom the case. In contrast, since we believe that consumer decisions are not only governed by classical economic principles, we focus on analyzing de facto consumer behavior.

**Consumer Product Search and Intermediation in a Joint Model**

Overall, we believe that existing studies have overlooked the connection between consumer search and intermediation in e-commerce. Although consumers constitute the focus of consumer product search, related studies do usually not differentiate between different vendor types, i.e. suppliers and intermediaries, which is our primary interest here. Analyzing consumer decisions has deepened our understanding of consumer motives and actions. However, gaining insights into the choices between intermediaries and suppliers requires a strict differentiation between these two types of market subjects. To the best of our knowledge, consumer information search processes and the choice between online intermediary and supplier shops have not been analyzed within an integrated framework. Therefore, we believe that this is the first approach that explicitly combines both aspects and analyzes how consumers actually decide between intermediaries and suppliers. In previous work, we analyzed how certain markets and transaction-related parameters impact this decision (Matt and Hess 2012). We now focus on examining specific consumer strategies and evaluate their efficiency. Thereby we also want to show that future research on consumer search in e-commerce should also account for different types of vendors, since we believe that large intermediary online shops differ significantly from supplier online shops. The underlying research model and imposed assumptions are outlined in the next section.
Research Model

Description of the General Model

Our model comprises a market consisting of three different types of market subjects: suppliers, intermediaries, and consumers. To simplify the model, our proposed market comprises several suppliers and only one intermediary. While adhering to budget restrictions, the consumers’ task is to find and buy the best digital music tracks, which can be purchased either from the intermediary and/or one or several of the suppliers. Figure 1 presents an overview of our conceptual research model.

Each music track has a certain price, utility, and a product genre, which represents a specific music style, artist or age, among others. The price \( p \) of a product \( x \) is determined randomly and underlies a uniform distribution within a range of \( p_{\text{min}} \) to \( p_{\text{max}} \). Although price distributions for music track may be different in praxis, we believe that a uniform distribution reduces the complexity for participants significantly. In line with this, the utility \( u \) of the product \( p_x \) is determined randomly and moves in a span of \( d \) units around the previously determined price of the product. Therefore:

**Price of product** \( p_x \): \[ p_x = [p_{\text{min}}, ..., p_{\text{max}}] \quad | \quad p_{\text{min}}, p_{\text{max}} > 0 \]

**Utility of product** \( p_x \): \[ u_x = [p_x - d, ..., p_x + d] \quad | \quad u_x, p_x, d > 0 \]

Each product’s genre is set randomly. We assume that each consumer has a “favorite genre” that remains constant and that corresponds with one of the values that are associated with each music track. If consumers buy a product \( p_f \) that matches their favorite genre, this product has a utility value that is, on average, \( f \) units higher than a non-favorite product at the same price (again, a uniform distribution is assumed):

**Utility for a product** \( p_f \) **that belongs to the participant’s favorite genre**: \[ u_f = u_x + f \quad | \quad u_x, f > 0 \]

Given a certain endowment in each round, consumers seek to maximize their personal utility by purchasing products (digital music tracks) for which the utility is greater than the cost. Participants have the opportunity to buy any number of products from one of the supplier shops or from the intermediary shop, as long as they have sufficient funds. However, a specific product can be purchased only once during a round. There is no competition for products between different consumers.

Suppliers and the intermediary differ in terms of their product assortment. Suppliers only carry products from one product genre, whereas intermediaries aggregate a small number of products from all genres and therefore have a broader product offering than each of the suppliers. On the other hand, despite a smaller range of products offered, suppliers possess a higher product depth, and therefore offer a larger number of products from a single genre, compared to the intermediary. This can be seen as a supplier’s
strategy to focus on specific niches – for instance, products they may want to sell exclusively or that are too specific to be sold at the intermediary shop.

We assume a uniform distribution of product genres across suppliers in the market, i.e. there is an equal number of suppliers carrying one of the available genres in the market. Participants do not know in advance which genre a particular supplier carries. The same applies to the exact value for product utilities and prices of both the intermediary and the suppliers shops. To learn more about a shop’s various products, consumers need to visit a shop. Once consumers have visited a shop, they get to know the genre of the products as well as the utilities and the prices. They may now choose to buy one or many of the products, provided they have sufficient funds. Consumers may visit each shop as often as they like and in any order (even repeatedly). Visiting a shop is independent of a purchase.

However, when visiting a shop (both intermediary and supplier) for the first time, consumers have to pay a certain amount of search costs in order to gain access to the shop’s products. In contrast, products from previously visited shops can be “recalled” without paying search costs again, i.e. only the first visit to a “new” shop involves search costs, but all subsequent visits to it in one round are free of charge. The rationale for this is that it takes time and effort for consumers to become familiar with a new online shop. These costs are presumably much larger when visiting an online shop for the first time. Thus, to simplify this, the costs are only incurred on the first visit to a shop (Hann and Terwiesch 2003).

