A Conflicting Relationship Between Online Product Page Viewing And Product Returns

Research-in-Progress

Yi Ding  
Department of Information Systems  
National University of Singapore  
15 Computing Drive, Singapore 117418  
yiding@comp.nus.edu.sg

Haifeng Xu  
Department of Information Systems  
National University of Singapore  
15 Computing Drive, Singapore 117418  
xu-haif@comp.nus.edu.sg

Bernard C. Y. Tan  
Department of Information Systems  
National University of Singapore  
15 Computing Drive, Singapore 117418  
btan@comp.nus.edu.sg

Abstract

Costly product returns have become a significant problem for most online retailers. In this study, we investigate the conflicting relationship between online product page viewing and product returns. Based on expectation disconfirmation theory, we explain two counteracting effects of product page viewing on product returns, and propose that more product page viewing leads to higher likelihood of product returns. Moreover, we examine the role of three IT systems, namely product recommendation systems, product visualization systems and consumer review systems, in attenuating the effect of product page viewing on product returns. By using a unique clickstream dataset, we employ a fixed effect logit model to test the research hypotheses. Our study has the potential to contribute to the extant literature by unveiling how consumers’ pre-purchase behaviors influence their return behaviors. Practitioners can also benefit from this research in deciding how to economically invest in IT systems to reduce product return rates.

Keywords: product returns, page viewing, expectation-disconfirmation theory, product recommendation systems, product visualization systems, consumer review systems
Introduction

Product returns have been deemed as main inconvenience for firms’ supply chain management and a drain on overall profitability (Petersen and Kumar 2009). According to the statistics from National Retail Federation (2013), the average return rates in retail industry reached 8.6% in 2013. The high incidence of product returns cost US manufacturers and retailers approximately $100 billion annually, reducing their profitability by an average of 3.8% (Blanchard 2007). To make matters worse, the product return rates at the online markets are even higher than those in the traditional bricks-and-mortar stores (Gera 2015).

According to Kurt Salmon’s study of about 50 online retailers, the return rates of experience goods, such as apparel, ranged from 20% to 30%, and that of hard goods, such as home products and toys, approached 10% (Internet Retailer 2013), both of which were significantly higher than the 8.6% average return rates in general retail industry (National Retail Federation 2013). Since the high product return rates erode the profitability of e-commerce companies and inhibit the prospects of their growth, it is critical for both e-commerce practitioners and researchers to investigate what factors lead to the high online product return rates as well as how to reduce them by making full use of the information technology (IT) systems at e-commerce websites.

Different from the offline context where consumers who can touch and feel the real product before they make a purchase decision, online consumers can only view the description, attributes, pictures and other customers’ reviews of the product on the screen of their own devices due to the limitation of virtual reality. Therefore, the lack of “touch and feel” experience probably results in high product fit uncertainty (“defined as the degree to which a consumer cannot assess whether a product’s attributes match her preference”) in the online shopping context, which in turn increases the likelihood that a consumer will return a product (Hong and Pavlou 2014 p.328). However, previous literature has shown that the disadvantage of lack of “touch and feel” experience and close inspection in online stores can, to some extent, be mitigated by the low information cost to view various web pages (Bronnenberg et al. 2014; Huang et al. 2009). That is, because it is convenient to search and view different product information at e-commerce websites (De et al. 2013; Kumar et al. 2005), online consumers are able to gain more information by viewing different product pages to mitigate product fit uncertainty (Huang et al. 2009; Shannon 2001). As product return rates reduce with the decrease of product fit uncertainty, it suggests a negative relationship between online page viewing and product returns.

By contrast, some findings in marketing literature imply a reversed relationship between online page viewing and product returns. For example, Diehl and Poynor (2010) found that more product alternatives viewed increase consumers’ expectation about matching their preferences. As the priori expectation is heightened, consumers are more likely to have negative expectation disconfirmation when they receive the product (Diehl and Poynor 2010). Considering the fact that product returns usually happen with negative expectation disconfirmation, this finding surprisingly suggests a positive relationship between online product page viewing and product returns, which is contrary to the relationship we propose in the previous paragraph. Therefore, in order to provide a clear understanding of the conflicting relationship between online product page viewing and product returns and to figure out feasible approaches to lower return rates, we conduct this study to investigate: How does online consumers’ product page viewing behavior influence product returns?

