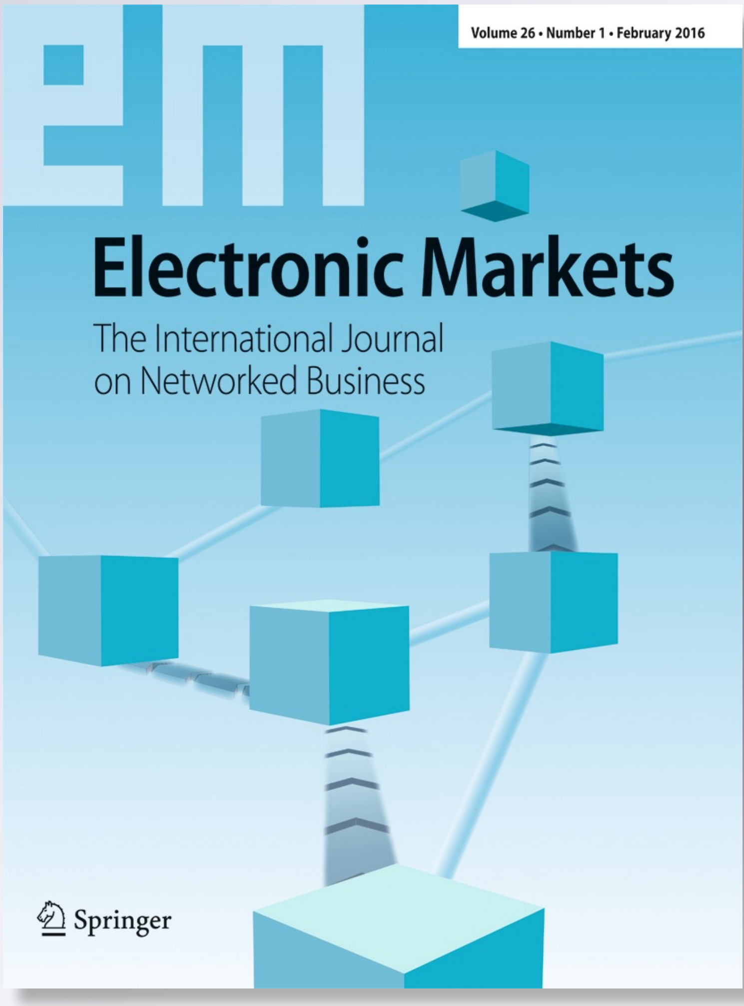
# *Product fit uncertainty and its effects on vendor choice: an experimental study*

**Christian Matt & Thomas Hess**

**Electronic Markets**
The International Journal on Networked Business

ISSN 1019-6781
Volume 26
Number 1

Electron Markets (2016) 26:83-93
DOI 10.1007/s12525-015-0199-5




Springer

source: https://doi.org/10.7892/boris.105537 | downloaded: 9.4.2024

Your article is protected by copyright and all rights are held exclusively by Institute of Information Management, University of St. Gallen. This e-offprint is for personal use only and shall not be self-archived in electronic repositories. If you wish to self-archive your article, please use the accepted manuscript version for posting on your own website. You may further deposit the accepted manuscript version in any repository, provided it is only made publicly available 12 months after official publication or later and provided acknowledgement is given to the original source of publication and a link is inserted to the published article on Springer's website. The link must be accompanied by the following text: "The final publication is available at link.springer.com".

Springer

Author's personal copy

Electron Markets (2016) 26:83–93
DOI 10.1007/s12525-015-0199-5

RESEARCH PAPER

# Product fit uncertainty and its effects on vendor choice: an experimental study

**Christian Matt**[1] · **Thomas Hess**[1]

Received: 2 February 2015 / Accepted: 25 August 2015 / Published online: 10 September 2015
© Institute of Information Management, University of St. Gallen 2015

**Abstract** Recommender systems and other Internet-enabled technologies have changed the surrounding conditions of pre-purchase evaluations on the Internet. In some cases consumers can now sample entire products prior to a purchase – hereby removing all uncertainty about whether a product fits their taste. While previous research has mainly focused on vendor and product quality uncertainty, it is still not clear how declining product fit uncertainty affects consumers. To close this gap, we conducted a laboratory experiment to analyze the effects on consumers' vendor selection. We find that full elimination of product fit uncertainty is beneficial for vendors, as it increases both the number of purchases and consumer loyalty. Interestingly, if product fit uncertainty is only partially eliminated, consumers do not necessarily show differential behavior for different levels of remaining product fit uncertainty. This has important implications for online vendors that consider the implementation of additional means to reduce product fit uncertainty.

**Keywords** Product fit uncertainty · Product evaluation · Experience goods

**JEL Classification** 2.20.3: Experiment · 3.080: Consumer behavior · 3.130: E-Commerce · 5.080: Media

Responsible Editor: Stefan Klein

✉ Christian Matt
matt@bwl.lmu.de

[1] Institute for Information Systems and New Media, Ludwigstr. 28 VG, 80539 Munich, Germany

## Introduction

While research has mainly focused on uncertainty related to vendor characteristics or the quality of products, insights on the assessment of product fit uncertainty and the effectiveness of concrete measures to reduce it remain scarce (Dimoka et al. 2012). This is to some degree surprising since a lack of product fit constitutes a key factor for low customer satisfaction and causes expensive product returns (Hong and Pavlou 2014). The research gap becomes even more problematic since recommender systems and other Internet-enabled technologies have changed the way products can be evaluated (Matt et al. 2013). By using these measures, product fit uncertainty can be reduced or even eliminated, e.g. by providing full length streaming samples. In the latter case, consumers are now fully aware of whether a product fits their taste prior to a purchase. This development is also important for the competition between offline and online vendors, given that even in "brick and mortar" stores a substantial removal of product fit uncertainty is not always given.