Before visiting another new shop (i.e. for which search costs accrue), participants have to make two key decisions. First, they must determine which of the products that have already been viewed are the most attractive, given their utilities and prices (product comparison decision). Second, they must decide whether to terminate or to continue the search by visiting additional shops (stopping decision).

Based on classical normative models of search, consumers should continue searching as long as the marginal gains from additional search steps are higher than their marginal costs (Sen et al. 2006; Stigler 1961). If consumers possess accurate market information, they should weigh accruing search costs against the attainable utility gain due to the inspection of new products that may have a higher utility than the previously inspected ones. If participants decide to terminate their search, they should select the products that offer them the overall highest utility without violating their budget restrictions. As consumers do not have to pay search costs for recalling products from previously inspected shops, products could belong to the currently inspected shop or to any of the previously inspected shops (Häubl et al. 2010).

This decision problem builds on the famous Knapsack Problem, which is used frequently in operations research and in computer science. The Knapsack Problem is considered to be NP-complete, i.e. there is no efficient way to compute optimal solutions for all varieties of the problem. However, the local task is even more complex than the basic Knapsack Problem, since participants do not have access to all the products at once, but must decide whether they want to visit another shop and pay additional search costs, thereby potentially decreasing their profit. Additionally, consumers need to choose between two different types of vendors (intermediary and suppliers) that offer different product ranges.

Owing to the problem’s complexity, participants are unable to calculate optimal decisions in advance and can therefore only apply intuitive strategies or heuristics. In the following section, we discuss optimization strategies for the following scenarios that may be of interest both to consumers as well as providers of e-commerce and consumer decision support systems:

a) Consumers need to select the best products after one or several shops have been visited and they have access to the respective product information.

b) Assuming a decision support system has full information on all products and all shops in the market, the goal is to identify an optimal decision strategy for consumers prior to conducting a search.

Optimization Strategies

Finding the Best Combination of Products Among a Set of Previously Inspected Products

We assume that consumers have visited at least one shop and therefore have access to at least one shop’s products. Consumers want to find the best combination of products (that are not dividable) among all the products they have inspected. These products should offer them the highest utility while not exceeding their budget. As mentioned before, the current model is based on the binary version of the Knapsack
Problem, which involves a set of items, each with a utility $u_i$ and a cost $c_i$, and the goal is to maximize the total utility $u$ while adhering to a budget restriction $B$. Therefore, the maximization function is:

$$\max \rightarrow u = \sum_{i=1}^{n} u_i \cdot y_i \quad \text{subject to:} \quad \sum_{i=1}^{n} c_i \cdot y_i \leq B \quad y_i \in \{0, 1\}$$

With the relaxation that products may be dividable, i.e. consumers can buy fractions of products, this problem becomes almost trivial to solve. In this case, an optimal solution is to sort all products according to their cost-utility ratio and to purchase the product with the highest cost-utility ratio first, before continuing with other products in the order of their cost-utility ratios until the price of the following product exceeds the remaining budget. The product, which is next in line, can only be bought partially, such that the remaining budget equals 0. This solution is optimal for consumers as it achieves the highest overall utility.

However, if products are not dividable, which happens to be the case for many products, the problem becomes much more complex. Applying the formerly described heuristic, a consumer’s budget may not allow him or her to purchase the product that would be next according to its cost-utility ratio. In such a case, the budget could be spent on other products with a lower cost-utility ratio that are cheaper and therefore still fit into the remaining budget. However, this approach may lead to choosing combinations of products that are not optimal with regard to their aggregated utility. The reason for this is that, together, a combination of products, although some of them having lower cost-utility ratios, can better “exploit” the remaining budget and therefore provide a higher total utility than when strictly purchasing products according to their cost-utility ratio.

Dynamic programming is a well-known method that can be used to efficiently (in “pseudo-polynomial time”) compute optimal solutions to the binary Knapsack Problem (Bellman 1956; Martello et al. 1999). There is a vast amount of literature on dynamic programming in various fields. Apart from computer science and mathematics, dynamic programming is mainly discussed in operations research. Dynamic programming breaks down complex problems into simpler subproblems to reduce the complexity and therefore the calculation time of the overall problem. To achieve this, the constructed subproblems are subject to certain conditions, which Bellman called the “principle of optimality.” Dynamic programming ensures exact (optimal) solutions and is applicable in a large variety of problems. If applicable to the current problem, it would thus be favorable compared the cost-utility ratio heuristic as described above.

However, in contrast to the classical Knapsack Problem, consumers do not see all potential products at once. Instead, consumers have to decide whether or not they want to pay additional search costs to expand their scope of potential products. Thus accruing search costs should also be taken into account when looking at the optimization problem. Nevertheless, in the current situation, in which consumers have already visited at least one shop (and after search costs have already been deducted), they can still calculate a utility-optimizing product combination by means of dynamic programming. Since search costs have already been paid and consumers can go back to any previously visited shop for free, all the inspected products (also from different shops), together, can be regarded as the set of potential products to which dynamic programming can be applied. Incurred search costs can be considered as sunk costs and they do have an influence on how large the remaining budget is. However, since they do not apply again for any of the products from the current choice set, they should not have an influence on the final purchase decision. Therefore, dynamic programming is applicable in the current scenario and will facilitate selecting the best product combination. Nevertheless, depending on the choice set, applying dynamic programming may be too complex to calculate optimal decision trees without any IT tools. Therefore, consumers may rather be able to apply the cost-utility ratio heuristic instead.