Moreover, in order to mitigate product fit uncertainty caused by the lack of “touch and feel” experience during online shopping, online retailers have implemented various IT systems to improve the “quality” of page viewing (De et al. 2013). For example, recommendation systems can navigate consumers with real-time guidance to find the product they want to buy (Bucklin et al. 2002); product visualization systems can provide consumers with alternative photos to help them see the rotation of the focal product (De et al. 2013); consumer review systems can provide online shoppers with others’ word of mouth to help them form a more realistic product expectation. However, although previous literature has shown that the use of these IT systems can enrich the information obtained from page viewing and thus encourage customers to make more purchases, how does the improvement of page viewing quality influence the relationship between product page viewing and product returns is still unknown. Therefore, in order to understand the

---

1 Kurt Salmon (http://www.kurtsalmon.com/) is a consulting firm specializing in retail industry.
role of IT systems in reducing product returns, we further investigate: *How does the use of IT systems influence the relationship between product page viewing and product returns?*

To answer these two research questions, we used a unique clickstream data set from one of the largest e-commerce websites in China. The data set contains consumers’ browsing, purchase and return information, which adequately serves to examine the proposed relationship in our study. We employed a fixed effect logit model to test the research hypotheses. The preliminary results imply a counterintuitive relationship that more product page viewing actually leads to higher likelihood of product returns. Therefore, our study has the potential to contribute to the extant IS and marketing literature by unveiling how consumers’ pre-purchase product page viewing influences their product return behaviors. Practitioners can also benefit from this research in deciding how to economically invest IT systems to reduce product return rates.

**Literature Review**

Costly product returns have become a significant problem for most online retailers. Intuitively, the most common reason for product returns is because of product defects. However, the *Wall Street Journal* indicated that poor product quality was not even among the top three reasons for product returns at e-commerce websites (Lawton 2008). Instead, many other factors, for example consumer preference mismatch and company return policy, may account for the high return rates. In academia, most of the previous literature focused on the impact of return policy on product return rates. For example, Wood (2001) found that return policy leniency increased purchase rates and return rates for consumers in remote purchase environments. Moreover, Chu et al. (1998) indicated that nonrefundable return policy could effectively decrease customers’ abusive returns.

In addition to return policy, other researchers have examined the influence of consumers’ purchase behavior on their product return decisions. For example, Petersen and Kumar (2009) found that customers’ product return propensity was influenced by some buying characteristics, such as whether products were purchased as gifts, or as sales items, and whether the purchases were conducted on a new shopping channel. Moreover, Anderson et al. (2008) indicated that consumers’ return rates were positively related to the price they paid. In other words, consumers are more likely to return expensive products because of the high perceived value of these products. Furthermore, Hong and Pavlou (2014)’s study emphasized the effect of product fit uncertainty on product returns in online markets. They argued that consumers experiencing higher product fit uncertainty in buying process were more likely to return products.

However, besides the effect of return policy and purchase related characteristics on product returns, limited light has been shed on the relationship between customers’ pre-purchase behavior and product returns. To our knowledge, one example is Bechwati and Siegal (2005)’s study which examined how consumers’ product viewing behavior influenced return rates. In their paper, they conducted a lab experiment to show that consumers who viewed products in a comparative manner in the pre-purchase stage were more vulnerable to the post-purchase disconfirmation information, leading to greater return propensity. Another study which investigated the influence of consumers’ pre-purchase behavior on product returns was De et al. (2013)’s study. They examined how web technologies used at e-commerce websites during pre-purchasing stage affected consumers’ post-purchase return behavior. In the context of online shopping, since product page viewing is the one of the most important approaches through which consumers can obtain various types of information to reduce product uncertainty, we focus on the relationship between consumers’ pre-purchase product page viewing and product returns in this study.