Online vendors have an interest in reducing product fit uncertainty since high levels thereof can harm sales. This is particularly relevant for experience goods, which differ from search goods as they require users to sample or purchase the product to evaluate its quality (Mudambi and Schuff 2010; Shapiro and Varian 1999). In addition, many experience goods are not eligible for product returns. However, from online vendors' point of view, the provision of measures to reduce product fit uncertainty usually does not come for free, as for instance, setup costs for recommender systems accrue as well as the risk that consumers could annul copy protection mechanisms to continue using content after the trial period has expired. Therefore, the provision of such measures needs to be

Author's personal copy



subject to a cost-benefit analysis (Matt and Hess 2012). Essential for these considerations is not only a concrete estimate of the costs, but also a profound understanding of how consumers evaluate products prior to a purchase, given different levels of product fit uncertainty. However, only recently research in information systems has begun to conceptualize product fit uncertainty (Hong and Pavlou 2014), but substantial findings on its effects on consumers are still missing. By omitting a key variable, previous research has missed the opportunity to present a complete picture of consumers' actual purchasing processes. As a consequence, online vendors still face challenges to estimate the effects of additional measures to reduce product fit uncertainty. We aim to close the research gap and to support online vendors in their critical endeavor and pose the following research question:

> *What is the influence of product fit uncertainty on consumers' purchase decisions and their vendor choices?*

We use a laboratory experiment to conduct our research since the applied methodology provides a high level of control, and enables us to design a decision-making environment in which potential influencing factors can be evaluated unequivocally. We take on consumers' perspective and frame our research as consumers' choice of an online vendor. Specifically, we implement two different online vendors for digital experience goods; one that offers a full coverage of product fit uncertainty, and one that does not. We hold that, if online vendors decrease product fit uncertainty, they will attract more consumers and increase purchases as well as customer loyalty. We further believe that a reduction in product fit uncertainty is more beneficial for online vendors if the general level of product fit uncertainty is high.

For our research, we incorporate the effects of Internet-enabled technologies that have substantially altered consumers' possibilities of product pre-purchase evaluations. New insights in this area are not only beneficial for online vendors who seek to optimize their online stores to boost sales; they are also needed to understand whether the recent technological changes and declining product fit uncertainty affects consumers' purchasing behavior. This study expands the current body of knowledge on product fit uncertainty by showing empirically how consumers' vendor choices are affected by differences in product fit uncertainty.

The remainder of the paper is organized as follows: We first introduce the conceptual foundations, followed by the research model and the hypotheses. Subsequently, we outline the applied methodology and present and discuss the results of our research. Lastly, we summarize further implications for both research and practice.

## Related literature

### Concepts and forms of uncertainty in e-commerce

In transactions (both online and offline), consumers usually have imperfect information on the intentions of vendors, the quality of products or their fit to their taste. Uncertainty is seen as the result of these information asymmetries and constitutes the "difference between information possessed and information required to complete a task" (Tushman and Nadler 1978). Uncertainty is used in different fields, such as psychology, engineering and physics. In the management literature and in the IS literature there are various subforms of uncertainty, including behavioral, environmental, transactional, knowledge, and choice uncertainty (Duncan 1972; Pavlou et al. 2007; Urbany et al. 1989).

Uncertainty is important for vendors since consumers' willingness to pay for goods varies along with their perceptions of uncertainty (Ba and Pavlou 2002; Kim and Benbasat 2010; Rao and Monroe 1996). Research distinguishes between vendor and product uncertainty, although product uncertainty has been rather neglected in previous research (Dimoka et al. 2012). Recent studies have found that product and vendor uncertainty are entangled together (Ghose 2009). Vendor uncertainty relates to uncertainty about vendors' actual intentions and their opportunistic behavior and has been frequently discussed since the beginning of e-commerce. A large share of the IS literature on mechanisms to reduce vendor uncertainty has focused on antecedents of trust and trust building strategies (Kim and Benbasat 2006; Kim et al. 2008), trusted third parties (Clemons 2007; Pavlou and Gefen 2004) and market and vendor guarantees (Clemons et al. 2013). Thus, certain challenges related to uncertainty about vendors' quality have already been solved (Benbasat et al. 2008; Dimoka et al. 2012).

Until recently, product uncertainty has been seen as one central construct. Now, the literature distinguishes whether the product uncertainty relates to uncertainty about the quality of products or uncertainty about the fit to consumers' taste (Hong and Pavlou 2014).[1] Product quality uncertainty relates to uncertainty that products might not be in the condition as promised, or that products' quality could be compromised (Pavlou et al. 2007). Such uncertainties can also occur due to vendors' inability to describe the product online or to provide an accurate analysis of the product's shortcomings (Dimoka et al. 2012; Ghose 2009).

However, even if products are of accurate quality, it does not necessarily mean that they fit every consumer's taste. Products with exactly the same quality level can be

[1] In the past, the IS literature has frequently discussed fit in the context of task technology fit (e.g., Beaudry and Pinsonneault 2005; Goodhue and Thompson 1995; Lee et al. 2007).

Author's personal copy



appreciated by some consumers and avoided by others. Product fit uncertainty is therefore defined as the degree to which consumers are unable to assess whether a product's attributes match their preferences (Hong and Pavlou 2014). For the sake of customer satisfaction and to decrease product returns, vendors' objectives should be to match consumers with products that best fit their tastes.

Both product quality uncertainty and product fit uncertainty vary across consumers and across products, while appropriate communication practices can help vendors to convince consumers of their products' quality (Weathers et al. 2007). For products which can be evaluated based on objective measures, product quality seems to be dominant, while for products that are evaluated based on subjective measures product fit is more dominant (Kwark et al. 2014; Sutton 1986). Higher product complexity or the experiential character of products usually foster higher overall product uncertainty (Lee and Huddleston 2006; Li and Hitt 2008). For used products, uncertainty is mainly impacted by the current product conditions, while for new products uncertainty is mainly related to consumers' limited knowledge or unfamiliarity with a product (Erdem et al. 2006; Wu et al. 2013). Therefore, the assessment of product fit involves consumers' experience with a specific product or similar products.

### Mechanisms to reduce product fit uncertainty

The economics literature presents various mechanisms to reduce information asymmetries and the resulting uncertainty. However, these mechanisms are no general remedy, i.e. they need to be applied in a specific context. For instance, while some mechanisms can be effective in reducing vendor product quality uncertainty, they are less effective in reducing product fit uncertainty.

Signaling mechanisms can be effective means for vendors to convince consumers of products' quality by sending signals that would otherwise be costly to achieve for vendors that offer low quality products (Lee et al. 2005). However, in e-commerce, it can be fairly inexpensive for the seller to create some false signals to deceive the transaction partner (Dellarocas and Wood 2008; Farrell and Rabin 1996; Resnick et al. 2006).

Money-back guarantees allow consumers to try out products and to return these in case they do not match the expected quality or do not fit consumers' taste (Moorthy and Srinivasan 1995). However, it is important for vendors to ensure that consumers have no possibility to benefit from the product after it has been returned. What is rather easy to establish for physical products presents a challenge for many digital goods, which might be copied easily and without any quality losses if no specific copy protection is used. In addition, after certain products (e.g. news articles) have been consumed once, consumers may no longer benefit from owning the product and may therefore no longer be willing to pay for it. Thus, money-back guarantees are usually only applied for specific types of goods that remain valuable to users after initial consumption (e.g. music and games).