**Identifying an Optimal Strategy for Consumers Prior to Conducting Search**

Determining which vendors, on average, have the most promising products in the current market is a complex task for consumers – even if consumers decide to buy just from only vendor per round. This is not only due to product prices being uniformly distributed within a certain range and exact prices only being disclosed after visiting a shop and paying search costs; it is also due to the uniform distribution of products’ utility in a certain range according to the product’s actual price. In addition, products may or may not belong to the consumer’s favorite genre and therefore they thus may have a higher utility to them.

Furthermore, as mentioned in the previous section, there are also various possibilities to combine
different products to maximize the consumer’s utility while abiding to budget restrictions. Therefore, the calculation of all possible price and product combinations is complex – both for humans and computer algorithms – if the product space becomes large. Things get even worse if we combine the possible product offer of several vendors and try to find optimal product combinations among these.

A possible way to calculate this would be to enumerate all potential product and price combinations for all vendors and to apply dynamic programming to the whole product space. However, even in small markets this can be complex. Furthermore, search costs, which apply only for certain products and combinations (only once per shop), would have to be taken into account. However, even in small markets this can be complex. We therefore illustrate an approach to decrease the problem’s complexity and make it scalable for an adoption even in larger market environments. At this, we therefore assume that a decision support system has full information on all products and shops, and aims to develop the optimal search strategy for consumers in a given market.

As mentioned before, in addition to the binary Knapsack Problem, products may come from different vendors and are only accessible after paying search costs. When applying this multiple shop assumption a separate “basket” for each of the shops can be built. In each basket all possible “product bundles” that can be aggregated based on the shops’ possible product combinations are put. Since there is also the possibility of no products being chosen from a shop, there are \( n^2 \) combinations per shop with \( n \) being the number of products in this shop. For each of these \( n^2 \) product combinations, the overall price and its total utility is calculated. Moreover, the search costs are deducted from the utility value.

One could subsequently combine all product bundles from different shops to try and find the best combination. Using the total number or vendors \( v \) and the number of products for each vendor \( n_v \), the maximum number of all feasible product bundle combinations \( N \) can therefore be calculated as:

\[
N = \prod_v (n_v + 1) - 1 \quad \mid n_v, v \geq 0
\]

However, the current problem contains the restriction of only one product bundle per shop on the purchase side (since a specific product can only be purchased once). In accordance, an additional restriction must be placed on the standard Knapsack Problem, i.e. that products belong to several baskets and only one product may be drawn per basket (while still adhering to the common functions of maximizing the total value and obeying the total budget restriction).

This extended version of the Knapsack Problem is referred to as the Multiple Choice Knapsack Problem (MCKP) (Sinha and Zoltners 1979). There are several heuristics and applications of the MCKP, for instance in research on sponsored search (Zhou and Naroditskiy 2008). Some of the approaches also use dynamic programming (Martello and Toth 1990). Transforming the current problem to make it applicable to MCSK-algorithms leads to a significant reduction in the overall problem’s complexity and therefore reduces processing times for providers of decision support systems.

However, in this case, we have to acknowledge again that consumers cannot apply such strategies without the further support of computer algorithms. Therefore the possible ideal outcomes of the described heuristics are probably not achievable by consumers. Thus, we conducted a laboratory experiment to analyze intuitive consumer behavior and what kind of strategies and heuristics consumers apply. The implementations as well as the results of the laboratory experiment are described in the next section.

**Application in a Laboratory Experiment**

**Implementation**

The experiment was fully computerized using the experimental software z-tree (Fischbacher 2007). We conducted eight sessions with eight rounds each. Our sample consisted of 160 participants, among there were 92 female and 68 male participants with an average age of 23.6 years (SD=2.74). Most of the participants were graduate and undergraduate students from various fields. Although we acknowledge that students’ income effects and opportunity costs may differ from those of other adults, we deliberately chose students for our subject population, not only because they are the most accessible population, but also because they generally constitute the group with the most experience in Internet usage in general and online shopping in particular. Furthermore, students should possess the knowledge and ability to respond
adequately to our experimental treatments to ensure internal and external validity (Bello et al. 2009). We thus believe that a sample consisting of university students serves as a good proxy for the web population.