**Theoretical Background and Hypotheses Development**

**Expectation-Disconfirmation Theory**

Expectation-Disconfirmation Theory (EDT) is one of the most widely used theories in consumer behavior research which explains consumer satisfaction and post-purchase behavior as a function of expectations, perceived performance and disconfirmation (Anderson and Sullivan 1993; Bhattacharjee 2001; Oliver 1980; Oliver 2010). The process of how customers form satisfaction and make post-purchase decisions in an EDT framework is as follows (Oliver 1980). First, customers form an initial expectation of a product in
the pre-purchase stage. Then, they evaluate the product and form perceptions about its performance upon receiving the product. After that, they compare the product performance with their pre-purchase expectation to determine the extent to which their original expectation is confirmed. When expected and perceived product performance do not match, consumers experience disconfirmation. Disconfirmation can either be negative in the case of a worse-than-expected product offering, or positive in the case of a better-than-expected outcome. Based on the extent of the disconfirmation, consumers may make post-purchase decisions such as whether to return the product.

In our research context, e-commerce differs from traditional offline commerce in terms of a delay in product delivery. This temporal separation of pre-purchase process and product confirmation process makes customers’ ex ante expectations play a more salient role in their satisfaction formation and post-purchase behavior, such as product returns (Hong and Pavlou 2014). Therefore, we leverage EDT as the theoretical foundation to investigate the relationship between product page viewing and product returns.

**Conflicting Relationship between Product Page Viewing and Product Returns**

Previous literature has suggested increasing pre-purchase page viewing behavior may have two counteracting effects on consumers’ return behaviors. Intuitively, more product pages viewed contain a potential larger choice set that increases the degree to which consumers’ preferences can be matched (Kuksov and Villas-Boas 2010). During the process of product page viewing, consumers gain more information about the product, including both search and experience attributes (Huang et al. 2009). The information from various product pages is combined when consumers evaluate the overall product set and determine the most preference matching item (Huang et al. 2009; Johnson and Russo 1984). In line with information theory (Shannon 1951), information gained during product page viewing helps mitigate product fit uncertainty. Since the decrease of product fit uncertainty lowers the likelihood of negative expectation disconfirmation, consumers are less likely to return the product when they viewed more product pages.

On the other hand, there is another school of reverse thoughts. Previous literature indicates that viewing more product alternatives will heighten consumers’ expectations about the choice matching their preferences (Diehl and Poylor 2010). Thus, they are more likely to have negative expectation disconfirmation due to the increased expectations. Specifically, viewing a larger product set allows customers to choose products more advantageously and gives them an impression about a better choice match (Simonson 1992). In addition, the alternatives in the product set have been revealed to offer a point of comparison for developing expectations about the targeted product (Taylor 1997). Consumers who have viewed more alternatives are more likely to have a better reference option to compare with the final purchased product (Bell 1985). They may also encounter more attractive product attributes and aggregate them as part of preferences to form a better “ideal” product (Chernev 2005; Dhar 1997). Under such circumstances, consumers’ expectations about the purchased product matching their preferences are increased after viewing more product pages. It in turn raises the likelihood of negative expectation disconfirmation, predicting a positive relationship between product page viewing and returns.

In order to address the conflicting relationship between product page viewing and product returns, we reviewed previous literature and found that contradictory to intuitions, viewing more pages might not necessarily lead to a better preference match (Diehl 2005; Griffin and Broniarczyk 2010; Moorthy et al. 1997). As suggested in the economics of information, the benefits of extra information becomes marginal after viewing a certain amount of products (Moorthy et al. 1997; Stigler 1961). Therefore, for consumers who purchased a product, the amount of product page viewing exceeding the threshold of making a purchase decision may only have the effect of increasing expectation of the product, but not enhancing consumers’ preferences match. Importantly, this effect might be even more salient when consumer selectivity (i.e., defined as consumers’ ability to distinguish the best preference matching option from the choice set) is reduced with more product pages viewed (Diehl 2005). Because more product page viewing reduces consumers’ cognitive resources (Gilbert 1989), when cognitive resources are low, consumers are less capable to process information accurately, which limits their ability to discern the superior products from the choice set (Martin et al. 1990).
To conclude, we argue that as product page viewing increases, the degree to which a consumer realizes better preference matches may not increase to the same extent as her expectation about the preference matching. The resultant higher likelihood of may lead to greater product return propensity as predicted in EDT. Thus we have:

H1. Consumers who viewed more product pages before purchasing are more likely to return the product.