Many studies have focused on the impact of online reviews in reducing product uncertainty (Benlian et al. 2012; Mudambi and Schuff 2010; Sun 2012; Zhu and Zhang 2010). Feedback mechanisms can serve as a signal for product quality, but they have also been susceptible to abuse by product suppliers creating biased reviews (Ba and Pavlou 2002; Dellarocas 2003; Kim and Benbasat 2010; Pavlou and Gefen 2004). Especially for certain experience goods, product characteristics can be rather difficult to describe and consumer tastes can vary significantly, thus making reviews less suitable for reducing product fit uncertainty.

Another major research stream in IS addresses recommender systems. Driven by a vast increase in the number of products per online shop, it is almost impossible for consumers to skip through all of these products (Brynjolfsson et al. 2011). High search costs and information overload can be one consequence (Hinz and Eckert 2010). Recommender systems seek to support consumers in finding the most relevant products and can lead to lower search costs. They create recommendations either upon similarities across products (content-based), users (collaborative filtering), or a hybrid combination of both (Adomavicius and Tuzhilin 2005; Xiao and Benbasat 2007). Recommender systems may be affected by difficulties to accurately describe certain product types and substantial differences in consumers' taste. Further, they have been susceptible to abuse by online vendors that preferably recommend high margin products.

Owing to the difficulties to assess product quality of experience goods prior to a purchase (Bock et al. 2012; Nelson 1970) many online shops offer free online samples to reduce product fit uncertainty (Chellappa and Shivendu 2005). Samples can for instance be excerpts of books or of music tracks. The extent of the samples can differ between vendors and changes over time have been observed (e.g. Apple increased its free sample length from 30 to 90 seconds in 2010). In certain cases it is even possible to sample the full product free of charge (e.g. YouTube and other streaming platforms host full videos of various songs). Full product samples enable consumers to obtain full information on product fit prior to a purchase, and thus product fit uncertainty is virtually eliminated. However, full samples are not common for all digital goods, presumably due to potential abuse by customers (Bhattacharjee et al. 2006).

Most research qualitatively assumes that lower product fit uncertainty is desirable for vendors, but empirical support and specifications of the positive effects are missing. Therefore it is difficult for online vendors to assess whether additional (usually costly) measures to reduce product fit uncertainty will

Author's personal copy



pay off. We contribute to this stream by providing new insights on how declining product fit uncertainty affects consumers' vendor choice and by doing so, supporting vendors in determining the necessity of adapting current procedures to reduce product fit uncertainty.

## Research model and hypothesis development

Based on the research gap identified above, our research analyzes two aspects: First, what is the effect of a reduction of product fit uncertainty on consumers' vendor choice decisions, and second, does this depend on the prevailing level of product fit uncertainty? We discuss each of the two aspects in the following and conclude with our hypotheses.

While online vendors can use signaling mechanisms, such as guarantees, to reduce vendor uncertainty, to convince consumers of products' quality and to establish consumer trust (Sha 2009), our analysis focuses solely on uncertainty in regard of product fit. As outlined before, online vendors have several options to reduce product fit uncertainty. Many online shops use recommender systems as a first filtering tool and offer free product samples on top to give consumers a better idea of products' characteristics (Kamis et al. 2008). However, if consumers still face a remaining level of pre-purchase product fit uncertainty, there are three potential outcomes after a purchase has been made: the product exceeds a consumers' expectations, it exactly matches expectations or it falls below expectations. Based on the outcome, consumers can be dissatisfied or satisfied and this can be the basis for future customer complaints (Bearden and Teel 1983; Tse and Wilton 1988).

If product fit uncertainty is present, consumers face difficulties to determine their willingness to pay. Consumers exhibit an uncertainty-adjusted willingness to pay for goods, which varies according to their perception of uncertainty and their subjective assessment of the expected quality and the fit of the product they will receive (Ba and Pavlou 2002; Kim and Benbasat 2009; Lee and Gosain 2002; Rao and Monroe 1996). If consumers realize after the purchase that the product does not fit their taste, they would have paid less ex ante.

Although the level of uncertainty avoidance is known to differ across individuals and across different cultures (Reimann et al. 2008), consumers tend to prefer certain rather than uncertain outcomes (Fox and Tversky 1995). Therefore, if consumers can buy a product from an online vendor that offers a full reduction of product fit uncertainty whereas another vendor does not, uncertainty avoidance should lead consumers to buy from the vendor that eliminates product fit uncertainty (holding all other factors constant). Thus, if online vendors include mechanisms that eliminate product fit uncertainty, we hold that this results in a competitive advantage and helps them to attract more customers, which we will measure in terms of purchases per vendor. We also hold that such mechanisms create a strong bond between the online vendor and the consumer which pays off in terms of consumers' repeated purchases with the same online vendor. We therefore suggest:

> *H1a*: *If online vendors eliminate product fit uncertainty, they will increase the number of purchases.*
> *H1b*: *If online vendors eliminate product fit uncertainty, they will increase the number of returning customers.*

We know from prior research that the extent of product fit uncertainty is known to differ across product types (Bock et al. 2012). Therefore, for certain goods it is easier for consumers to assess product fit prior to a purchase than for others. Internet-enabled technologies have substantially altered the way products can be evaluated prior to a purchase. Although consumers can profit from these advancements, it might still be difficult for them to quantify the remaining level of product fit uncertainty. Because of this, consumers often apply heuristics or guesses to assess uncertainty levels and therefore, concepts of perceived uncertainty are applicable here (Pavlou et al. 2007).

If consumers assess uncertain outcomes, they weigh up the opposing directions of the uncertain outcomes differently. According to prospect theory, people fear potential losses more than they appreciate equally large potential gains (Kahneman and Tversky 1979). Therefore, if potential gains and losses are equally distributed around a common mean, but the magnitude differs, consumers are likely to choose the option with the smaller maximum loss.