To encourage participation, we applied an incentive-compatible payment schema. After each round $i$ participants received the payoff $y_i$, which was calculated based on the sum of the accumulated utility $u_i$ of all purchased products $x$ and the remaining account balance $b_i$ in the specific round, whereas the account balance $b_i$ is not only decreased by products purchases, but also by accruing search costs. The total payoff $y$ is the sum of the payoffs from all different rounds:

**Payoff after each round:**

$$\text{max} \rightarrow y_i = b_i + \sum x u_{ix}$$

**Total payoff:**

$$y = \sum_i y_i$$

In each of the 8 rounds, participants received an endowment of 100 experimental units to spend on digital music tracks. In order to avoid latent participants preferences, i.e. participants rather buy products they like irrespective of the utility they provide in the experiment, we did not use real songs, artists and vendor names. In each of these 8 rounds, the price $p$ of a product $x$ was determined randomly and ranged from 10 to 25 experimental units. Based on the product’s final price, its utility $u$ was drawn randomly in a span of 10 experimental units around the previously determined price. Products belonging to the participant’s favorite genre received 15 additional experimental units.

**Price for product $x$:**

$$p_x = [10 \ldots 25]$$

**Utility for product $x$:**

$$u_x = [p_x - 10 \ldots p_x + 10]$$

**Utility for a product $y$ that belongs to the participant’s favorite genre:**

$$u_x = u_y + 15$$

We mapped the scenario in a lab environment with a two-group design. The groups differed according to the number of supplier shops in the market. The idea that a higher number of suppliers may have an influence on intermediation goes back to the model of Baligh and Richartz (1964). They maintained that intermediaries are especially beneficial to the overall market if a higher number of suppliers is present. According to their model, all consumers need to get in touch with all suppliers in order to get complete information on prices. A bridging intermediary that connects suppliers and consumers can therefore mean significant cost savings if many suppliers are present. However, since it is difficult to implement a very large number or suppliers in the laboratory, we chose to implement a second group with a slightly higher number of suppliers, also in order to check for differences between these settings, but rather to validate potential findings in a different setting.

The uniform distribution of product genres in the market also impacts participant’s likelihood of finding products in their favorite genre in a supplier shop. An increase in the number of supplier shops in the market also means an increase in the number of supplier shops that do not carry a participant’s favorite genre (however, the ratio remains the same; thus there are also more shops that carry the participant’s favorite genre). Therefore, in some cases finding products from their favorite may take consumers longer and involve additional search costs.

Table 1 summarizes the main vendor characteristics of the two groups.

<table>
<thead>
<tr>
<th>Table 1. Differences Between Supplier and Intermediary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Offer Intermediary</td>
</tr>
<tr>
<td>Number of Products</td>
</tr>
<tr>
<td>Number of Genres</td>
</tr>
<tr>
<td>Songs per Genre</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>Number of Intermediaries</td>
</tr>
<tr>
<td>Group A</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>Group A</td>
</tr>
<tr>
<td>3</td>
</tr>
</tbody>
</table>

**Results**

In order to identify what kind of strategies participants applied during the experiment, we conducted an
additional questionnaire at the end of the experiment. As part of this questionnaire, participants could choose between several predefined strategies, but also had the opportunity to describe their own strategy in case it did not match any of the provided ones. In addition, we randomly analyzed selected cases and compared the answers from the questionnaire with the data from the experiment.

Overall, the candidates applied nine different strategies. Distinguishing between these strategies, we identified four groups of consumers according to their level of determination in respect to which search strategy they applied and whether or not they updated their preferences based on interim search results. Table 2 shows an overview of the frequency distributions as well as the different strategies’ respective profits in the two different treatment groups. We define the profit \( P_i \) per round \( i \) as the initial endowment \( e_i \) in this round minus the total costs \( \sum p_{ix} \) for all purchased products \( x \) plus the utility stemming from the purchases \( \sum u_{ix} \) less the accrued search costs \( s_i \):

\[
P_i = e_i - \sum_{x} p_{ix} + \sum_{x} u_{ix} - s_i
\]

The strategies are grouped according to the classification schema as shown in Table 2. The strategy names indicate the number of shops consumers visited and the order in which they were visited. A relation with an arrow (e.g., “Intermediary->1 Supplier”) means that participants first went to the intermediary and then, immediately after, went to one supplier shop without any further constraints. In contrast to this, brackets indicate that the following visits were subject to certain constraints, for instance if the favorite genre had not been found at the previous shop.

The average profit values of the different strategies should be handled with care since some of the strategies were only applied by very few participants and therefore cannot be considered statistically accurate. We therefore omit to report profit differences across the different strategies. Overall, we see only minor differences between the two groups’ distribution of strategies. In both cases the majority of participants only visited the intermediary. Since most of the other strategies were applied quite seldom, we also refrain from the statistical testing of profit differences between the two groups. We subsequently explain the four strategy types.