**Moderating Role of IT System Usage**

As aforementioned, a consumer’s return behavior resulted from pre-purchase product page viewing attributes to 1) heightened expectations about the purchased product matching her preferences; and 2) the relatively low degree to which a consumer realizes preference matches. Therefore, the factors which affect these two mechanisms may have a moderating effect on the proposed relationship between product page viewing and product returns.

In the e-commerce context, previous research has revealed these two mechanisms can be influenced by consumers' increasing use of IT systems in both product screening and evaluation stages (West et al. 1999). In particular, during the product screening process, recommendation systems guide consumers to construct individual-specific choice sets and navigate them to products that provide better preference fit (Simonson 2005). In the product evaluation process, consumer usage of product-oriented technology in each product page is revealed to have significant influence on a customer’s expectation about the certain product (De et al. 2013). These evidences imply that the relationship between product page viewing and product returns can be moderated by consumer usage of these IT systems.

Hence, in this study, we introduce consumer usage of three IT systems, i.e., product recommendation systems, product visualization systems and consumer review systems, as moderators which may influence the relationship between product page viewing and product returns.

**Product Recommendation Systems**

Recommendation system is widely implemented in e-commerce websites to offer consumers products which probably match their preferences (Pereira 2001). It acts like a sales clerk in an offline department store who guides customers to find the products most matching their needs (Häubl and Murray 2006). In the online environment, product recommendation systems can provide consumers with real-time guidance about what products they may be interested in based on their browsing histories and preferences (Bucklin et al. 2002). During the process, recommendation systems perform resource-intensive information processing job to screen, narrow and sort the available product alternatives for online customers (Xiao and Benbasat 2007). Hence, consumers can free up some processing capacity in evaluating product alternatives and make better quality decisions (Häubl and Murray 2006; Häubl and Trifts 2000). Moreover, using recommendation systems enables customers to conveniently locate and pay attention to options matching their preferences, which increases the probability of finding preference matched items (Xiao and Benbasat 2007).

In addition, consumers’ preferences are concretized during the recommendation system use. Specifically, prior literature has revealed that online product recommendation systems induce product considerations that are more in line with consumers’ preexisting preferences (Dellaert and Häubl 2012). This makes consumers more certain about what they want and find the best preference match from the promising product option set (Dellaert and Häubl 2012). The higher probability of consumers’ preference match could attenuate the negative effect of page viewing on return behaviors. Hence, we posit:

H2: Frequent usage of recommendation systems attenuates the effect of consumers’ product page viewing on their return behaviors.

**Product Visualization Systems**

We focus on alternative photos as visualization systems that enable consumers visually experience product attributes which otherwise are difficult to learn (De et al. 2013; Dimoka et al. 2012). Alternative photos allow a consumer to look at the product from different dimensions. In a general e-commerce
website, this visualization system contains mostly factual information of how a focal product looks from the front, back and sides (De et al. 2013).

As suggested in the prior studies, consumption of this kind of factual information about a product makes customers have a more realistic pre-purchase expectation about that product (De et al. 2013). Specifically, alternative photos of different product dimensions convey a detailed and comprehensive product profiling, which helps a consumer have a better understanding of the product and confirm whether it matches her preferences (Hong and Pavlou 2014). This means that the gap between pre-purchase expectation and post-purchase product performance perception will be smaller (Anderson and Sullivan 1993). It in turn helps adjust the heightened expectations that preferences can be matched during more product page viewing process to a more realistic degree. Hence we propose:

H3: Frequent usage of product visualization systems attenuates the effect of consumers’ product page viewing on their return behaviors.

**Consumer Review Systems**

Online consumer review is an emerging source of product information with growing popularity and importance (Chen and Xie 2008). Online consumer reviews, as consumer-created information, are more relevant to customers than seller-created product description. While seller-created product information is more product oriented describing product attributes in terms of technical specifications, consumer reviews are more likely to be user oriented (Bickart and Schindler 2001). They describe product attributes in terms of usage conditions and measure product performance from users’ perspective (Bickart and Schindler 2001).