Online vendors can differ in the extent to which they reduce product fit uncertainty for consumers. First, this can be due to different measures that online vendors apply. While customer reviews and recommender systems presumably reduce product fit uncertainty only to some degree, full product samples or money-back guarantee can fully eliminate product fit uncertainty since consumers have access to the entire product prior to a purchase or they can return it at no cost. Second, there can be differences in the quality of the applied mechanisms, e.g. some online vendors might use state of the art search technologies or better fitting recommender algorithms than others (Huang et al. 2007; Wang and Benbasat 2008). Assuming that consumers can buy similar products from different online vendors, which differ in the extent to which they reduce product fit uncertainty, consumers' tendency to avoid uncertainty should direct them to buy from those online vendors that offer the lowest level of product fit uncertainty. Further, the advantage of reducing product fit uncertainty should become larger, the higher the difference in product fit uncertainty towards the products that are offered by other vendors is. We therefore conclude:

> *H2a*: *An elimination of product fit uncertainty is more beneficial for online vendors in terms of purchases if the general level of product fit uncertainty is high.*

Author's personal copy



*H2b*: *An elimination of product fit uncertainty is more beneficial for online vendors in terms of returning customers if the general level product fit uncertainty is high.*

## Experimental layout

To assess our hypotheses we conducted an economic laboratory experiment models the consumers' perspective. A total of 96 participants (47 male, 49 female, average age 24.32 years), consisting of mostly graduate and undergraduate students from various fields, complete the experiment. We selected students as participants for our experiment, not simply because this is the most accessible population, but also because of their broad experience in Internet usage and online-shopping in general. The participants were randomly assigned to two different groups, which differed in the level of the applied product fit uncertainty. The experiment comprised three phases, one initial training phase and two different treatment phases with five rounds each. We implemented multiple rounds per treatment to reduce singular outlier effects. In order to prevent fatigue during the experiment, participants received interim information on their current payout level. To ensure that participants understood the task we provided elaborate instructions including sample screens, which provided a clear picture of the experiment. To avoid latent participant intentions, i.e. persistent preferences which are not related to the current experiment, we did not show actual URLs, websites or products.

### Experimental task

In each round, participants' task was to purchase a digital experience good that provided the highest utility after deducting all search costs necessary for finding this product. We applied search costs for newly inspected product to account for participants' opportunity costs.

Participants could choose to purchase products from two different online vendors. One of the two online vendors integrated new technological advancements and due to this, offered products without product fit uncertainty. This vendor is referred to as the "state of the art (SOTA)" vendor. The other vendor on average offered the same goods, but without additional mechanisms to reduce product fit uncertainty and is therefore called "conventional vendor". Product fit uncertainty for the conventional vendor was mapped as a lottery-based variance factor that affected a product's utility, with the true utility being revealed to participants only after the purchase.[2] Therefore, when inspecting products from the conventional vendor, participants saw two different utility values, each with a 50 % chance of being drawn. In contrast to this, since the SOTA vendor eliminated all product fit uncertainty, the final utility of its products was revealed to participants immediately.

We assigned a specific utility to each product, which was based on a uniform distribution and that ranged from 100 to 200 experimental units for the SOTA vendor, and from 100 +/− $x$ to 200 +/− $x$ experimental units for the conventional vendor, with $x$ being the product fit uncertainty factor.

Utilities for *products i* and *j*:

$$\text{Conventional vendor}: \quad u_i = [100 + / - x \ldots 200 + / - x]$$

$$\text{SOTA vendor}: \quad u_j = [100 \ldots 200]$$

In every round participants could choose to buy either from the conventional vendor or the SOTA vendor and they could inspect as many products as they wished, while freely switching between the two vendors.

Also in electronic markets, search for different products and vendors involves costs. Search costs have a major impact on consumer search, while lower search costs should be beneficial to consumers (Bakos 1997; Brynjolfsson et al. 2011; Johnson et al. 2004). Therefore, for each newly inspected product, participants incurred a monetary cost which represented search costs. In contrast to this, returning to any of the previously inspected products was free of charge, i.e. all products that had been inspected once remained accessible during that round for free. Longer search efforts could lead participants to finding better experience products, but search costs increase. Participants' objective was to maximize the difference between the utility of the purchased product and the total search costs incurred at that point.

To increase participant motivation, payment depended on participants' results in the experiment. After each *round k*, participants received the *payoff* $y_k$ which was calculated by subtracting the *search costs* $c_k$ from the accumulated balance of the purchased product's *utility* $u_k$ in each round. The total *payoff y* was the sum of the payoffs from all the single rounds:

$$\text{Payoff after each round } k: \quad y_k = u_k - c_k$$

$$\text{Total payoff}: \quad y = \sum y_k \qquad \text{with } y_k \geq 0$$

### Treatment parameters

We implemented a mixed design, consisting of two groups with one training phase and two different treatments (Phase I-II) each, while one phase consisted of five rounds. The treatments differed in the level of product fit uncertainty and the search costs for the inspection of a novel product. Table 1 summarizes the different treatments' primary characteristics and the values of the treatment parameters (in experimental units).

[2] In accordance with random utility theory, a product's overall utility is a single value that integrates all attributes of a product including its price (McFadden 1986).

Author's personal copy



**Table 1** Parameter Values for the Different Phases and Groups

| Phase | Group | Product Fit Uncertainty | | Search Costs | |
|---|---|---|---|---|---|
| | | Conventional | SOTA | Conventional | SOTA |
| I | A | 10 | 0 | 10 | 10 |
| | B | 30 | 0 | 10 | 10 |
| II | A | 10 | 0 | 10 | 2 |
| | B | 30 | 0 | 10 | 2 |

Group B had a high product fit uncertainty in the form of a standard deviation that accounted for 20 % of the average product utility. For Group A, product fit uncertainty was significantly lower with a standard deviation that was 1/3 of those of Group B. To analyze whether a reduction of product fit uncertainty between Groups A and B had an effect, we tested for differences in participants' vendor selection choices.

We decided to vary the implemented search costs in two levels to account for the possibility that the level of search costs may have affected our results. In Phase I search costs were assumed to be equal to the amount of the low product fit uncertainty scenario of Group A, whereas in Phase II, the search costs of the SOTA vendor were only 20 % of the search costs of the conventional vendor. We decreased search costs only for the SOTA vendor as this accounts for the advantages of employing new technological innovations such as novel search technologies.

## Results

An overview of the results is provided in Table 2 which, for each of the two phases, reports the average values for the number of inspected products, the total search costs and the profits per participant as well as the share of purchases conducted at each of the two vendors. The share of consecutive purchases per round for the two vendors is provided in Table 3. Based on this, we define consumer loyalty as the share of two consecutive purchases at the same vendor within one phase.

The Kolmogorov-Smirnoff test as well as other graphical indicators showed that most of the data did not follow a normal distribution; the following results are therefore based on non-parametric tests. To test the effects of the presence of the product fit uncertainty reduction, the results within both groups were compared first. In Phase I the SOTA vendor experienced a significantly higher number of search requests (as indicated by the number of inspected products) than the conventional vendor for both groups (for Group A and B: $p < 0.01$; Wilcoxon-Signed-Rank-Test). If participants were indifferent towards both vendors, each of the two vendors should have accounted for approximately 50 % of the purchases. However, in both groups the SOTA vendor accounted for significantly more than 50 % of the purchases in Phase I (for Group A and B: $p < 0.01$; $\chi^2$-test). Furthermore, as indicated in Table 3, the SOTA vendor also had the largest number of consecutive purchases, thus indicating an increase in customer loyalty (for Group A and B: $p < 0.01$; $\chi^2$-test). Altogether, in Phase I, the SOTA vendor was viewed as more favorable by participants. The lower search costs in Phase II reinforced this tendency and led to a further increase in the number of inspected products, purchases and the level of customer loyalty. Hence, the gap between the conventional and the SOTA vendor became larger (all of the aforementioned tests revealed $p$-values of <0.01). Thus, there is support for Hypotheses 1a and 1b.