### Table 2. Distribution of Strategies in Laboratory Experiment

<table>
<thead>
<tr>
<th>Strategy Type</th>
<th>Strategy Name</th>
<th>Strategy ID</th>
<th>Group A Frequency</th>
<th>Group A Profit</th>
<th>Group B Frequency</th>
<th>Group B Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predetermined Search Strategies</td>
<td>Intermediary</td>
<td>1.1</td>
<td>65,00%</td>
<td>42,81</td>
<td>57,50%</td>
<td>41,74</td>
</tr>
<tr>
<td></td>
<td>Intermediary -&gt; 1 Supplier</td>
<td>1.2</td>
<td>1,25%</td>
<td>54,04</td>
<td>1,25%</td>
<td>41,83</td>
</tr>
<tr>
<td></td>
<td>Intermediary -&gt; 2 Suppliers</td>
<td>1.3</td>
<td>0,00%</td>
<td>0,00</td>
<td>2,50%</td>
<td>33,83</td>
</tr>
<tr>
<td>Adaptive Search Strategies</td>
<td>1 Supplier (Intermediary)</td>
<td>2.1</td>
<td>10,00%</td>
<td>32,93</td>
<td>10,00%</td>
<td>39,32</td>
</tr>
<tr>
<td></td>
<td>2 Suppliers (Intermediary)</td>
<td>2.2</td>
<td>2,50%</td>
<td>32,58</td>
<td>1,25%</td>
<td>35,29</td>
</tr>
<tr>
<td></td>
<td>1 Supplier (All Suppliers)</td>
<td>2.3</td>
<td>2,50%</td>
<td>47,52</td>
<td>3,75%</td>
<td>40,76</td>
</tr>
<tr>
<td></td>
<td>1 Supplier (1 Supplier)</td>
<td>2.4</td>
<td>1,25%</td>
<td>44,38</td>
<td>0,00%</td>
<td>0,00</td>
</tr>
<tr>
<td>Changing Strategies</td>
<td>Changing Strategies</td>
<td>3</td>
<td>17,50%</td>
<td>40,73</td>
<td>21,25%</td>
<td>39,27</td>
</tr>
<tr>
<td>No Specific Strategy</td>
<td>No Specific Strategy</td>
<td>4</td>
<td>0,00%</td>
<td>0,00</td>
<td>2,50%</td>
<td>39,98</td>
</tr>
</tbody>
</table>

Predetermined search strategies:

We named this group “predetermined search strategies”, since participants commit themselves to a certain number and type of shops prior to starting their search activities – independent of what products they may find until the last shop is visited. In our case, the majority of participants went to the intermediary only without considering any suppliers’ offers. Probably for the sake of convenience, many consumers tend to directly address large online retailers, which virtually carry almost all products, so they do not have to invest in any further search activities. Given the large market share of well-known intermediaries in some e-commerce markets (such as Amazon for books), this share does not seem
abnormally high.

Although we do not see any participants restricting their search to a single supplier, this could well be the case in practice if consumers have a favorite supplier shop and are fully convinced that they will find the product they are looking for in this specific shop. We believe that this consumer group is probably the most loyal to certain vendors and it takes significant effort to make these consumers change their habits.

Adaptive Search Strategies:

In contrast to Group a) participants in Group b) adopt their further search paths subject to certain conditions. In our case, this constraint usually depends on whether or not participants have already found their favorite genre or not. This seems particularly reasonable if participants are uncertain about the vendor’s product offer or the vendor’s price level.

In combination with this, constraints based on the current budget are also plausible in order to ensure that the remaining budget still allows for further purchases even after deducting the search costs of visiting another shop. For this reason, most participants in this group apply a strategy, where they follow a riskier choice first (i.e. visiting a supplier). However, in case they do not find their favorite genre, they visit the rather safe but less promising (i.e. with less niche products from their favorite genre) option of the intermediary immediately after. However, some participants (labeled as “Supplier (All Suppliers)” were willing to visit all suppliers in the market, even if this meant spending almost their entire budget on search costs.

Changing strategies:

Approximately one fifth of the participants applied more than one strategy during the experiment. This indicates that a substantial amount of consumers does not seem to have stable search strategies. On average, the “strategy changers” did not reveal significantly higher profits than those who did not change their strategies. However, we believe that unstable preferences may make these consumers more vulnerable to external factors, such as promotions.

No specific strategy:

A small percentage of consumers in Group B did not apply any kind of strategy, but rather searched for products randomly. It should be taken into account that, compared to real online markets, participants faced a very simple market and were provided with more information than usual, which probably made it easier for them to come up with a specific strategy. Therefore, we maintain that the share of “non-strategic” consumers is probably much larger in practice. Moreover, this group may be easily influenced by external information. However, if used appropriately, recommender systems may provide substantial benefits for these consumers.