Previous literature has indicated that online consumer reviews help customers construct more realistic pre-purchase expectations that their preferences can be matched (Chen and Xie 2008). Consumer reviews are usually posted by users based on their experiences, which are influenced by their usage situations and idiosyncratic tastes (Chen and Xie 2008; Goh et al. 2013). According to Toulmin (2003)’s argument model, consumers may not only post “claims” whether the focal product matches their preferences (e.g., “the juicer is great for me”), but also the “grounds” (e.g., “it only takes half a minute to get fresh orange juice and cleaning it up just takes 1 minute”); “warrant” (e.g., “the juicer greatly saves my breakfast making time”); and “rebuttals” (e.g., “but the juicer may not be ideal for three people due to its limited size”). These personal product experience reviews help consumers match product attributes with their own preferences. Hence, customers are enabled to gain a deeper understanding of the product and form more realistic expectations that their preferences can be matched.

In our case, while more product page viewing heightens consumers’ expectations about preference match, their careful examination of other customers’ reviews could effectively make the expectations more realistic. Thus, we hypothesize:

H4: Frequent usage of consumer review systems attenuates the effect of consumers’ product page viewing on their return behaviors.

**Figure 1. Research Model**
Methodology

Data Description

The data for this study is obtained through collaboration with one of the largest e-commerce websites in China. The website provides a wide range of products covering most categories of kitchenware, electric appliances, digital products, food, accessories, apparel, etc. Consumers can explore these products freely with available assistance of the recommendation system. Recommended links would present in each of the consumer’s viewing pages based on her prior browsing histories and preferences. Moreover, in each product page, visualization system (i.e., alternative photos) and consumer reviews are provided for consumers to gain additional information on the focal product. As to product returns, the focal e-commerce company has a relatively lenient return policy with 15 days of unconditional returns.

The data set contains consumers' browsing information as well as their purchase and return records from June 1st to June 30th in 2012. During the period, we have consumers' browsing information, recorded as a sequence of URLs with timestamps and click actions. Therefore, we are able to get the full text and HTML content of each page through recapturing the web page by URL (Montgomery et al. 2004). Moreover, what links consumers have clicked within each page (e.g., alternative photos and consumer reviews) are also recorded for the reference of IT system usages.

We also have the order records of purchases and returns for each consumer. The order data contain information of customer unique identification, shopping session unique identification, transaction time, the price paid, and whether the item was returned. Here, a session is defined as “a period of sustained Web browsing or a sequence of page viewings” (Montgomery et al. 2004, p.581). In the focal e-commerce website, if a consumer has no page viewing in 20 minutes, the session is assumed to be ended, and the next page viewing starts a new session.

Model Specification

All the variables are operationalized at the session level. As to the dependent variable, product return is a binary variable in which 1 represents the product has been returned and 0 indicates the product is kept. There may be more than one purchased (or returned) product in a session. Since the dependent variable is a binary variable, we hire a panel logit model to analyze the proposed hypotheses. The model specification is as follows.

\[
Pr(Product\_Return = 1 | X ) = \Lambda \left( \alpha + \beta_1 \cdot Page\_viewed + \beta_2 \cdot Page\_viewed \times Recommendation + \beta_3 \cdot Alternative\_photo + \beta_4 \cdot Page\_viewed \times Consume\_review + \beta_5 \cdot Controls + \epsilon \right)
\]  

(1)

where \( \Lambda(x) = e^x / (1 + e^x) \), and \( \alpha \) captures unobserved consumer-specific effects.

The independent variable, product page viewing (page_viewed), is measured by how many product pages a consumer has viewed before purchasing a certain product at a shopping session. Specifically, we count the number of product pages one has viewed that are in the same category with the focal purchased (or returned) product.

For consumers' usage of recommendation systems (Recommendation), we calculate the percentage of product pages navigated from recommended links among all product pages viewed. Consumers’ usage of product visualization systems (Alternative_photo) is measured by the proportion of viewed product pages including actions of clicking alternative photos among all the product page views. In a similar vein, for consumer review system usage (Consumer_review), we calculate it as the percentage of viewed product pages including actions of clicking consumer review label among all the product page views. Clicking on the consumer review label enables shoppers to open the commenting session and read others’ reviews.