To analyze the effects of varying levels of product fit uncertainty, differences between Groups A and B in Phase I and in Phase II were compared. Our assumption was that a higher level of product fit uncertainty is favorable for the SOTA vendor. However, the data showed that search requests for the SOTA vendor and the conventional vendor did not differ significantly between the two groups in each of the two phases, whereas the SOTA vendor had even slightly less search requests compared to the conventional vendor in Phase II (Phase I: $p = 0.886$; Phase II: $p = 0.750$; Mann-Whitney-U-Test). This was also true for the differences in the share of purchases at both vendors – the differences were not significant in both phases and the SOTA vendor accounted for even slightly less purchases than the conventional vendor in Phase II (Phase I: $p = 0.209$; Phase II: $p = 0.837$; $\chi^2$-test). In addition, the share of loyal customers was also in line with this and there were no significant differences in both phases (Phase I: $p = 0.123$; Phase II: $p = 0.123$; $\chi^2$-test). Therefore, independent of the conventional vendor's level of product fit

**Table 2** Descriptive Results for the Different Phases

| Phase | Group | No. of Inspected Products | | Search Costs | Profit | Share of Purchases at | |
|---|---|---|---|---|---|---|---|
| | | Conventional | SOTA | Total | Total | Conventional | SOTA |
| I | A | 0.88 | 1.67 | 25.50 | 153.37 | 36.25 % | 63.75 % |
| | B | 0.68 | 1.81 | 24.92 | 152.48 | 30.83 % | 69.17 % |
| II | A | 0.16 | 3.98 | 9.57 | 177.35 | 5.00 % | 95.00 % |
| | B | 0.16 | 3.80 | 9.18 | 173.89 | 5.42 % | 94.58 % |

Author's personal copy



**Table 3** Share of Consecutive Purchases at the Conventional and the SOTA Vendor

| Phase | Group | Consecutive Vendor Choices | | | |
|---|---|---|---|---|---|
| | | Conventional - > Conventional | SOTA - > SOTA | Conventional - > SOTA | SOTA - > Conventional |
| I | A | 20.31 % | 45.31 % | 15.10 % | 19.27 % |
| | B | 16.67 % | 57.29 % | 12.50 % | 13.54 % |
| II | A | 0.52 % | 94.27 % | 2.60 % | 2.60 % |
| | B | 1.04 % | 87.50 % | 7.29 % | 4.17 % |

uncertainty the SOTA vendor accounted for a similar share of purchases and loyal customers. Apparently, participants placed a larger focus on whether or not a product underlies product fit uncertainty rather than on the actual magnitude of the product fit uncertainty. Hence, Hypotheses 2a and 2b were not supported.

## Discussion and further implications

The results from the experiment have interesting implications, both for theory and practice. First, the experiment has shown that a reduction in product fit uncertainty can help online vendors to attract more consumers. Although the uncertainty-inherent alternative in our experiment had an expected value that was equal to the uncertainty-free alternative of the SOTA vendor (i.e. in the long run there should be no substantial utility differences between the two options), consumers had a preference towards the vendor without product fit uncertainty. Approximately two-third of the participants showed uncertainty-averse behavior, which is in line with theory, stating that consumers generally tend to avoid uncertainty (Holt and Laury 2002). This can be explained by behavioral economics and the phenomenon of "loss aversion", which indicates that consumers value potential losses greater than potential gains (Tversky and Kahneman 1991, 1992). According to Abdellaoui et al. (2007), the psychological impact of losses is twice as high as of gains. However, at the same time this means that approximately one-third of the participants did not behave in an uncertainty-averse way. One reason for this could be the comparably small investments participants needed to make in our experiment and the fairly small consequences of an unfavorable outcome for their payment.

A second focal point of the experiment was to analyze the effect of different magnitudes of product fit uncertainty. In line with this, previous research has questioned what the ideal level of free sampling is and has taken both the quality uncertainty reduction as well as the revenue generation perspective into account (Halbheer et al. 2014). We varied the magnitude of product fit uncertainty between the two groups, while the expected value of the conventional vendor's products was equal to the value of the SOTA alternative. According to prospect theory and the concept of loss aversion, larger losses are weighted higher than equal gains (Kahneman and Tversky 1979). However, participant behavior did not significantly deviate between the high and the low uncertainty scenario. Thus, higher levels of product fit uncertainty (and thus higher potential losses) did not lead to a further increase of the share of consumers who decided to purchase from the SOTA vendor. Taking into account the overall high preference towards the SOTA vendor for both groups, this indicates that consumers seem to highly value a full elimination of product fit uncertainty, while a variation of the extent of a partial product fit uncertainty reduction may not necessarily have a strong influence on consumers' vendor choices. Apparently, consumers tend to see the presence of product fit uncertainty rather as a "black and white" decision and accordingly their vendor choices are not perfectly uncertainty-adjusted. However, it is important to note that in our experiment, participants presumably had much better chances to assess the concrete level of remaining product fit uncertainty than in practice. Our results have shown that the positive effects of a full product fit uncertainty reduction can be further stimulated by a simultaneous reduction of search costs, which in practice can be achieved by employing better user interfaces, personalized services and effective recommender systems, among others.

The results have important implications for online vendors. We see the integration of new Internet-enabled technologies to reduce eliminate product fit uncertainty as a key variable that online vendors could use to stimulate their business and to increase profits. Better-fitting recommendations and extended previews will help vendors to reduce product fit uncertainty, especially for experience goods and for other goods that are currently still difficult to describe. For instance, for hotel search, interactive 360° videos could give users more information and a better experience prior to a booking. For clothes, first online shops provide other users' assessments of size/body fit, i.e. how well an item in a given size has fit to their body. Other websites offer novel features that enable users to virtually view how the clothes will look on their body. Although all these measures will help to lower product fit uncertainty, they will presumably not be able to fully eliminate it. For a full elimination of product fit uncertainty, online vendors will have to provide either technology-enabled full product

Author's personal copy



samples (which is not technologically possible or economically reasonable for all product types), or they need to establish other policies that fully eliminate product fit uncertainty (e.g. convenient product returns at no cost). However, from online vendors' rationale, the provision of these measures to reduce product fit uncertainty usually involves both benefits and costs. As demonstrated in our experiment, a full reduction of product fit uncertainty can lead to a substantial increase in sales and thus may compensate for the higher costs. Using a cost-benefit analysis, online vendors should seek to maximize the difference between potentially higher revenues and accruing costs.