Replication as a Simulation

Implementation

In order to evaluate the efficiency of the participants’ strategies on a larger scale and to gain statistical accuracy, we replicated the laboratory experiment as a simulation. For this, we kept all underlying assumptions regarding the characteristics of the market subjects and the distribution of products, prices, and utilities constant; we merely replaced the participants from the laboratory experiment with computerized algorithms on the input side. In the simulation, we implemented all the strategies that were identified in the laboratory experiment (except for participants with changing or no specific strategy) and ran 2 x 1000 simulations (1000 for Group A, 1000 for Group B) for each strategy in order to calculate average profit values. In addition, we implemented all strategies in two versions to better account for the potential challenges humans face when have to choose the best product combination if products are not dividable and if they must not exceed their budget. Therefore, we executed the following:

a) Dynamic programming: As mentioned before, a dynamic programming heuristic guarantees selecting the optimal product combination for any given product set and budget (Bellman 1956). Instead of using dynamic programming, this could also be implemented using a “brute-force-approach,” i.e. enumerating and trying all possible product combinations to receive the optimal outcome. However, dynamic programming has the advantage that it is also scalable for more
complex environments with a higher number of products to choose from.

b) Cost-utility ratio: This entails the rather intuitive approach that most humans tend to apply (Martello and Toth 1990). Here, consumers rank all the products they had inspected at the time according to their cost-utility ratio. Consequently, consumers buy the products in the order of the highest to the lowest cost-utility ratio, until the budget does not allow for more purchases. However, since we assume that digital music products are not dividable, non-optimal product combinations may be chosen. Therefore, the cost-utility heuristic does not lead to exact solutions and therefore only leads to profit values that are equal or lower than those obtained by using dynamic programming.

Results

The goal of the simulation is not to identify how well participants executed a single strategy, but to obtain reliable values for the average profit that could have been achieved using a specific strategy. We furthermore compare these values to the overall average that participants achieved in the laboratory. This helped us to evaluate how well “the masses” do on average and therefore provides insights into whether additional decision support is needed on a broad scale. Table 3 shows the on average achievable profit values for all strategies and how well participants did in the laboratory experiment in comparison to if they had all strictly followed a single strategy.

The differences in profits between Group A and Group B tend to be rather small. Only for strategies 2.3 and 2.4 the differences were statistically significant at the .05 level. That is a first indication that some strategies pay off more for smaller or larger markets. However, this remains to be tested in settings where the differences in the number of suppliers in the market are bigger. In most cases the differences between dynamic programming and the cost-utility ratio heuristic are also small and only in a few cases does the rather intuitive cost-utility ratio approach score much worse. However, in a few cases, the values for dynamic programming are lower than for the cost-utility ratio. This is due to statistical error, since we computed new random variables for all 1000 iterations of both techniques. Owing to its randomness, we did not seek to replicate the behavior for participants that did not apply any strategy or used several strategies.

Table 3. Comparison of Profit Results in Laboratory Experiment and Simulation

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Measure Strategy</th>
<th>Laboratory</th>
<th>Independent Strategies 1.1</th>
<th>1.2</th>
<th>1.3</th>
<th>Dependent Strategies 2.1</th>
<th>2.2</th>
<th>2.3</th>
<th>2.4</th>
<th>Changing 3</th>
<th>None 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>A 3 Suppliers</td>
<td>Dynamic Programming</td>
<td>34.57</td>
<td>39.14</td>
<td>34.28</td>
<td>14.98</td>
<td>37.45</td>
<td>26.70</td>
<td>37.93</td>
<td>33.23</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>A 3 Suppliers</td>
<td>Difference to Laboratory</td>
<td>13.23%</td>
<td>-0.83%</td>
<td>-56.67%</td>
<td>7.75%</td>
<td>-22.75%</td>
<td>9.74%</td>
<td>-3.88%</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>A 3 Suppliers</td>
<td>Cost-Utility-Ratio</td>
<td>39.87</td>
<td>26.20</td>
<td>11.28</td>
<td>36.30</td>
<td>27.14</td>
<td>38.43</td>
<td>31.70</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>A 3 Suppliers</td>
<td>Difference to Laboratory</td>
<td>15.33%</td>
<td>-24.22%</td>
<td>-67.38%</td>
<td>5.59%</td>
<td>-21.48%</td>
<td>11.17%</td>
<td>-8.30%</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>A 3 Suppliers</td>
<td>Frequency in Laboratory</td>
<td>65.00%</td>
<td>1.25%</td>
<td>0.00%</td>
<td>10.00%</td>
<td>2.50%</td>
<td>2.50%</td>
<td>1.25%</td>
<td>17.50%</td>
<td>0.00%</td>
<td></td>
</tr>
<tr>
<td>B 6 Suppliers</td>
<td>Dynamic Programming</td>
<td>32.85</td>
<td>40.01</td>
<td>34.51</td>
<td>15.41</td>
<td>35.14</td>
<td>25.78</td>
<td>28.01</td>
<td>26.70</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>B 6 Suppliers</td>
<td>Difference to Laboratory</td>
<td>21.78%</td>
<td>5.04%</td>
<td>-53.10%</td>
<td>6.95%</td>
<td>-21.54%</td>
<td>-14.74%</td>
<td>-18.74%</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>B 6 Suppliers</td>
<td>Cost-Utility-Ratio</td>
<td>39.68</td>
<td>25.41</td>
<td>10.44</td>
<td>35.56</td>
<td>23.14</td>
<td>28.10</td>
<td>26.33</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>B 6 Suppliers</td>
<td>Difference to Laboratory</td>
<td>20.77%</td>
<td>-22.67%</td>
<td>-68.22%</td>
<td>8.23%</td>
<td>-29.56%</td>
<td>-14.46%</td>
<td>-19.86%</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>B 6 Suppliers</td>
<td>Frequency in Laboratory</td>
<td>57.50%</td>
<td>1.25%</td>
<td>2.50%</td>
<td>10.00%</td>
<td>1.25%</td>
<td>3.75%</td>
<td>0.00%</td>
<td>21.25%</td>
<td>2.50%</td>
<td></td>
</tr>
</tbody>
</table>