---

\(^2\) The company has requested to remain anonymous.
The control variables involve characteristics of products and consumers. From the product perspective, we include the actual price paid and the percentage of discount enjoyed which would influence product returns (Anderson et al. 2008). Someone may argue that different product types (i.e., search/experience goods) may have different levels of product fit uncertainty and require different degrees of involvement (Hong and Pavlou 2014). To address this issue, we use product category fixed effect model to control for the influence of different product types. We do not include product return leniency as a control variable since the focal e-commerce website implements a flat return policy across all product types. From the consumer perspective, we control for customers’ familiarity with the website using the number of their previous visits. At last, date dummies are also included in the model to control for the time effect.

**Preliminary Results**

We used a sample of 58,384 consumers with 91,552 products purchased, among which 5,791 products were returned. The average return rate was 6.3%, and the average number of product pages viewed is 5.9. Table 1 reports the descriptive statistics of the variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return</td>
<td>0.063</td>
<td>0.243</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Page_viewed</td>
<td>5.901</td>
<td>8.919</td>
<td>1</td>
<td>275</td>
</tr>
<tr>
<td>Recommendation (%)</td>
<td>0.054</td>
<td>0.164</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Alternative_photo (%)</td>
<td>0.268</td>
<td>0.316</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Consumer_review (%)</td>
<td>0.038</td>
<td>0.132</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Price_paid (per item)</td>
<td>873.765</td>
<td>1448.207</td>
<td>0</td>
<td>43999</td>
</tr>
<tr>
<td>Discount (%)</td>
<td>0.178</td>
<td>0.315</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Total_visit_number</td>
<td>18.634</td>
<td>46.710</td>
<td>1</td>
<td>1226</td>
</tr>
</tbody>
</table>

Table 2 reports the correlations among all the interested variables. As indicated in Table 2, the correlations between three moderators (i.e., usage of recommendation systems, alternative photo viewing and consumer review reading) and the independent variable (i.e., product page view number) are weak (i.e., <0.10). This validates the following analysis of moderation effect.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Return</th>
<th>Page_viewed</th>
<th>Recommendation</th>
<th>Alternative_photo</th>
<th>Consumer_review</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Page_viewed</td>
<td>0.048</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recommendation</td>
<td>0.011</td>
<td>0.088</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alternative_photo</td>
<td>0.014</td>
<td>-0.075</td>
<td>-0.057</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Consumer_review</td>
<td>0.011</td>
<td>-0.010</td>
<td>0.018</td>
<td>0.051</td>
<td>1</td>
</tr>
</tbody>
</table>

We tested H1 in this research-in-progress paper. In order to eliminate the unobservable individual effects, we employed the fixed effect logit model in Stata 12.0. The result suggests that consumers’ product page viewing has a positive effect on product returns (i.e., \( \beta = 0.0176, p < 0.01 \); No. of Customers=1520 and No. of observations=7159). That means, 1 more product page viewed increases the product return probability.

\(^3\) Note that the number of observations in FE Logit significantly drops as the model requires within-subject variation in dependent variables (Wooldridge 2010).
by 1.78% (i.e., its log odd ratio is 0.0176). Hence, H1 is supported. Other hypotheses will be tested in the complete paper.

**Conclusion**

In this study, we investigate a conflicting relationship between consumers’ product page viewing and their product return behaviors. Contradictory to intuitions, our preliminary results show that more product page viewing actually leads to higher likelihood of product returns. This research has the potential to make both theoretical and practical contributions. Theoretically, first, we enrich the understanding of customers’ return behaviors by unveiling the influence of consumers’ pre-purchase product page viewing on returns. While extant return literature only focuses on the focal purchased product (De et al. 2013), we incorporate the effect of all product pages viewed before purchasing on consumers’ return behavior. Second, we further investigate the moderating role of three IT systems which may influence the relationship between page viewing and product returns. This implies consumers’ product page viewing would have different levels of impact on returns with different IT system usage. Moreover, through examining the moderation role of consumer IT system usage, our study also contributes to the literature of recommendation systems, product visualization systems and consumer review systems by revealing their effects on product returns. Third, this is the first empirical study using consumers’ real browsing data and purchase data to examine the relationship between page viewing behavior and product returns. From a managerial aspect, the future findings of this research help e-commerce firms decide how they should economically invest in IT systems to make consumers’ page viewing more efficiently and reduce product return rates.
References