Online vendors need to distinguish three types of effects: First, the potential positive effects in form of higher revenues. No product fit uncertainty means lower barriers for consumers to purchase products and can result in higher spending per customer. Second, vendors face the negative effects in form of costs for the establishment of additional measures to reduce product fit uncertainty. This includes costs related to the technical implementation and operation of new technologies (e.g. product samples with digital rights management protection). The extent of these costs can vary significantly, based on concrete technologies to be implemented, the vendor's current technological competencies, and the complexity of the current information systems in use. Third, as another negative aspect, lost revenues could accrue due to potential abuse of additional measures to reduce product fit uncertainty. Among others, consumers could manage to illegally download streaming samples without paying for them. Therefore, the technological protectability of the product has to be considered.

Further, online vendors need to take short-term and long-term effects into consideration. This holds especially for factors related to competition. Not only in the case of Google has history told us that technological advancements can lead to a substantial competitive advantage within a short period of time. Likewise, our results confirm that a superior level of pre-purchase product evaluations and the elimination of product fit uncertainty could lead to substantial changes in consumers' favor. If competition allows, it might even be possible for vendors to charge higher prices for the elimination of product uncertainty. The provision of products without product fit uncertainty could be particularly profitable for vendors, if there is only a low overall level of product fit uncertainty and thus the risk of product returns is comparably low. This is similar to insurances, where in the presence of low uncertainty, many consumers still opt to purchase a full damage waiver even if they have to pay a substantial surcharge for it, and even if they could bear the financial consequences of an accident. Research has provided suggestions on how companies can exploit strong levels of uncertainty avoidance and how they can encourage consumers to opt for such insurances (Camerer and Kunreuther 1989; Kunreuther et al. 2001). For the case of digital experience goods this would mean that online vendors could offer extensive product fit uncertainty measures in markets where chances for product misfit are rather low. This could apply for instance to repeated purchases within one clearly defined product category (e.g. a specific band's songs) or purchases of successor products – if a user has positively evaluated its predecessor. It could also apply to products that have already been shown to fit a large number of consumers (blockbuster products) and therefore the likelihood of fitting other users is likely to be higher than for specific niche products. In general, such mechanisms might be more relevant for experience goods, since price alone is not necessarily a good indicator of their product quality or fit (Bergemann and Välimäki 2006; Gale and Rosenthal 1994).

As noted, the provision of money-back guarantees represents another alternative to fully reduce product uncertainty. However, while the costs for the technological implementation are presumably low, potential losses due to abuse may constitute a challenge. Thus, online vendors need to think about how they can protect their content and whether the product type is suitable for timely limited full product previews. While music and video games are typically used over a longer time horizon, other product types (e.g. news articles) are often only consumed once and, thus, these products have little to no value for users after the initial consumption. Hence, for such products, free sampling or a money-back guarantee can easily be abused. Instead of money-back guarantees, online vendors could also think about offering product exchanges to skim the revenue from the product purchase. In practice, online vendors might be able to charge higher prices for giving consumers the option to trade a purchased song for another song in case they did not like their first purchase. However, consumers intended usage frequency for the product still has to be considered in this case. If ordinary consumption for a product takes place only once, consumers would still get a "buy 2 get 1 free" deal. Further, when offering product returns, online vendors need to assure that they have a large product offer to ensure that consumers will find a suitable exchange for their initial purchase.

## Conclusion

In this paper, we sought to analyze the effects of new Internet-enabled technologies that aim to reduce product fit uncertainty on consumers' vendor choice decisions. Reducing product fit uncertainty is important for online vendors since high levels of uncertainty may lead consumers to refrain from purchases. In addition, technology-enabled changes to pre-purchase product evaluations are also of high importance for the competition between offline and online channels as the latter have for long been known to include higher challenges for pre-purchase evaluations. However, due to recommender systems and free

Author's personal copy



full-length samples, consumers enjoy new possibilities of pre-purchase evaluations online, which they do not enjoy offline.

We decided to test the effects of declining product fit uncertainty using the example of digital experience goods. Product fit uncertainty plays a large role for these types of goods and the new technological advancements can fully play their strengths. We presented an experiment-based consumer-centric approach and contributed to the theoretical body of knowledge on product fit uncertainty. We also drew practical implications for online vendors that need to think about additional investments to reduce product fit uncertainty and thus rely on a profound understanding of consumer behavior in this context.

First, our study shows that online vendors can benefit from a full elimination of product fit uncertainty and considerably increase the number of purchases in their shops. Furthermore, consumers do not only choose their shops more often, but also show a higher loyalty and buy from these vendors repeatedly. Thus, online vendors will most likely benefit from a substantial increase in revenues, whereas even a higher willingness to pay seems plausible and should be subject to further studies. However, a full elimination of product fit uncertainty may not be technologically feasible or economically reasonable (e.g. due to potential abuse) for certain types of products. We therefore suggest testing the validity of this study's findings in accordance with other market scenarios and product types.

Second, online vendors that offer a partial elimination of product fit uncertainty substantially fall behind those vendors, who offer a full elimination of product fit uncertainty. Further, this does not necessarily depend on the differences in remaining product fit uncertainty between these two vendors. The results demonstrate that many consumers do not want to encounter any form of product fit uncertainty when purchasing digital experience goods – even if the general level of product fit uncertainty is already low. This means that even if consumers know quite well what kind of product they are looking for and even if they can to some degree assess, whether a product fits their needs, they still tend to avoid facing remaining levels of product fit uncertainty. Online vendors may be able to profit from this strong tendency to avoid product fit uncertainty by charging higher prices (if competition permits) for offering a full elimination of product fit uncertainty. The determination of consumers' willingness-to-pay for such services presents an opportunity for future research.

Our results suggest that product fit uncertainty should no longer be neglected, both in research and in practice, as it substantially determines consumers' vendor choice decisions. For certain products and scenarios, we even suspect that product fit uncertainty may have a stronger impact than the previously more frequently discussed factors vendor and product quality uncertainty. Further research in this area can support a better adaption of online shops to consumer' needs and further stimulate the growth of online channels.