This study focused on the profit differences between different strategies executed in the simulation and the average values achieved by participants in the laboratory experiment. Since the laboratory values represent the average profit of all participants (i.e. the average of all different strategies), it is no surprise that some of the strategies executed in the simulation scored higher than the laboratory average whereas others scored lower (except for Strategy 1.2. all profit values are significantly different from the laboratory average at the .05 level). However, the differences between the best and the worst strategy are up to 68%, illustrating the economic impact that choosing the wrong search strategy may have. At the same time, this indicates a deficit of certain consumer groups to handle such decisions, even in small and controlled...
environments. It is also important to note that we cannot conclude which of the four strategy groups is the most promising as there are also significant differences within these groups. This indicates that finding an appropriate strategy may well depend on a concrete purchasing scenario. Likewise, this also means that consumers should not always follow a single strategy, but adapt their strategy according to the situation at hand. We have doubts that most consumers will always be able to identify optimal strategies. This further supports the claim that consumer decision support systems (for instance in the form of recommender systems) can be very important tools to assist consumers in this process.

Discussion and Conclusion

Theoretical and Practical Implications

This article examined the relationship between online intermediaries and supplier shops as an explicit consumer decision process and investigates applied consumer search behavior and strategies. It thereby builds upon consumer product search and intermediation theory. We modeled a case in which consumers had to maximize their personal utility by purchasing digital music tracks (either from a supplier or intermediary online shop) after accounting for search costs. We now highlight three interesting findings for the further development and combined application of both theories.

First, based on the findings from the laboratory experiment we know that consumers take into account different vendor types and their product offer when deciding how to search for products. A large vendor with an almost comprehensive offer may even lead many consumers to completely fade out other purchasing options. Therefore a uniform implementation of vendor characteristics, as performed in most research to date, does neither fully account for the current e-commerce landscape nor for actual consumer behavior. We believe that the findings reported in this paper are a first step towards developing a new, consumer-centric understanding of the interactions between suppliers and intermediaries and that continuing on this path will contribute to explaining and predicting the potential need for intermediaries in e-commerce. Apart from the benefits for intermediation theory, we hold that also future research on consumer product search should implement different types of vendors in order to gain a more comprehensive picture of consumer behavior in e-commerce.

Second, evidence from a laboratory experiment led us to identify certain consumer strategies that can be grouped into four categories. These groups are differentiated according to how established consumers’ search strategies are prior to conducting a search and whether they take interim search results (here mostly finding a preferred product genre) into account when deciding whether or not to continue their search. We subsequently categorize the four consumer types according to their search strategies’ level of pre-determination, from being rather undetermined and open to external influences to being the least flexible and influenceable. Therefore, we distinguish between consumers, who:

a) Do not apply any kind of search strategy.
b) Change search strategies without any changes to the search environment.
c) Condition their further search decisions based on their interim search results.
d) Have a predefined strategy of visiting a certain number of vendors prior to conducting search.

A small share of consumers seems to have no search strategy in mind and, instead, appears to act intuitively instead of strategically. Moreover, these consumers are probably the most vulnerable to external influences. Another group of consumers does not commit itself to one specific search strategy. They seem to have less determined search preferences. We believe that these consumers may also not be very prone to use specific vendors (and not just in terms of their search strategy) and could therefore be a suitable target for marketing campaigns. The third group of consumers is influenced by interim search results. Conditions affecting their decisions may be related to finding a specific product or genre or falling below certain time or money levels. However, although these consumers are actively involved in the search process, this does not necessarily mean that the best results are achieved. One possibility is that consumers are frustrated, because they have not found a specific product yet, and therefore misjudge their chances to find the product in question and continue their search until they have found it, irrespective of the amount of accruing search costs. However, the overall majority of consumers establishes their personal search strategies in advance and adheres to it until a predefined number of shops had been
visited, independent of the products they encounter during the search. This contradicts classical search models, according to which consumers update their preferences based on interim results.

Intermediaries as well as suppliers may profit from our classification since it may help them to better align their product offer to consumers’ needs, better estimate their chances of acquiring a new consumer and improve their online advertising. It may therefore be useful to focus their advertising on new consumers as well as existing customers with rather undetermined search strategies. In the case of existing consumers with determined preferences, vendors may want to increase lock-in effects to make it even harder for them to deviate from their current habits. However, consumers should not perceive these lock-in effects as negative enchainment, but as positive services and efforts that are made to avoid disappointing them. For instance, instead of setting contractual obligations or standards, vendors could provide extensive personal or automatic shopping assistance services, such as a complete buying history with a central management for complaints as well as prefilled payment and shipping information in order forms.

Third, we conducted an additional simulation that allowed us to evaluate and compare the efficiency of all the strategies that were applied by participants in the laboratory experiment. Our findings imply that there are significant differences between the efficiency of the different strategies and that, even in small markets with moderate complexity, many consumers are not able to select the most appropriate strategy. Given that real e-commerce markets are much more complex and contain a much larger number of suppliers and products, it seems quite likely that a large share of consumers will bear sufficient efficiency losses due to the challenges of handling complexity. Moreover, a strict avoidance of search and decision efforts may lead many consumers to directly search and buy from large intermediaries that seem to offer nearly all the products in a market – almost irrespective of how competitive the intermediary’s prices are.

Therefore, we suggest that providers of online shops further invest in technologies that will encourage consumers to stick to their website (Li et al. 2006; Xue et al. 2006). One possibility would be to develop intelligent decision support systems for consumers (Häubl and Trifts 2000; Kamis et al. 2008). However, this suggestion does not come without any constraints: First of all, these systems must not be abused by providers; otherwise consumers may recognize the negative utility that the system provides. For instance, recommender systems could lead consumers to buy products that guarantee the highest margin for the vendor. In addition to that, providers should consider that the development and the operation of these systems imply a cost for them, which may or may not be compensated for by an increase in consumers’ willingness-to-pay. Furthermore, if additional information services are provided at no cost, consumers can make use of these free services and purchase from other vendors that do not offer additional information, but lower costs instead (Wu et al. 2004). Lastly, most of the classical recommender systems do not offer sufficient information to cover the problem of choosing between various types of vendors, as they just provide information on single shop’s products. Our study illustrates the consumers’ need for product recommendations on a market-spanning basis. In contrast, comparing different vendors, price search systems provide consumers with recommendations on where to find a specific product at the lowest price. However, in this case, consumers should already be aware of the product they are looking for. We therefore propose the need for efficient recommender systems that provide recommendations for best matching products and compare the overall offer and price levels of various online shops. Ideally, these systems should take various conventional implicit and explicit consumer preferences into account, such as previous purchases, personal interests, and usage behavior. External information, such as shop quality or accruing lock-in-costs, should also be taken into account. According to which of the four strategy type groups the consumer belongs to as well as the complexity of the task at hand, should determine how proactive the recommender system should act.

**Limitations and Future Research**

This study has some limitations that should be noted. First, although we sought to provide a fairly general scenario, circumstances for other markets and products may differ from ours. For instance, in other scenarios, search cost values may be much lower compared to the average price of a product. Moreover, the differences between suppliers and intermediaries may be larger or smaller. Digital music intermediaries, for instance, may find it difficult to add additional value to the final products since there is usually no significant difference in the quality of the products (most vendors nowadays offer music with comparably large bitrates). Based on this, there may also be substantial differences between
intermediaries’ and suppliers’ prices, which we did not incorporate into our model.

Second, in our case, consumers entered a market with different product offerings and vendors in every round. In reality, consumers may build relationships of trust with certain vendors, which may have a strong impact on their future purchase decisions (Kim and Gupta 2009). Therefore, buyers who have had positive experiences with certain online sellers are probably more likely to obtain their price information directly from their preferred sellers. One factor that is likely to influence a positive experience with a known vendor is satisfaction with the offered prices. This may also influence a consumers’ decision between intermediaries and suppliers. If consumers are happy with the intermediaries’ service quality and prices in addition to their, in many cases comprehensive, product offer coverage, there may be little reason to shop at any supplier shop in the future. In fact, if consumers are satisfied with their current provider, they are even less likely to search for other vendors (Cao et al. 2003; Sen et al. 2006). Therefore, it is important for vendors to create awareness of and trust towards their online shops in order to set a profound basis for a long-term business relationship.

Third, despite our attempts to provide a comprehensive picture, the methodology we applied and our quest for simplicity led us to exclude other potentially relevant factors and to make various assumptions. In our model, search efforts imply a certain cost for consumers. However, search efforts could also imply positive effects for consumers, such as an increased level of expertise or feelings of flow (Aggarwal and Mazumdar 2008; Mathwick and Rigdon 2004). Moreover, consumers may not necessarily obtain full information about products’ utility after a first inspection.

We did not cover potential contractual relationships between consumers and vendors of digital products such as monthly subscriptions, which may have an impact on consumers’ freedom to switch vendors. Consumers may also face potential technologically based lock-in effects – for example, different file formats.

We have now identified certain strategies that consumers apply when choosing between different types of vendors. We will further investigate why consumers apply these strategies and what could make them alter their habits. Future research should also try to validate the results in a more generalized setting including different market conditions. Moreover, it seems worth to expand the present research to a broader variety of products. We also see further potential in widening the scope of existing research on recommender systems to recommendations across various shops. At this, future research should investigate whether existing insights on intra-shop recommendations can be extended to a market-spanning perspective.

References