However, we must acknowledge several limitations of this study. To avoid latent participant preferences, we did not use real vendor names, websites and products. Nevertheless, in practice consumers may tend to build relationships of trust with certain vendors and could therefore be more accustomed to their websites. In addition, consumers may also face technological lock-in effects (e.g. due to certain standards and formats) that hinder them from easily switching to other vendors (Burkard et al. 2012; Hess and Matt 2013). Contractual aspects (such as subscription services) can also constrict consumers' choice of vendors. There may be other factors that affect consumers' initial and repeated purchase intentions that we could not consider (Chiu et al. 2014). To be able to clearly isolate the effects of matter, we assumed that measures to reduce product fit uncertainty were free to consumers. However, certain vendors may be tempted to allocate the costs for the product fit uncertainty reduction to consumers. Price differences across vendors could play an important role in consumers' vendor selection. It therefore seems worthwhile to quantify how much consumers are willing to pay for encountering less product fit uncertainty.

**Acknowledgments** The authors are very grateful to the senior editor and two anonymous reviewers for their encouragement and their excellent comments during the development of this manuscript. They also appreciate the very helpful feedback of the AMCIS 2012 participants on earlier versions of this manuscript.

## References

Abdellaoui, M., Bleichrodt, H., & Paraschiv, C. (2007). Loss aversion under prospect theory: a parameter-free measurement. *Management Science*, *53*(10), 1659–1674.

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, *17*(6), 734–749.

Ba, S., & Pavlou, P. A. (2002). Evidence of the effect of trust building technology in electronic markets: price premiums and buyer behavior. *MIS Quarterly*, *26*(3), 243–268.

Bakos, J. Y. (1997). Reducing buyer search costs: implications for electronic marketplaces. *Management Science*, *43*(12), 1676–1692.

Bearden, W. O., & Teel, J. E. (1983). Selected determinants of consumer satisfaction and complaint reports. *Journal of Marketing Research*, *20*(1), 21–28.

Beaudry, A., & Pinsonneault, A. (2005). Understanding user responses to information technology: a coping model of user adaptation. *MIS Quarterly*, *29*(3), 493–524.

Benbasat, I., Gefen, D., & Pavlou, P. A. (2008). Special issue: trust in online environments. *Journal of Management Information Systems*, *24*(4), 5–11.

Benlian, A., Titah, R., & Hess, T. (2012). Differential effects of provider recommendations and consumer reviews in e-commerce transactions: an experimental study. *Journal of Management Information Systems*, *29*(1), 237–272.

Bergemann, D., & Välimäki, J. (2006). Dynamic pricing of new experience goods. *Journal of Political Economy*, *114*(4), 713–743.

Author's personal copy




Bhattacharjee, S., Gopal, R. D., Lertwachara, K., & Marsden, J. R. (2006). Consumer search and retailer strategies in the presence of online music sharing. *Journal of Management Information Systems*, *23*(1), 129–159.

Bock, G. W., Lee, J., Kuan, H. H., & Kim, J. H. (2012). The progression of online trust in the multi-channel retailer context and the role of product uncertainty. *Decision Support Systems*, *53*(1), 97–107.

Brynjolfsson, E., Hu, Y. J., & Simester, D. (2011). goodbye pareto principle, hello long tail: the effect of search costs on the concentration of product sales. *Management Science*, *57*(8), 1373–1386.

Burkard, C., Widjaja, T., & Buxmann, P. (2012). Software ecosystems. *Wirtschaftsinformatik*, *54*(1), 43–47.

Camerer, C. F., & Kunreuther, H. (1989). Decision processes for low probability events: policy implications. *Journal of Policy Analysis and Management*, *8*(4), 565–592.

Chellappa, R. K., & Shivendu, S. (2005). Managing piracy: pricing and sampling strategies for digital experience goods in vertically segmented markets. *Information Systems Research*, *16*(4), 400–417.

Chiu, C.-M., Wang, E. T. G., Fang, Y.-H., & Huang, H.-Y. (2014). Understanding customers' repeat purchase intentions in b2c e-commerce: the roles of utilitarian value, hedonic value and perceived risk. *Information Systems Journal*, *24*(1), 85–115.

Clemons, E. K. (2007). An empirical investigation of third-party seller rating systems in e-commerce: the case of buysafe. *Journal of Management Information Systems*, *24*(2), 43–71.

Clemons, E. K., Jin, F., Wilson, J., Ren, F., Matt, C., Hess, T., & Koh, N. (2013). The role of trust in successful ecommerce websites in China: Field observations and experimental studies. In *Proceedings of the 46th Hawaii International Conference on System Sciences (HICSS 2013)*, Maui, HI, USA.

Dellarocas, C. (2003). The digitization of word of mouth: promise and challenges of online feedback mechanisms. *Management Science*, *49*(10), 1407–1424.

Dellarocas, C., & Wood, C. A. (2008). The sound of silence in online feedback: estimating trading risks in the presence of reporting bias. *Management Science*, *54*(3), 460–476.

Dimoka, A., Hong, Y., & Pavlou, P. (2012). On product uncertainty in online markets: theory and evidence. *MIS Quarterly*, *36*(2), 395–426.

Duncan, R. B. (1972). Characteristics of organizational environments and perceived environmental uncertainty. *Administrative Science Quarterly*, *17*(3), 313–327.

Erdem, T., Swait, J., & Valenzuela, A. (2006). Brands as signals: a cross-country validation study. *Journal of Marketing*, *70*(1), 34–49.

Farrell, J., & Rabin, M. (1996). Cheap talk. *The Journal of Economic Perspectives*, *10*(3), 103–118.

Fox, C. R., & Tversky, A. (1995). Ambiguity aversion and comparative ignorance. *The Quarterly Journal of Economics*, *110*(3), 585–603.

Gale, D., & Rosenthal, R. W. (1994). Price and quality cycles for experience goods. *The Rand Journal of Economics*, *25*(4), 590–607.

Ghose, A. (2009). Internet exchanges for used goods: an empirical analysis of trade patterns and adverse selection. *MIS Quarterly*, *33*(2), 163–291.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, *19*(2), 213–236.

Halbheer, D., Stahl, F., Koenigsberg, O., & Lehmann, D. R. (2014). Choosing a digital content strategy: how much should be free? *International Journal of Research in Marketing*, *31*(2), 192–206.

Hess, T., & Matt, C. (2013). The internet and the value chains of the media industry. In S. Diehl, & M. Karmasin (Eds.), *Media and convergence management* (pp. 37–55). Berlin/Heidelberg: Springer.

Hinz, O., & Eckert, J. (2010). The impact of search and recommendation systems on sales in electronic commerce. *Business & Information Systems Engineering*, 2(2), 67–77.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, *92*(5), 1644–1655.

Hong, Y., & Pavlou, P. A. (2014). Product fit uncertainty in online markets: nature, effects, and antecedents. *Information Systems Research*, *25*(2), 328–344.

Huang, Z., Zeng, D. D., & Chen, H. (2007). Analyzing consumer-product graphs: empirical findings and applications in recommender systems. *Management Science*, *53*(7), 1146–1164.

Johnson, E. J., Moe, W. W., Fader, P. S., Bellman, S., & Lohse, G. L. (2004). On the depth and dynamics of online search behavior. *Management Science*, *50*(3), 299–308.

Kahneman, D., & Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, *47*(2), 263–291.

Kamis, A., Koufaris, M., & Stern, T. (2008). Using an attribute-based decision support system for user-customized products online: an experimental investigation. *MIS Quarterly*, *32*(1), 159–177.

Kim, D., & Benbasat, I. (2006). The effects of trust-assuring arguments on consumer trust in internet stores: application of toulmin's model of argumentation. *Information Systems Research*, *17*(3), 286–300.

Kim, D., & Benbasat, I. (2009). Trust-assuring arguments in b2c e-commerce: impact of content, source, and price on trust. *Journal of Management Information Systems*, *26*(3), 175–206.

Kim, D., & Benbasat, I. (2010). Designs for effective implementation of trust assurances in internet stores. *Communications of the ACM*, *53*(2), 121–126.

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: the role of trust, perceived risk, and their antecedents. *Decision Support Systems*, *44*(2), 544–564.

Kunreuther, H., Novemsky, N., & Kahneman, D. (2001). Making low probabilities useful. *Journal of Risk and Uncertainty*, *23*(2), 103–120.

Kwark, Y., Chen, J., & Raghunathan, S. (2014). Online product reviews: implications for retailers and competing manufacturers. *Information Systems Research*, *25*(1), 93–110.

Lee, Z., & Gosain, S. (2002). A longitudinal price comparison for music cds in electronic and brick-and-mortar markets: pricing strategies in emergent electronic commerce. *Journal of Business Strategies*, *19*(1), 55–71.

Lee, H.-J., & Huddleston, P. (2006). Effects of e-tailer and product type on risk handling in online shopping. *Journal of Marketing Channels*, *13*(3), 5–28.

Lee, B.-C., Ang, L., & Dubelaar, C. (2005). Lemons on the web: A Signalling Approach to the Problem of Trust in Internet Commerce. *Journal of Economic Psychology*, *26*(5), 607–623.

Lee, C.-C., Cheng, H. K., & Cheng, H.-H. (2007). An empirical study of mobile commerce in insurance industry: task–technology fit and individual differences. *Decision Support Systems*, *43*(1), 95–110.

Li, X., & Hitt, L. M. (2008). Self-selection and information role of online product reviews. *Information Systems Research*, *19*(4), 456–474.

Matt, C., & Hess, T. (2012). Facilitating consumers' evaluation of experience goods and the benefits for vendors. *Proceedings of the 18th Americas Conference on Information Systems (AMCIS 2012)*, Seattle, WA, USA.

Matt, C., Hess, T., & Weiß, C. (2013). The differences between recommender technologies in their impact on sales diversity. In *Proceedings of the 2013 International Conference on Information Systems (ICIS 2013)*, Italy, Milan.

McFadden, D. L. (1986). The choice theory approach to market research. *Marketing Science*, *5*(4), 275–297.

Moorthy, S., & Srinivasan, K. (1995). Signaling quality with a money-back guarantee: the role of transaction costs. *Marketing Science*, *14*(4), 442–466.

Mudambi, S. M., & Schuff, D. (2010). What makes a helpful online review? A study of customer reviews on Amazon.com. *MIS Quarterly, 34* (1), 185–200.

Author's personal copy



Nelson, P. (1970). Information and consumer behavior. *The Journal of Political Economy*, *78*(2), 311–329.

Pavlou, P. A., & Gefen, D. (2004). Building effective online marketplaces with institution-based trust. *Information Systems Research*, *15*(1), 37–59.

Pavlou, P., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: a principal-agent perspective. *MIS Quarterly*, *31*(1), 105–136.

Rao, A. R., & Monroe, K. B. (1996). Causes and consequences of price premiums. *Journal of Business*, *69*(4), 511–535.

Reimann, M., Lünemann, U. F., & Chase, R. B. (2008). Uncertainty avoidance as a moderator of the relationship between perceived service quality and customer satisfaction. *Journal of Service Research*, *11*(1), 63–73.

Resnick, P., Zeckhauser, R., Swanson, J., & Lockwood, K. (2006). The value of reputation on ebay: a controlled experiment. *Experimental Economics*, *9*(2), 79–101.

Sha, W. (2009). Types of structural assurance and their relationships with trusting intentions in business-to-consumer e-commerce. *Electronic Markets*, *19*(1), 43–54.

Shapiro, C., & Varian, H. R. (1999). *Information rules: a strategic guide to the network economy.* Boston: Harvard Business Press.

Sun, M. (2012). How does the variance of product ratings matter? *Management Science*, *58*(4), 696–707.

Sutton, J. (1986). Vertical product differentiation: some basic themes. *The American Economic Review*, *76*(2), 393–398.

Tse, D. K., & Wilton, P. C. (1988). Models of consumer satisfaction formation: an extension. *Journal of Marketing Research*, *25*(2), 204–212.

Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. *The Academy of Management Review, 3*(3), 613–624.

Tversky, A., & Kahneman, D. (1991). Loss aversion in riskless choice: a reference-dependent model. *The Quarterly Journal of Economics*, *106*(4), 1039–1061.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323.

Urbany, J. E., Dickson, P. R., & Wilkie, W. L. (1989). Buyer uncertainty and information search. *Journal of Consumer Research*, *16*(2), 208–215.

Wang, W., & Benbasat, I. (2008). Attributions of trust in decision support technologies: a study of recommendation agents for e-commerce. *Journal of Management Information Systems*, *24*(4), 249–273.

Weathers, D., Sharma, S., & Wood, S. L. (2007). Effects of online communication practices on consumer perceptions of performance uncertainty for search and experience goods. *Journal of Retailing*, *83*(4), 393–401.

Wu, J., Wu, Y., Sun, J., & Yang, Z. (2013). User reviews and uncertainty assessment: a two stage model of consumers' willingness-to-pay in online markets. *Decision Support Systems*, *55*(1), 175–185.

Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: use, characteristics, and impact. *MIS Quarterly*, *31*(1), 137–209.

Zhu, F., & Zhang, X. (2010). Impact of online consumer reviews on sales: the moderating role of product and consumer characteristics. *Journal of Marketing*, *74*(2), 133–148.